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APPLIANCE PURCHASE AND USAGE ADAPTATION TO A PERMANENT TIME OF DAY ELECTRICITY RATE SCHEDULE

by

Jerry A. Hausman, MIT

and

John Trimble, ORNL

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Section I: Introduction

To date, about 15 times of day (TOD) electricity pricing experiments or demonstrations have been conducted.[1] Three of the experiments are still ongoing; the rest were of typically limited duration of 1-3 years. All social and economic experiments suffer from problems of limited duration in the interpretation of their results. For instance, Hausman (1982) discusses potential duration effects in the negative income tax experiments. In the Seattle-Denver NIT experiment where duration effects can be measured, he finds a significant difference in response according to the known duration of the experiments for different groups. In the TOD electricity rate experiments a further problem occurs beyond pure duration effects. Since almost all electricity use takes place in conjunction with durable appliance use, a short run experiment is unlikely to induce a significant change in household durable holdings. Thus, at best the experiments are valuable in estimation of the Marshallian short run response where the capital stock is held fixed. In Connecticut where the designers recognized this problem and offered a buy-back provision for durables, no household response in terms of appliance purchases was forthcoming. Given the transitory nature of experiments, this outcome is not surprising. Also we would not expect appliance stores and electrical contractors to respond to

[1] Recent summaries of the results are contained in Aigner (1981), Hill et. al. (1979) and Miedema and White (1980).

a shift among a small segment of the population where the shift is known to be transitory.

Other problems which also occur with the TOD rate experiments are their voluntary nature or their use of incentives systems which attempt to cause the net effect of TOD prices to be revenue neutral. Aigner (1981) discusses these issues for the TOD experiments. Aigner-Hausman (1980) find that the estimated price elasticities can change significantly when the incentive schemes are accounted for. Since under the provisions of the National Energy Act utilities must produce a framework for TOD price schedules, a public interest in TOD rate schedules seems likely to continue.

In this paper we investigate the effects of a permanent TOD rate schedule. At the Central Vermont Public Service Corporation (CVPSC), optional TOD rates have been offered since January 1976. The TOD rate schedule is not an experiment, but it is expected to continue indefinitely by the utility and presumably by its customers. The CVPSC customers face one of three price schedules for electricity. The details are given in Table 1. The standard rate schedule is an inverted block structure. It consists of a fixed monthly charge of $6.91 with an initial block price of 3.10¢ per kwh. Beyond 200 kwh per month the price increases to 7.92¢ per kwh. The major alternative for the household is to choose TOD rates. The TOD rate schedule consists of a fixed charge of $9.02 per month and two prices for peak and off-peak usage. Peak prices are charged for two periods during the day which total 7 hours and for which the price is 14.636¢ per kwh. The off-peak price is 2.649¢ per kwh. The winter months are the peak season with TOD prices in effect from January 1 to April 30. During the non-winter months, the TOD rate structure reverts to that of the conventional rate although the price charged is lower. An initial fee of $25 is made for the signalling equipment. The other major alternative is the all electric rate which continues a fixed charge of $13.83 per month with a rate of 5.570¢ per kwh. The all electric rate is no longer offered to new customers.[1]

Table 1. CVPSC Residential Electricity Rates

		Winter Rates		
Customer	Fixed Change	Peak	Off-Peak	Summer Rates
Conventional	$6.91	-	3.10¢, 7.92¢	3.10¢, 3.52¢
TOD	$9.02	14.636¢	2.649¢	2.649¢
All Electric	$13.83	-	5.570¢	2.667

As of 1980 approximately 900 or 1% of all CVPSC residential accounts had chosen TOD rates. About 70% of the total are formerly all electric customers. The savings among TOD customers are significant. Basic-use TOD customers average annual expenditure is about 43% less than conventional rate—households. The total electric TOD customers paid an average of 66% less per kwh than did conventional rate customers. Annual savings of $300-500 are not

[1] Two other rate schedules combine the conventional rate with special rates for electric water heaters and electric storage heat. We account for these schedules in our demand estimations in Section 4.

uncommon. In 1980 a survey was made of a sample of CVPSC customers. Sample design considerations are given by Hausman and Trimble (1980). A stratified random sample was made for non-TOD customers together with a suvery of all TOD customers. The survey information was combined with usage data for the years 1979-1980. In this paper, we analyze part of the data from the survey along with the usage data.

While a study of permanent TOD electricity usage has many advantages over a TOD experiment, certain shortcomings should be recognized. First, the ability to transfer our results to other areas is severely limited by the fact that Vermont has a winter peak while the great majority of areas have a summer peak. Household response is expected to be quite different since non-electric alternatives to electric heat during the winter, e.g., wood heat, are probably greater than alternatives to air conditioners. On the other hand, the ability to adapt to temperature fluctuations is less in the winter than in the summer. Second, since the choice of TOD is voluntary, our estimates must adjust for the self-selection aspect of the data. We adjust for self-selection in our estimation. Lastly, cross price elasticities for peak and off-peak usage cannot be estimated since all TOD users face the same rates. In some of the experiments the rates were varied across households to permit estimation of these cross price effects. Still, the main advantage of permanent TOD data is evident here. We find a significant response of households to TOD rates through appliance purchases. For instance, about 60% of our sample have purchased a timer to control hot water use and about 50% have purchased a timing device for household heating. We also find that these devices have a significant effect on both peak and off-peak usage shares and also total electricity consumption. Thus, the potential long term effects of TOD rate schedules are found. Furthermore, if a significant proportion of U.S. households were on TOD rate schedules the response might be expected to increase since appliance manufacturers would offer a broader range of durables to take advantage of the differential TOD rates.

The plan of the paper is as follows. In Section 2 we estimate a model of appliance purchase behavior by TOD rate customers. We focus on three appliances, all of which are timers that allow households to take direct advantage of the large differential in TOD rates. In Section 3 we develop a model of choice of TOD and electricity usage. In Section 4 we estimate the choice and usage model for both TOD and non TOD households. In all three sections we find that the availability of permanent TOD rate schedules has an important influence on household behavior.

II. Appliance Choice with Time of Day Prices[1]

Currently used econometric models of appliance choice consider the tradeoff between the initial cost of an appliance and its operating cost which depends on the electricity price faced by the household. Intended utilization which may depend on socioeconomic factors and weather conditions as well as the cost per unit of output of the appliance enters the choice process, and it is affected by both the appliance characteristics and the price of electricity. Thus, in his model of air conditioner choice, Hausman (1979) used the size and efficiency (EER) of the air conditioner model, the initial cost of the air conditioner, the marginal price of electricity, and the number of cooling degree days faced by the consumer.[2] He found that utilization is affected by cost per unit of output and by weather. In turn, the appliance choice depended on utilization and the initial cost of the appliance. Hausman also found that consumers used a relatively high implicit

[1] The analysis here is based on Hausman (1980b) in which a complete model of the process is discussed. However, data limitations precluded the use of the model in the current situation. Therefore, we outline the main considerations and then fit a less elaborate econometric specification.

