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PRICE EFFECTS OF ENERGY-EFFICIENT TECHNOLOGIES: A STUDY OF RESIDENTIAL DEMAND FOR HEATING AND COOLING

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ABSTRACT

This paper applies a mixed engineering and econometric model to empirically analyze behavioral interaction with new energy-efficient appliances and thermal improvements. The hypothesis is that energy efficient technologies lower the effective price of the services they provide and consequently reduce electricity consumption by smaller amounts than would be anticipated in engineering estimates. The approach incorporates prior engineering knowledge about the interactive effects of weather, appliance efficiencies, and thermal integrity of dwellings to explore treatment groups in an experiment conducted in Florida.

PRICE EFFECTS OF ENERGY-EFFICIENT TECHNOLOGIES: A STUDY OF RESIDENTIAL DEMAND FOR HEATING AND COOLING[1]

SECTION 1: INTRODUCTION

Since the onset of the energy crisis more than a decade ago, policy makers and energy planners have strongly supported legislation and programs to promote installations of energy-efficient technologies. Consequently, there are now numerous utility and government policies in effect to provide information about and reduce the private costs of those technologies. In many instances, the case for those policies has been founded on relatively naive engineering estimates of the savings that the technologies could deliver.

Meanwhile economists have argued that those engineering estimates of energy savings are too high. Improvements in electrical equipment efficiencies and dwelling thermal characteristics are expected to increase the intensity with which the associated appliances are used, thereby attenuating some of the expected conservation from higher efficiencies.[2]

The reasoning is simply that the marginal cost, i.e., the price, of the service provided by the new (more efficient) appliance will be lower and, therefore, will induce increased use of that appliance. This paper reports how we developed models and data sets to test and measure this price effect. Our evidence supports the hypothesis and provides valuable parameters to determine how much the effect reduces engineering estimates of potential conservation.

This analysis was feasible because Florida Power and Light Company (FPL) recently undertook a pioneering study designed, in part, to test and measure the price effect for two dominant residential electricity services: air conditioning and heating. That study, initiated in 1981, sought to determine

how electricity usage levels change after homeowners install one of three technology combinations: (1) upgraded attic insulation, or (2) upgraded insulation and a high-efficiency central air conditioner with conventional electric furnaces, or (3) upgraded insulation and a high-efficiency heat pump. Through a lengthy and sophisticated sampling process, FPL identified a large random sample of all its residential customers that live in single-family dwellings and have central electric heat (CEH) and central air conditioning (CAC)--the all electric customers that account for almost half of its residential electricity usage. Then, four subgroups were randomly selected from this large group. One was assigned to be a control group and the other three to receive, at no charge, one of the three conservation technology combinations.

A distinguishing feature of the FPL study was the random and exogenous choice to install technology combinations that span a wide range of equipment efficiencies. This allows comparisons of differences in electricity usage from among the four customer groups without concerns about possible simultaneity of new appliance purchases and their intensity of use after they are placed into service--a concern that a accompanies any comparative study of customers who bought and installed their own technologies, Dubin and McFadden (1984). Such comparative studies are further hampered by the extreme rarity of installed heat pumps and air conditioners that are state-of-the-art. This is a special problem because the efficiencies of new heat pumps and air conditioners have remained fairly constant until very recent years. Consequently, detecting the price effects of efficiency improvements is difficult or impossible in such studies due to the small amount of efficiency variation across study households.

The FPL study has three other especially important features. First, all households included in the study were monitored with two electricity meters.

One was a recorder that measured total household electrical loads every 15 minutes. The other was a regular electricity meter that measured the monthly kWh usage of the central heat pump or air conditioner. Second, the study included a thorough engineering-oriented survey that collected detailed engineering information about each dwelling--especially about its space-conditioning system and attic insulation--as well as socioeconomic and appliance ownership data. Third, the study incorporated variation in tail-block electricity rates across study participants. Although all FPL customers are billed under the same inverted-block electricity rate, some customers are served through cooperatives or municipal utilities that retail electricity purchased from FPL. Each retailer adds to the FPL rates a unique flat charge per kWh as a franchise charge and/or a utility tax. This billing procedure introduces sample variation in prices, since some sample members are direct FPL customers and some are served through the retailers.

The FPL service territory is also unique. As shown in Figure 1, it covers nearly half the land area in the State of Florida, stretching more than 700 miles from north to south and encompassing considerable weather variation. This is shown in Figure 1 by the substantial differences in heating-degree days and cooling-degree days at each of its three major weather stations, for which hourly weather data were available. In addition, electricity is the dominant residential heating source in the FPL service territory. This is due, in part, to the general availability of natural gas and, in part, to annual heating requirements that are very moderate, thus making the annualized cost of electric heat more competitive.

The data from this experiment offer many obvious opportunities for electricity demand analyses, but in this paper we concentrate on one of those options. Our specific purpose is to study the effect of efficient conservation

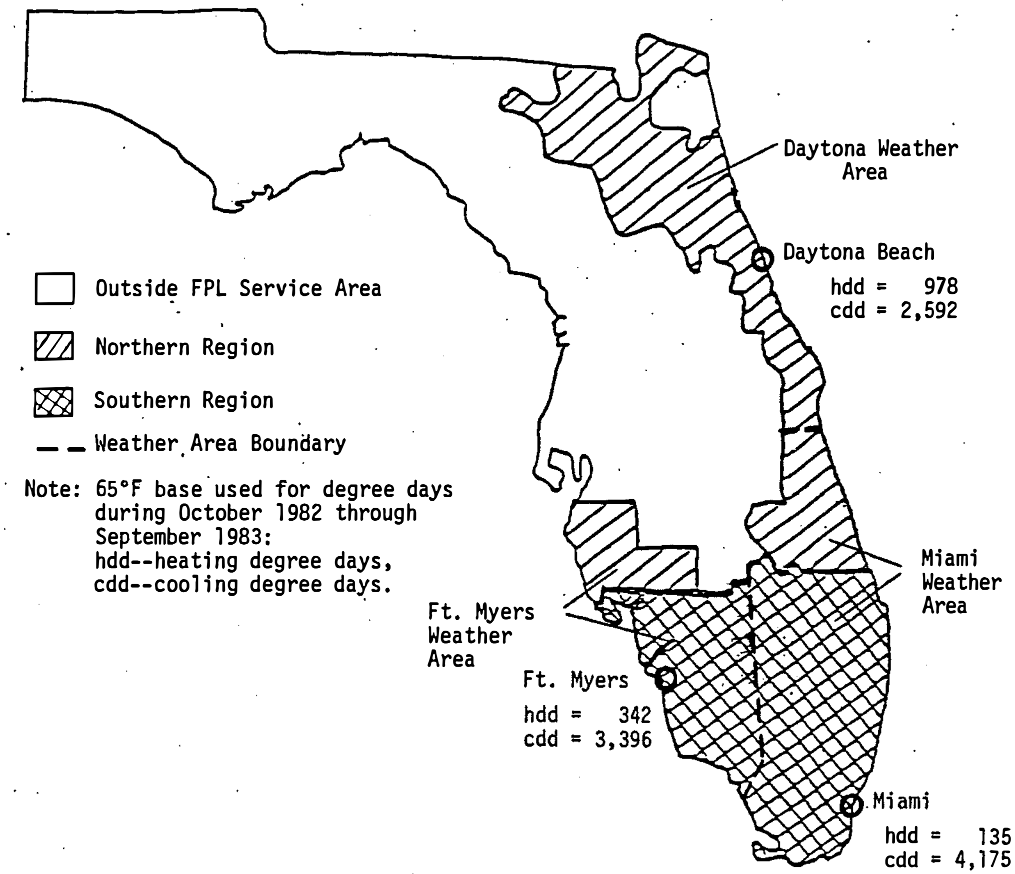

Figure 1. FPL service territory, weather areas, and regional divisions.

technologies on the use of electricity for heating and cooling. Our analysis is restricted to all-electric residences and to aggregate monthly and annual kWh consumption. However, with some modification, the technique could be extended, using this data set, to examine the effects of each technology on kW demand during peak hours for the utility system. This analysis considerably improves our understanding of the demand for electricity in air conditioning and space heating. Both are crucial electrical loads not only to FPL but also to many other electric utilities because they dominate residential electricity use during the hours when system demand is highest and, consequently, when both generating capacity and marginal fuel costs are at their peaks.

