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An econometric study of residential electricity demand

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I. INTRODUCTION

The need for better understanding of households' consumption choices with respect to electricity is widely appreciated. Utilities base their capacity planning, marketing and pricing strategies upon their knowledge and forecasts of consumer demand. Regulators must examine and evaluate utility performance and policy based upon their understanding of the consuming market. Legislatures and social agencies require an understanding of electricity demand in order to structure effective energy assistance programs for low and fixed income citizens.

In order to analyze the need for future power plant construction, utilities must have reliable forecasts of electricity use. Inaccurate forecasts can have serious repercussions. If a utility fails to build additional needed capacity, blackouts may result. Additionally, prospective and existing customers may locate elsewhere to be assured of an adequate energy supply. If a utility builds an unneeded power plant, customers and/or stockholders may be faced with substantial financial burdens. Because large resource decisions are made based upon electricity demand forecasts, the need for accuracy is very important.

Knowledge of electricity demand and consumer behavior also affects the marketing decisions of utilities. Many companies are currently using or investigating energy management as a method of avoiding construction of new generating facilities. A recent publication by Smith (1981) suggests that three methods exist to curtail growth in electricity use. First, a reduction in demand may be achieved by legislation limiting use, self-denial, or economic manipulation of demand. Second, increases in the efficiency of appliances could slow energy usage growth. Third, the substitution of alternative fuels could be used. If economic methods are to be used, it will be necessary to better understand the factors which affect electricity use. Also, a better understanding of the components of electricity demand will allow utilities to estimate the effects of higher efficiency appliances on electricity sales.

Utility pricing decisions also require detailed knowledge of customers consumption habits. Many utilities offer their customers a time-of-day (TOD) rate structure. The purpose of TOD rates are twofold: (1) to help the utility shift its sales to lower demand times (off-peak) and (2) to allow customers to minimize their utility charges. These rates allow a utility to utilize newer, more efficient generating facilities by reducing peak load and the need for purchasing costly on-peak power or generating with peak load generators. In order to design a TOD rate, the utility must have an accurate estimate of the price sensitivity of its sales throughout the day.

Promotional rates also require that a utility identify factors important to sales. If a utility wishes to promote particular end uses of electricity (electric spaceheat for example) it must be able to identify the factors which affect that market. In order to design a rate which will predictably increase the saturation of electric spaceheat, the utility must know how electricity prices and other factors affect spaceheat use. Thus, utility pricing policies are very dependent upon an understanding of household consumption habits.

Public utility commissions (PUCs) oversee utility policies and activities as they relate to consumers. PUCs must have essentially the same knowledge and information about consumers as utilities in order to evaluate utility actions. Recently, PUCs have begun to closely analyze utility power plant additions due to the high cost of additional generating capacity. Rate structures are also scrutinized to assure that residential consumers are only paying their "fair share" of utility expenses. PUCs also have come under some pressure to study the "rate shock" which may occur when utilities increase rates to reflect new nuclear plants in rate base. It appears that PUCs will need to commit more resources to the study of consumer demand in order to answer these and other questions in the future.

Numerous state legislatures (most notably California) have taken great interest in residential electricity rates. The concept of "lifeline" rates has become a popular notion in recent times. Lifeline rates are to be structured such that low and fixed income households may consume some minimum level of electricity at a cost that will not cause unnecessary financial hardship. Discovering what this lifeline or base use is, and what the appropriate charge should be has proven to be quite difficult. Numerous factors such as household size, income, climate and health problems would appear to be important in setting these rates (Burgess and Paglin (1981)). Other factors such as actual unit energy consumptions (UECs) of appliances and surveys detailing the appliance holdings of low income households could also help to define lifeline consumption levels.

Econometric methods allow for the in-depth analysis of residential electricity consumption. The relationships of various factors to electricity consumption can be estimated and examined. Econometric models may allow utilities to better forecast their sales and aid in marketing and rate decision. The effects of various rate changes and rate structure can be estimated prior to their enactment. PUCs can use econometric models to analyze the rate shock effects on consumers as well as the effects of other price changes. Models may also help PUCs evaluate utility decisions regarding capacity additions. Legislators can utilize econometric models to estimate lifeline consumption and the appropriate rates to accomplish social goals and objectives.

This study will examine residential energy consumption and formulate and estimate models of demand which will explain that consumption. The general methodology of this study will be to review the existing econometric studies in the field for theoretical and empirical model specifications, attempt to discover and correct deficiencies in those studies, postulate and estimate demand models, and interpret those models in a practical and useful manner.

II. DISCUSSION AND EVALUATION OF THE LITERATURE

Until the mid 1970s, most econometric studies of residential electricity demand relied upon some type of aggregate data for estimation. In most cases, average electricity consumption per customer (on a state or SMSA level) was related to other "average" explanatory variables such as average price per kiloWatt-hour (kWh), average household income, average household size, and so forth. The use of aggregate data prevented the examination of some of the household level determinants of demand, such as explicit appliance stocks and the distribution of income. Some examples of studies employing aggregate data are Houthakker (1951); Moore (1970); Wilson (1971); Halvorsen (1975); Taylor, Verleger and Blattenberger (1977); and Taylor, Blattenberger and Rennhack (1982).

Beginning with Wilder and Willenborg (1975) researchers began to examine household level data, generally utilizing household characteristics surveys and utility billing records. This mitigated the possible biases and limitations associated with aggregate data and allowed for more detailed examination of the factors thought to affect electricity usage at the household level.

Two principal approaches have been followed: (1) single and multiple equation models of total household electricity demand and (2) conditional demand analysis which attempts to model the various end-uses of electricity consumption. Both of these approaches have produced reasonable and useful results, although applications of the relatively new conditional demand analysis have been limited by its need for extremely detailed household appliance holdings information. This review will focus first on the total household demand method and then examine conditional demand analysis.

A. Total Household Demand

One of the first studies utilizing household level data was undertaken by Wilder and Willenborg (1975). This study used appliance and demographic surveys and monthly utility billing records for 274 households in a single metropolitan area. In postulating their model of consumption, Wilder and Willenborg recognized that prices and consumptions levels are simultaneously determined through the interaction of a demand equation and a price equation, and the inherent inverse relationship between consumption and average price attributable to the decreasing block rate structure. This simultaneous approach to electricity demand modeling was pioneered by Halvorsen (1975).

Wilder and Willenborg's price equation, simulating the rate schedule faced by the households, postulated the average price per kWh to be a function of consumption per household and a dummy variable denoting "all-electric" households. Because of their total dependence on electricity and thus necessarily higher average consumption, all-electric households are billed according to a rate schedule which displays lower marginal prices in the high consumption blocks. This preferential treatment given to all-electric homes allows for "shifts" of the rate schedule "supply curve" and enables identification of the demand relationship.

Drawing upon the derived demand nature of electricity consumption, Wilder and Willenborg estimated a four equation model which incorporated equations for: (1) the stock of electrical appliances, (2) the size of the residence, (3) the household's electricity demand, and (4) the rate schedule. As a proxy for the household appliance stock, Wilder and Willenborg chose the number of appliances, A, (chosen from a list of five major electricity consuming appliances) owned by a household.

The appliance stock equation used was:

$$A = b_0 \, Y^{b1} \, e^{b2R} \, N^{b3} \, e^{u2};$$

where: A = number of appliances owned chosen from a list;

Y = annual gross family income;

R = dummy variable for race of household;

N = variable representing age of household head;

u2 = random error term.