[2] Even with non time of day prices for electricity a problem arises in defining the appropriate price of electricity due to the existence of declining block rate price schedules. Hausman, et. al. (1979) derive appropriate procedures for this problem. However, it is not clear that consumers may react to the average price rather than the marginal price of electricity. Dubin (1980) attempts to distinguish between the response to marginal or average prices for electricity by households.

discount rate in making the tradeoff between initial purchase price and the operating costs of the different air conditioner models. Recently, Dubin and McFadden (1983) have analyzed the choice of appliance for a model of space heat and water heat appliance choice along with the utilization of these appliances. They consider the choice between electricity and natural gas appliances and estimate a logit model on a subset of households who use one of the two fuels exclusively. Their results indicate that the tradeoff between operating costs and initial capital cost is the primary factor in household choice. Furthermore, they also find evidence of a high implicit discount rate with a similar range to Hausman's findings for the choice of air conditioners.

We would now like to consider how econometric models of appliance choice might differ with time of day (TOD) electricity prices. The important change is that a single price of electricity no longer exists. The operating cost of the appliance will depend on the time of day that utilization occurs. Substantial changes in appliance choice may result from introduction of time of day prices. Consider the case of air conditioner purchase under a 2-price TOD system.

Suppose that the peak rate is charged from 8am-8pm during the summer months with off peak prices charged during the remainder of the day. Also suppose that the ratio of peak to off-peak price is large since the ratio has varied from about 5 to 16 in the TOD experiments which have been conducted. With utilization held constant the immediate effect of TOD prices on appliance choice would be to cause a shift to much more energy efficient air conditioners. Currently available home air conditioning systems do not permit storage of cooling capacity, so that during utilization the electricity price faced by the household would rise substantially. The higher price results from the fact that air conditioners (which cause the summer peak) are used primarily during the hours of the day when peak prices occur. A crude utilization weighted average price of electricity would probably be about 4 times higher than the current marginal electricity price so that the tradeoff toward more efficient air conditioners, e.g., those air conditioners with higher EER, would be more favorable despite their higher initial purchase price.

But when utilization is permitted to change an effect occurs in the opposite direction. Suppose because of the higher TOD peak prices during the hottest part of the day that the consumers raise the thermostat setting by five degrees. Then the utilization of the air conditioner will fall by a factor of about one-fourth. The optimal consumer choice would then be a <u>less</u> energy efficient air conditioner than he would otherwise have chosen with utilization held constant. In fact, if intended utilization falls by a sufficient amount it is possible that the consumer would choose a <u>less</u> energy efficient appliance under TOD prices than under constant electricity prices. The sum total of these two opposite effects can only be determined using empirical estimates of consumer demand. On a priori grounds it is impossible to say which effect will dominate. Thus, it is important to recognize that while the consumer faces a higher simple average price of electricity, it is not necessarily the case that he will choose a more energy efficient appliance. It is safe to assume that the consumer will utilize his appliance less during peak electricity periods, but the type of appliance he buys depends both on the initial capital cost and a utilization weighted average cost of electricity. We need to know how utilization of the appliance will change with the introduction of TOD prices to analyze how appliance choice will be affected.

In the survey of permanent TOD customers in Vermont, we focus on three appliances which are purchased primarily because of the large differences in electricity prices between peak and off-peak periods. These appliances are: (1) timers for heaters (2) timers for water heaters and (3) timers for refrigerators. The timers can be bought separately or can be installed together as part of a control panel which costs approximately $300. They also can either be of the set-back type for heat or of the type which completely turns off an appliance such as the water heater or the refrigerator. TOD prices are used in Vermont only during the winter and consist of a three-hour period in the morning which occurs between 7a.m. and 12 noon and a four-hour period between 4p.m. and 10p.m.[1] The ratio of peak to off-peak price is about 6.25 to 1.

Thus, some household choose to heat by an alternative source during peak hours (mainly wood) or to turn off the electricity to the appliance altogether during peak hours and presumably limit use as with refrigerators. It is interesting to note that it may well be 'energy inefficient' in terms of kWh's consumed to turn off a regrigerator for a seven hour period each day. But from a household's point of view and from the electric utility's cost point of view, this outcome may be the correct response to the economic incentives which arise from TOD electricity prices.

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[1] The periods are staggered across households.

We now estimate a multivariate probit model to determine household characteristics of TOD customers who purchase these timers. The estimated probabilities are also required for the usage equations which we estimate in later sections. Given the diversity in the types of timers and the lack of knowledge of operating cost since individual appliances are not metered as with the data set that Hausman (1979) used in his non-TOD study, we do not estimate a model of the tradeoff between purchase price and operating cost. Instead, we focus on household characteristics to see how adaptation to TOD prices has occurred. The probit model takes the form

$$(2.1) \qquad u_{ij} = X_{ij}\beta_j + \varepsilon_{ij} \quad \text{for i=1, N household and j=1,3 appliances.}$$

The latent 'utility' variable u_{ij} is assumed to be positive if household i purchases appliance j and negative otherwise. The joint density of the ε_{ij} is assumed independent across households with a trivariate normal density of mean zero and correlation matrix

$$(2.2) \qquad V\begin{pmatrix}\varepsilon_{i1}\\ \varepsilon_{i2}\\ \varepsilon_{i3}\end{pmatrix} = \begin{bmatrix}1 & & \\ \rho_{12} & 1 & \\ \rho_{13} & \rho_{23} & 1\end{bmatrix}$$

We would expect to observe positive correlations given the technology of control panels. For household i define $y_i = (y_{i1}, y_{i2}, y_{i3})$ where each $y_{ij} = 1$ indicates timer j is owned and $y_{ij} = -1$ indicates that it is not owned. The joint probability of ownership is then

$$(2.3) \qquad pr(y_i | X_{i1}, X_{i2}, X_{i3}) = pr(u_{ij}y_{i1} > 0,\ u_{i2}y_{i2} > 0,\ u_{i3}y_{i3} > 0)$$

$$= (y_{i1}y_{i2}y_{i3}) \int_{y_{i1}(x_{i1}\beta_1)}^{y_{i1}\infty} \int_{y_{i2}(x_{i2}\beta_2)}^{y_{i2}\infty} \int_{y_{i3}(x_{i3}\beta_3)}^{y_{i3}\infty} \phi(u,u_2,u_3;(y_{i1}y_{i2})\rho_{12})$$

$$(y_{i1}y_{i3})\rho_{13}, (y_{i2}y_{i3})\rho_{23})\, du_1 du_2 du_3$$

where ϕ is the standardized trivariate normal density. Maximum likelihood is used to estimate the unknown β_j's and ρ_{ij}'s with the trivariate normal distribution evaluated by means of an algorithm of Daley (1975).