Our approach implements the general theoretical notions described above. We view the "consumed product" as cooled or heated residential space, rather than as electricity used by air conditioners and furnaces. This perspective leads to a unique specification of the product price which measures the full cost to the customer of changing his thermostat setting, rather than a price that is simply denominated in terms of cost per kWh. This approach requires application of an engineering model of heat transfer. With this technique we can incorporate both information about engineering features (dwelling insulation, floor space, equipment efficiencies) and prior engineering knowledge about the interactive effects about these features on electrical heating and cooling loads.

In Section 2 we develop the theory and estimation methods to achieve our objective. Section 3 describes the development of our analysis data set. In Section 4 we outline our estimation models and report our findings. Section 5 summarizes the approach and implications of the paper. An appendix provides further details on design features of the FPL experiment.

SECTION 2: SPECIFICATION OF CONDITIONAL DEMAND MODELS

2.1 THEORY

The demand for energy by the household is a derived demand arising from the production of household services--services that are delivered by household appliance durables. Therefore, to understand the residential demand for energy we must understand the residential demand for that 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 appliance stock. Our conditional demand analysis has the unique feature that the durable stock for the largest usage of energy (space and air conditioning) is set exogenously in the sample design.[3]

2.1.1 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, since heating to an interior temperature τ^* requires a costly energy input there is 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, conditional on the choice of fuel type. Expenditures on fuel i are $(p_i/e_i)Q(\tau,t)$ where p_i is the price of fuel i and e_i is the efficiency of the heating system using fuel i. We write:

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

for which the Lagrangian (with multiplier ζ) is:

$$L = U^*[\alpha(\tau^* - \tau),Z] + \zeta[W - Z - (p_i/e_i)Q(\tau,t)] \qquad (2)$$

The first-order conditions are:

$$L_\tau = -U_1^*\alpha - \zeta(p_i/e_i)Q_\tau(\tau,t) = 0 \quad \text{and} \qquad (3)$$

$$L_Z = U_2^* - \zeta = 0 \quad \text{so that} \qquad (4)$$

$$-U_1^*/U_2^* = p_iQ_\tau(\tau,t)/(\alpha e_i) \qquad (5)$$

We see from (5) 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 $\tau - t$, $Q(\tau,t) = a + b(\tau - t) + c(\tau - t)^2$. In this case, condition (5) becomes:

$$-U_1^*/U_2^* = p_i[b + 2c(\tau - t)]/(\alpha e_i) \qquad (6)$$

An alternative formulation of the decision problem assumes that the optimum level of energy is calculated directly by the consumer. Write utility in the form:

$$\begin{aligned} U^*[\alpha(\tau^* - \tau),Z] &= U^*[\alpha(\tau^* - t) - \alpha(\tau - t),Z] \\ &= U^*[\alpha(\tau^* - t) - \alpha G(Q),Z] \end{aligned} \qquad (7)$$

where $G(Q) = \tau - t$ is the implicit solution to $Q(\tau,t) = a + b(\tau - t) + c(\tau - t)^2$. For $\tau \leq \tau^*$, increases in τ are associated with greater utility and greater energy demands. We therefore take the solution to the quadratic equation in which $G'(Q) > 0$.

The consumer's optimization problem becomes:

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

$$(p_i/e_i)Q + Z \leq W \qquad (8)$$

The first-order conditions for (8) are:

$$-\alpha U_1^*G'(Q) - U_2^*(p_i/e_i) = 0 \qquad (9)$$

which is equivalent to (6) as $Q_\tau(\tau,t) = (G'(Q))^{-1}$.

As Dubin (1984) demonstrate, strong conditions are required to ensure the existence of an optimization in energy demand which is dual to the household production formulation. From a theoretical vantage we prefer the household production approach. Furthermore, no additional complexity is added when we specify demand systems that correspond to the first-order conditions (5). 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 (5). Then, the equivalent standardized problem is:

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

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

$$RSP = (p_i/e_i)[Q(\hat{\tau},t) - Q_\tau(\hat{\tau},t) \cdot \hat{\tau}] \qquad (10)$$

As the budget constraint in (10) 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 calculations employs an energy thermal load model for the residence.

2.1.2 Thermal Load Technique

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.[4] 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 quite accurate when detailed information on building characteristics exist. The methodology incorporates complex nonlinear relationship between 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 estreme 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., which are 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. In this approach, two households with equivalent building characteristics facing identical weather patterns would be predicted to have the same energy demand. In this way we adopt a strategy of incorporating an engineering/thermal projection into our energy demand analysis. In reality, we realize that the demands may vary significantly between otherwise identical households due to differences in income, households size, activity patterns, and the cost of energy. That is, departures from the engineering estimates are due to socioeconomic sensitivity in the rate of appliance stock utilization.

Secondly, we use the engineering/thermal load techniques 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.

2.2 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:

$$Y^e_{it} = \sum_{j=1}^{J} UEC^j_{it}\ \delta^j_i(X^j_{it}\beta^j) + Z_i\gamma + \varepsilon_{it} \tag{11}$$

where Y^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 socioeconomic 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 electricity, 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:

$$UEC^j_{it} = H^j_{it}\alpha^j + v^j_{it} \tag{12}$$

where H^j_{it} = vector of characteristics of appliance j for household i in period t, α^j = vector of parameters associated with H^j_{it}, v^j_{it} = error term in linear specification of UEC. Combining (11) and (12) we obtain:

$$Y^e_{it} = \sum_{j=1}^{J} \delta^j_i (H^j_{it}\alpha^j)(X^j_{it}\beta^j) + Z_i\gamma + \varepsilon_{it} + \tilde{v}_{it} \tag{13}$$

where:

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

The purpose of the engineering/econometric approach is to minimize the measurement error $\tilde{v}_{it}$ 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 engineering data and emphasizes the structure of the estimated equation.

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:

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

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

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

$E(\varepsilon_t\varepsilon_s') = \sigma_{ts}I_N$ t,s = 1,2,...,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 $E(\varepsilon_{it}\varepsilon_{jt})$ give the contemporaneous cross-sectional covariances, assumed to be zero. The complete covariance structure has the Seemingly Unrelated Regression (SUR) form: $V(\varepsilon) = \Sigma_T \otimes I_N$ with $\Sigma_T = (\sigma_{ts})$ 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 hypothesis is equivalent to the random effects model and lends itself to simple econometric estimation. Alternatively, it is possible that Σ_T has an autoregressive structure in which $E(\varepsilon_{it}\varepsilon_{is}) = \rho^{|t-s|}$. 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.

Finally, the data in our study permit the co-estimation of the usage of air conditioning and space conditioning. We are, therefore, able to separate the total usage in (11) into its components:

$$Y_{it}^{SH} = UEC_{it}^{SH}\delta_i^{SH}(X_{it}^{SH}\beta^{SH}) + \varepsilon_{it}^{SH} \quad (14)$$

$$Y_{it}^{AC} = UEC_{it}^{AC}\delta_i^{AC}(X_{it}^{AC}\beta^{AC}) + \varepsilon_{it}^{AC} \quad \text{and} \quad (15)$$

$$Y_{it}^{e} \equiv Y_{it}^{SH} + Y_{it}^{AC} + Z_i\gamma \quad (16)$$

Equations (14), (15), and (16) are consistent with equation (11) where j = SH or AC denote space and air conditioning, respectively.

