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THE RETURNS TO INSULATION UPGRADES: RESULTS FROM A MIXED ENGINEERING/ECONOMETRIC MODEL*

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ABSTRACT

This paper estimates a new model of residential electricity demand. It differs from previous work in two ways. First, we utilize individual monthly billing data in a pooled time-series/cross-section framework. Second, we use an engineering/thermal load technique to model the household space-heating technology. This allows more precise separation of the effects of economic variables from those of weather, and permits simulation of the effects of various conservation policies.

We estimate the model using data from the Pacific Northwest, and use the results to analyze three conservation measures: a price increase, a reduction in thermostat settings, and an improvement of insulation levels. We find average rates of return for insulation upgrades of 4.9 percent for ceilings and 8.3 percent for walls.

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I. Introduction

Electric utilities are increasingly turning to conservation programs to curtail demand growth, as an alternative to increasing supply through construction of expensive generating capacity. Such policies may use building codes to impose mandatory energy-efficiency standards for new construction, or they may use utility-sponsored informational and incentive programs to induce consumers to adopt such measures voluntarily. In the Pacific Northwest, for example, mandatory standards for new residences are under consideration by the Northwest Power Planning Council. Utilities that fail to adopt these or equivalent standards by January 1987 would be subject to a 10 percent surcharge on power that they buy from the Bonneville Power Administration.

Proposals of this kind raise such questions as, how much energy will be saved as a result of the policy? What are the costs of obtaining these savings? Do mandatory standards impose behavior on consumers that they would not voluntarily and rationally choose?

In this paper we formulate a new model of residential energy demand that allows such questions to be addressed. We estimate the model using data from the Pacific Northwest, and use the results to analyze the effects of various conservation measures for existing dwellings.

This study differs from previous work in two major respects. First, we utilize individual monthly billing data in a pooled time-series/cross-section framework. This permits a seasonally disaggregated analysis that considers possible correlation of individual behavior over time. In contrast, previous studies of seasonal demand based on disaggregated survey data have attempted to estimate independent equations for each month.[1] Our empirical results suggest a strong correlation of unobservable variables over time, so that treating billing periods as independent may cause confidence intervals on parameter estimates to be too narrow.

Second, we use an engineering/thermal load technique to model the household production technology for space-heating confort. This allows more precise separation of the effects of economic variables from those of weather, and permits variation over time in key weather-sensitive parameters.

In addition, the thermal modeling approach allows us to use the model for policy analysis, which would not be possible under a traditional "pure econometric" methodology. We demonstrate the model's usefulness by simulating the effects of three conservation measures: a price increase, a reduction in thermostat settings, and an insulation improvement. We find average rates of return for insulation upgrades of 4.9 percent for ceilings and 8.3 percent for walls.

The following section discusses the theory of residential

energy demand conditioned on a fixed appliance stock, and develops the engineering/econometric approach used in our estimation. Section III develops the specification used in our empirical work. Section IV describes the data, and Section V presents results. In Section VI we use the model for policy analysis. Section VII concludes.

II. Specification of Conditional Demand Models - Theory

The demand for energy by the household is a derived demand arising from the production of household services. The technology that provides household services is embodied in the household appliance durable. To understand the residential demand for energy we must understand the residential demand for durable equipment and model both simultaneously. This section develops an economic/econometric framework in which the demand for energy is made conditional on a durable stock.

Residential Heating and Comfort

Let $U(\tau,Z)$ denote the utility derived from consumption of a vector of goods Z in an environment with ambient temperature τ. It is reasonable to assume that utility is increasing in τ up to a temperature τ^* which provides blissful comfort. Below τ^* occupants feel too cool and above τ^* feel too hot. If heating (or cooling) were free, consumers would set their thermostats at τ^*. However, as heating to an interior temperature τ^* requires a costly energy input, there exists a trade-off between the comfort of the ambient space and the price of obtaining this comfort.

Following Brownstone (1980) and Hausman (1979), we assume that the utility function $U(\tau,Z)$ is separable in comfort and goods consumption. Further, we assume that the utility derived from ambient temperature τ, has the linear form $\alpha(\tau^* - \tau)$ with $\alpha < 0$, $\tau \leq \tau^*$ so that $U(\tau,Z) = U^*[\alpha(\tau^* - \tau),Z]$. Suppose that the BTUH heating required to maintain interior temperature τ with exterior temperature t is given by $Q(\tau,t)$. The consumers' optimization problem is to maximize utility $U^*[\alpha(\tau^* - \tau),Z]$ subject to the budget constraint which allocates wealth W between expenditures on goods Z and on fuel $(p_i/e_i)Q(\tau,t)$ where p_i is the price of fuel i and e_i is the efficiency of the heating system using fuel i in BTUH per unit of fuel. We write:

$$\underset{\tau,Z}{\text{maximize}}\ U^*[\alpha(\tau^* - \tau),Z] \text{ subject to } (p_i/e_i)Q(\tau,t) + Z \leq W \tag{1}$$

for which the Lagrangian (with multiplier ξ) is:

$$L = U^*[\alpha(\tau^* - \tau),Z] + \xi[W - Z - (p_i/e_i)Q(\tau,t)]. \tag{2}$$

The first-order conditions are:

$$L_\tau = -U_1^*\alpha - \xi(p_i/e_i)Q_\tau(\tau,t) = 0$$

and

$$L_Z = U_2^* - \xi = 0 \tag{3}$$

so that

$$-U_1^*/U_2^* = p_i Q_\tau(\tau,t)/(\alpha e_i). \tag{4}$$

We see from (4) that the marginal rate of substitution between comfort and other goods depends on the "price of comfort" which itself is a function of the level of comfort. In our empirical work we approximate the thermal function by a quadratic in the temperature difference $\tau - t$,

$$Q(\tau,t) = W_0 + W_1(\tau - t) + W_2(\tau - t)^2. \tag{5}$$

In this case, condition (4) becomes:

$$-U_1^*/U_2^* = p_i(W_1 + 2W_2(\tau - t))/(\alpha e_i). \tag{6}$$

A minor difficulty arises due to the dependence of price on level of comfort. In this case we pose the optimization problem using an appropriately defined rate structure premium (RSP). Let $\hat{\tau}$ denote the solution to (4). An equivalent standardized problem is then:

$$\underset{\tau,Z}{\text{maximize}}\ U^*[\alpha(\tau^* - \tau),Z] \qquad \text{subject to}$$

$$(p_i/e_i)Q_\tau(\hat{\tau},t)\ .\ \tau + Z < W - RSP \qquad \text{where}$$

$$RSP = (p_i/e_i)[Q(\hat{\tau},t) - Q_\tau(\hat{\tau},t)\ .\ \hat{\tau}] \tag{7}$$

As the budget constraint in (7) appears in constant prices, standard econometric specifications for the demand system may be applied. The price of comfort, $(p_i/e_i)Q_\tau(\hat{\tau},t)$, may be approximated by calculating the change in billing period utilization associated

with a degree change in the household thermostat setting. A convenient way to perform the latter calculation employs an energy thermal load model for the residence.

While there are many models available to calculate heating and cooling requirements, most are designed to be used by contractors and architects on individual dwellings where detailed measurements are available.[2]

Engineering/thermal load models calculate the amount of heat entering and leaving the residence for each hour of the day and are capable of determining loads for space-conditioning end uses. These calculations require detailed input including data on the physical, thermal, and operational characteristics of the dwelling as well as location specific hourly temperature data. These models are highly specialized to determine both static and dynamic heat transfer.

The engineering/thermal load technique has been found to be quite accurate when detailed information on building characteristics exists. The methodology incorporates complex non-linear relationships among weather, building characteristics, and thermal loads and thus provides significant a priori information in our statistical analysis. Furthermore, the technique may be used to assess the impact of conservation and load management programs that affect building characteristics, as well as to provide estimates of system load at extreme weather conditions.