We estimated the probit model on a sample of 151 TOD households for whom we also had TOD usage data and who were year-round Vermont residents.[1] Of these 151 households 59 had purchased timers for electric heat, 89 households had purchased timers for water heaters, and 16 had purchased timers for their refrigerators. Table 2 gives the 3x3 table of appliance holdings and a clear pattern of non-independence is present

In Table 3 we present estimates of the multivariate probit model. As expected, the most important factor in purchasing a timer is the use of the appliance as either a primary heat source or as a water heater. Income does not seem an important determinant of purchase behavior except for the case of the refrigerator timer where the coefficient is both large and precisely

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[1] We eliminated vacation homes from the analysis since clear indications exist that both their appliance choice behavior and usage patterns differ significantly from year-round residents.

Table 2

	Heat	Hot Water	Refrigerator	All	Total
Heat	6 .040	46 .305	1 .007	6 .040	59 .391
Hot Water	46 .305	30 .199	7 .046	6 .040	89 .589
Refrigerator	1 .007	7 .046	2 .013	6 .040	16 .106

estimated. Households who rent are less likely to purchase the timers although we do not measure the effect very precisely. Years on TOD rates does not seem an important factor in purchase behavior. Also, households which heat primarily with wood are much more likely to purchase a hot water timer presumably since they have an alternative source of hot water during peak hours. We also find very significant correlation among the stochastic terms with ρ_{12}, for example, estimated to equal .736. Thus households may well organize their living patterns to take advantage of the cost savings that the timers permit. Lastly, note that the χ^2 test against only a constant in each of the 3 equations is found to be very significant.

In this section we have discussed how appliance purchases can be altered by the introduction of TOD electricity rates. Our data indicate in Vermont where a permanent TOD rate schedule has existed for 5 years that a significant proportion of the population have altered their appliance holdings to take advantage of the TOD rates. This finding is in contrast to the many TOD experiments where little or no change in appliance holdings is observed even when financial incentives were offered to counteract the short term aspect of the experiment. We now use our estimated probit model of appliance holdings to investigate how electricity usage is altered, both by the existence of TOD rates and by purchases of the timers. Given the permanent character of Vermont TOD rates, we hope to find the long run response which might occur is permanent TOD rates were adopted more widely.

Table 3: Multivariate Probit Estimates (with asymptotic standard errors)

Variable	Heat	Water Heat	Refrigerator
1. Constant	-1.04	-1.18	-4.68
	(.945)	(.781)	(1.43)
2. Log income (1000's)	-.161	.131	.593
	(.207)	(.178)	(.287)
3. Electric Heat Primary	1.07	-	-
	(.330)		
4. Northern Vt.	.257	-.285	-
	(.427)	(.415)	
5. Electric Water Heater	.248	.804	-
	(.438)	(.384)	
6. Rents	-.246	-.468	-
	(.927)	(.401)	
7. Years on TOD rates	.058	-.046	.099
	(.106)	(.103)	(.159)
8. Number of adults	-	.203	.637
		(.150)	(.358)
9. Wood heat primary	.038	.452	-
	(.303)	(.226)	

ρ_{12} = 736 (.094) ρ_{13} = .321 (.282) ρ_{23} = .416 (.219)

OBS = 151 log LF = -210.0 χ^2_{17} = 73.6

III. Peak Usage and Prices for TOD and Non-TOD Customers

How well do the TOD households adjust to the large difference in peak and off-peak prices? As the rate schedules in Table 1 indicate, TOD households pay 2.649¢ per off-peak kwh and 14.636¢ per peak kwh. The conventional rate is 7.92¢ per kwh beyond 200 kwh per month. Significant expenditure savings are possible if the household alters its behavior to take advantage of the off-peak TOD rate; in fact, large savings are made by the TOD households. Here we would like to estimate a model of peak and off-peak usage by TOD households to find how their adaptation depends on household characteristics, income, and appliance holdings.

In this section we construct an integrated model which has three characteristics with respect to household electricity consumption: (1) choice of TOD or non-TOD rates, (2) household expenditure for electricity consumption, (3) household consumption of peak and offpeak electricity. As we explained before, Vermont is unique in the sense of a permanent TOD rate schedule for the past 5 years. Heuristically, households will choose the TOD rate schedule if they are better off under such a plan. But this decision depends on their expenditure pattern and prevailing TOD and non TOD electricity prices. Our model is a 'two level' model of electricity consumption. The lower level estimates a conditional demand function to determine peak and off peak electricity consumption as a function of TOD electricity prices and total electricity expenditure. But in contrast to previous research on TOD experiments, our conditional demand functions are not assumed to be homothetically separable. Atkinson (1979), Hausman et al. (1979), and Caves and Christensen (1980) among others have previously estimated conditional homothetic demand functions for peak and offpeak consumption. However, the homotheticity assumption seems unduly restrictive so we specify instead a generalized Gorman polar form (GGPF) at the lower level which dispenses with the homotheticity assumption.[1] Instead we test for homotheticity given our empirical estimates.

Two stage budgeting then requires an additively separable utility function at the upper level of the utility model. We use the Stone-Geary LES system which for a two good upper level, consisting of a composite good and electricity expenditure, is not unduly restrictive. One price index which arises from the lower level determines electricity expenditure at the upper level. This index along with a second price index which arises from the GGPF determine the household choice of TOD or non TOD rate schedules. Since the three levels of the model, TOD choice, electricity expenditure, and peak and off-peak consumption, are derived together we pay especially close attention to the stochastic specification of the model. Rather than including additive error terms in each equation as is the custom of most demand analysis, we include the stochastic terms in the original utility specification.

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[1] Kohler (1983) has recently claimed that the choice of homothetic separable function forms has led to spurious results in the TOD experiments. Parks (1983) demonstrates the mistake in Kohler's results. Nevertheless, the homotheticity assumption can be removed.

The stochastic disturbances then enter the model in a natural way with important implications for both interpretation and estimation. Since we estimate the model by maximum likelihood, the stochastic disturbances have an important role both in model specification and estimation.