Estimation of the joint system is accomplished under the (SUR) framework where we allow possible correlation in the disturbances for space and air conditioning usage. The error structure for (14) and (15) is then:

$$V(\varepsilon^{SH}) = \Sigma_T^{SH} \otimes I_N$$

$$V(\varepsilon^{AC}) = \Sigma_T^{AC} \otimes I_N$$

$$E(\varepsilon^{SH}\varepsilon^{AC}) = \Sigma_T^{SHAC} \otimes I_N$$

which is consistent with a fully specified seemingly unrelated regression in which separate equations are estimated for each billing period and each space conditioning type.

SECTION 3: DATA DEVELOPMENT

This section describes how we developed our analysis data sets to estimate equations (14) and (15). Those equations include three types of variables: household and pure data, actual electricity usage, and unit energy consumption (UEC) values for air conditioning and heating.

3.1 HOUSEHOLD AND PRICE DATA

Detailed household data were available from three sources. The first was the energy audit and interview data from the survey that included 2,000 customers. This survey included detailed engineering data such as the configuration, capacity and amperage of central air conditioners and heat pumps. It also included details on dwelling characteristics such as square footage, attic insulation levels, and types of walls and floors. Finally, it included a complete inventory of appliance ownership and socioeconomic data.

A second source was an "inspection report" which provided engineering data for new conservation technologies that were installed during the study. The third was the "change reports" which provided new appliance and socioeconomic data for new occupants of dwellings included in the study.

We developed our electricity price data using both the billing records for study participants and the FPL rate structure (Table 1). This was necessary since FPL customers pay slightly different rates depending on their location within the service territory. In certain localities flat charges per kWh are added to customers' bills as a franchise charge (in municipalities that retail power that is purchased from FPL) and as a local tax. These charges are unique to localities which may impose either, neither, or both. We determined the amount of these surcharges for each customer by first calculating the amount of each customer's bill using just the basic FPL rate. The

Table 1. FPL RESIDENTIAL RATE STRUCTURE

Rate component	Billing year[a] 1982	1983
Fixed charge ($/month)	5.09	5.15
Energy charge (¢/kWh)		
First 750 kWh	5.599	5.842
Over 750 kWh	6.617	6.842

[a]The 1983 billing year began with readings on and after December 23, 1982.

surcharge is the difference between this amount and the amount of the bill divided by the amount of kWh consumption. The average tail-block rate among participants was about 7.8¢/kWh for 1982 and 8¢/kWh for 1983, so the average surcharge was about 1.2¢/kWh (cf. Table 1).

3.2 ELECTRICITY USAGE VARIABLES

A heat pump provides both heating and air conditioning--it can transfer indoor heat to the outdoors or outdoor heat to the indoors. At temperatures above the so-called "balance point"--between 35°F and 40°F--heat pumps can extract enough heat from the outdoor air to maintain comfortable indoor temperatures. Below that point, heat supplied by the outdoor unit is supplemented by heat from some other backup source to meet heating requirements. Usually, that source is a set of resistance heating coils, very similar to a conventional electric furnace.

These features impose important limitations on our kWh usage data for heat pumps, i.e., the heating, ventilation, and air conditioning (HVAC) readings from the meters on the outdoor heat pump units. In the months when some heating is used, it is possible that those readings represent only part of the heating load, the rest being due to the resistance backup. In addition, it is not uncommon to use both air conditioning and heating during a winter month in Florida. So the readings may include some air conditioning usage for those months as well. Consequently, the HVAC readings from heat pumps are unambiguous for only the summer months when all HVAC usage is measured and represents only air conditioning. For the three summer months, July through September, we adopted adjusted HVAC readings from both heat pumps and straight cool units as a measure of kWh usage for air conditioning.

Because of these ambiguities, we dropped participants with heat pumps from our sample for the fall, winter, and spring quarters. Our measures of air conditioning usage, X^{AC}, in those quarters were adjusted HVAC usage for only those participants with straight cool units.

We had to adjust the HVAC readings for split systems because they excluded the indoor fan component of the electrical load. Based on discussions with HVAC engineers we adjusted those values by a factor.[5]

$$f = x/(x-w)$$

where

f = multiplication factor,

x = ratio of the system design capacity rating (in Btus per hour) to the EER rating, where both ratings are determined at design conditions, and

w = wattage of the indoor fan.

The design capacities and the EER ratings of each air conditioner and heat pump were available from the FPL survey data. Wattage estimates for the indoor fan motors were approximated for us by FPL engineers and were based on typical motor horsepower ratings for fan motors in systems of various capacities. We applied essentially this same procedure to adjust the HVAC readings for usage by the pump motor in water-based systems.

We converted both these adjusted values of kWh usage for air conditioning and the total kWh usage values (from the whole-house meters) to aveage daily values for each billing month, dividing by the number of days in the corresponding billing month.

To determine electricity usage for space heating, we substituted these two average daily usage values into equation (16), along with an estimate of baseline usage correspondsing to the $Z\gamma$ terms.[6] The solution to this equation is our measure of X^{SH} for equations (14) and (15). Our estimate of baseline usage for each household was the average difference for a summer day between its total electricity use and its use for air conditioning.[7] Section 4 reports

an analysis of the contribution of various end-use appliances to these baseline usage values.

3.3 UNIT ENERGY CONSUMPTION

Unit energy consumption (UEC) estimates for heating and cooling are engineering approximations of electricity use for those end-uses during a certain time period. Since our electricity usage variables are average daily values during billing months, our goal was to construct UECs for the same periods.

Figure 2 is a simple schematic of our method. As shown, two types of intermediate variables are developed to construct UEC estimates: thermal (heating and cooling) loads (Btus/hr) and unit operating efficiencies. Although several costly and sophisticated models are available to estimate thermal loads, most are not well suited to our purposes and data. We chose to implement the Dubin-McFadden model which produces reasonable estimates of thermal loads that are integrated over periods at least 24 hours long.

The thermal model generates hourly estimates of heating or cooling loads that are aggregated to project total daily and monthly loads. The basic form of the model equations is

$$Q(\tau,t) = \max[0, \text{Btu}] \tag{17}$$

where

$$\text{Btu} = a + b\Delta + c\Delta^2,\ \Delta>0$$
$$= 0,\ \Delta\leq 0$$
$$\Delta = \tau - t \text{ for cooling, and}$$
$$= t-\tau \text{ for heating}$$

The parameters a,b, and c are household-specific functions of dwelling, climate, and occupants characteristics such as

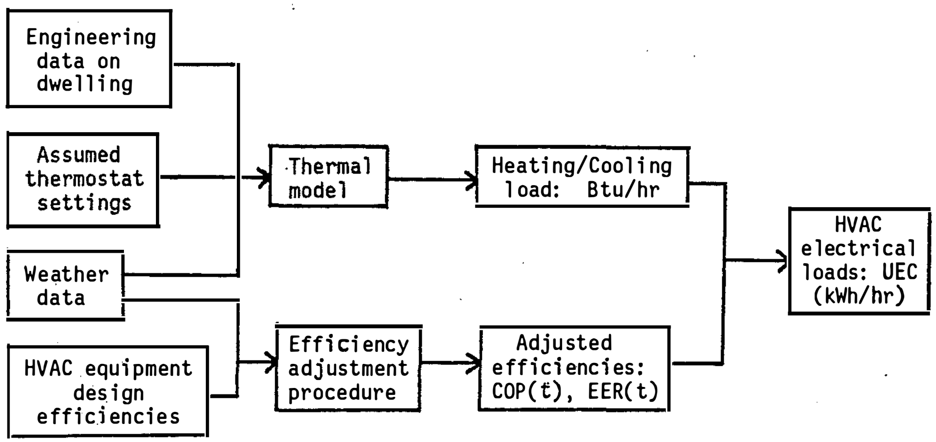

Figure 2. Method to construct UEC estimates for HVAC electricity usage.