The limitations of the thermal load technique include its detailed data requirements and its computational complexity. A model

that has been specifically designed for application to household survey data is developed in Dubin and McFadden (1983). This thermal model makes reasonable assumptions about dwelling characteristics and operating practices that are not coded in typical survey data while utilizing all information about insulation levels, window counts, etc., that is readily available. The approach also simplifies the task of providing detailed weather data and is able to process summary measures such as temperature means and extremes. The methodology is superior to the use of simple degree-day measures while allowing calculations on large samples of dwellings.

The thermal load technique is combined with billing cycle data in our study in two unique ways. First, we use the Dubin-McFadden thermal model to estimate billing cycle load on a household by household basis, assuming an indoor temperature τ of 70 degrees F. For a given day, the heating load is found by evaluating equation (5) using the daily mean outdoor temperature for t, with coefficients W_i determined by the thermal model. In this approach, two households with equivalent building characteristics facing identical weather patterns would be predicted to have the same energy demand. In reality, we realize that the demands may vary signficantly between otherwise identical households due to differences in income, household size, activity patterns, and the cost of energy. We thus adopt a strategy of incorporating an engineering/thermal projection into our energy demand analysis. Departures from the engineering estimates are due to socio/economic sensitivity in the rate of appliance stock

utilization.

Secondly, we use the engineering/thermal load technique to estimate the cost of comfort. Here the estimated change in energy input required to effect a one degree change in ambient temperature is multiplied by the marginal price of the fuel input. In the next section we combine the engineering/economic approach in an econometrically estimable model.

III. Specification of Conditional Demand Models - Estimation

An econometric conditional demand model is developed by noting that a household's total electricity consumption in any period is simply the sum of the electricity used by each appliance in that period:

$$X^e_{it} = \sum_{j=1}^{J} UEC^j_{it}\ \delta^j_i(X^j_{it}\beta^j) + Z_i\gamma + \varepsilon_{it} \qquad (8)$$

where X^e_{it} = demand for electricity in period t by household i, UEC^j_{it} = unit energy consumption of electricity of appliance j in period t by household i, δ^j_i = indicator of appliance j ownership by household i, X^j_{it} = vector of socio-economic variables affecting utilization of appliance j by household i, in period t, β = vector of parameters associated with X^j_{it}, Z_i = vector of socio-economic variables affecting time-independent usage of electricty, γ = vector of parameters associated with Z_i, ε_{it} = error term for household i in period t.

The term $Z_i\gamma$ accounts for the presence of electric refrigerators, ovens, ranges, microwave ovens, freezers, washers, and

clothes dryers. For our purposes, the UEC's associated with these appliances are of secondary interest only and we view β as the parameters of interest.

A pure conditional demand approach approximates the terms UEC^j_{it} by functions of variables related to the technology of the appliance. A common specification for the UEC of space conditioning represents this term as a linear function in square feet, insulation levels, heating degree days, etc. To illustrate this approach we write:

$$UEC^j_{it} \equiv W^j_{it}\alpha^j + \nu^j_{it} \tag{9}$$

where W^j_{it} = vector of characteristics of appliance j for household i in period t, α^j = vector of parameters associated with W^j_{it}, ν^j_{it} = error term in linear specification of UEC. Combining (8) and (9) we obtain:

$$X^e_{it} = \sum_{j=1}^{J} \delta^j_i (W^j_{it}\alpha^j)(X^j_{it}\beta^j) + Z_i\gamma + \varepsilon_{it} + \tilde{\nu}_{it} \tag{10}$$

where:

$$\tilde{\nu}_{it} = \sum_{j=1}^{J} \delta^j_i \nu^j_{it}(X^j_{it}\beta^j)$$

The purpose of the engineering/econometric approach is to minimize the measurement error $\tilde{\nu}_{it}$ through a thorough thermal modeling of the space conditioning appliance technology. We argue that the engineering/econometric approach is superior to the pure conditional

demand methodology because it efficiently and effectively incorporates all relevant available engineering data and emphasizes the structure of the estimated equation.

Our empirical work focuses on space heating and water heating as the end uses that are, a priori, the largest contributors to cross-sectional and seasonal variation in energy consumption in the Northwest. Lacking a thermal prediction of water heating UEC, we represent this term by a linear approximation. To reduce the number of parameters to be estimated, we subtract the term $Z_i\gamma$ from the left-hand side of equation (8), using values of γ reported in the literature (Lawrence and Parti (1984)). If the UEC values γ are measured with error, this approach may reduce the precision of estimates of the parameters β^j, but will not bias the estimates if the measurement errors are uncorrelated with the right-hand-side variables.

The form of equation (8) used in our empirical analysis is then:

$$X^e_{it} - Z_i\gamma = UEC^{SH}_{it}\delta^{SH}_i(X^{SH}_{it}\beta^{SH}) + \delta^{WH}_i(X^{WH}_{it}\beta^{WH}) + X^M_{it}\beta^M + \varepsilon_{it} \tag{11}$$

where the superscripts SH, WH, and M denote space heat, water heat, and miscellaneous uses, respectively. The "miscellaneous" term captures consumer response for all end uses, other than space and water heating, that are not contained in Z_i.

In our estimation we recognize the time-series/cross-section structure of the billing data and exploit the correlation of individual effects over time to increase efficiency. Specifically, we assume that the disturbances in each billing period are homoscedastic and uncorrelated which implies:

$$E(\varepsilon_t \varepsilon_t') = \sigma^2_{tt} I_N, \quad t = 1,2,\ldots T \quad \text{where}$$

$$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{Nt})' \quad \text{denotes the column vector}$$

of disturbances for individuals ($i = 1,2,\ldots,N$) in period t. Regarding the covariance matrix of the disturbances of two different time periods:

$$E(\varepsilon_t \varepsilon_s') = \sigma_{ts} I_N \qquad t,s = 1,2,\ldots T$$

Note that the diagonal elements are the covariances of individual behavior over time $E(\varepsilon_{it}\varepsilon_{is})$ and that the off-diagonal elements $E(\varepsilon_{it}\varepsilon_{js})$ give the contemporaneous cross-sectional covariances, assumed to be zero. The complete covariance structure has the Seemingly Unrelated Regression (SUR) form:
$V(\varepsilon) = \sum_T \otimes I_N$ with $\sum_T = (\sigma_{ts})$ and $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots \varepsilon_T)'$.

Viewing the time-series cross-section of individual billing data as a SUR econometric system permits important tests regarding the structure of individual demand over time. It is possible, for example, that the disturbances in individual demand behavior are equi-correlated over time. This might arise from the omission of

important unobservable individual characteristics (e.g., "conservation-mindedness") that are time-invariant. This hypothesis is equivalent to the random effects model and lends itself to simple econometric estimation. Alternatively, it is possible that $\sum_T$ has an auto-regressive structure in which $E(\varepsilon_{it}\varepsilon_{is}) = p^{|t-s|}$. In this case the correlation between individual disturbances is strongest in adjacent billing periods and diminishes over time. This pattern might be caused by an unobserved weather or price component.

Given the importance of space heating in the Pacific Northwest, we postulate a model whose structure differs between the heating season and all other months. We thus pool the data into winter and nonwinter seasons, and estimate separate coefficients for each season while accounting for correlations of errors among all periods.

IV. Variable Definitions

The form of equation (11) used in estimation contains interactions of the X^j_{it}, δ^j_i, and (where relevant) UEC variables on the right-hand side, and net consumption $X^e_{it} - Z_i\gamma$ on the left-hand side.