In the analysis of electricity consumption, a separability assumption is usually required by the data. Since customers in a given service area face identical prices for other goods, we cannot estimate the effect of other prices on electricity consumption in a given cross section of data. Even with panel data over a few years, it is unlikely that sufficient price variation will exist to permit estimation of nonelectricity price effects. Beyond this form of separability, it is convenient to impose two stage budgeting as a further assumption. It has been the empirical finding of researchers in the field that significantly better results arise from estimation of conditional demand functions for peak and offpeak consumption than from unconditional demand functions.

The form of the utility function for our model is

$$(3.1) \qquad u = f(x_1, f_2(x_2))$$

where peak and offpeak electricity consumption enter the vector x_2 and are separable from the composite commodity x_1. For two stage budgeting we consider the conditional expenditure function for budget stage 2[1]

$$(3.2) \qquad e(p_2, u_2) = \min_{x_2} \{ p_2 x_2 | f_2(x_2) > u_2 \}$$

[1] This topic is discussed by Gorman (1971), Blackorby, et al. (1978), and Deaton and Muellbauer (1980).

where p_2 are prices in budget stage 2. The overall expenditure function takes the form

$$(3.3) \qquad e(p_1,p_2,u) = \min_{x_1,u_2} (p_1x_1 + e_2(p_2,u_2) | f(x_1,u_2) \geq u)$$

so that 'quantity' of utility chosen in sector 2

$$(3.4) \qquad u_2 = \tilde{u}_2(p_1,p_2,u)$$

is a function of all prices. In the special case of homothetic separability the conditional expenditure function of equation (3.2) takes the form $e_2(p_2,u_2) = u_2\Pi_2(p_2)$ so that the overall expenditure function of equation (3.3) specializes to $e(p_1,\Pi_2(p_2),u)$ where $\Pi_2(\cdot)$ serves as a price index for budget stage two prices. The quantity index which corresponds to the homothetically separable form of equation (3.4) is derived by the use of Sheppard's lemma

$$(3.5) \qquad u_2 = \frac{\partial e(p_1,\Pi_2(p_2),u)}{\partial \Pi_2} .$$

We then have price and quantity indices in the sense that expenditure on group 2, $y_2 = \Pi_2(p_2)\cdot u_2 = \Pi_2(p_2)f_2(x_2)$. This derivation which is close to Hausman, et al. (1979) leads to a very convenient econometric specification, but it has the unacceptable implication that the conditional expenditure elasticity of all quantities in x_2 is unity. We now relax this assumption by moving to a generalized Gorman polar form (GGPF) for the lower level utility function.

We drop the use of homothetic separability but maintain the separability assumption of equation (3.1). Instead of assuming homothetic separability we substitute equation (3.4) into the conditional expenditure function of equation (3.2) to determine total expenditure on electricity to be

$$(3.6) \qquad y_2 = p_2x_2 = e_2(p_2,u_2) = \tilde{g}(p_1,p_2,u)$$

where u_2 is the maximum level of utility for budget level 2. Equation (3.6) demonstrates that without a further assumption the upper level budget decision will depend upon all prices. However, the existence of a price index for budget level 2 would permit equation (3.6) to take the special form

$$(3.7) \qquad y_2 = g(p_1,\Pi_2(p_2),y)$$

so that electricity expenditure would now depend on overall family income y and the price index for electricity expenditure. Therefore, we drop the requirement of a quantity index and instead use the Gorman conditions to write the utility function of equation (3.1) in additively separable form

$$(3.8) \qquad f(x_1,x_2) = \tilde{f}(f_1(x_1) + f_2(x_2))$$

where the conditional indirect utility function takes the Gorman generalized polar form

$$(3.9) \qquad v_2(p_2,y_2) = \tilde{v}_2(y_2/\Pi_2(p_2)) + \Lambda_2(p_2)$$

and where the function $v_2(\cdot)$ is 'quasi-homothetic' only because of the fixed cost, or committed expenditure term $\Lambda_2(p_2)$. The utility maximization problem then becomes

(3.10) $$\max u = \tilde{f}(\sum_{i=1}^{n} \tilde{v}_i(y_1/\Pi_i(p_i)) + \sum_{i=1}^{n} A_i(p_i)) \text{ s.t. } \sum_{i=1}^{n} y_i = y$$

for the general case of n sectors. Note that the $\sum A_i(p_i)$ drops out of the maximization but its role is important since it allows for nonlinear within group expenditure elasticities because of its role as a fixed cost. While the additivity assumption is certainly strong in the n sector case, c.f. Deaton and Muellbauer (1980), in the 2 sector case its implications are much weaker, especially when sector one is comprised of a Hicksian composite commodity. We now apply the Gorman solution to the TOD electricity demand situation.[1]

For the lower level GGPF specification of conditional demand of equation (3.8) we choose a GGPF with price indices which are close to the indices of the AIDS specification of Deaton and Muellbauer (1980). Note we only observe the lower level demands for TOD households. Let p_{21} denote the peak price p_{22} denote offpeak price and p_{23} denote the non-TOD price. The overall price index for committed electricity expenditure is $A(p_2) + p_{21}\varepsilon + p_{22}\varepsilon_2$ where the deterministic part takes the second order flexible functional form

(3.11) $$\log A(p_2) = \alpha_o + \alpha \log p_{21} + (1-\alpha) \log p_{22} + \frac{\gamma}{2} (\log \frac{p_{21}}{p_{22}})^2 .$$

The second price index for uncommitted electricity expenditure is

[1] Anderson (1979) has applied the GGPF to a 16 good demand system on aggregate data with 4 groups using an 'additive perfect price aggregation' (APPAM) model. Poirier and Melino (1982) have proposed application of the APPAM model to TOD data. Our model is more general than APPAM since it is second order flexible while th APPAM model is first order flexible. Our treatment of the stochastic disturbances is also somewhat more rigorous than the APPAM approach.

$$(3.12) \quad \log B(p_2) = \beta \log p_{21} + (1-\beta)\log p_{22} + \frac{\theta}{2}\left(\log \frac{p_{21}}{p_{22}}\right)^2.$$

Note that for non-TOD households $B(p_2) = p_{23}$, and $A(p_2) = e^{\alpha_o} p_{23}$ where α_c determines committed demands. Given the stochastic specification and choice of price indices peak period electricity expenditure takes the non-linear in parameters form

$$(3.13) \quad p_{21}x_{21} = A(p_2)\left(\alpha + \gamma \log \frac{p_{21}}{p_{22}}\right) + \left(y_2 - A(p_2) - p_{21}\varepsilon_1 + p_{22}\varepsilon_2\right)\left(\beta + \theta \log \frac{p_{21}}{p_{22}}\right) + p_{21}\varepsilon_1$$

which depends on total electricity expenditure y_2 and prices p_2, but not on the composite commodity price p_1 or total household income y. Note that equation (3.13) is not homothetic because the first term represents committed expenditure while the second term represents uncommitted expenditure. The stochastic term ε_1 arises in committed peak period demand while ε_2 arises from committed offpeak period demand. Given peak period expenditure in equation (3.12), offpeak period consumption follows from the adding up restriction $p_{21}x_{21} + p_{22}x_{22} = y_2$.