- Square footage and number of stories,
- Amount of attic, wall, and floor insulation,
- Number, type, and size of windows and doors,
- Prevailing wind speed and ground temperatures within a season, and
- Number of occupants.

Equation (17) was evaluated for each study participant and for each hour of the 12-month period included in our analysis.

The second type of intermediate variable was the operating efficiency estimates for heating and cooling. They approximate the kWh required per Btu of heating or cooling load. Because HVAC equipment efficiencies are sensitive to temperature variations they were also calculated for each hour of the 12-month study period.

The operating efficiency numbers most commonly used by HVAC equipment retailers are energy efficiency ratios (EERs) for air conditioning and coefficients of performance (COPs) for heating. Both values are measures of heat transferred per unit of energy (electricity) consumed at specific design (indoor and outdoor temperature and humidity) conditions. Specifically, design EER is

$$EER^* = \frac{\text{heat rejection (Btu/hr)}}{\text{heat input (watts)}}$$

and design COP is

$$COP^* = \frac{\text{heat output (Btu/hr)}}{\text{heat input (Btu/hr)}}$$

Since most heating and cooling takes place when temperatures are quite different from design conditions, it was necessary to represent EER and COP as functions of temperature and design values, i.e., as

$$EER(t) = f(EER^*, t) \quad \text{and}$$

$$COP(t) = q(COP^*, K^*, t)$$

where EER(t) and COP(t) are temperature-sensitive measures of EER and COP, and K^* is the design heating capacity. We constructed these functions as piecewise linear approximations of typical unit performance data presented in Collie (1979). These functions represent the decline in efficiencies as temperatures become extreme: EER declines and COP rises with temperature over the relevant temperature ranges.[8]

To construct hourly estimates of kWh requirements for heating and cooling, the hourly values of equation (17) were divided by

$$E_c^* = EER(t) * 10^3 \quad \text{and}$$
$$E_H^* = COP(t) * 3.413 \tag{18}$$

Then these hourly estimates were aggregated over all the hours in each billing month to obtain the UEC estimates for each customer.

This sequence of operations was completed for two assumed thermostat settings for heating, and two for cooling. The FPL survey data showed that the average study participant kept his thermostat at about 77°F in summer and 68°F in winter. However, there was considerable customer-to-customer variation in these reported settings. After examining the reported range of settings, we chose to compute UECs at 67°F and 70°F for heating and at 75°F and 78°F for cooling.

We computed the "price of comfort"--see equation (6)--as the cost of changing thermostat settings by one degree, which is unique for each customer in each month. The estimates are the product of the FPL tail-block electricity rate (adjusted for franchise charges and local taxes) and the projected change in kWh requirements for a one-degree thermostat change. The latter was approximated as the average difference per degree change between the two UEC estimates for each season.

Since it was necessary to assume single reference values of UEC for estimating equations (14) and (15), we selected the estimate based on 70°F for heating and the estimate based on 75°F for cooling.

SECTION 4: ESTIMATION MODELS AND FINDINGS

This section reports our estimation models (Section 4.1) and results (Section 4.2). These models are designed primarily to test whether residential customers use less electricity for heating and cooling as the service price increases, and to determine the effects of income and household occupancy on those end uses. One version of the models is designed to test whether the so-called Hawthorne effect is a significant factor, i.e., whether the mere fact that study participants knew they were being experimented upon (and benefited from that fact) had an effect independent of the nature of the experiment.[9] We also seek to measure the extent to which conservation behaviors persist from season to season. Finally, we report conditional estimates of electricity usage for purposes other than space conditioning, and verify our technique for approximating electricity usage for heating

4.1 ESTIMATION MODELS

For estimation we divided both sides of equations (14) and (15) by our estimates of UEC.[10] The corresponding estimation equations are:

$$UA_t = \alpha_0 + \alpha_1 \text{ PCOOL}_t + \alpha_2 \text{ INCOME} + \alpha_3 \text{ NOCCPT} + \varepsilon A_t \tag{19}$$

$$UH_t = \beta_0 + \beta_1 \text{ PHEAT}_t + \beta_2 \text{ INCOME} + \beta_3 \text{ NOCCPT} + \varepsilon H_t \tag{20}$$

where

$UA_t = Y_t^{AC}/UEC_t^{AC}$ for month t

$UH_t = Y_t^{SH}/UEC_t^{SH}$

$PCOOL_t = P_t(\Delta UEC_t^{AC}/\Delta\tau) = P_t\, \lambda^{AC}$

$PHEAT_t = P_t(\Delta UEC_t^{SH}/\Delta\tau) = P_t\, \lambda^{SH}$

P_t = FPL tail-block rate plus surcharges

$\lambda^{AC},\lambda^{SH}$ = change in kWh required per degree change of the thermostat setting for heating and cooling, respectively

INCOME = an index for family income where 1 refers to income below $10,000 per year; 2, $10,000 to $20,000; 3, $20,000 to $30,000; 4, $30,000 to $40,000; 5, $40,000 to $45,000; and 6, above $45,000

NOCCPT = the number of occupants in the dwelling

$\underline{\alpha},\underline{\beta}$ = regression coefficients

$\varepsilon A_t, \varepsilon H_t$ = error terms.

Table 2 reports mean values of these regression variables for each of the four calendar quarters included in our analysis.

In preliminary regressions we considered other models with interactions between income and price and with separate variables to designate the number of occupants by age group. Generally, those models were not as effective as the simpler versions of equations (19) and (20).[11]

We did, however, use another version of these two models to test the so-called Hawthorne effect, i.e., in this case, the hypothesis that even after accounting for prices, income, and demographics, there are remaining differences among the electricity usage of the four study groups. This would occur if, for example, customers who received new air conditioners or heat pumps systematically altered their usage not only because of the change in the price of comfort but also simply because they obtained a windfall capital gain. To test this we also estimated versions of equations (19) and (20) with indicator variables for each treatment group.

4.2 FINDINGS

We estimated both equations (19) and (20) using the Seemingly Unrelated Regression (SUR) procedure. To avoid severe data losses we applied SUR within each of the four calendar quarters of the study. Data losses occur any time that one of the regression variables is missing for the period covered by SUR. Since most (327) of the 504 customers have missing usage data for at least one

Table 2. MEANS OF REGRESSION VARIABLES

	Quarter			
Variable	Oct-Dec 1982	Jan-Mar 1983	Apr-Jun 1983	Jul-Sep 1983
UA	0.43	0.51	0.35	0.51
UH	--	0.69	--	--
PHEAT	--	0.19	--	--
PCOOL	0.56	0.23	0.20	0.46
INCOME	3.70	3.61	3.67	3.58
NOCCPT	3.14	3.09	3.17	3.26

month, we chose calendar quarters as reasonable representations of periods in which electricity consumption patterns are most correlated.