The dependent variable, NETKWHDAY, is calculated as follows. First, mean daily consumption X^e_{it} is calculated for each billing period. Second, using typical UECs reported in the literature, base consumption is calculated as

QEBASE = 4.0(# of refrigerators) + 3.9(freezer)
+ 2.1(electric cooking) + 0.24(clothes washer)

+ 0.4(dishwasher) + 3.0(clothes dryer)

+ 0.8(# of black-and-white televisions)

+ 1.4(number of color televisions).

Then NETKWHDAY is calculated as the difference X^{e}_{it} - QEBASE.

On the right-hand side, daily space heating usage (UEC^{SH}_{it}) is the mean daily kwh during a billing period required to maintain an indoor temperature of 70 degrees F. It is calculated by determining the thermal load for each day, and averaging these values over a billing period.

Variables interacted with UEC^{SH} include a constant, income, a dummy variable indicating the presence of a wood backup heating system, and the marginal price of comfort. The comfort price represents the cost of increasing indoor temperature by one degree Fahrenheit. It is calculated by multiplying the tail-block marginal price (evaluated at 5000 kwh per month) by the mean daily kwh required to increase indoor temperature from 69 to 70 degrees, as calculated by the thermal model.

The water heat dummy variable is interacted with a constant, income, tail-block marginal price of electricity, number of household members, and a dummy variable indicating presence of a dishwasher.

Variables in the "miscellaneous usage" term include an intercept, number of rooms in the residence, number of household members, income, marginal price of electricity, and rate structure premium. Price variables are evaluated at 1000 kwh per month. Based on preliminary analysis indicating possible commercial uses of energy

by some residences, dummy variables for business equipment are also included; details are given in Dubin and Henson (1985, Volume II).

Definitions of all variables and constructions used in this analysis are presented in Table 1.

The data used to estimate this model are a subset of 615 single-family households from the Pacific Northwest Residential Energy Survey conducted in 1979 by the Bonneville Power Administration. Households are selected to have one of six space heating systems,[3] at least one billing period of energy consumption data, and non-missing values for all variables used in the analysis; for details see Dubin and Henson (1985, Volume II). Of these 615 households, 442 are billed monthly and together contain 5014 billing periods; the remaining 172 households contain 1000 bimonthly periods, giving a total of 6014 billing periods of valid data. So that units are comparable across all observations, all energy consumption variables are measured as daily averages.

Variable means for winter and nonwinter periods are presented in Tables 2A and 2B, respectively, for the entire sample and for three subsamples defined by space heat and water heat fuels. Based on preliminary examination of temperature data, we define the winter heating season to consist of all billing periods with beginning dates in November through February.

TABLE 1

VARIABLE DEFINITIONS

Variable	Definition
ELECDSHW	1 if electric dishwasher, 0 otherwise
ESPACEHT	1 if electric space heat, 0 otherwise
EWATERHT	1 if electric water heat, 0 otherwise
EWHHSLDMEM	EWATERHT*NHSLDMEM
EWHDISH	EWATERHT*ELECDSHW
EWHPRICE	EWATERHT*MP5000
EWHINC	EWATERHT*INCOME
INCOME	Total household annual income, thousands (class midpoint)
IRRPUME	1 if irrigation pump on household meter, 0 otherwise
KWHDIFDAY	Mean daily kwh required to increase indoor temp 1 degree F
MP1000	Marginal price of electricity at 1000 kwh/month, cents/kwh
MP5000	Marginal price of electricity at 5000 kwh/month, cents/kwh
NETKWHDAY	Mean daily net kwh used during billing period (see text)
NHSLDMEM	Number of household members
NROOMS	Number of rooms in dwelling unit
OFFMACHINE	1 if office machinery on household meter, 0 otherwise
RP1000	Rate structure premium at 1000 kwh/month, dollars/month
SHPRICE	Marginal price of space heating comfort = KWHDIFDAY*MP5000
SUSHEDAY	ESPACEHT*UECSH
SUSHEPDAY	ESPACEHT*UECSH*SHPRICE
SUSHEYDAY	ESPACEHT*UECSH*INCOME
SUSHEWDAY	ESPACEHT*UECSH*WOODBACKUP
UECSH	Mean daily space heating UEC from thermal model (see text)
WELDER	1 if welding equipment on household meter, 0 otherwise
WOODBACKUP	1 if wood backup heating system, 0 otherwise

TABLE 2A

VARIABLE MEANS BY SUBSAMPLE: WINTER

	Entire Sample	Subsample 1	Subsample 2	Subsample 3
Observations	1984	823	557	604
ELECDSHW	0.3382	0.3026	0.3824	0.3460
ESPACEHT	0.4148	1.000	0.0000	0.0000
EWATERHT	0.6956	1.000	1.000	0.0000
EWHHSLDMEM	2.272	3.532	2.874	0.0000
EWHDISH	0.2329	0.3026	0.3824	0.0000
EWHPRICE	1.294	1.801	1.949	0.0000
EWHINC	15.25	21.16	23.05	0.0000
INCOME	22.44	21.16	23.05	23.61
IRRPUMP	0.02117	0.02430	0.02513	0.01325
KWHDIFDAY	4.774	4.437	5.368	4.685
MP1000	1.944	1.772	1.881	2.236
MP5000	1.981	1.801	1.949	2.255
NETKWHDAY	55.30	107.2	26.65	10.96
NHSLDMEM	3.284	3.532	2.874	3.323
NROOMS	6.218	5.996	6.305	6.439
OFFMACHINE	0.01815	0.0000	0.02154	0.03974
RP1000	2.882	3.073	2.609	2.872
SHPRICE	10.14	8.548	11.30	11.25
SUSHEDAY	75.15	181.2	0.0000	0.0000
SUSHEPDAY	684.1	1649.	0.0000	0.0000
SUSHEYDAY	1710.	4121.	0.0000	0.0000
SUSHEWDAY	56.03	135.1	0.0000	0.0000
WELDER	0.02571	0.03159	0.03052	0.01325
WOODBACKUP	0.6200	0.7120	0.6535	0.4636

Subsamples:
1. Electric space and water heat
2. Nonelectric space heat, electric water heat
3. Nonelectric space and water heat

TABLE 2B

VARIABLE MEANS BY SUBSAMPLE: NONWINTER

	Entire Sample	Subsample 1	Subsample 2	Subsample 3
Observations	4030	1701	1111	1218
ELECDSHW	0.3335	0.3057	0.3825	0.3276
ESPACEHT	0.4221	1.000	0.0000	0.0000
EWATERHT	0.6978	1.000	1.000	0.0000
EWHHSLDMEM	2.295	3.553	2.884	0.0000
EWHDISH	0.2345	0.3057	0.3825	0.0000
EWHPRICE	1.301	1.822	1.931	0.0000
EWHINC	15.30	21.14	23.13	0.0000
INCOME	22.60	21.14	23.13	24.16
IRRPUMP	0.02134	0.02234	0.02880	0.01314
KWHDIFDAY	3.608	3.297	4.220	3.485
MP1000	1.939	1.793	1.863	2.211
MP5000	1.977	1.822	1.931	2.236
NETKWHDAY	23.62	40.95	17.38	5.103
NHSLDMEM	3.291	3.553	2.884	3.297
NROOMS	6.218	6.011	6.311	6.422
OFFMACHINE	0.01787	0.0000	0.02160	0.03941
RP1000	2.945	3.170	2.656	2.895
SHPRICE	7.596	6.327	8.797	8.272
SUSHEDAY	21.16	50.14	0.0000	0.0000
SUSHEPDAY	171.4	406.0	0.0000	0.0000
SUSHEYDAY	485.5	1150.	0.0000	0.0000
SUSHEWDAY	15.91	37.70	0.0000	0.0000
WELDER	0.02581	0.03057	0.03240	0.01314
WOODBACKUP	0.6233	0.7090	0.6517	0.4778

Subsamples:
1. Electric space and water heat
2. Nonelectric space heat, electric water heat
3. Nonelectric space and water heat

V. Empirical Results

As noted above, the time-series/cross-section structure of the data suggests that omitted variables may be correlated over time. If such correlation is present, ordinary least squares (OLS) coefficient estimates will be inefficient and predictions based on the model will be unnecessarily imprecise. Furthermore, if the correlation structure is autoregressive, the estimated standard errors will be biased downward since the regressors are positively autocorrelated (Johnston (1984,311-13)). Hence we are likely to overestimate the true statistical significance of variables in the equation.