We now move up to the top level to determine electricity expenditure. Because of the additive separability assumption required for the two-level budgeting in equations (3.8) and (3.10), we are severely limited in appropriate functional forms. We choose the Stone-Geary LES which is second order flexible given the existence of 2 sectors for the composite commodity and electricity expenditure. For non TOD households electricity expenditure is determined by

$$(3.14) \quad y_2 = \delta(y - C) + (1 - \delta)\,(A(p_2) + p_{23}(\varepsilon_1 + \varepsilon_2))$$

where C is committed nonelectricity expenditures and p_{23} is the non TOD price which varies across households. The first term of equation (3.14) corresponds to uncommitted expenditure while the second term corresponds to committed electricity expenditure. Note how the sum of the stochastic terms enters the total expenditure equation as would be expected. For TOD households total electricity expenditures has an additional term which arises from fixed costs, F, which include timer purchases and 'habit changes'. The equation for total electricity expenditure for TOD households is

$$(3.15) \quad y_2 = \delta(\,y - C - (F + \varepsilon_F)) + (1 - \delta)(A(p_2) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2)$$

where fixed costs are allowed to vary in the population according to the stochastic term ε_F.

From our specification of the two levels of electricity demand and expenditure we derive the indirect utility function where we normalize the price of the composite commodity to be unity. Let q denote a dummy variable for choice of TOD and the indirect utility function is

$$(3.16) \quad v(p_2,y) = y - C - (A(p_2) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2) - q(F + \varepsilon_F)/B^{\delta}(p_2)$$

where $A(p_2) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2$ is the price index for committed expenditures and $B(p_2)$ is the price index for uncommitted expenditures. Note that equation (3.16) has the LES form. The expenditure equations follow from application of Roy's identity to equation (3.16). The choice equation for TOD is then calculated to be

$$(3.17)\quad pr(TOD) = pr[y - C - (A(p_T) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2) - q(F + \varepsilon_F))/B^\delta(p_T) > (y - C - (A(p_N) + p_{23}(\varepsilon_1 + \varepsilon_2)/B^\delta(p_N)]$$

where p_T and p_N stand for TOD prices and non TOD prices respectively. Note that instead of a 'reduced form' probit choice equation, the choice model of equation (3.17) is fully integrated with the demand models. The choice model may be further considered for δ very small so that $B^\delta(p_T) \approx \beta^\delta(p_N) \approx 1$ the utility comparison becomes

$$(3.18)\quad A(p_T) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2 - F - \varepsilon_F \gtrless A(p_N) + p_{23}(\varepsilon_1 + \varepsilon_2)$$

so the choice depends essentially on the price index for committed expenditure and fixed costs. Therefore the price index from the lower level of the two stage budgeting procedure has an important role to play. Furthermore, it simplifies the model because it provides the connection between cost minimization and utility maximization in our model of TOD choice and electricity demand.

IV. Choice of Service and Usage for TOD and Non-TOD Households

In this section we examine choice of TOD, total usage patterns by both TOD and non-TOD households. The data consists of 132 TOD households and 206 non-TOD households, and peak demand by TOD households. The usage data are one reading for each household during the period January-April 1980 when the winter TOD rate schedule is in use. Since most households are in a two month billing cycle, their readings will be for either January-February or February-March. We attempt to adjust for the difference in months by including heating degree days in our usage equations. Two types of exceptional readings exist. A small number of households are on a 30 day billing cycle. We adjusted these household readings to reflect a 60 day bill. Another small group of households had missed a reading and so the reading was for greater than sixty days. We again adjusted the readings for a 60 day bill. Thus, all our estimated coefficients should be interpreted on a two month reading basis.

TOD households use substantially more electricity than do non-TOD households. Average bimonthly TOD usage in our sample is 4224.9 kwh which with the average TOD price of 4.56¢ per kwh comes to $192.85. When the $9.02 per month fixed charge is included, the mean bimonthly bill is $210.89.[1] Average bimonthly non-TOD use is 1165.9 kwh in the sample. At the mean price of 6.27¢ per kwh plus the fixed charge of $6.91 per month the average bimonthly bill in the sample is $86.92.[2] Note that in a crude sense that higher

[1] This rather high amount reflects the fact that about 76% of TOD households use electric heat.

[2] Actually, the all electric rate needs to be accounted for here also. We do so in our estimation, but here attempt to keep the example straightforward by only considering the two primary rate schedules.

usage goes with a lower price. But since households choose to go on the TOD rate schedule, it seems incorrect to combine both sets of households onto a single rate schedule. Some households probably choose TOD rates, and the possibility of substantially lower prices, because they are large users with electric heat. Therefore in estimating the demand functions and associated price indices we must account for underlying differences in households, especially with respect to electric heat.

To estimate the model we first derive the likelihood function which corresponds to equations (3.11)-(3.17). The model consists of three basic equations which we repeat here. First, the household chooses TOD prices from the choice equation if

$$(4.1) \quad y - C - (A(p_T) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2) - q(F + \varepsilon_F)/B^{\delta}(p_T) > (y - C - (A(p_N) + p_{23}(\varepsilon_1 + \varepsilon_2)/B^{\delta}(p_N)$$

where $A(p_T)$ corresponds to the first price index for time of day prices and $A(p_N)$ is for non-TOD prices. This index corresponds to committed expenditure while the second price index $B(\cdot)$ corresponds to uncommitted expenditure. The variables F stands for fixed costs while q is an indicator variable for TOD. The next equation is expenditure on electricity and differs for the TOD and non-TOD households:

$$(4.2.a) \quad y_2 = \delta(y - C - (F + \varepsilon_F)) + (1 - \delta)(A(p_T) + p_{21}\varepsilon_1 + p_{22}\varepsilon_2)$$

$$(4.2.b) \quad y_2 = \delta(y - C) + (1 - \delta)(A(p_N) + p_{23}(\varepsilon_1 + \varepsilon_2))$$

The first equation corresponds to overall electricity expenditure by TOD households while the second equation corresponds to non-TOD households who have no fixed costs and face a constant price over the day. The last equation of the model which is expenditure during the peak period pertains only to the TOD households since we have no data for the non-TOD households. The expenditure equation is

$$(4.3) \qquad p_{21}x_{21} = A(p_T)(\alpha + \gamma \log \frac{p_{21}}{p_{22}}) + (y_2 - A(p_T) - p_{21}\varepsilon_1 + p_{22}\varepsilon_2)(\beta + \theta \log \frac{p_{21}}{p_{22}}) + p_{21}\varepsilon_1$$

Note that both price indices enter the peak period expenditure equation since the $B(p_T)$ index arises in the uncommitted expenditure segment. The likelihood function now follows from a specification of the stochastic terms $\varepsilon_1, \varepsilon_2, \varepsilon_F$. We choose them to be multivariate normal $\varepsilon \sim N(0,\Sigma)$. Thus, the first equation corresponds to a nonlinear probit choice equation for TOD. The other two equations correspond to nonlinear demand equations. Since the stochastic disturbances enter all the equations of the model, the appropriate estimator is (full information) maximum likelihood.