Following a logarithmic transformation the equation was estimated by ordinary least squares (OLS). All coefficient estimates were of the expected signs and significant at the 5% level. The R-square was 0.31, not uncharacteristically low relative to other cross-sectional estimations of appliance stock models (for example, see Garbacz (1983)).

The residence size equation, also estimated in logarithmic form using OLS was postulated as:

$$H = a_0 \, Y^{a1} \, F^{a2} \, e^{a3R} \, e^{u1};$$

where: H = number of rooms in residence;

Y = annual gross family income;

F = total number of persons residing at dwelling;

R = dummy variable for race of household;

u1 = random error term.

Again, the estimated coefficients were all of the expected sign, however only income and family size were significant at the 5% level. The R-square of 0.27 indicated the relatively, but not unusually low explanatory power of the model.

The preceding two equations, appliance stock and residence size, could be consistently estimated by OLS because none of the explanatory variables were considered to be endogenous. The relatively low R-square values suggest that improvements may be possible in the two equation specifications. First, theory implies that the price of electricity (a complementary good) might be a factor in the size of the appliance stock. Other things equal, lower electricity prices would probably tend to encourage the ownership of electrical appliances. The inclusion of price in the appliance stock model would add an endogenous variable, and thus require a simultaneous equation estimation approach for appliance stock equation. Second, the addition of a variable indicating the dwelling age might aid in explaining the number of appliances possessed. It may be the case that newer homes, because of higher current-carrying wiring and recent trends toward dual career families (and the need for more labor-saving appliances), might possess more electrical appliances. These modifications to the appliance stock equation might improve its explanatory power.

The residence size equation may yield improved results if residence square-footage, a more accurate size measure, were used instead of number of rooms. Additionally, dummy variables to indicate the dwelling type (single family, multi-family detached, apartment, or mobile home) might increase the model's explanatory power (Hirst, Goeltz, and Carney (1982)).

The demand equation used by Wilder and Willenborg was:

$$E = c_0 \, Y^{c1} \, H^{c2} \, A^{c3} \, e^{c4D} \, P_a^{\,c5} \, e^{u3};$$

where: E = household electricity consumption in kWh;

Y = annual gross family income;

H = number of rooms in residence;

A = number of appliances owned;

D = dummy variable indicating season of survey;

P_a = average price per kWh;

$u3$ = random error term.

The demand equation and the following price equation were estimated in logarithmic form using two-stage least squares (2SLS):

$$P_a = d_0 E^{d1} e^{d2L} e^{u4};$$

where: P_a = average price per kWh;

E = household electricity consumption;

L = dummy for "all-electric" house;

$u4$ = random error term.

The R-square values associated with the 2SLS estimation were 0.50 and 0.35, respectively. All estimated coefficients in both equations were significant at the 5% level and of the expected sign. Because the estimation occurred in log-log specification, the estimated coefficients represent constant elasticities. The estimated price elasticity was -1.00 and the estimated income elasticity was 0.16. The authors compared their elasticity estimates with studies using aggregate data and found their results to be consistent with the previous works.

Wilder and Willenborg also estimated the demand equation using OLS, a technique which would likely attribute the inherent inverse relationship between consumption and price due to decreasing block pricing and the negative slope of the demand curve. The R-square reported was 0.76, with all estimated coefficients significant at the 5% level. The OLS estimation appeared to overstate price elasticity (-2.65 versus -1.00) and understate income elasticity (0.12 versus 0.16).

The study by Wilder and Willenborg serves to illuminate many of the issues considered in other studies of the residential demand for electricity. Among the issues are: (1) choice of a price variable (marginal versus average), (2) measurement of the electricity consuming appliance stock (weighted index versus simple sum), (3) functional form of the estimating equation(s), (4) modeling of weather effects (interaction terms versus simple degree-days), and (5) selection of other explanatory variables for use in the demand equation. Two studies to be examined used "micro-data", meter readbook or census-tract data. Although these studies relied upon aggregate data, the level of aggregation was much lower than the level usually encountered and the studies address several of the issues mentioned above. Additionally, several studies utilizing nationwide, household level data will also be examined for their insights and contributions.

1. Price Variable Selection

A study by Acton, Mitchell and Sohlberg (1980) addressed the declining marginal price rate structure and its representation for modeling purposes. Because of the multi-price rate schedule, which generally includes a fixed monthly charge, the budget constraint the household faces is non-convex and piece-wise linear. This leads to the possibility of multiple utility maximizing bundles of electricity consumption and "other goods". However, because the relationship between marginal price and quantity demanded is single-valued (determined by the rate schedule), the observed demand curve approximates an ordinary demand curve. An individual household's demand curve will be discontinuous in the regions of the block rate changes, but aggregation across customers facing several tariffs with different rate blocks will fully approximate a continuous demand curve. Thus, the use of marginal price, as suggested by marginalist economic theory, will lead to a demand function which may be estimated using econometric methods.

The need for customers facing different block rate structures makes the use of marginal price questionable for the study currently being undertaken. Due to the cross-sectional time-series data available to this study, the pooling of data will provide some variation in tariffs. This suggests the use of both marginal price, and average price with a price equation for the modeling purposes of the current study.

Average price has often been used in studies of residential electricity demand. Some authors have argued that households respond to their total bill, and seldom familiarize themselves with marginal prices (Garbacz (1983)). If this is the case, then from a behavioral standpoint the use of average price is justifiable. However, it should be noted that it may not be necessary for households to be aware of marginal rates in order to respond to them. Parti and Parti (1980) argue that the choice of price variable should be made largely on empirical grounds and proceed to use a lagged average price on that basis. Numerous other studies also debate the issue with differing conclusions.

In general, average price is a biased proxy for marginal price (Acton, Mitchell, and Sohlberg (1980)). First, under a decreasing block rate schedule, the average price approaches the marginal price as electricity consumption increases. Average price will be less representative of marginal price in low consumption households and more representative in high consumption households. This will cause estimates of the slope of the demand curve to be biased upward. Halvorsen (1975) has demonstrated that when using a logarithmic specification for the price and demand functions the marginal and average price elasticity estimates are identical and the estimated demand functions differ only by a constant. That result suggests that the non-uniform distortion between average and marginal price is not a problem if the logarithmic specification is accurate, and elasticities are the object of investigation.

Second, because average price is usually measured as average revenue per kWh, an errors-in-variables bias occurs. The inclusion of the dependent variable as a divisor of an independent variable will bias the estimated price coefficient away from zero. The magnitude of the bias is unknown, and future studies of electricity demand may help to shed some light on this issue.

An average price approach was used by Garbacz (1983) in a study utilizing household data from a national survey. The three equation model used consisted of: (1) a demand equation, (2) an average price equation, and (3) an appliance stock equation. Garbacz argued that while average price may not be the "best" price variable, it served the purpose of the study. The three equations were estimated using two-stage least squares (2SLS). The price equation was essentially similar to that of Wilder and Willenborg (1975) and will not be elaborated upon.

One other study which used the average price method and household level data was Hirst, Goeltz, and Carney (1982). This study used single equation models and OLS estimation to investigate the demand for energy and electricity. The authors used average price per BTU of energy as a price variable due to the various fuels in use. Although no explicit mention was made of rate structures, it would be reasonable to assume that the BTU input to the households was largely billed at a decreasing block rate. If so, perhaps a price equation and a 2SLS estimation would have been more appropriate.

Behavioral theory suggests that average price will lead to meaningful results, although perhaps not identical to those that would be produced using marginal price. Thus, by estimating demand models using both average and marginal price, this study will empirically investigate the marginal versus average price issue.