Residuals from a preliminary OLS regression (not reported[4]) can be used to estimate the intertemporal correlation structure of the disturbances. For a given household, the residuals from the nonwinter equation form a 12-element vector with the four winter months missing. For each of the 374 households having 12 complete monthly bills, we replace the missing elements with residuals from the winter regression. These complete residual vectors are then used to estimate the 12x12 matrix of correlations among periods.

If the disturbances follow a first-order autoregressive pattern, the correlation matrix will be striped with ones on the main diagonal and with elements in the kth off-diagonal stripe equal to ρ^k, where ρ is the autocorrelation coefficient (see Kmenta (1971,510).) Under the error-components hypothesis, all off-diagonal elements will be equal to ρ, which must be positive.

The computed OLS residual correlation matrix is presented in

Table 3. The matrix has elements generally declining in value from the main diagonal, implying an autocorrelation structure suggestive of omitted time-varying weather or price effects.

Efficient estimates of the coefficients, and consistent estimates of their standard errors, can be obtained by a modification of Kmenta's generalized least squares (GLS) procedure (1971,508-12). The first step is to calculate the autocorrelation coefficient from the combined winter/nonwinter residuals by

$$\hat{\rho} = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} e_{it} e_{i,t-1}}{\sum_{i=1}^{N} \sum_{t=2}^{T} e_{it}^2}.$$

Then all variables are quasi-differenced by the transformation

$$X^*_{it} = X_{it} - \hat{\rho} X_{i,t-1}, \quad t = 2,\ldots,T . \tag{12}$$

Following Prais and Winsten (1954), we retain the first observation for each household by the transformation

$$X^*_{i1} = X_{i1} \sqrt{1 - \hat{\rho}^2}. \tag{13}$$

This transformation of the first observation is important for efficiency, given the relatively short time series. Finally, the model is estimated by OLS using the transformed data.

We allow ρ to differ between households billed monthly and those billed bimonthly. Estimated values for these groups are 0.6898 and 0.7283, respectively.

TABLE 3

CORRELATIONS OF OLS RESIDUALS ACROSS BILLING PERIODS
(374 households with 12 complete bills)

	u1	u2	u3	u4	u5	u6
u1	1.0000	0.5358	0.2594	0.0995	0.0402	0.0561
u2	0.5358	1.0000	0.5931	0.4271	0.3692	0.3623
u3	0.2594	0.5931	1.0000	0.7317	0.5955	0.4410
u4	0.0995	0.4271	0.7317	1.0000	0.6973	0.5770
u5	0.0402	0.3692	0.5955	0.6973	1.0000	0.7956
u6	0.0561	0.3623	0.4410	0.5770	0.7956	1.0000
u7	0.0796	0.3488	0.2811	0.3267	0.6061	0.7172
u8	0.1551	0.4120	0.2287	0.2293	0.5418	0.6389
u9	0.2430	0.3336	0.1650	0.1773	0.3460	0.5699
u10	0.4246	0.3478	0.1193	0.0467	0.2539	0.3695
u11	0.5178	0.3218	0.0253	-0.0566	-0.0044	0.0703
u12	0.5293	0.4908	0.1133	-0.0212	0.0096	0.0879

TABLE 3 (continued)

	u7	u8	u9	u10	u11	u12
u1	0.0796	0.1551	0.2430	0.4246	0.5178	0.5293
u2	0.3488	0.4120	0.3336	0.3478	0.3218	0.4908
u3	0.2811	0.2287	0.1650	0.1193	0.0253	0.1133
u4	0.3267	0.2293	0.1773	0.0467	-0.0566	-0.0212
u5	0.6061	0.5418	0.3460	0.2539	-0.0044	0.0096
u6	0.7172	0.6389	0.5699	0.3695	0.0703	0.0879
u7	1.0000	0.7776	0.6096	0.4559	0.1749	0.1436
u8	0.7776	1.0000	0.6807	0.6269	0.3943	0.2855
u9	0.6096	0.6807	1.0000	0.6959	0.4960	0.3662
u10	0.4559	0.6269	0.6959	1.0000	0.8038	0.5306
u11	0.1749	0.3943	0.4960	0.8038	1.0000	0.6651
u12	0.1436	0.2855	0.3662	0.5306	0.6651	1.0000

GLS estimates of the winter and nonwinter models are reported in Table 4. Most of the water-heat and miscellaneous-usage coefficients are relatively imprecise, especially in the nonwinter equation. Indeed, the only significant water heat variable is the lead term in the nonwinter equation. Neither marginal price nor income has a significant effect in the absence of electric space heating. On the other hand, the significance of rate structure premium in the winter equation is surprising given theoretical expectations and previous studies that have found no effect.

The strongest results to emerge are those regarding space heat usage. Most coefficients are of the expected sign and indicate statistically significant price and income effects, even in the short run, for households with electric space heat. The similarity of space heat coefficients between the winter and nonwinter equations suggests that seasonal variation in the responsiveness of space heating usage to economic variables is adequately captured by variation in UECSH.[5]

While the signs of the price and income effects correspond to theoretical expectations, the positive coefficient on SUSHEWDAY implies that electricity consumption for space heating increases with UECSH by a larger amount if a household owns a wood backup heating system. One explanation might be that the backup system, especially if it is a fireplace, is used for aesthetics rather than for heating comfort, and reduces overall heating efficiency through chimney losses. Finally, the coefficient on SUSHEDAY sufficiently smaller than unity to suggest that the thermal model might be overpredicting

TABLE 4

GLS ESTIMATES (absolute t-statistics in parentheses)

	Winter	Nonwinter		Winter	Nonwinter
MP1000	-6.030	-1.202	EWHPRICE	7.967	-2.064
	(1.302)	(0.7519)		(1.384)	(1.062)
RP1000	-2.096	0.09619	EWHINC	0.3804	0.05321
	(2.006)	(0.2588)		(1.231)	(0.5267)
SUSHEDAY	0.5688	0.4116	INCOME	0.008062	0.04571
	(18.48)	(19.30)		(0.03234)	(0.5394)
SUSHEPDAY	-0.01706	-0.01458	NHSLDMEM	3.186	2.666
	(7.892)	(8.370)		(1.649)	(3.878)
SUSHEYDAY	0.002440	0.003592	NROOMS	-0.1880	-0.1775
	(3.074)	(6.724)		(0.2017)	(0.5495)
SUSHEWDAY	0.04969	0.000009	WELDER	25.34	0.4701
	(2.243)	(0.0006)		(2.833)	(0.1462)
EWATERHT	-16.97	13.41	OFFMACHINE	11.21	5.587
	(1.004)	(2.338)		(1.066)	(1.447)
EWHHSLDMEM	1.969	0.4698	IRRPUMP	-16.44	-0.7187
	(0.8989)	(0.6128)		(1.698)	(0.2038)
EWHDISH	-1.554	-1.319	CONSTANT	22.28	-2.445
	(0.3993)	(0.9773)		(1.545)	(0.4817)
R-squared				0.6018	0.4732
Observations				1944	3984
SSE				676800	587900
Std. Error				18.75	12.17

space heating usage by a larger amount than can be explained by the effects of price, income, and the presence of wood backup systems.[6]

Elasticities with respect to marginal price and income are presented in Table 5. Short-run elasticities, conditional on appliance holdings, are evaluated at the subsample means reported in Table 2. Unconditional or "long-run" elasticities are evaluated at global sample means.[7] These values are generally within, but at the low end, of the range of those reported in other studies as surveyed, for example, in Taylor (1975), Hartman (1979), and Bohi (1981). Based on the estimated covariance matrix of the coefficients, the elasticities for the all-electric subsample are the only ones that are statistically different from zero. Even for this group, however, demand is quite inelastic with respect to both price and income in the short run. In addition, the elasticities are fairly similar between the winter and nonwinter.