To construct the likelihood function denote an indicator variable $u_i = 1$ if the household chooses TOD and zero otherwise. The observable vector of dependent variables for TOD households is then $(u_i = 1, y_i, y_{2i})$ and for the non-TOD households it is $(u_i = 0, y_i)$ where we integrate out the peak period expenditure. For TOD households the likelihood contribution is

$$(4.4) \qquad f(u_i, y_i, y_{2i}) = \frac{1}{\omega_{33}} \phi\left(\frac{\eta_{3i}}{\omega_{33}}\right) \frac{1}{\omega_{22}} \phi\left(\frac{\eta_{2i}}{\omega_{22}}\right) \Phi\left(\frac{\eta_{1i}}{\omega_{11}}\right)$$

where the first term arises from the peak period expenditure equation. Its density is univariate normal where the 'residual' $\eta_{3i} = \varepsilon_1(p_{21} - p_{21b}) + \varepsilon_2 p_{22}$. where $b = \beta + \theta \log \frac{p_{21}}{p_{22}}$ and ω_{33} is the standard deviation which corresponds to this combination of ε's. Likewise, the second term arises from the total electricity expenditure equation, where we condition its residual on the first residual. The last term is the probit equation where we condition on both previous residuals. For the non-TOD households the likelihood contribution has two terms

$$(4.5) \qquad f(u_i, y_i) = \frac{1}{r_{22}} \phi\left(\frac{\tau_{2i}}{r_{22}}\right)\left(1 - \Phi\left(\frac{\tau_{1i}}{r_{11}}\right)\right)$$

Here the residual in the expenditure equation is $\tau_{2i} = (1-\delta)p_{23}(\varepsilon_1 + \varepsilon_2)$. The second term is again the probit equation for choice of TOD where we condition on τ_{2i}. The log likelihood which we maximized with the BHHH algorithm then has the form[1]

$$(4.6) \qquad L = C + \sum_{i \varepsilon TOD} -\frac{1}{2}\log\omega_{33}^2 - \frac{1}{2}\log\omega_{22}^2 - \frac{\eta_{3i}^2}{2\omega_{33}^2} - \frac{\eta_{2i}^2}{2\omega_{22}^2} + \log \Phi\left(\frac{\eta_{1i}}{w_{11}}\right)$$

$$+ \sum_{i \varepsilon NTOD} -\frac{1}{2}\log r_{22}^2 - \frac{\tau_{2i}^2}{2r_{22}^2} + \log\left(1 - \Phi\left(\frac{\tau_{1i}}{r_{11}}\right)\right).$$

While the likelihood function is reasonably nonlinear we did not encounter too much difficulty in finding the maximum.

[1] The Jacobian of the LF is unity.

A possible problem exists with the likelihood function of equation (4.6). Our sample is not random; we oversampled TOD households. Hausman and Trimble (1981) give the sampling plan. Since the sample is based on the choice equation outcome an adjustment needs to be made to the likelihood function. Manski and McFadden (1981) discuss estimators in the discrete choice case. Our problem is more complicated here since we have two equations in addition to the choice equation. However, it can be demonstrated that only the component of the likelihood function which corresponds to the choice model needs to be adjusted. In that case if the first equation were a logit equation rather than a probit equation the estimates would still be consistent so long as the denominators of equation (4.1) are close to unity or are equal, both of which they turn out to be in estimation. The difference between a probit specification and a logit specification of the choice model is very unlikely to cause any problem. Nevertheless, to guard against any problem we also estimated the model using the weighted ML approach of Manski and Lerman (1977). The likelihood function of equation (4.6) is changed to have weights w_i in front of both probit terms. We found this likelihood function extremely slow to converge. Furthermore, the results were very similar to the nonweighted likelihood function. Therefore, most of the results which we present arise from the unweighted likelihood function. Whether some alternative estimator proposed by Manski and McFadden (1981) for the choice based case would be easier to work with remains a topic for further research.

Before we turn to the results two other econometric complications need to be mentioned. First, in the model formulation the existence of timers is used as a right hand side variable. To avoid potential endogeneity we use the predicted probabilities from the appliance choice model as instrumental variables. The other econometric problem is that non-TOD households do not face a constant electricity price because of the existence of a lifeline rate in Vermont.

We need to construct a price index for non-TOD households since they face a non-constant marginal price schedule.

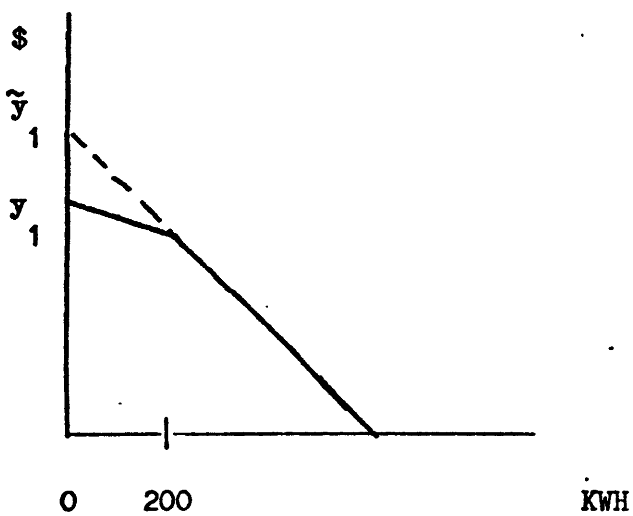

FIGURE 1

In Figure 1 we draw the inverted rate schedule faced by non-TOD customers. The first block of 200 kwh has a marginal price of 3.10¢ per kwh. Beyond that point the price rises to 7.92¢ per kwh. Since the price schedule is convex, which is different from the usual declining block rate schedule which is non-convex, we used a relative straightforward technque. We estimated a reduced form probit equation for households to be above or below

200 kwh. The average price is then estimated as $\bar{p} = .0310\,\pi_1 + .0792\,\pi_2$ where the π_j's are the estimated probit probabilities of being in each block. The estimated price is then used as an instrument in the non-TOD household usage equation. Household income could also be adjusted from y_1 using a weighted probability average of $\tilde{y}_1$ and y_1, see Hausman et. al. (1979) and Taylor (1976). But since $\tilde{y}_1 - y_1$ equals \$9.64 and average y_1 exceeds \$20,000 the adjustment will not affect the estimates.