2. Appliance Stock Measurement

One factor which is readily identifiable in household electricity consumption is the stock of electrical appliances. As previously discussed, Wilder and Willenborg (1975) used a simple sum of the number of appliances possessed by a household (chosen from a list of five appliances). The measure was significant and of the proper sign when used in estimation of the demand equation.

Because all appliances do not consume the same amount of electricity, Garbacz (1984b) has suggested that appliances be weighted by their relative consumptions of electricity.

Using several data sources Garbacz developed weightings for twelve appliances based upon average annual usages. Unlike Wilder and Willenborg who postulated a recursive model of the appliance stock, Garbacz estimated the appliance stock equation jointly with the demand and price equations. Due to the long service lives of major electrical appliances (water heaters, furnaces, air conditioners, etc.) the treatment of appliance stock as endogenous may be questionable. Other studies such as Burgess and Paglin (1981) and Acton, Mitchell, and Sohlberg (1980) have used approaches that explicitly accounted for some major appliances and/or used weighted indexes for other, residual appliances.

The nature of electrical appliances would suggest that a simple, unweighted aggregation may not reflect the true appliance stock. Garbacz's appliance weighting method appears to correct for that deficiency, however it requires accurate estimates of appliance consumptions for implementation. A third, unexplored approach would entail weighting the appliances by their kiloWatt (kW) ratings and aggregating. This would provide an index of consumption potential, which unfortunately would not recognize differentials in appliance utilization. An empirical analysis may help reveal which specification of appliance stock is best suited for use in estimating the household demand for electricity.

3. Functional Form of the Estimation

Most studies of electricity demand have relied upon a logarithmic specification of all equations, and log-log estimation techniques. This specification implies that the derivatives of electricity consumption with respect to its determinants are, in general, functions of the levels of all independent variables. The corresponding elasticities of the specification are constants, however. Based upon Halvorsen (1975), the logarithmic specification does imply the same price elasticity estimate for either marginal or average price approaches. This has likely been a primary reason for the use of logarithmic specifications.

The choice of model specification entails both theoretical and empirical arguments. Many studies estimate numerous specifications and select a "best" model on the basis of goodness-of-fit. This criterion along with energy engineering theory seems appropriate for selection among various specifications.

4. Weather Effects

Weather is perhaps the single most important factor in household electricity consumption during the heating and cooling seasons. Most econometric studies either disregard weather effects or incorporate a degree-day variable, perhaps interacted with structure size. A proper evaluation of the modeling efforts used in econometrics first requires an examination of the theory of energy engineering.

The basic household energy balance equation for central space conditioning is:

$$q = \Sigma_i (U_i * A_i * T_i),\ i=1 \text{ to } n \text{ surfaces};$$

where: q = net thermal energy requirement;

U_i = thermal conductivity of surface i;

A_i = area of surface i;

T_i = temperature differential across surface i.

The energy requirement, q, is net of the effects of any heat sources or sinks, such as household members, mechanical equipment, and auxiliary heating or cooling devices. Thermal conductivity, U_i, is the inverse of the common "R-value" and must be evaluated for each surface enclosing the living area. The values of A_i and T_i correspond to the surface area across which the heat transfer occurs and the temperature differential across the surface. It can easily be seen that a complete household space conditioning energy balance requires a large quantity of detailed information.

In their demand equation, Hirst, Goeltz, and Carney (1982) used variables to capture the influence of weather and structure size on electricity consumption. The cooling variable, CDD, was defined as the product of cooling degree-days, floor area, and percentage of rooms cooled. The heating variable, HDD, was defined similarly except that the entire household was assumed to be heated. Without further study it is unclear how adequate a proxy household size (square feet) is for household surface area. The type of house (one or two story, ranch, etc.) would lead to differences in the surface area, given the same floor space.

The use of degree-days is likely to be a reasonable proxy for the temperature differential, however knowledge of the actual household indoor temperature would perhaps provide a more accurate base than the conventional 65 degree F. base in use.

In his three-equation model of electricity use, Garbacz (1984a) includes cooling and heating degree-days in both the demand and appliance stock equations. It is postulated that the weather faced by the household determines both the size of the space conditioning stock and its utilization rate. In the appliance stock equation, heating and cooling systems are weighted by the number of rooms in the dwelling. Thus, Garbacz indirectly makes space conditioning consumption a function of the number of rooms and degree-days. The same criticisms apply to this study as to the previous one, with the additional question of whether the number of rooms is superior to square-footage as a proxy for dwelling surface area.

Acton, Mitchell, and Sohlberg (1980) follow an approach similar to Garbacz, including degree-day measures in both the appliance stock and demand equations. No attempt was reported to include dwelling size, possibly because the study utilized meter readbook data and average household size was not reported.

The variable specification for weather in these and other studies favors a degree-day or degree-day and dwelling size product. Without the availability of detailed household structural information, the product of degree-day and dwelling size seems to be a practical solution.

5. Other Explanatory Variables

Of the studies previously discussed in part or in whole, most incorporate the price of electricity, household income, appliance stock, and a measure of household size (either structure size or number of occupants) into the demand equation. The studies of Hirst, Goeltz, and Carney (1982), Acton, Mitchell, and Sohlberg (1980), and Garbacz (1984a) also examine the influence of weather by either including it directly in the demand equation or indirectly through an appliance stock equation.

Hirst, Goeltz, and Carney introduce the year the dwelling was built and disaggregate the number of occupants into adults and children. They argue that older homes may have technological constraints on electricity consumption (such as lower current-carrying wiring). These technological constraints may also lead older homes to have higher average consumption. Those homes may have inadequate thermal insulation, leading to higher usage. This would ultimately appear to be an empirical question. The disaggregation of members into children and adults allowed study of their differential effects on consumption. It was found that children had a lesser effect on consumption than did adults.

Two studies dealt with the issue of the price of substitute fuels, both through the demand equation and one through the appliance stock equation in addition. The empirical results are mixed, with incorrect signs and insignificant coefficients occurring in several of the months used for estimation. The problems of substitute fuel availability and technological substitution possibilities complicates the choice of a substitute fuel. Garbacz (1984a) created an index of alternative fuel prices to overcome some of the difficulties. This appears to be an area for future research and empirical study.

The variables suggested by these and other studies for use as determinants of demand include own-price, household income, dwelling size, number of household members, a measure of weather, an alternative fuel price and a measure of the appliance stock. Several specifications of the variables have been suggested and warrant further study.

B. Conditional Demand

One of the earliest published works utilizing the conditional demand analysis approach is that of Parti and Parti (1980). This type of econometric modeling attempts to disaggregate the total household demand for electricity into its component parts. An econometric model is postulated for each end-use of electricity (i.e., water heating, space heat, etc.) and the individual end-use equations are summed to arrive at total household demand.

Estimation is carried out using the observed variable, total household electricity use, as the dependent variable. This method of estimating the end-use consumptions of electricity is much less expensive than direct metering, yet still allows for the examination of the various factors that effect the consumption of electricity through each of several specific appliances.

In their research, Parti and Parti postulated that the electricity use through a given appliance could be written as:

$E_i = f_i(V)$ for $i = 1$ to n;

where: E_i = electricity consumption of ith appliance;

f_i = household demand function of ith appliance;

V = vector of explanatory variables.

If the demand functions are linear then the electricity consumption through the ith appliance can be written as:

$$E_i = \Sigma_j b_{ij} V_j \text{ for } i = 0 \text{ to } N; \tag{1}$$

where: b_{ij} = parameter associated with V_j;

V_0 = constant term;

E_0 = consumption through unspecified appliances.

Thus, if metered data were available on the ith appliance, this demand function could be directly estimated using econometric methods.