VI. Simulation and Policy Analysis

In this section we analyze the effects of three alternative conservation measures. The first policy scenario is a ten percent increase in the price of electricity. The second scenario is a five-degree reduction in thermostat setting. The third measure is an upgrade of insulation levels to r-values of 19.5 for ceilings and 9.45 for walls, the minimum standards proposed by ASHRAE. The effects of each policy are analyzed for the entire sample and for the subset of households having electric space heat. Finally, we estimate rates of

TABLE 5A

PRICE AND INCOME ELASTICITIES: GLS, WINTER

	Marginal Price	Income
Conditional (Short-Run):		
Electric space heat, electric water heat	-0.2283	+0.1705
Nonelectric space heat, electric water heat	+0.1570	+0.3360
Nonelectric space heat, nonelectric water heat	-1.2302	-0.0174
Unconditional:	-0.2366	+0.2331

TABLE 5B

PRICE AND INCOME ELASTICITIES: GLS, NONWINTER

	Marginal Price	Income
Unconditional (Short-Run):		
Electric space heat, electric water heat	-0.2890	+0.1519
Nonelectric space heat, electric water heat	-0.3582	+0.1319
Nonelectric space heat, nonelectric water heat	-0.5208	+0.2164
Unconditional:	-0.3182	+0.1684

return for upgrades of ceiling and wall insulation.

Our simulation procedure uses the model estimates from Table 6 to predict, for each month, the change in mean daily energy consumption that would result from the mean changes in the explanatory variables under each policy. Standard errors are computed using the estimated variance-covariance matrix of the coefficients.[8]

The effects of a price change are straightforwardly analyzed by increasing the marginal price of electricity in each of the interaction variables in which it appears. Analysis of thermostat reductions and insulation upgrades is more difficult, requiring generating new values of UECSH using the thermal equation (5). Changes in thermostat settings affect only the indoor temperature τ, while changes in insulation require re-running the engineering thermal-load model to generate new values of the coefficients, W_i. Either case involves substantial programming effort and computing.

Our approach, which is easily implemented without sacrificing precision, is to approximate equation (5) by an auxiliary regression of UECSH on variables that enter into the thermal model. Explanatory variables in this regression are number of floors, number of rooms, floor area, wall area, window area, r-values of insulation for ceiling and wall; these variables interacted with mean daily heating degree-days for the billing period (HDD); and the same variables interacted with HDD squared. In this regression HDD, calculated to a 65-degree base, serves as a proxy for the indoor-outdoor temperature differential (τ - t). The same procedure is used to generate

predictions for KWHDIFDAY. Both equations fit well with R^2 values of 0.95 and 0.86, respectively.[9]

Changes in insulation levels can be analyzed directly using these equations, since r-values appear as explanatory variables. To analyze thermostat reductions, we use a linear approximation to the thermal load function. To simulate the effects of a k degree thermostat reduction, we reduce the predicted value of UECSH by k times the predicted value of KWHDIFDAY. This approximation obviously works best for small thermostat changes, and will overstate (understate) the effects of the policy if UECSH increases faster (slower) than linearly with temperature setting.

For comparison, the seasonal distribution of mean values of NETKWHDAY under the base case is shown in Figure 1. The range is from 13 kwh per day in June and July to 63 in December for the entire sample, and from 20 to 130 kwh per day for all-electric households.

The effects of a 10 percent increase in marginal price are illustrated in Figures 2A and 2B for all-electric households and for the entire sample, respectively. The vertical axes measure the change in daily consumption, relative to the base, brought about by the policy. The graphs show mean changes, with prediction intervals of width plus and minus one standard error. As expected, the largest reductions occur in winter months among all-electric households, averaging 4.5 kwh per day in December. In contrast, there is very little effect in the summer months.

Unlike price changes, which affect all consumers, thermostat

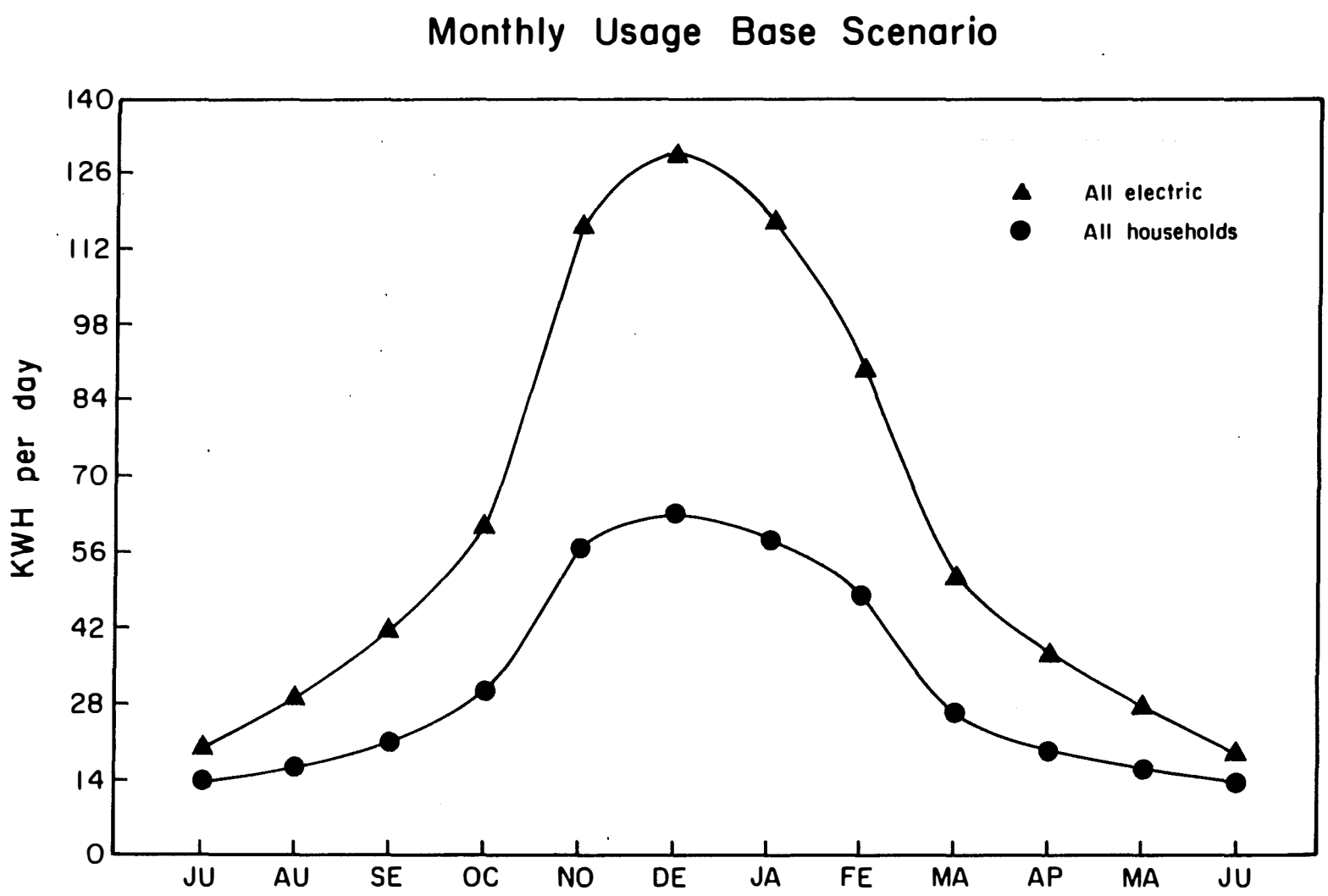
Monthly Usage Base Scenario
KWH per day
140
126
112
98
84
70
56
42
28
14
0
JU
AU
SE
OC
NO
DE
JA
FE
MA
AP
MA
JU
All electric
All households