Since 200 kwh is supposed to only be a 'lifeline' amount, we expect most household's usage to exceed it. The mean price is predicted to be 7.47¢ per kwh which corresponds to an estimate of π_2 of .907 which is very close to the actual value in our sample of .904. The 10th percentile is still 6.87¢ per kwh which again indicates that predicted non-TOD price is fairly close to the value in the upper block. We use the predicted marginal price as an instrument in the non-TOD choice and electricity expenditure equations.

The estimated coefficients and asymptotic standard errors are presented for our model in Table 4.1. The left hand column gives the unweighted estimates while the right hand column gives the weighted estimates for a somewhat simpler specification. We first discuss the components of the price index

$$(4.7) \qquad \log A(p_T) = \alpha_o + \alpha \log p_{21} + (1-\alpha)\log p_{22} + \frac{\gamma}{2}\left(\log \frac{p_{21}}{p_{22}}\right)$$

TABLE 4.1

TOD Choice and Expenditure Equations

Variable	Unweighted Estimates	Weighted Estimates
α_o Components		
1. Constant	1.101 (.338)	.448 (.478)
2. Electric Heat Primary*HHD	.736 (.137)	.837 (.114)
3. Electric Heat Secondary*HHD	.065 (.110)	.125 (.142)
4. Electric Water Heater	.293 (.211)	.642 (.304)
5. Children	-.128 (.120)	-.347 (.201)
6. Adults	.009 (.084)	.237 (.144)
7. Adults at Home in Day	.064 (.112)	.380 (.191)
α Components		
8. Constant	.988 (.096)	.862 (.181)
9. EH Primary*Prob. of Timer	-.594 (.118)	-.656 (.337)
10. EH Secondary*Prob. of Timer	-.324 (.132)	-.425 (.324)
11. Elec. Hot Water*Prob. of Timer	-.114 (.065)	-- --
12. Prob. of Refrigerator Timer	-.006 (.007)	-- --
13. Yrs. on TOD	-.124 (.128)	-- --
14. γ-Committed Second order term	-.040 (.006)	-- --

TABLE 4.1
(Continued)

Variable	Unweighted Estimates	Weighted Estimates
15. β	.690 (.235)	.537 (.101)
16. θ-Uncommitted Second order term	-.298 (.155)	-- --
17. δ-Uncommitted exp. term	.007 (.003)	.009 (.003)
<u>Fixed Cost Components</u>		
18. Constant	.031 (.022)	.081 (.117)
19. Electric Heat	.006 (.018)	.019 (.116)
20. Rents	.026 (.011)	.043 (.153)
WTS	--	TOD=.033,NTOD-EH=.711, NTOD-NEH=1.71
Obs	338 LF = 407.3	338 LF LF = 505.2
Σ	$\begin{bmatrix} .322 & & \\ .147 & 2.60 & \\ -.006 & .018 & .005 \end{bmatrix}$	$\begin{bmatrix} .265 & & \\ .247 & 2.67 & \\ -.007 & .037 & .007 \end{bmatrix}$

The first seven coefficients correspond to the constant α_o and lead to a percentage shift upwards corresponding to their coefficients. Note that electric heat has large effect on the price index. Secondary electric heat and an electric water heater have smaller but important effects. The demographic characteristics of the family have a smaller effect which we could not estimate very precisely. The next seven coefficients correspond to the coefficient α which multiplies the peak electricity price in the price index. Note the importance of the presence of timers in decreasing the price index. The timers for electric heating are very important while the timers for water heating and for refrigerators have a smaller effect. The variable for years on the TOD plan has a small effect on the price index, but we could not estimate it at all precisely. The second order term coefficient γ is estimated relative precisely and has the correct curvature for the price index.

We now turn to the uncommitted expenditure and its price index. The coefficient of uncommitted expenditure δ is estimated to be quite small as one might expect. Because of the unimportance of uncommitted expenditure we estimated only two coefficients for the price index $B(p_E)$. Note that peak price is the major explanation of the uncommitted price index since

$$(4.8) \qquad \log B(p_E) = \beta \log p_{21} + (1-\beta)\log p_{22} + \frac{\theta}{2}\left(\log \frac{p_{21}}{p_{22}}\right)^2 .$$

Lastly, we turn to the coefficients for fixed costs. The presence of electric heat or renting status both raise fixed costs for the households. Fixed costs are estimated to vary between 30 and 300 dollars which seems reasonable and is remarkably in line with the estimated cost of the timers.

We now examine how these estimated parameters affect our three equations (4.1)-(4.3) which determine choice of TOD and electricity expenditure. Examination of the choice equation (4.1) indicates that we deleted the cost component C from the model since it was practically not identified with uncommitted electricity expenditure so close to zero. Since δ = .007 the denominators of the two choice functions are virtually identical--the denominators are within .001 of each other. The choice of TOD thus becomes a comparison of the price indices $A(p_T)$ for TOD and $A(p_N)$ for non-TOD together with the fixed costs as we indicated in equation (3.18). For primary electric heat customers the average estimated price index on TOD prices is .23 while for non-TOD price the average estimated index is .25. On average the indirect utility for these customers if they choose TOD is 4.40 while if they choose non-TOD it is 4.34. Significant variation exists across individual households, but the conclusion is that the average electric heat customer will prefer to shift to TOD rates. In fact, over half of all TOD households have primary electric heat.

However, if we examine non-electric heat customers we find that TOD prices are not nearly so favorable. The price index for TOD prices is .16 while the average index for non-TOD prices it is .11. These indices lead to a prediction of a much smaller proportion of nonelectric heat households on TOD which is what we observe in the data.

For the electricity expenditure equation we find almost all electricity expenditure to be committed given our very small estimate of δ. This indicates the extreme nonhomotheticity of overall electricity demand. In fact, our estimated income elasticities range between .13 and .25 for the different groups depending on whether they have electric heat. These estimates are similar to previous estimates of income elasticitiesfrom non-TOD samples. For TOD households uncommitted expenditure is about 14% of total expenditure while for non-TOD households it is about 18%. Our estimated price elasticities from the expenditure equations are .16 for TOD households and .19 for non-TOD households. Households with electric heat have higher estimated elasticities as expected. These price expenditures are lower than are commonly estimated on non-TOD monthly bill data and reflect the relative importance of committed expenditure. Also, we have carefully treated the potential endogeneity of electric prices in this study which can lead to upward biased elasticity estimates if it is not correctly treated.