The lack of availability of appliance-level consumption data led Parti and Parti to aggregate demand equations across the appliance holdings of the household to arrive at total household consumption. This can be written as:

$$E = \Sigma_i E_i; \tag{2}$$

where: E = total household consumption;

E_i = consumption through appliances 1 to N or through the unspecified group of appliances.

For any household, E_i is given by equation (1) if the household possesses the ith appliance. For households not possessing the ith appliance, E_i is equal to zero. For appliance i, define a dummy variable A_i which takes the value of 1 if the ith appliance is present and the value 0 otherwise. Equation (2) can then be rewritten as:

$$E = \Sigma_i \ \Sigma_j \ b_{ij}V_jA_i, \ A_0 = 1; \tag{3}$$

where E, b_{ij}, V_j, and A_i are as previously defined.

Numerous parameter restrictions were imposed prior to estimation due to the extremely large number of parameters involved. For example, the price, income, and family size effects were constrained to be equal for several of the appliances.

Parti and Parti also demonstrated that an estimation of the conditional demand function with independent variables in their deviation form would directly determine the average household electricity use per appliance. The average electricity use through the ith appliance can be written as:

$$E_i = \Sigma_j \ b_{ij}V_{ij} \ , \ i= 0 \text{ to } N; \tag{4}$$

where: E_i = average estimated use through ith appliance;

V_{ij} = conditional means of explanatory variables.

Multiplying each side of equation (4) by A_i, summing across i, and rearranging:

$$0 = \Sigma_i \ E_iA_i - \Sigma_i \ \Sigma_j \ b_{ij}V_{ij}A_i; \text{ where: } i= 0 \text{ to } N. \tag{5}$$

Adding the right hand side of equation (5) to the right hand side of equation (3) provides:

$$E = \Sigma_i \ E_iA_i + \Sigma_i \ \Sigma_j \ b_{ij}V_jA_i - \Sigma_i \ \Sigma_j \ V_{ij}A_ib_{ij}. \tag{6}$$

Equation (6) can be rearranged yielding:

$$E = \Sigma_i \, E_i A_i + \Sigma_i \, \Sigma_j \, b_{ij}(V_j - V_{ij})A; \qquad (7)$$

demonstrating that the intercept terms reflect the average electricity consumption through each of the ith specified appliances when the explanatory variables are used in deviation form. The means of the explanatory variables were evaluated for only those households which possessed the ith appliance.

The estimated values of the dummy variables, A_i, ($i = 0$ to N) are the average estimated electricity usages of the N specified appliances and the unspecified set of appliances. Thus, the conditional demand analysis approach provides both parameter estimates of the effects of behavioral, economic, and technical variables on consumption and estimates of average annual appliance electricity usage.

The explanatory variables included in the demand equations were the price of electricity, household income, household square-footage, number of household members, and two variables to capture weather effects. Parti and Parti chose to use a weighted average of the previous two months average price of electricity based upon an empirical investigation of various price measures.

The authors suggest that the choice of a price variable is largely an empirical matter, in contrast with other works discussed previously in this paper which suggest the superiority of marginal price. The two weather variables, one describing heating requirements and one cooling requirements, were constructed using daily high and low temperatures. Parti and Parti explain that the measures are more indicative of the weather profile than are the traditional degree-days based on average temperatures. Each of the explanatory variable did not appear in every appliance demand equation and several interaction terms were used where appropriate (for example, weather was interacted with household square-footage).

The method of estimation used in this study was an instrumental variable approach. Parti and Parti regressed variables indicating rate zones (dummies), the standardized household consumption of electricity, and the number of days in the billing cycle on average price to obtain the instrumental variable estimator. This predicted value was then used in the estimation of the demand equation. The data for this study were comprised of survey interviews of 5286 San Diego area households augmented with accompanying utility billing records and weather information.

Two basic sets of empirical results were presented: (1) the estimated price and income elasticities on a monthly basis, and (2) the estimated average annual use per appliance. For the most part, the estimated price elasticities were reasonable when compared to other studies (Wilder and Willenborg (1975); Acton, Mitchell, and Mowill (1975); and

Taylor, Verleger, and Blattenberger (1977)). The average annual price elasticity reported was -0.58, arrived at by weighting the monthly elasticities by the fraction of annual consumption occurring in that month. The highest monthly price elasticity was reported for December, while the lowest was in January. This finding appears to be counter-intuitive, as one might expect adjacent months to have similar characteristics. Income elasticity was very consistent throughout the year with a weighted-average annual estimated value of 0.15.

When compared to engineering estimates of average annual electricity use, the conditional demand estimates were found to be similar, however not in total agreement. Conditional demand estimates of electricity use through space conditioning systems were in general one-half the engineering estimates. The moderate weather during the period of data collection was suggested as a possible cause of the discrepancy. Average use estimates for water heaters, dishwashers, and color television sets were higher than the engineering estimates. Other appliance use estimates (black and white television sets, dryers, freezers, electric ranges, and refrigerators) were generally bracketed by their engineering estimates.

III. MODEL FORMULATION

Drawing on the previous discussion of the literature, economic and econometric methods, and energy engineering practices, several models of the residential demand for electricity will be formulated. Three seasonal specifications will initially be postulated, reflecting the type of space conditioning equipment (heating, air conditioning, or neither) likely to be in use. The three seasons to be used in the analysis are: (1) the heating season (November through April), (2) the cooling season (June through September), and (3) the transitional season (May and October).

The seasonal specification was chosen because studies by Garbacz (1984b), Parti and Parti (1980), and Acton, Mitchell, and Sohlberg (1980) suggest price and income effects are more similar within season than between seasons. For example, Garbacz concludes that summer months are more price inelastic than winter months, potentially attributable to the lack of fuel substitution available for air conditioning. Acton, Mitchell, and Sohlberg show similar results for price elasticities.

The months were grouped into seasons due to the relatively homogeneous weather occurring on average in the included months. The heating season contains on average 90.7 percent of the 65 degree base seasonal heating degree-days and no 65 degree base seasonal cooling degree-days. The cooling season contains 91.4 percent of the average seasonal cooling degree-days and only minimal heating degree-days. The transitional months contain both heating and cooling degree-days, however, neither contains more than 6.5 percent of the average seasonal heating or cooling degree-days.

It will be assumed that electrically heated households will utilize their heating systems during the heating season and that air conditioned households will utilize their air conditioning equipment during the cooling season. Further, it will be assumed that neither heating nor cooling systems are in use during the transitional months.

The formulation will first proceed for the models of total household demand. This will be followed by model development using the conditional demand analysis technique.

A. Total Household Demand

The residential demand for electricity is a derived demand, in part derived from the demand for the services provided by electricity consuming equipment. As such, the stock of appliances and the associated utilization rates of those appliances require consideration when specifying the demand equation. Real electricity price and real household income are two economic factors affecting the utilization rate of the appliance stock (Wilder and Willenborg (1975)).

Additionally, the size of the dwelling, the number of occupants, and the weather will also affect the intensity of use of the appliance stock. These factors will be incorporated into the three seasonal demand equations.

1. Primary Heating Season Models

The basic demand equation to be estimated for the pooled months in the heating season is:

$$\begin{aligned} USE = b_0 &+ b_1 P_a + b_2 Y + b_3 ADULTS + b_4 CHILD + b_5 APPL \\ &+ b_6 SQFT{*}HDD{*}DUMH + b_7 SQFT{*}HDD{*}(1-DUMH) \\ &+ b; \end{aligned} \tag{1}$$

where: USE = household electricity use in kWh;

P_a = ex-post average real price of electricity in \$/kWh (fixed service charge extracted);

Y = real household income in \$;

ADULTS = number of adult occupants;

CHILD = number of child occupants;

APPL = simple-sum of appliances selected from:
electric clothes dryer
food freezer
electric range
dishwasher
microwave oven
clothes washer;

SQFT = dwelling size in square feet;

HDD = 65 degree base heating degree-days;

DUMH = dummy variable (=1 if electric heat, =0 else);

b = random error.