Tables 3 through 6 report the regression coefficients and t-statistics from each of the four quarterly regressions. The upper set is without indicator variables for treatments in the experiment. The lower set includes the indicators: IU for insulation upgrade, HEAC for a high-efficiency air conditioner and insulation upgrade, and HEHP for a high-efficiency heat pump and insulation upgrade. Each table also reports two overall regression statistics: R^2 and weighted mean square error for the system. Generally the R^2 values were unimpressive, reflecting a large amount of unexplained variation in the ratio of actual to projected electricity use for HVAC. Nonetheless, the regressions were all statistically valid in the sense that the R^2 values for each system were significantly different from zero at the .01 level.[12]

Elasticities

In Table 7 we report elasticities that correspond to the regression coefficients from the first set of coefficients in these tables.[13] The elasticities are calculated at the mean values of the regression variables. Except for two late fall months, November and December, and an early spring month, May, when cooling equipment is used less intensively, all of the price elasticity coefficients are highly significant. Even in the three months when they are not significant, the estimates have the correct sign but are near zero. Other estimates range in magnitude from -0.84 in February to -0.12 in the hottest months, August and September. Generally, elasticities are higher in those months when cooling is least required, i.e., when cooling degree days are smaller. This seems reasonable since occupants may be more willing to shut off their air conditioning when outdoor temperatures are in the high 70s and low 80s during only midday periods than when temperatures get into higher ranges and stay relatively high all night.

Table 3. WINTER REGRESSION EQUATIONS

Month	Regression coefficients						
	Intercept	PHEAT	PCOOL	INCOME	NOCCPT	IU	HEAC
	Without Treatment Indicators						
January	0.90**	-1.87**	--	0.01	0.04		
	(5.34)	(-5.22)		(0.14)	(1.03)		
	0.42	--	-1.29**	0.08	0.02		
	(1.45)		(-3.11)	(1.25)	(0.33)		
February	1.01**	-1.47**	--	-0.01	0.02		
	(8.07)	(-6.48)		(-0.74)	(0.69)		
	3.59**	--	-28.61**	0.22	0.05		
	(1.94)		(-3.75)	(0.52)	(0.10)		
March	1.01**	-1.74**	--	-0.04	0.03		
	(6.28)	(-5.08)		(-1.13)	(0.88)		
	1.20**	--	-6.03**	0.19	-0.09		
	(2.13)		(-3.54)	(1.49)	(-0.59)		
	With Treatment Indicators						
January	0.91**	-1.88**	--	+0.00	0.04	-0.12	0.28**
	(5.03)	(-5.24)		(0.11)	(0.89)	(-1.02)	(2.06)
	0.25	--	-1.40**	0.09	0.04	0.51**	-0.29
	(0.81)		(-3.32)	(1.42)	(0.61)	(2.41)	(-1.17)
February	1.00**	-1.48**	--	-0.02	0.01	-0.09	0.29**
	(7.60)	(-6.58)		(-0.79)	(0.51)	(-1.12)	(3.07)
	2.45	--	-30.40**	0.29	0.17	3.33**	-1.78
	(1.24)		(-3.92)	(0.68)	(0.37)	(2.48)	(-1.15)
March	0.98**	-1.73**	--	-0.04	0.03	-0.04	0.24*
	(5.73)	(-5.05)		(-1.15)	(0.79)	(-0.37)	(1.92)
	1.21**	--	-6.39**	0.21	-0.07	0.30	-0.75
	(1.99)		(-3.66)	(1.56)	(-0.47)	(0.72)	(-1.54)

Note: All coefficients are from the SUR systems whose weighted R^2 = 0.051 and 0.072 for the systems with and without treatment indicators, respectively. Total observational units = 252. Significance levels are denoted by asterisks: 10 percent (*) and 5 percent (**). T-statistics are in parentheses. The dependent variable for each regression is the ratio of actual kWh usage to projected kWh usage, or UEC values.

Table 4. SPRING REGRESSION EQUATIONS

Month	Regression coefficients					
	Intercept	PCOOL	INCOME	NOCCPT	IU	HEAC
	Without Treatment Indicators					
April	0.39**	-1.00**	0.08**	-0.04		
	(3.05)	(-3.60)	(2.72)	(-1.32)		
May	0.05	-0.05	0.05**	0.01		
	(0.76)	(-0.48)	(3.43)	(0.63)		
June	0.21**	-0.32**	0.67**	0.04**		
	(3.18)	(-3.50)	(4.40)	(2.57)		
	With Treatment Indicators					
April	0.45**	-1.09**	0.08**	-0.04	-0.04	-0.15
	(3.27)	(-3.80)	(2.72)	(-1.29)	(-0.46)	(-1.48)
May	0.08	-0.04	0.05**	0.01	-0.06	-0.03
	(1.09)	(-0.31)	(3.36)	(0.52)	(-1.30)	(-0.51)
June	0.22**	-0.31**	0.06**	0.04**	-0.02	-0.00
	(2.97)	(-3.18)	(4.35)	(2.50)	(-0.43)	(-0.03)

Note: All coefficients are from the SUR systems whose weighted R^2 = 0.080 and 0.0854 for the systems with and without treatment indicators, respectively. Total observational units = 282. Significance levels are denoted by asterisks: 10 percent (*) and 5 percent (**). T-statistics are in parentheses. The dependent variable for each regression is the ratio of actual kWh usage to projected kWh usage, or UEC values.

Table 5. SUMMER REGRESSION EQUATIONS

Month	Regression coefficients						
	Intercept	PCOOL	INCOME	NOCCPT	IU	HEAC	HEHP
			Without Treatment Indicators				
July	0.29** (5.79)	-0.17** (-2.44)	0.06** (5.33)	0.03** (2.50)			
August	0.36** (7.89)	-0.14** (-2.84)	0.04** (3.91)	0.03** (2.99)			
September	0.35** (7.73)	-0.12** (-2.69)	0.05** (4.60)	0.03** (3.08)			
			With Treatment Indicators				
July	0.27** (4.81)	-0.17** (-2.24)	0.06** (5.32)	0.03** (2.55)	0.03 (0.80)	0.07 (1.60)	0.01 (0.19)
August	0.35** (6.90)	-0.13** (-2.41)	0.04** (3.86)	0.03** (2.89)	-0.00 (-0.08)	0.07 (1.57)	0.02 (0.56)
September	0.35** (6.89)	-0.12** (-2.35)	0.05** (4.55)	0.03** (3.02)	-0.01 (-0.29)	0.06 (1.33)	-0.00 (-0.03)

Note: All coefficients are from the SUR systems whose weighted R^2 = 0.049 and 0.056 for the systems with and without treatment indicators, respectively. Total observational units = 396. Significance levels are denoted by asterisks: 10 percent (*) and 5 percent (**). T-statistics are in parentheses. The dependent variable for each regression is the ratio of actual kWh usage to projected kWh usage, or UEC values.

Table 6. FALL REGRESSION EQUATIONS

Month	Regression coefficients					
	Intercept	PCOOL	INCOME	NOCCPT	IU	HEAC
			Without Treatment Indicators			
October	0.30** (4.15)	-0.32** (-3.54)	0.05** (3.49)	0.04** (2.80)		
November	0.08 (1.27)	-0.02 (0.23)	0.03** (2.47)	0.02 (1.35)		
December	0.04 (0.50)	-0.00 (-0.00)	0.04** (2.36)	0.01 (0.88)		
			With Treatment Indicators			
October	0.28** (3.65)	-0.29** (-2.99)	0.05** (3.35)	0.04** (2.70)	0.01 (0.20)	0.04 (0.74)
November	0.08 (1.14)	-0.00 (-0.05)	0.03** (2.40)	0.02 (1.30)	-0.00 (-0.05)	0.02 (0.34)
December	0.02 (0.27)	-0.01 (-0.11)	0.04** (2.42)	0.02 (0.97)	0.04 0.79	-0.01 (-0.23)

Note: All coefficients are from the SUR systems whose weighted R^2 = 0.064 and 0.070 for the systems with and without treatment indicators, respectively. Total observational units = 214. Significance levels are denoted by asterisks: 10 percent (*) and 5 percent (**). T-statistics are in parentheses. The dependent variable for each regression is the ratio of actual kWh usage to projected kWh usage, or UEC values.