The last equation we consider is the peak period expenditure equation for the TOD households. We find extremely strong evidence against the assumption of homothetic separability in TOD electricity consumption. Our estimated elasticity of peak period expenditure with respect to total electric expenditure at the mean of the data is estimated to be .346 with a standard error of .314. Since almost all models of TOD electricity consumption have made the homotheticitiy assumption, our results cast considerable doubt on this specification. Our estimated income elasticity of .35 is well below the unitary value assumed in most previous studies. Furthermore, it is significantly less than unity at a .05 test level.[1]

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[1] However, the income elasticity from the weighted estimate is not significantly less than unity. Our finding of nonhomothenticity should also be considered with the voluntary nature of the TOD plan in mind. Households which consume relatively more electricity off peak are more likely to choose the TOD plan.

V. Conclusions and Policy Recommendations

Considerable interest exists in TOD electricity pricing in the U.S. We have estimated a model which considers choice of TOD as well as electricity expenditure. Since Vermont offers almost the only data from a permanent voluntary TOD program we can consider the advisability of a shift to TOD prices. We do not do a complete cost-benefit calculation since we would need marginal electricity production costs as well planned expenditures on new capacity for the forseeable future to make the appropriate calculation. Instead, we consider the more narrow question of whether consumers would be made better off by a shift to TOD prices. Presumably, households which have chosen TOD prices did so because they were made better off. The question we consider is whether aggregate consumers surplus would increase if a mandatory TOD plan were adopted, rather than a voluntary program.

To make the calculation we take the indirect utility function of equation (3.16) and the estimated parameters and calculate average consumers surplus across various household groups. We estimate that a voluntary TOD program has an average consumers surplus of $198 per year for electric heat customers (in 1980 dollars). If the program were changed to mandatory TOD prices, consumers surplus drops on average to $180 per year. Therefore, aggregate consumers surplus among electric heat households would increase although some households are made worse off under a mandatory plan. When we consider non-electric heat households under the current voluntary plan we find average consumers surplus is less than $10 per year since so few households choose TOD if they do not have electric heat. Under a mandatory TOD program the average non-electric heat households is made worse off by

$174 per year. When we average across all households we find a voluntary TOD program increases consumers surplus by $72 per year per household. However, a mandatory TOD program decreases consumers surplus by $42 dollars per year.

Firm policy conclusions cannot be based on these estimates because future electricity prices may change. We would expect significant changes if generating capacity is increased and most of the capital expenditure is included in the TOD peak prices. But given our results, we find that a voluntary TOD program has much to recommend it so long as TOD households do not cross-subsidize non-TOD households. A mandatory TOD program is not nearly so favorable in terms of households perceived welfare.

DATA APPENDIX

The initial combined 1979 and 1980 weather and usage data set received from Central Vermont Public Service Corp. (CVPSL) and processed to include weather data includes 10,993 records describing 684 accounts. Each record contains:

CID	10 digit account ID. (See below).
TYPE	1-month or 2-month reading cycle
DATE	Date of scheduled meter reading. Not actual read date.
RCODE	Rate code (See table 2).
KWH	KWH for that rate code (Blank for 1979 read dates)
NDAYS	Number of days in scheduled cycle
HDD	Number of Heating Degree Days in scheduled cycle

The initial file had rate codes as shown in Table 1.

TABLE 1

RATE CODES AND DISTRIBUTION IN INITIAL FILE

		Before Transformation		After Transformation	
Rate Code	Type	Frequency	Percent	Frequency	Percent
Blank	Unspecified	2049	18.6	166	15.2
01	Residential	1015	9.2	118	10.8
03	Off-Peak Water Heating	1287	11.7	119	10.9
07	Security Lighting	55	.5	---	----
08	All-Electric	192	1.7	12	1.1
10	Cable TV or Commercial Resale	23	.2	---	----
11	Time of Day (TOD)	20	.2	3	.3
11A	TOD - Peak	2238	20.4	334	30.5
11B	TOD - Off-Peak	3940	35.8	334	30.5
46	Storage Heating	62	.6	9	.8
60	Storage Heating	59	.5	---	----
61	Storage Heating	53	.5	---	----

Table 1 also defines the various rate codes. These customer accounts match the survey responses from the survey instrument described in Hausman-Trimble (1981).

We first selected one read date from each account. There were two requirements for inclusion. First, there had to be at least one non-zero KWH reading for that read date. Second, the reading had to be in February, March, or early April (1-3). If there was more than one read date during that period, the first date was selected. Using this procedure, 649 accounts were selected. They were distributed as follows:

FEB	MARCH	APRIL	SUBTOTAL	MISSING	TOTAL
295	338	16	649	35	584

On inspection, the data was determined to include accounts which had neither time-of-day (TOD) readings, nor residential service readings. These accounts were excluded. In particular, any reading for rate codes 07, 10, 60 and 61 were eliminated. This procedure left 336 customers with TOD readings. (However, only 333 customers had both a peak and off-peak reading.) The resulting file, which still combined TOD and non-TOD customers, had a distribution of rate codes as shown in the two right-hand columns in Table 1.

Two extracts were made from this dataset, one with only TOD customers and the second with only non-TOD customers. Both datasets were produced merging the 1980 usage data with the datasets which had been used in the early stage of this research and contained both survey data and 1979 usage data. The resulting datasets were as follows:

	NUMBER OF OBSERVATIONS		
	TOD	NON-TOD	TOTAL
1979 data	151	249	409
1980 data	132	206	338

A number of assumptions were made in creating the dataset. All 1979 account ID's were 10-digits. Over 100 of the 1980 ID's were only 9-digits. After multiplying these ID's by 10, many of them matched 1979 accounts. It was assumed that a mistake had been made either with the 1979 or the 1980 data. Accordingly, ID's were multiplied by 10 when appropriate.

A second major assumption had to do with rate codes. Most of the non-TOD individuals had blank rate codes. These accounts were assigned rate codes according to their 1979 rates. Several of the TOD accounts also had blank rate codes. They were assigned to peak and off-peak usage as appropriate.

These files were reformatted to have only one record per customer. Accounts with storage heating (rate code 46) were eliminated entirely. This accounted for the loss of four TOD customers and one non-TOD customer.

In order to use the data in the regression programs, one further change was made. For the TOD accounts, usage on special off-peak water heaters was added to the total off-peak usage. A dummy variable was used to indicate that the individual had the special water heater rate. For the non-TOD accounts, the water heater usage was added to the regular usage and a dummy variable was used to indicate the existence of the special electric heating rate.

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