The consumption variable (USE) is from utility billing records and measures the total household electricity consumption during the month. The price variable (P_a) is the average price of electricity ((total utility bill less fixed service charge)/total kWh use) and is also from utility records. Average price is deflated by the CPI-U (1967=100) to reflect real price. Income (Y) is the midpoint value of an income range response collected by a telephone survey of participating households. Income is also deflated by the CPI-U for the first month of the study to reflect real income. The number of adults (ADULTS) and number of children (CHILD) are coded actual from the survey data.

Hirst, Goeltz, and Carney (1982) found significant differences in the relative effects of children and adults on household consumption, and thus, the number of household occupants will be disaggregated in the current study.

The appliance stock measure (APPL) is the number of the following appliances possessed by the household: electric clothes dryer, food freezer, electric range, dishwasher, microwave oven, and clothes washer. This index is similar to that used by Wilder and Willenborg (1975).

The final terms, SQFT*HDD*DUMH and SQFT*HDD*(1-DUMH), represent the effect of weather per square foot of dwelling for electrically heated and non-electrically heated homes, respectively. Weather is measured by 65 degree base heating degree-days. These variables allow for the differing effects of weather between the two household types. Energy engineering theory suggests that both household types will increase their utilization of space conditioning equipment as more degree-days are incurred, and electrically heated homes will have a larger use of electricity per degree-day.

Because of the decreasing block pricing used to price electricity, the price of electricity is inherently negatively related to the quantity purchased. If left uncorrected, this reverse causality would be likely to ascribe a larger negative effect to the estimated price coefficient than is actually present. This study will postulate a price equation similar to that of Wilder and Willenborg (1975) and Garbacz (1984a) to describe the structure of the price relationship. The price equation for months of the heating season is:

$$P_a = a_0 + a_1 USE + a_2 DUMGEN + a_3 DUMRATE + a_4 DUMFEE + a; \qquad (2)$$

where: DUMGEN = dummy for pre / post generation addition, (=0 if pre, =1 if post);

DUMRATE = dummy for electrically heated home rate code (=1 if electric heat, =0 otherwise);

DUMFEE = dummy for franchise fee (=1 if 1% fee, =0 otherwise);

a = random error.

The dummy variable indicating pre/post generation facility addition (DUMGEN) demarcates an approximately 25 percent general rate increase collected after the electric plant generation addition. The dummy variable indicating the customer preferential rate (DUMRATE) denotes those households consuming under the lower price schedule during the heating season. DUMRATE and DUMH (used interactively in the demand model with weather effects) refer to the same subset of customers, those using electric heat. The dummy variable, DUMFEE, denotes customers subjected to a 1% city fee.

In the first stage of the 2SLS estimation, the exogenous variables of equation (1) are substituted into equation (2) to obtain the predicted average price equation. These predicted prices are designed to be purged of their correlation with the error term in equation (1). Following estimation, these predicted average prices are then used in the second stage of the 2SLS to estimate the demand equation (1). The first stage price equation (in substituted form) to be estimated is:

$$\begin{aligned} P_a = z_0 &+ z_1 Y + z_2 \text{ADULTS} + z_3 \text{CHILD} + z_4 \text{APPL} \\ &+ z_5 \text{SQFT*HDD*DUMH} + z_6 \text{SQFT*HDD*(1-DUMH)} \\ &+ z_7 \text{DUMGEN} + z_8 \text{DUMRATE} + z_9 \text{DUMFEE} + z; \end{aligned} \tag{2a}$$

The variables DUMGEN and DUMFEE provide identification as they are exogenous to the demand equation (1) and provide information regarding exogenous price changes. Estimation results for both equation (2), the structural price model, and equation (2a), the first stage price model will be presented. When additional demand/price models are specified in this chapter, only the structural demand and price models will be presented. Estimation (2SLS) will occur using the substitution method presented above.

In addition to the linear specification, logarithmic specifications of the two previously outlined models will be investigated using the two-stage least squares estimation method.

The demand and price equations to be estimated in double log form are:

$$\begin{aligned} \ln(USE) = d_0 &+ d_1\ln(P) + d_2\ln(Y) + d_3\ln(ADULTS) \\ &+ d_4\ln(CHILD) + d_5\ln(APPL) \\ &+ d_6\ln(SQFT*HDD)*DUMH \\ &+ d_7\ln(SQFT*HDD)*(1-DUMH) + d; \end{aligned} \tag{3}$$

and

$$\begin{aligned} \ln(P_a) = c_0 &+ c_1\ln(USE) + c_2DUMGEN + c_3DUMRATE \\ &+ c_4DUMFEE + c; \end{aligned} \tag{4}$$

where c and d are random error terms. The resulting estimated coefficients represent constant elasticity estimates (except for dummy variable coefficients). When natural logarithm arguments would be zero, the value of the argument will be set to 0.0001 as per Garbacz (1984a) to avoid the undefined nature of logarithms of zero.

In order to investigate the effects of decreasing block pricing, if left uncorrected by a price equation and 2SLS, equations (1) and (3) will also be estimated using OLS. Further, the effect of using the marginal price of electricity will be investigated by again estimating equations (1) and (3) using RMP, real marginal price of electricity in place of the real average price.

2. Alternative Heating Season Models

As an alternative to the appliance measure in the basic demand equations (1) and (3), a new measure of the appliance stock, APPL1, will replace APPL. The alternative measure weights each appliance possessed by the household using Garbacz (1984b) weighting scheme. The weights reflect the relative average electricity consumed through the various appliances. The weights that will be used are:

Electric clothes dryer	=	11;
Food freezer	=	16;
Electric range	=	8;
Dishwasher	=	4;
Microwave oven	=	2;
Clothes washer	=	1.

This weighting structure is thought to better reflect the electricity usage effects of each of the possessed appliances.

The alternative demands equations replacing equations (1) and (3) are:

$$USE = e_0 + e_1P_a + e_2Y + e_3ADULTS + e_4CHILD + e_5APPL1 + e_6SQFT*HDD*DUMH + e_7SQFT*HDD*(1-DUMH) + e; \quad (1')$$

and

$$\ln(USE) = f_0 + f_1\ln(P) + f_2\ln(Y) + f_3\ln(ADULTS) + f_4\ln(CHILD) + f_5\ln(APPL1) + f_6\ln(SQFT*HDD)*DUMH + f_7\ln(SQFT*HDD)*(1-DUMH) + f; \quad (3')$$

where e and f are random error terms. The price equations, equations (2) and (4) will be utilized in conjunction with equations (1') and (3'), respectively for 2SLS estimation.

3. Primary Cooling Season Models

The primary demand equation to be estimated for the pooled summer months is:

$$USE = h_0 + h_1P_a + h_2Y + h_3ADULTS + h_4CHILD + h_5APPL + h_6SQFT*CDD*DUMAC + h_7SQFT*CDD*(1-DUMAC) + h; \quad (5)$$

where: CDD = 65 degree base cooling degree-days;

DUMAC = dummy variable (=1 if A/C present, =0 else);

h = random error.

The summer period demand equation is comparable to the winter period demand equation, with the substitution of CDD and DUMAC for HDD and DUMH, respectively.