The price elasticities of demand for electricity used in space heating are relatively high for all three winter months. The estimates range from -0.52 to -0.81.

All of these price elasticity estimates confirm the notion that homeowners will use their air conditioning and heating more intensively when the effective price of comfort is lower. Based on these results, we should expect that the pure engineering approach overestimates the conservation potential of various strategies. For example, engineering models often assume that a percentage improvement in thermal efficiency--i.e., a percentage reduction in UEC values--will translate into an identical percentage reduction in electricity usage, i.e., that

$$\eta_{Y,UEC} = 1 = d\ln Y/d\ln UEC.$$

However, it can easily be shown from equations (19) and (20) that, while assuming only UEC and λ vary due to thermal improvements,

$$\eta_{Y,UEC} = 1 + \eta_{Y,P} \cdot \eta_{\lambda,UEC} \tag{21}$$

where

$$\eta_{\lambda,UEC} = d\ln\lambda/d\ln UEC.$$

A separate set of regressions showed that the value of $\eta_{\lambda,UEC}$ for cooling varies from about 0.1 during summer months up to 0.15 in nonsummer months. For heating it varies between about 0.1 and 0.16. These values imply, using equation (21), that actual conservation for cooling would be as much as 13 percent below engineering estimates for nonsummer months, but only about 1 or 2 percent below those estimates during peak summer months.[14] This seasonal difference naturally derives from the low price elasticities in the peak summer season. These results illustrate that actual energy savings due to thermal improvements and improvements in HVAC equipment efficiencies are below those estimated from engineering models. Attenuation of these engineering

Table 7. ELASTICITIES OF DEMAND FOR ELECTRICITY IN SPACE COOLING AND HEATING

	Elasticity		
Month	Price	INCOME	NOCCPT
	Cooling		
January	-0.59**	0.60	0.15
February	-0.84**	0.33	0.06
March	-0.68**	0.73	-0.27
April	-0.58**	0.83**	-0.35
May	-0.07	0.75**	0.12
June	-0.35**	0.56**	0.29**
July	-0.16**	0.41**	0.17*
August	-0.12**	0.26**	0.18**
September	-0.12**	0.30**	0.18**
October	-0.41**	0.42**	0.30**
November	-0.03	0.48**	0.24
December	-0.00	0.62**	0.21
	Heating		
January	-0.52**	0.03	0.19
February	-0.81**	-0.13	0.11
March	-0.73**	-0.25	0.18

Note: All elasticities and significance levels are based on parameters of the regressions without treatment indicators.

effects is due to behavioral responses to lower effective prices of comfort levels.

It is notable that responses are less pronounced during system peak months. That is, one should expect to see larger percentage reductions in electricity consumption and kW demand for air conditioning--due, say, to high efficiency units--during peak summer months than during other months. Consequently, these results anticipate improved annual load factors for high-efficiency air conditioning compared to existing units.[15]

Overall, these results probably account for electricity savings that are below engineering expectations in our simple comparisons of average usage between treatment groups and the control group. Equation (21) demonstrates that expected energy savings must account for the consumption effects of reductions in the cost of comfort.

The income elasticities for cooling range between 0.30 and 0.83 are statistically significant for all nonwinter months. The income elasticities for heating are less plausible, but none are significantly different from zero.

The number of household occupants seems to have little effect during months when little cooling is required. However, the coefficients are statistically significant in all months from June to October, all relatively heavy cooling months. The elasticity estimates vary from 0.17 to 0.30 for those months, e.g., indicating that adding a third person to a two-person household would increase electricity use for cooling by 9 to 15 percent.

Hawthorne Effects

The lower set of regressions in Tables 3 through 6 include treatment indicators. For the fall, winter, and spring, heat pump customers were excluded so only the insulation upgrade (IU) and the group (HEAC) with a high-efficiency air conditioner and an insulation upgrade are compared to the control group in

those months. To test for differences among treatment groups, we conducted a Chow test of the hypothesis that all treatment indicator coefficients are simultaneously zero in each of the four systems. The computed F-statistics for those tests were 0.213, 0.0, 0.414, 0.036 for the winter, spring, summer, and fall regression systems, respectively. Those values were well below the critical F-values, even at the 10 percent significance level. Based on these tests, we cannot reject the hypothesis that all of the treatment indicator coefficients are zero. In other words, after accounting for household-to-household differences in weather, HVAC efficiencies, thermal integrity of dwellings, service price, income, and demographic factors, the treatment group indicators fail to account for a significant amount of additional variation in electricity usage. Overall, this indicates either that there is no Hawthorne effect or, less likely, that it exists and is about the same in each treatment group, despite the large differences in the value of the equipment given to the participants.

Despite this overall finding, it is instructive to examine more closely the results of the winter regressions for two reasons. First, it was during the winter months that customers in the HEAC group were found, in simple comparisons of means, to have considerably higher overall electricity usage than the control group, even though their electricity usage for air conditioning was about the same. Second, the computed F-value for the Chow test in the winter regression was closest to the critical F-value, although it was still less than 20 percent of that value. Nonetheless, some of the individual treatment indicator coefficients were statistically significant (Table 3). Specifically, the HEAC treatment indicator was significant and positive in the space heating equation for all three winter months. These results suggest strongly that customers in the HEAC group increased their electricity use for heating during winter months, over and above the average customer's response to other factors explicitly accounted for in each regression equation. The same may have been true for cooling electricity use by the insulation upgrade group in two of the three winter months.

Correlation of Conservation Behaviors

To determine whether customers who conserve on electricity usage during summer months also do so during the winter, we conducted two analyses: (1) a simple calculation of correlation coefficients and (2) an examination of correlations among residuals from estimates of a system incorporating equations (19) and (20).

The questionnaire data from the FPL study provided information on reported daytime and nighttime thermostat settings for each customer. We calculated correlation coefficients among these settings and among kWh usage values for a representative winter and summer month: February and September. Since we included all customers whether they had heat pumps or straight-cool units, only the total kWh usage values were meaningful for February. Both total and HVAC kWh were used for September.

The calculated correlation coefficients are reported in Table 8. The results show what we would expect:

- Summer daytime thermostat settings are highly and positively correlated with summer nighttime settings, and negatively correlated with winter daytime and nighttime settings. In simple terms, people who keep their homes relatively cool in summer also keep them relatively warm in winter. Similar correlations exist for other thermostat settings.
- High thermostat settings in summer are strongly associated with lower kWh usage during both summer and winter.
- Similarly, high thermostat settings in winter are generally associated with high usage in both winter and summer.
- Finally, as expected, there is a very strong positive correlation between summer and winter usage values.

Table 8. SIMPLE CORRELATIONS AMONG THERMOSTAT SETTINGS AND SELECTED USAGE VALUES

	Correlation coefficients					
	Thermostat setting			kWh usage		
				September		
Variable	Summer night	Winter day	Winter night	Total	AC	February total
Thermostat setting						
Summer day	0.67**	-0.12**	-0.08	-0.18**	-0.21**	-0.20**
Summer night		-0.02	-0.15*	-0.18**	-0.19**	-0.15**
Winter day			0.54**	-0.01	0.01	0.09*
Winter night				0.11*	0.09*	0.12*
kWh usage						
September total					0.88*	0.72**
September AC						0.53**

*Significant at the 5 percent level.

**Significant at the 1 percent level.

These correlations alone confirm our expectation that conservation attitudes--or the lack of them--are consistent from season to season.