FIGURE I

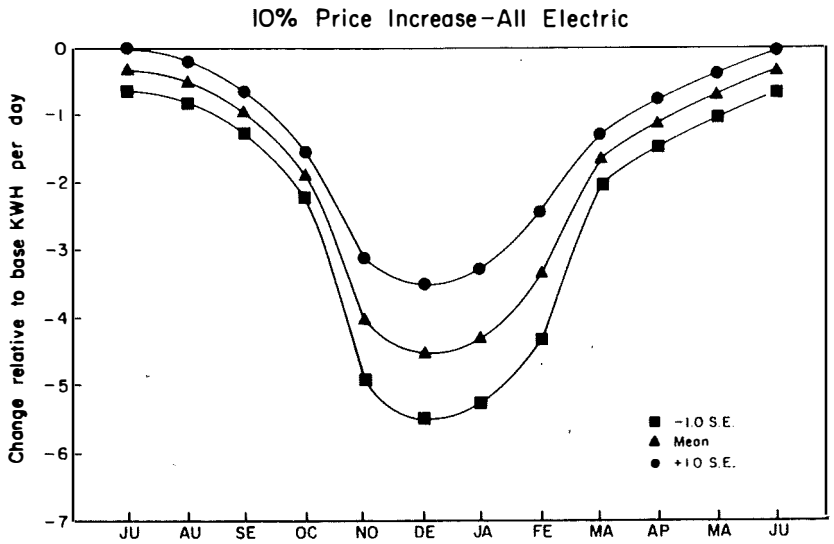

FIGURE 2A

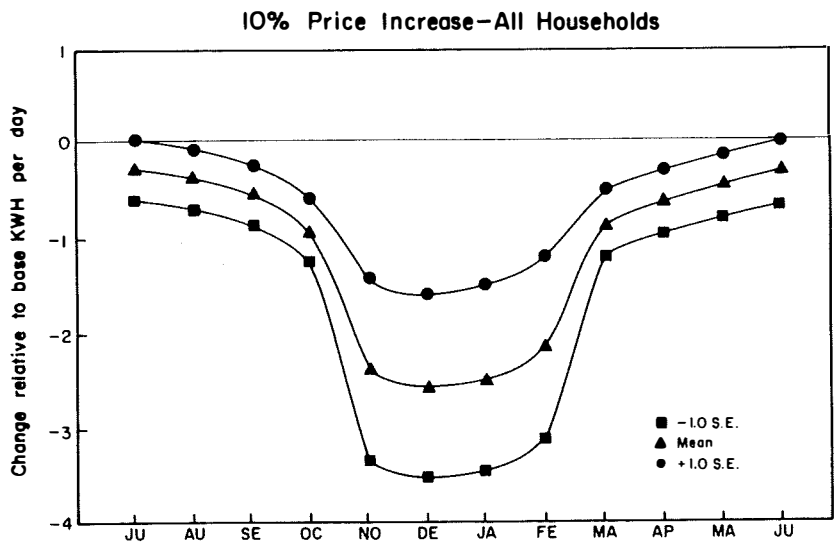

FIGURE 2B

reductions and insulation upgrades affect only consumers with electric space heat. The effects of a thermostat reduction on the latter group are shown in Figure 3A; effects averaged over the entire sample are given in Figure 3B. These changes are roughly two and a half times as large as those induced by the price increase, with much smaller standard errors.

A natural question is, what sorts of policies would lead consumers to reduce thermostat settings? One possible source of such behavior would be changes in tastes, or "conservation awareness," possibly due to information efforts by utilities. Alternatively, utilities might shift the consumer's budget constraint by increasing prices. The analysis above suggests that a 10 percent price increase might be roughly equivalent in its impact on consumption to a thermostat reduction of about two degrees. Our analysis does not suggest that such a price increase would lead to such a thermostat reduction, since reduced consumption of comfort is only one of many possible response to a price increase.

A policy having roughly the same effects as a five degree thermostat reduction is an upgrade of insulation to ASHRAE standards, illustrated in Figures 4A and 4B. Our analysis considers only retrofits of existing houses. Of 185 all-electric households in our sample, 180 (97.3 percent) are below the ASHRAE standard for wall insulation, 108 (58.4 percent) are below the standard for ceilings, and 105 (56.8 percent) are below standards for both walls and ceilings. While almost all households are below the wall standard,