The price equation to be estimated for the summer months is:

$$P_a = g_0 + g_1 USE + g_2 DUMGEN + g_3 DUMFEE + g; \tag{6}$$

where g is a random error term. Absent from the summer price equation is the DUMRATE term. DUMRATE is a dummy variable indicating those households who consume from a preferential price schedule due to their all-electric homes. The discounted rate is not available in the summer months, and thus all households base their electricity purchase decisions on the same rate schedule.

Analogous to the winter period model specification, the summer month demand and price equations will also be estimated in double log form. The two equations are:

$$\begin{aligned} \ln(USE) = l_0 &+ l_1 \ln(P) + l_2 \ln(Y) + l_3 \ln(ADULTS) \\ &+ l_4 \ln(CHILD) + l_5 \ln(APPL) \\ &+ l_6 \ln(SQFT*CDD*DUMAC) \\ &+ l_7 \ln((SQFT*CDD)*(1-DUMAC)) + l; \end{aligned} \tag{7}$$

and

$$\ln(P_a) = k_0 + k_1\ln(USE) + k_2DUMGEN + k; \qquad (8)$$

where l and k are random error terms.

4. Alternative Cooling Season Models

As in the winter period case, the variable APPL1, a use-weighted index of the household's appliances, will be substituted for APPL in the summer period demand equations (5) and (7). This yields the alternative demand equations (5') and (7'):

$$\begin{aligned} USE = m_0 &+ m_1P_a + m_2Y + m_3ADULTS + m_4CHILD \\ &+ m_5APPL1 + m_6SQFT*CDD*DUMAC \\ &+ m_7SQFT*CDD*(1-DUMAC) + m; \end{aligned} \qquad (5')$$

and

$$\begin{aligned} \ln(USE) = n_0 &+ n_1\ln(P_a) + n_2\ln(Y) + n_3\ln(ADULTS) \\ &+ n_4\ln(CHILD) + n_5\ln(APPL1) \\ &+ n_6\ln(SQFT*CDD)*DUMAC \\ &+ n_7\ln(SQFT*CDD)*(1-DUMAC) + n; \end{aligned} \qquad (7')$$

where m and n are random error terms.

5. Primary Transitional Season Models

The primary demand equation to be estimated for the transitional month period is similar to summer and winter period models. From the assumption that neither heating nor cooling systems are significantly employed during the transition months, no space conditioning term is included in the model. Thus, the basic demand equation for the transitional period is:

$$USE = q_0 + q_1P_a + q_2Y + q_3ADULTS + q_4CHILD + q_5APPL + q; \qquad (9)$$

where q is a random error term. The price equation for the transitional months is that of the winter period, due to the October through May time period of the preferential electricity rate.

The price equation is:

$$P_a = p_0 + p_1USE + p_2DUMGEN + p_3DUMRATE + p_4DUMFEE + p; \qquad (10)$$

where p is a random error term.

The transitional month demand and price equations will be estimated in double log specification also. The two resultant equations for estimation are:

$$\ln(USE) = s_0 + s_1\ln(P) + s_2\ln(Y) + s_3\ln(ADULTS) + s_4\ln(CHILD) + s_5\ln(APPL) + s; \qquad (11)$$

and

$$\ln(P_a) = r_0 + r_1\ln(USE) + r_2DUMGEN + r_3DUMRATE + r_4DUMFEE + r; \qquad (12)$$

where r and s are random error terms.

6. Alternative Transitional Season Models

As with the summer and winter period models, the transitional period estimation will also utilize the use-weighted appliance stock measure, APPL1. The resultant equations (9') and (11') are:

$$USE = t_0 + t_1P_a + t_2Y + t_3ADULTS + t_4CHILD + t_5APPL1 + t; \qquad (9')$$

and

$$\ln(USE) = v_0 + v_1\ln(P) + v_2\ln(Y) + v_3\ln(ADULTS) + v_4\ln(CHILD) + v_5\ln(APPL1) + v; \qquad (11')$$

where t and v are random error terms.

7. Additional Considerations

In order to examine the effects of using marginal price instead of average price, all of the above equations will be estimated using the real marginal price (RMP) of electricity. Additionally, relative gains in estimating efficiency may be achievable if pooling of seasons can occur. Coefficients and effects of the various determinants will be investigated and the appropriate pooling of data examined.

B. Conditional Demand

As previously discussed, conditional demand analysis disaggregates the household appliance stock and directly estimates the unit energy consumption of each appliance. Following the lead of Parti and Parti (1980), an econometric specification for each major appliance will be formulated. The individual appliance models will then be aggregated into a single equation representing total household electricity use.

As household electricity use is an observed measure, the aggregate equation can then be estimated using several techniques. This study will utilize OLS with both the real marginal price and average price measures. Previous studies suggest that average price, and to a lesser extent, marginal price may be inherently negatively related to electricity use. Thus, the use of these measures may tend to overstate the true price effect.

The major purpose of conditional demand analysis is to arrive at electricity use estimates, and not necessarily price elasticities. The potential bias introduced will play a small role in UEC estimates, and is noted for own-price elasticity estimates.

As discussed by Aigner, Sorooshian, and Kerwin (1984), the success of conditional demand analysis in isolating individual appliance usage and determinants requires that appliance ownership patterns be well mixed. The need for appliance dispersion requires that an investigation of appliance holdings be made prior to model specification.

The nine major appliances chosen for investigation are dehumidifiers, food freezers, electric ranges, dishwashers, clothes washers, electric clothes dryers, air conditioners, electric space heating, and microwave ovens. The appliance saturation level for each appliance is:

dehumidifiers (DEHUM)	45.7%
freezers (FREEZ)	56.2
ranges (ERANGE)	71.0
dishwashers (DW)	70.5
washers (WASH)	90.5
dryers (EDRYER)	54.3
air conditioners (DUMAC)	78.0
electric heating (DUMH)	10.5
microwave ovens (MWAVE)	59.0.

The nearly universal ownership of clothes washers (90.5%) suggests that isolating their electricity use via conditional demand analysis may prove difficult. Because of this high appliance ownership rate, and the relatively low electricity consumption of clothes washers, washers will not be included in the current study. No other appliance saturation level exceeds that of air conditioners (78.0%).

In order to further investigate the dispersion of appliance holdings, correlation coefficients were calculated between each of the remaining appliances. The variables indicating appliance ownership are binary, with 1 indicating the presence of the appliance and 0 indicating that the appliance is not owned. The correlation coefficients for the eight appliances are presented in Table 3-1.

Those appliances which have the greatest saturation, air conditioners, dishwashers, ranges, and microwave ovens display the greatest correlation of mutual ownership. As no correlation exceeds 0.50 for any pair of appliances, all eight appliances will initially be used for analysis.

Following model estimation, one or more appliances may be relegated to the unspecified appliance list if isolation of their electricity use fails. Those appliances with the lowest electricity use, dishwashers and microwave ovens, will be removed from the model first.

1. Appliance Specific Demand Models

a. Dehumidifiers The climate in Iowa is variable, with substantial outdoor humidity in the summer months and a relatively high ground water table. Thus, dehumidifier use is not limited to the summer period and may or may not be weather sensitive. As a conservative specification, the average real price of electricity and real household income will be specified as determinants of humidifier demand. The model specification for dehumidifiers is:

$$USE_1 = b_{10} + b_{11}P_a + b_{12}Y + e_1; \qquad (13)$$

where: USE_1 = electricity consumption through dehumidifiers;

e_1 = random error;

and all other determinants are as previously specified.