To examine this question further, we estimated a system of equations incorporating equations (19) and (20). However, we included only the space heating equation for the months December through April and only the space cooling equation for the remaining months. We also eliminated all customers with heat pumps. Then we estimated all 12 equations as a complete system using SUR, and examined the intercorrelations among the residuals from those regressions. If conservation behaviors are consistent, we would expect positive correlations between the residuals of the heating and cooling equations.

This expectation is realized as shown in Table 9. In all cases, the correlations between residuals are positive and in all but one case they are statistically significant. So the evidence from this analysis supports the findings of the simple correlations: conservation behaviors are persistent year-around.

Conditional kWh Estimates for Non-HVAC Appliances

Separate meter readings on air conditioning and total electricity usage provided a residual usage value for all other appliances. This was the value that we used, along with air conditioning usage readings, to estimate kWh usage for space heating in winter months. However, availability of these residual values also provides an opportunity to attribute the residual usage to the appliances in each dwelling.

To do this, we regressed the residual value on indicator variables that represent the appliance holdings of each household. The regression was a combined cross-section and time series model for all summer months and excluded the very small number of customers without either or both an electric range and an electric water heater. The regression was highly significant and had

Table 9. INTERCORRELATION OF RESIDUALS FROM REGRESSIONS OF MONTHLY HVAC kWh USAGE BY THE FPL STRAIGHT COOL CUSTOMERS

	Correlation coefficients									
	Heating months			Cooling months						Heating month
HVAC variable	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Nov	Dec
Heating months										
January	0.69**	0.67**	0.54**	0.28**	0.47**	0.50**	0.45**	0.43**	0.17*	0.61**
February		0.92**	0.76**	0.17*	0.42**	0.41**	0.39**	0.39**	0.12	0.44**
March			0.87**	0.20*	0.46**	0.49**	0.49**	0.45**	0.18*	0.57**
April				0.18*	0.44**	0.52**	0.58**	0.53**	0.21*	0.60**
Cooling months										
May					0.76**	0.58**	0.46**	0.52**	0.78**	0.16*
June						0.79**	0.61**	0.64**	0.68**	0.38**
July							0.79**	0.80**	0.57**	0.53**
August								0.89**	0.50**	0.56**
September									0.55**	0.49**
November										0.16*

*Significant at the 5-percent level.

**Significant at the 1-percent level.

Note: These partial correlation coefficients are computed from the variance-covariance matrix, Σ_T^{SHAC}, of the residuals from the SUR regression of equations (14) and (15).

an R^2 value of 0.32. Table 10 shows the estimated regression coefficients which represent the average daily kWh usage associated with the major remaining household appliances.

The table also shows FPL engineering estimates of average daily usage from an FPL customer information brochure. As shown, the statistical estimates are, in many cases, strikingly similar to the FPL engineering estimates. The major differences are observed for electric clothes dryers, freezers, and color televisions. Actual usage for clothes dryers and color TVs seems higher and usage for freezers seems lower than FPL estimates, at least for this particular population of customers. Generally, the favorable comparisons of our statistical estimates with the FPL estimates gives some assurance that our estimates of residuals are valid and appropriate for use in estimating space heating loads.

Table 10. COMPARISON OF STATISTICAL AND ENGINEERING ESTIMATES OF AVERAGE DAILY kWh USAGE BY APPLIANCE CATEGORY

Appliance category	Average daily kWh usage	FPL engineering estimates†
Swimming pool pump	15.21**	12.50
Sprinkler system pump	0.43	0.93
Electric dishwasher	1.52	3.00
Electric clothes dryer	8.25**	2.60
Manual and/or frost-free refrigerator	4.41**	2.6 - 6.83
Manual and/or frost-free freezer	1.73*	4.5 - 6.27
Color television	6.21**	1.0
Attic or whole-house fan	1.03*	1.0
All other appliances, excluding central heating and central cooling	2.13	-

Note: Based on a pooled time-series cross section regression for all experiment customers, Summer 1983.

*Significantly different from zero at 5 percent level of statistical significance.

**Significantly different from zero at one percent level of statistical significance.

†<u>Typical Energy Requirements of Electric Household Appliances</u>, Florida Power and Light Company.

SECTION 5: SUMMARY AND CONCLUSIONS

This analysis has demonstrated empirically a critical behavioral interaction with new energy-efficient appliances and thermal improvements: these technologies lower the effective price of the services they provide (or are associated with) and, consequently, reduce electricity consumption by smaller amounts than anticipated in engineering estimates. Specifically, we estimate that, for the particular FPL residential customers we studied, actual conservation for cooling would be as much as 13 percent below engineering estimates during nonsummer months but only about 1 or 2 percent below those estimates during the peak summer months. We estimated that conservation for heating would be in the range of 8 to 12 percent below engineering estimates.

Our approach used a mixed engineering and econometric model that was particularly effective for incorporating prior engineering knowledge about the interactive effects of weather, appliance efficiences, and thermal integrity of dwellings. We found that, after accounting for differences among these factors from one treatment group to another in the FPL experiment which provided the underlying data, there were no remaining overall differences attributable to a so-called Hawthorne effect of each treatment. Such an effect may have been plausible in this study since customers in treatment groups were, in some cases, given rather valuable heating and cooling equipment free of charge. However, there is one caveat to this finding: during winter months customers who received high efficiency air conditioners may have used unusually high amounts of electricity for space heating.

In separate analyses, we analyzed correlations between reported daytime and nighttime thermostat settings during summer and winter, and between those values and kWh usage in representative summer and winter months. We also

examined the correlation of residuals between cooling and heating usage equations. Both analyses supported the notion that individual customers who conserve electricity are persistent in that behavior during all months. They keep their houses warmer in summer and cooler in winter.

Finally, we conducted a conditional demand analysis of differences between total and air conditioning load in summer months. This analysis produced appliance usage estimates that generally compared quite favorably with FPL engineering estimates and validated our approach to approximating space heating loads.

APPENDIX A: EXPERIMENTAL DESIGN

FPL residential customers were selected and enrolled into the study through a large-scale screening and survey effort. Late in 1981 FPL mailed a one-page questionnaire to about 15,000 of its residential customers living in single-family dwellings. Their responses indicated whether their houses had or could accommodate any insulation in their attics and whether they had central, all-electric heating and cooling systems. Then, in early 1982, FPL randomly selected 2,000 customers from among those of the 15,000 that had central, all-electric systems. Those 2,000 customers were then visited by an energy auditor who collected engineering data on each dwelling and its heating and cooling equipment, as well as appliance and socioeconomic data. Later in 1982 FPL drew four random samples, totaling 504 customers, from among the sample of 2,000. One of those four was a control group whose members received $50 each to participate in the study. Customers in the other three groups were given one of the following conservation technology combinations:[16]

- Attic insulation upgrades to achieve insulation effectiveness of at least R-19, or
- Both attic insulation, if not already at least R-19, and a high-efficiency central air conditioner, or
- Both attic insulation, if not already at least R-19, and a high-efficiency central heat pump.

Although the sample selection and assignment to study groups was random, customers in the FPL study were stratified, i.e., divided into strata or subgroups and then randomly selected in equal numbers from each subgroup. The strata were defined according to the location, the existing attic insulation level, and the historical electricity usage associated with each dwelling. The study included 6 past usage levels in the South, roughly the area in the Miami weather region in Figure 1; and 6 in the North, the rest of FPL's service

territory. Within each of the 12 region-usage strata, customers were further divided according to their prior insulation levels. Those insulation categories are shown in Table A-1, along with the number of study participants in each, for each of the four study groups.