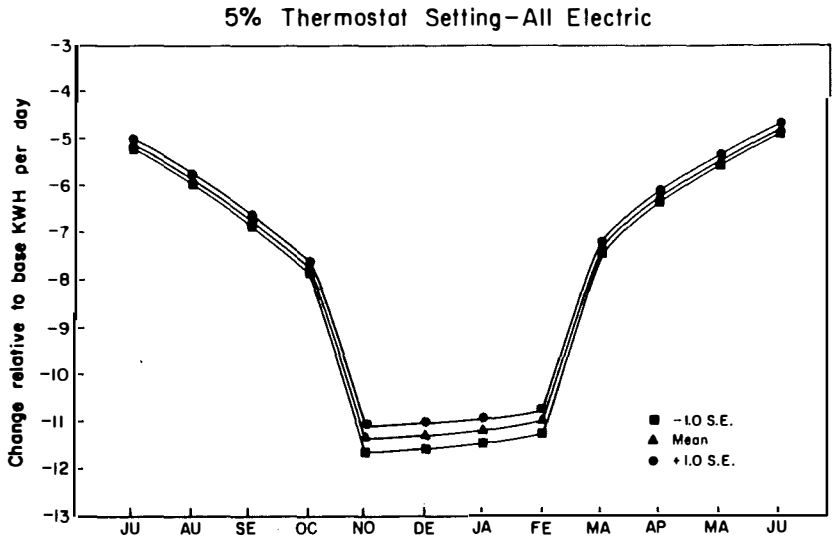

FIGURE 3A

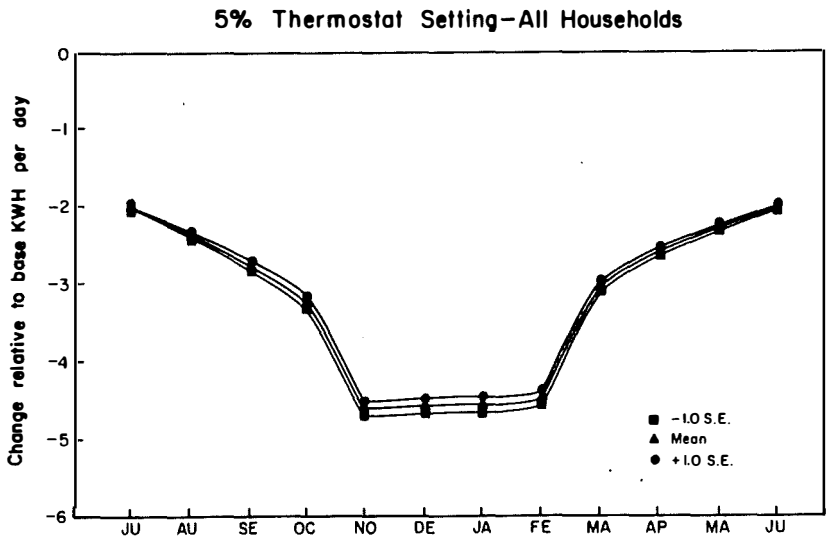

FIGURE 3B

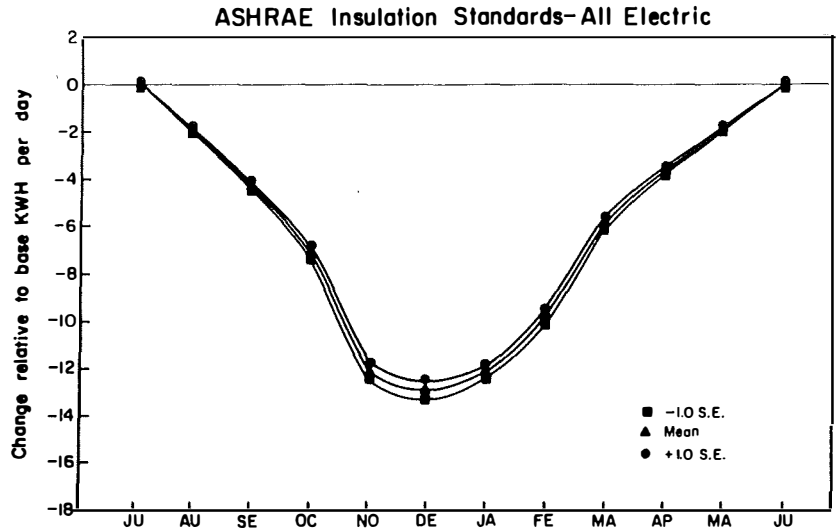

FIGURE 4A

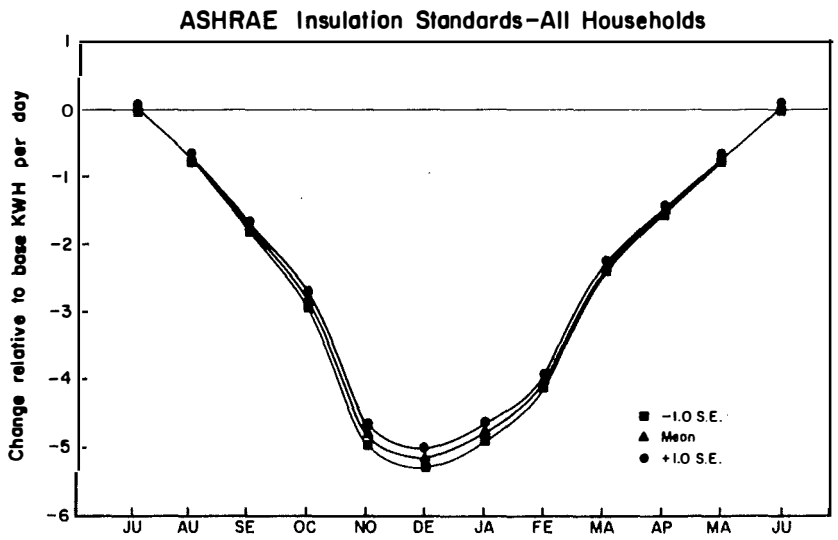

FIGURE 4B

only about half are (also) below the ceiling standard. For households that are below at least one of the standards, the mean annual cost saving from upgrading is $38.45.

To compute rates of return for insulation upgrades, we treat ceiling and wall improvements as separate investment decisions by the consumer. Holding ceiling insulation at its observed level, we increase wall insulation to the ASHRAE standard and determine the resulting reduction in energy consumption. The same procedure is used to find energy savings from ceiling upgrades, holding wall insulation at its base-case level.

Materials and labor costs per square foot for insulation retrofits to various r-values are available in Means (1985). The data reported are for an uninsulated structure with wood siding and assume fiberglass insulation is added. We calculate the materials cost at the observed base-case r-value and at the ASHRAE standard, and take the difference to be the incremental cost of materials for the upgrade. The incremental labor cost contains a component that varies with materials and, for walls, a fixed component for drilling and patching wall holes from outside. All costs are for 1978 and are adjusted for cost-of-living differences smong cities.

Results are presented in Table 6. For both ceilings and walls, the average household below the ASHRAE standard is about 28-29 percent below the standard. The mean rates of return are 4.9 percent for ceiling upgrades and 8.3 percent for walls. Though the cost of the average wall upgrade is twice as large as that of the average ceiling

improvement, the annual energy saving is over three times as large.[10]

These results suggest that the average household that is below the ASHRAE ceiling standard has chosen rationally. For this household, a policy that seeks to encourage ceiling upgrades would be an inefficient use of resources. On the other hand, for many households the rate of return to wall improvements is attractive relative to alternative investment prospects. It is, therefore, somewhat surprising that this option has been foregone by nearly everyone in our sample. An informational program designed to assist consumers in evaluating the costs and benefits of wall insulation improvements might be useful in speeding elimination of a disequilibrium situation.

Furthermore, such a policy would have the largest payoffs for smaller structures and those that are far below the ASHRAE standard. This is evident from regressions of rates of return on income, square feet, and base-case r-value, reported in Table 7. Better-insulated homes have lower rates of return only for wall upgrades. Larger structures have lower rates of return for both ceiling and wall improvements: as structure size increases so do insulation costs, but energy savings decline.[11]

Among households that are below ASHRAE, one might expect an inverse relationship between rate of return and income, the latter being a determinant of accessibility to credit markets. When the effects of structure size and insulation levels have been considered, however, income has no significant effect.

TABLE 6

COSTS AND RETURNS FOR INSULATION UPGRADES

	Ceiling	Wall
Number of Observations	108	180
Mean R-Value	14.13	6.72
Std. Dev. of R-Value	4.89	1.40
Mean Retrofit Cost	$221.20	$460.60
Mean Annual Energy Savings	$ 9.27	$ 32.26
Mean Rate of Return	4.9%	8.3%

TABLE 7

REGRESSIONS FOR RATE OF RETURN
(Absolute t-statistics in parentheses)

	Ceiling	Wall
Income	0.000281 (1.235)	-0.00008 (0.2962)
Square Feet of Ceiling	-0.00005431 (9.937)	
Square Feet of Wall		-0.00003985 (9.546)
Base-Case R-Value	-0.0005214 (1.143)	-0.01467 (7.233)
Constant	0.1242 (13.38)	0.2364 (16.25)
R-Squared	0.5169	0.5283
Observations	108	180
SSE	0.05509	0.2441
Std. Error	0.02301	0.03724

While disequilibrium levels of wall insulation may persist due to imperfect information, they may arise initially if the present rate of return to retrofits is higher than what was available at the time of construction. This raises interesting questions regarding the extent to which insulation benefits are capitalized into housing values, and the speed with which builders respond to such incentives in altering construction practices. Unfortunately the absence of house value data in this sample precludes such analysis.

Insulation options for new dwellings could be analyzed by reestimating the model for a sample of recently built homes. This would allow consideration of a broad menu of policy choices, including changes in construction standards.

VII. Conclusions

This study has examined a model of residential electricity demand using a pooled cross-section/time-series of micro-data on individual households over a series of billing periods. We have found significant, though small, short-run price and income responsiveness in electricity consumption for space heating. The elasticities do not differ substantially between the winter heating season and the rest of the year.