Table 3-1. Appliance correlations

	FREEZ	ERANGE	DW	MWAVE	DUMAC	EDRYER	DUMH
DEHUM	0.10	0.06	0.20	0.16	0.03	0.02	0.08
FREEZ	1.00	0.06	0.18	0.26	0.21	0.06	0.10
ERANGE		1.00	0.45	0.23	0.25	0.22	0.20
DW			1.00	0.48	0.46	0.33	0.22
MWAVE				1.00	0.29	-.01	0.08
DUMAC					1.00	0.14	0.16
EDRYER						1.00	0.23
DUMH							1.00

b. Food Freezers The electricity consumption of food freezers is generally modeled in engineering terms, and seldom approached by econometric methods. Engineering thermodynamics suggests that the electricity by freezers is related to infiltration (opening and closing), heat loss (insulation and surrounding air temperature), mechanical efficiency (age of unit), and the mass (weight) of goods frozen.

The current study has no measure of unit age available, nor is information provided about the surrounding air temperature. Both infiltration and the mass of goods frozen would appear to be a function of household size. Other things equal, the more family members, the more likely the freezer to be opened. Additionally, the more family members, the greater the mass of food frozen. From the findings previously cited in this study, a differential effect will be allowed for adults and children. The model specification for food freezers is:

$$USE_2 = b_{20} + b_{21}P_a + b_{22}Y + b_{23}ADULTS + b_{24}CHILD + e_2 \tag{14}$$

where: USE_2 = electricity consumption through freezers;

ADULTS = number of adult members in household;

CHILD = number of child members in household.

c. Electric Ranges The principal determinants of electricity consumption through ranges are frequency and duration of range use. While this may be more of a behavioral relationship, reflecting household tastes and preferences, it is reasonable to hypothesize a relationship related to number of household members. Similar to Parti and Parti (1980) the model specification for electric ranges is:

$$USE_3 = b_{30} + b_{31}P_a + b_{32}Y + b_{33}ADULTS + b_{34}CHILD + e_3; \tag{15}$$

where USE_3 is electricity consumption through ranges.

d. Dishwashers The case for the electricity consumption determinants of dishwashers is directly analogous to that of electric ranges. Thus, the model specification for dishwashers is:

$$USE_4 = b_{40} + b_{41}P_a + b_{42}Y + b_{43}ADULTS + b_{44}CHILD + e_4; \tag{16}$$

where USE_4 is electricity consumption through dishwashers.

e. Microwave Ovens Again, consumption through microwave ovens is also determined by similar factors to electric range and dishwasher determinants. The model specification to be used for microwave ovens is:

$$USE_5 = b_{50} + b_{51}P_a + b_{52}Y + b_{53}ADULTS + b_{54}CHILD + e_5; \tag{17}$$

where USE_5 is electricity use through microwave ovens.

<u>f. Air Conditioners</u> The appropriate specification of space conditioning models is more complex than that of many appliances. As discussed earlier in this chapter, a central factor determining usage through air conditioners is the weather-household size interaction. The specification of the air conditioner demand equation follows directly from the specification of the air conditioning determinant in the total household demand models. Thus, electricity use through air conditioners will be modeled as:

$$USE_6 = b_{60} + b_{61}P_a + b_{62}Y + b_{63}CDD*SQFT + e_6; \qquad (18)$$

where USE_6 is electricity consumption through air conditioners.

<u>g. Electric Clothes Dryers</u> The determinants of electricity consumption through clothes dryers are identical to the determinants used for ranges, microwaves, and freezers. The specified demand equation for clothes drying is:

$$USE_7 = b_{70} + b_{71}P_a + b_{72}Y + b_{73}ADULTS + b_{74}CHILD + e_7; \qquad (19)$$

where USE_7 is electricity consumption through clothes dryers.

h. Electric Space Heating   Along with air conditioning, electric space heating has been discussed at length earlier in this chapter. The principal determinants of space heat use are weather and dwelling size. The demand equation specified for space heating is:

$$USE_8 = b_{80} + b_{81}P_a + b_{82}Y + b_{83}HDD*SQFT + e_8; \qquad (20)$$

where USE_8 is electricity consumption through space heating.

i. Unspecified Appliances   Conditional demand analysis requires that the appliances not directly specified by equation be modeled as a group. For this study, electricity use through clothes washing machines and television sets were surveyed and not directly modeled. As the saturation of both appliance groups is very high, and no other appliance were surveyed, no measure of appliance stock will be included in the unspecified appliance equation.

This is in contrast to Parti and Parti (1980) where a count of unspecified appliances was included in their unspecified appliance equation.

Conceptually, unspecified appliances include hair dryers, stereos, televisions, computers, small electric kitchen appliances, and a host of others. Both the frequency and duration of use of these appliances is, in all likelihood, a function of relative lifestyle differences.

In a fashion similar to that used for total household demand models, the use through unspecified appliances will be modeled as:

$$USE_0 = b_{00} + b_{01}P_a + b_{02}Y + e_0; \tag{21}$$

where USE_0 is electricity consumption through unspecified appliances. Notice that this is a very simple model and does not include measures of household size or composition. Due to the collinearity inherent in conditional demand models, the effects of children and adults are left relegated to those appliances which are expressly thought to be dependent on household size. This potential omitted variable bias may bias the estimated electricity use of common block (non-space heating) appliances.

2. Conditional Demand Models

The observed electricity usage for this study is total household usage. In order to perform estimation using conditional demand analysis, the nine appliance models must be aggregated. The general form of the aggregation is:

$$E = \Sigma_i E_i; \tag{22}$$

where: E = total household electricity use (observed);

E_i = appliance specific electricity use.

Aggregating the eight appliance demand equations and the unspecified appliance equation formulated above:

$$E = b_{00} + b_{01}P_a + b_{02}Y + e_0 + A_1(b_{10} + b_{11}P_a + b_{12}Y + e_1) + A_2(b_{20} + b_{21}P_a + b_{22}Y + b_{23}ADULTS + b_{24}CHILD + e_2) + A_3(b_{30} + b_{31}P_a + b_{32}Y + b_{33}ADULTS + b_{34}CHILD + e_3) + A_4(b_{40} + b_{41}P_a + b_{42}Y + b_{43}ADULTS + b_{44}CHILD + e_4) + A_5(b_{50} + b_{51}P_a + b_{52}Y + b_{53}ADULTS + b_{54}CHILD + e_5 + A_6(b_{60} + b_{61}P_a + b_{62}Y + b_{63}CDD*SQFT + e_6) + A_7(b_{70} + b_{71}P_a + b_{72}Y + b_{73}ADULTS + b_{74}CHILD + e_7 + A_8(b_{80} + b_{81}P_a + b_{82}Y + b_{83}HDD*SQFT + e_8); \quad (23)$$

where A_i is 1 if the appliance is held by the jth household or 0 otherwise.

Parti and Parti (1980) provides a discussion of the parameter constraints imposed prior to their estimation. They suggest that the high degree of correlation between the regressors (price, income, adults, child) will fail to provide identification of the appliance specific parameters.

To correct for this assumed multicollinearity, Parti and Parti imposed numerous restrictions on the parameters of the "common block" appliances. Common block appliances are relatively low electricity consumption appliances with identical demand equation determinant specification.

Following the above outlined method, price, income, adults, and child effects will be constrained to be equal for freezers, ranges, dishwashers, microwaves, and clothes dryers. Additionally, the price and income effects of dehumidifiers will also be constrained with the common block.