Four customers in each prior insulation category were randomly selected from each of the 12 region-usage categories for Study Groups I and II. For technical reasons, several households were eliminated from among the remaining customers in the sample of 2,000. Then, 12 customers were randomly selected from each region-usage category without regard to their prior insulation levels. Six were randomly assigned to Study Group III and six to Study Group IV. The customers eliminated from these two groups had either a heat pump already in place or a type of system that was quite difficult to replace.[17]

Besides the selection constraints already mentioned, all of the study participants had to meet several other conditions, e.g., available space and wiring had to be compatible for installing electricity meters and customers with more than two central systems were excluded. These conditions and their effects on customer selection probabilities are detailed in Clayton (1983).

A recording meter was installed on the whole-house electricity load of all experiment participants. This produced data on total electricity consumption every 15 minutes for the duration of the study, October 1982 through December 1983. Another simple watt-hour meter (the usual type for residences) was attached to the outdoor unit. For so-called split systems, the metered load included the compressor and outdoor fan motor, but excluded the indoor fan motor and resistance heating coils (if any). For so-called package systems, the readings included the compressor and both fan loads.[18] Readings for water-based systems excluded the water pump motors as well.[19] The watt-hour meters on both the whole-house and outdoor units were read at the end of billing months and on the working day nearest the last day of each calendar month.[20]

Table A-1. SIZE AND DISTRIBUTION OF FPL STUDY GROUPS BY PRIOR INSULATION LEVELS

Study group	Prior insulation category[a] $R\leq10$	$10<R\leq13$	$13<R<19$	$R\geq19$	Total
I Control	48	48	48	72	216
II Insulation upgrade[b]					
Add R-19	48	-	-	-	48
Add R-11	-	48	48	-	96
III Insulation upgrade and high-efficiency air conditioners		72			72
IV Insulation upgrade and high-efficiency heat pump[c]		72			72

[a]Insulation is measured by its resistance or R-factor.

[b]Each customer with attic insulation below R-19 received the minimum of two increments, either R-19 or R-11, to achieve at least on R-19 rating.

[c]Customers in this portion of the study were randomly selected without regard to their prior insulation level. Only those with less than R-19 received an upgrade.

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FOOTNOTES

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[2]kWh consumption is simply the product of the capital stock (kW capacity) times the rate of utilization (the proportion of time the appliance is used) times the inverse of efficiency (the amount of electrical service or work produced per kWh of input) or kWh = S · U/E. Typical engineering models assume that S and U remain constant. Simple economic theory suggest that when E is increased U will also increase.

[3]Issues of simultaneity are discussed in Dubin and McFadden (1984).

[4]Examples are NBSLD, developed by the National Bureau of Standards; DOE-2, developed by Lawrence Berkeley Laboratory 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.

[5]This factor is theoretically sensitive to variations in temperatures, but a separate analysis showed that very little accuracy was sacrificed by assigning constant values to the factor.

[6]These estimates were developed for each billing month, but only for customers with straight-cool central units.

[7]This approach assumes that non-HVAC uses of electricity are relatively constant over time, an assumption supported by internal FPL data. For example, samples of FPL's residential customers seemed to use about the same amount of electricity from month-to-month for electric clothes dryers, pool pumps, and water heaters.

[8]The COP of resistance heating is always 1 whereas COPs for heat pumps are about 2.7 at design conditions. As temperatures fall, overall COP declines for two reasons: (a) more resistance backup must be used and (b) the compressor unit itself operates less efficiently (and shuts down completely at very cold temperatures). Our estimate of EER(t) is

$$EER(t) = EER^* + 0.07\ (95-t)$$

approximated from the data in Collie (1979, p. 36). Our estimate of COP(t) is

$$COP(t) = (1-SHP) + SHP \cdot COP^{**}$$

where

$$COP^{**} = COP^* + 0.025 \cdot Min[t-47,0] + 0.01 \cdot Max[t-47,0],$$

$$SHP = Min[K(t)/Q(\tau,t),1],$$

$$K(t) = K^* + h \cdot Min[t-47,0] + g \cdot Max[t-47,0],$$

$$h = -0.7175 + 0.011312\ K^* + 0.0000781\ (K^*)^2,$$

$$g = -0.09525 + 0.0012708\ K^* + 0.0003038\ (K^*)^2, \text{ and}$$

K^* = design capacity of the heating system, in thousands of Btus per hour (Q is defined accordingly); K^* is zero for simple resistance heating systems.

This equation reflects approximate changes in the COP of the heat pump portion of the heating system, as well as the share of the heating load, SHP, that is met with the heat pump. The COP of the overall heating system is the share-weighted sum of the COP of the backup resistance heating and that of the heat pump portion of the system, COP**. The parameters h and g are based on simple regressions of data in Collie (1979, p. 34) and reflect the effects of ambient temperature variations on the actual capacity of the heat pump portion. The coefficients used to develop COP** are approximated from data in Collie (1979, p. 35).

[9]The Hawthorne effect was first suggested by a 1928 study of factory workers in Hawthorne, New Jersey. Workers' productivity appeared to increase regardless of changes--some actually expected to be counterproductive--in their working conditions (Roethlisberger and Dickson, 1939).

[10]Note that our estimates of UEC are adjusted to reflect the estimated efficiency of the heating and cooling units.

[11]Other regression specifications were considered as well, using data for a single month of the summer season. These included a double logarithmic version of equations (19) and (20), as well as other linear versions such as a model with UEC values on the right-hand side and only actual usage or Y values on the left-hand side. Although all versions gave similar results, the ratio model reported here was preferred because its parameters are easy to interpret directly and because it performed as well as the others in terms of traditional statistical measures.

[12]Equivalent to an F-test on all nonintercept parameters in each system.

[13]The elasticity of electricity use with respect to the electricity price can be developed from equation (19). Since

$$\partial Y^{AC}/\partial P = \alpha_1 \lambda^{AC} UEC^{AC},$$

$$\eta_{Y^{AC},P} = \partial \ln Y^{AC}/\partial \ln P = \alpha_1\ UA^{-1}\ PCOOL.$$

Therefore, $\eta_{Y^{AC},P}$ is identical to $\eta_{UA,PCOOL}$.
Similar calculations are appropriate for other elasticities.

[14]For example, in February, equation (21) is approximately 1 + (-.84)(0.16) = 0.87, which implies that the reduction in actual usage is 13 percent of the engineering estimate.

[15]Load factor is average annual kW demand (instantaneous usage) divided by kW demand at the time of system peak.

[16]A high-efficiency air conditioner was defined as a unit with an energy efficiency rating (EER) of 10 or greater; and a high-efficiency heat pump as a unit with an EER of 8 or greater. An EER is the heat (in Btus) that a properly sized unit can remove from a house per watt of electrical energy input at design (certain temperature and humidity) conditions.

[17]These included both water-based and so-called package air-conditioning systems.

[18]Split systems are the most common. The outdoor unit contains a compressor, a condensor coil, and the outdoor fan. This unit is connected to the indoor unit via two refrigerant lines (supply and return). The indoor unit has an evaporation coil and a fan that forces warm indoor air past the coil which absorbs heat into the continuous supply of liquid refrigerant that circulates through it. Package systems have the same components. The main difference is that they incorporate both the indoor and outdoor components into a single box or package. This package, which is like a window unit in design, is connected directly to the duct system for the whole house.

[19]Water-based systems are unique in that the outdoor coil is submerged in a continuous flow of water, which serves the same purpose as outdoor air in conventional systems. That is, the water absorbs or yields heat depending on whether the unit is operated in the cooling or heating mode. A water pump is required to supply the water from a lake or other source.

[20]Billing months are the approximately 30-day periods that begin on the date each customer's meter is read. Meters are usually read on 20 or 21 working days of each month, so there are a corresponding number of billing cycles in each month.