While the model does well in explaining space heating consumption, results for water heating and miscellaneous end-uses are relatively imprecise. Such results, coupled with good overall fits, are symptomatic of multicollinearity or lack of variability in the

data. This problem is compounded by the relatively short time dimension of our sample, with only weather, and to a slight extent prices, varying across billing periods. A longer time series with more variability, particularly in prices, might allow estimation of richer specifications.

Despite these qualifications, the model fits quite well and is useful for policy analysis. Our simulations suggest, for example, that the rate of return to improvements of ceiling insulation in existing houses may be too low to warrant policy encouragement by electric utilities. On the other hand, there may be significant returns to upgrades of wall insulation, particularly in smaller, less-insulated homes.

FOOTNOTES

* Research support was provided by the Bonneville Power Administration and the Northwest Power Planning Council under grant number DE-AI79-83BP13579.

1. For example, see Parti and Parti (1980), Archibald, Finifter, and Moody (1982), and Garbacz (1984).

2. NBSLD, developed by the National Bureau of Standards, DOE-2, developed by Lawrence Berkeley Laboeratory for the Department of Energy, BLAST developed by the Army Civil Engineering Research Laboratory, and the residential building model developed by the Ohio State University for the Electric Power Research Institute.

3. These systems are: (1) electric forces air, (2) gas forced air, (3) oil forced air, (4) electric baseboard, (5) gas hot water, and (6) oil hot water.

4. Available from the authors on request.

5. Interpretation of the space-heat interaction terms is complicated because they involve UECSH. If the thermal model were to predict exaotly the change in space heating consumption necessary to maintain an indoor temperature of 70 degrees, and if there were no consumer response to economic variables, then the coefficient on SUSHEDAY would be unity and the other space-heat coefficients would be zero. The coefficients on SUSHEPDAY and SUSHEYDAY can

be interpreted as the amounts by which changes in the price of comfort and in income, respectively, modify the effect of UECSH on NETKWHDAY. The signs on these coefficients conform to the predictions of economic theory.

An alternative interpretation of these results is that the effects of changes in price and income on total consumption vary both cross-sectionally and seasonally with variation in space heating load. This effect is complicated because all households with electric space heat also have electric water heat.

To illustrate, consider a simple model of the form

$$Q_{it} = \beta_0 P_{it} + \beta_1^{SH} d_i^{SH} Q_{it}^{SH} + \beta_2^{SH} d_i^{SH} Q_{it}^{SH} K_{it} P_{it} + \beta_1^{WH} d_i^{WH} + \beta_2^{WH} d_i^{WH} p_{it}$$

where Q_{it} is total consumption, d^j is a dummy indicating use of electricity for end use j (SH = space heat, WH = water heat), Q_{it}^{SH} is UECSH, K_{it} is KWHDIF, and P_{it} is the marginal price of electricity (so $K_{it}P_{it}$ is the "price of comfort"). Then the effect of a one-kwh per day change in the thermal prediction of space-heat usage is

$$\partial Q_{it}/\partial Q_{it}^{SH} = \beta_1^{SH} d_i^{SH} K_{it} P_{it}$$

which is just $\beta_1^{SH} d_i^{SH}$ times the price of comfort, which will vary both across individuals and over time with both K_{it} and P_{it}. The effect of a one-cent per kwh change in marginal price is given by

$$\partial Q_{it}/\partial P_{it} = \beta_0 + \beta_1^{SH} d_i^{SH} Q_{it}^{SH} K_{it} + \beta_1^{WH} d_i^{WH}$$

which varies with both Q_{it} and K_{it}. Since households with electric space heat also have electric water heat, $d_i^{WH} = 1$ for all observations with $d_i^{SH} = 1$, but not conversely.

6. The magnitude of the coefficient, around .5, implies that the thermal model might be overpredicting by a factor of about two. The effect of such a multiplicative measurement error is to bias the coefficient downward proportionally, although the model can still be used to produce <u>unbiased</u> elasticity estimates and predictions of total consumption.

In any event, as is usual in the case with errors in variables, consistent estimates can be obtained by the use of an instrumental variable for UECSH. The only requirement for such an instrument is that it be uncorrelated with the measurement error; hence some linear combination of variables used as inputs into the thermal model--such as square feet, insulation levels, and heating degree days--will suffice.

A complication with such methods is that bias and inconsistency in the parameter estimates may arise from other sources. In particular, as pointed out by Dubin and McFadden [1984], if unobserved variables that affect appliance choice are correlated with unobservables that affect utilization, as is likely, then the space and water heat dummy variables in the equation will be endogenous. In this case the appropriate instrumental variables technique uses as instruments for the dummies their expected values (fitted probabilities) predicted

from the appliance-choice model.

Some attempts to estimate the model using such instrumental variables techniques produced unreliable results. However, we found no conclusive evidence that GLS estimates from this sample are inconsistent due to either measurement error or appliance endogeneity.

7. For example, the short-run price elasticity can be evaluated, using $\partial Q/\partial P$ from note 5, as

$$\xi_{SR} = (\partial Q/\partial P)(P/Q) = (\beta_0 P + \beta_2^{SH} d^{SH} Q^{SH} KP + \beta_2^{WH} d^{WH} P)/Q.$$

Evaluated at subsample means this becomes:

$$\xi_{SR} = [\beta_0 E(P|d^{SH}) + \beta_2^{SH} d^{SH} E(Q^{SH} KP|d^{SH}) + \beta_2^{WH} d^{WH} E(P|d^{WH})]/E(Q|d^{SH}, d^{WH}).$$

The unconditional elasticity is evaluated at the mean for the entire sample:

$$\xi = [\beta_0 E(P) + \beta_2^{SH} E(d^{SH} Q^{SH} KP) + \beta_2^{WH} E(d^{WH} P)]/E(Q).$$

Though not <u>conditioned</u> on appliance holdings, this does not include the full long-run effect of price on appliance holdings through changes in $\text{Prob}(d^j = 1)$. Thus it might be interpreted as an intermediate-range or "quasi-long-run" elasticity.

8. Let X be the TN x K matrix of observations on the K explanatory variables, ordered first by time period and then by household. Let $L = \frac{1}{N}(I_T \otimes J)$ where J is a 1 x N vector of ones, so that L is

T x TN. Then $\bar{X} = LX$ is a T x K matrix of means across households. Let $\bar{X}^0$ denote the matrix of means computed from the observed data under the base case, and $\bar{X}^1$ denote means under a particular policy. The predicted mean changes in monthly consumption brought about by the policy are given by the T x 1 vector $\hat{y}^1 - \hat{y}^0 = (\bar{X} - \bar{X}^0)\hat{\beta}$, where $\hat{\beta}$ is the GLS estimate of β. The standard errors of the predictions are the square roots of the diagonal elements of the matrix $V(\hat{y}^1 - \hat{y}^0)$ $= (\bar{X}^1 - \bar{X}^0)V(\hat{\beta})(\bar{X}^1 - \bar{X}^0)'$.

9. Complete results are available from the authors on request. The prediction standard errors calculated in note 8 do not consider errors in these auxiliary regressions; that is, they are conditioned on the parameter estimates for the auxiliary regressions. The correct prediction intervals, taking into account all sources of error, will be wider than those shown in Figures 3 and 4.

10. Our simulations predict mean changes in consumption that would have occurred had the exogenous variables been different, for billing periods July 1978 through June 1979. To the extent that weather in this year was typical of long-run average weather, these rates of returns can be interpreted as long-run expected rates.

11. The simple correlations between retrofit cost and square feet are +0.3033 for ceiling and +0.8884 for wall; correlations between energy savings and square feet are -0.2629 for ceiling and -0.3298 for wall.

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