The resultant reduced form equation is:

$$
\begin{aligned}
E = {} & b_{00} + A_1 b_{10} + A_2 b_{20} + A_3 b_{30} + A_4 b_{40} + A_5 b_{50} + A_6 b_{60} \\
& + A_7 b_{70} + A_8 b_{80} + b_{01} P_a + b_{02} Y + (A_1 + A_2 + A_3 \\
& + A_4 + A_5 + A_7) b_1 P_a + (A_1 + A_2 + A_3 + A_4 + A_5 \\
& + A_7) b_2 Y + (A_2 + A_3 + A_4 + A_5 + A_7) b_3 ADULTS \\
& + (A_2 + A_3 + A_4 + A_5 + A_7) b_4 CHILD + A_6 (b_{61} P_a \\
& + b_{62} Y + b_{63} CDD*SQFT) + A_8 (b_{81} P_a + b_{82} Y \\
& + b_{83} HDD*SQFT) + e. \qquad (24)
\end{aligned}
$$

As previously demonstrated, when equation (24) is estimated in conditional deviation form, the resulting intercept terms provide direct estimates of the average electricity consumption per appliance.

IV. DATA

The data used in this study were largely obtained from a major midwestern electric utility company. The data were collected as an extension of the utility's on-going electric load research activities as mandated by the Public Utilities Regulatory Policy Act (PURPA).

Sources utilized by the utility were telephone interviews conducted in the fall of 1982 and internal utility billing records. Additionally, the dataset has been augmented with weather information and the Consumer Price Index, CPI (1967 = 100).

The utility-supplied data consisted of electricity usage, billing history, and various household-specific information for 105 randomly selected residential households. Billing and electricity usage data were available for the period from November 1982 through November 1984. The time period of the data is particularly interesting as an approximately 26% rate increase occurred in October of 1983. This rate increase followed a period of relatively stable electricity rates.

The dataset consists of the specific information for each household described in Table 4-1. These data were transformed and recoded for use throughout the study. Each recoded/transformed variable in the study is described at the time it is introduced.

Table 4-1. Variable descriptions

Variable	Description	Coding
USE	Electricity use by month	(actual)
BILL	Total cost of electricity	(actual)
MP	Marginal price of electricity	(actual)
ID	Case identification number	(actual)
CITY	City of customer electric service	(actual)
DIV	Company division	(actual)
MEM	Number of household members	(actual)
AGE	Categorical age of head of household	(interval)
WEATHER	Indication of weatherization activity	(dummy)
YEAR	Actual year structure was built	(actual)
NROOMS	Number of rooms in dwelling	(actual)
SQFT	Square footage of dwelling	(actual)
AC	Presence of air-conditioning	(dummy)
FURN	Furnace fuel	(interval)
DEHUM	Presence of dehumidifier	(dummy)
FREEZ	Presence of food freezer	(dummy)
RANGE	Presence of electric range	(dummy)
DW	Presence of dishwasher	(dummy)
DRYER	Presence of electric dryer	(dummy)
INCOME	Household income (1982)	(interval)
CHILD	Number of children	(actual)
TEMP	Average indoor air temperature	(actual)
MWAVE	Presence of microwave oven	(dummy)
BWTV	Presence of black and white television	(dummy)
CTV	Presence of color television	(dummy)
WASH	Presence of clothes washer	(dummy)
HDD	65 degree heating degree days	(actual)
CDD	65 degree cooling degree days	(actual)
CPI	Consumer price index (1967=100)	(actual)
MONTH	Month of data	(actual)
DUMGEN	Indication of pre/post rate increase	(dummy)

The means and standard deviations for each of the variables in the dataset are presented in Table 4-2.

Information for furnace fuel type (FURN), nominal income (INCOME), and indoor air temperature (TEMP) was incomplete from the surveys.

Furnace fuel type was easily completed from utility billing records. Each household's furnace fuel is identified by the household's electric utility rate code.

Initially, 15 of the 105 households refused to provide income information. In the winter of 1987, an exit interview was conducted with many of the households to complete the missing data. Following the exit interview, 6 households still refused to identify their income level. An additional direct contact with the households was not attempted at the request of the utility.

In attempting to estimate income levels for these households, two relationships were examined. The regression coefficient of AGE (age of head of household) bore a negative relationship with income and had an R-Square of 4%. Visual inspection of a scatter plot also suggests that little relationship exists between AGE and INCOME.

Physical house size (SQFT) was also examined, and provided an R-Square of 5% and a positive coefficient. As neither relationship had substantial explanatory power, and since the AGE relationship failed to display the expected

Table 4-2. Descriptive statistics

Variable	Mean	S.E. Mean	N	Label
USE	1325.02	20.09	2520	KWH PER MONTH
BILL	97.36	1.30	2520	MONTHLY BILL
MP	.06	.00	2520	MARGINAL PRICE
CITY	1.64	.01	2520	FRANCHISE FEE DUMMY
DIV	2.14	.03	2520	COMPANY LOCATION
MEM	3.02	.03	2520	HH MEMBERS
AGE	2.75	.02	2520	AGE OF HEAD
WEATHER	.39	.01	2520	DUMMY FOR WEATHERIZATION
YEAR	1953.36	.53	2520	YEAR BUILT
NROOMS	7.26	.04	2520	NUMBER OF ROOMS
SQFT	1839.76	17.09	2520	HH SQFT
AC	.90	.01	2520	AC DUMMY
FURN	.86	.01	2232	FURNACE FUEL
DEHUM	.48	.01	2520	DEHUMIDIFIER DUMMY
FREEZ	.59	.01	2520	FREEZER DUMMY
ERANGE	.75	.01	2520	ELEC RANGE DUMMY
DW	.70	.01	2520	DISHWASHER DUMMY
DRYER	1.22	.01	2520	DRYER FUEL
INCOME	29439.59	268.63	2376	NOMINAL INCOME
CHILD	1.09	.02	2520	NUMBER OF CHILDREN
TEMP	75.06	.10	1896	AVG INDOOR TEMP
MWAVE	.62	.01	2520	MICROWAVE DUMMY
BWTV	.44	.01	2520	DUMMY FOR BW TV
CTV	.94	.00	2520	DUMMY FOR COLOR TV
WASH	.95	.00	2520	DUMMY FOR WASHER
HDD	481.96	10.67	2520	65 HEAT DEGREE DAYS
CDD	107.33	3.47	2520	65 COOLING DEGREE DAYS
CPI	3.02	.00	2520	CPI-U 1967
MONTH	6.50	.07	2520	MONTH OF YEAR
DUMGEN	.50	.01	2520	GENERATION ADD DUMMY

positive relationship, the mean value of income was used for the 6 missing cases.

To investigate the effect of the substitution of average income for missing values, several household electricity demand models were estimated excluding missing values. No significant changes in regression coefficient significance or magnitude were evidenced.

The last variable with missing data, indoor air temperature (TEMP), will not be used in this study. Because desired indoor air temperatures are not necessarily the same in every season, a single indoor air temperature measure is inappropriate. Additionally, an analysis of the TEMP variable revealed that some responses were apparently an average temperature, while other responses were seasonal temperatures.

V. EMPIRICAL MODEL RESULTS AND DISCUSSION

A. OLS Average Price Total Demand Models

Initially, three models of household electricity demand were estimated using the average price of electricity. These models correspond to equations (1), (5), and (9) of Chapter III, and reflect winter, summer, and the transitional season, respectively.

1. Winter Season

All estimated coefficients in the winter season model are highly significant (1% level), with the exception of real income. In addition, real income bears a negative relationship with electricity use. This result is not consistent with theoretical expectations, or with previous studies.

The own-price elasticity (evaluated at the mean) is -0.74668. This elasticity is similar to those reported by Moore (1970) and Asher and Habermann (1978). Both of the aforementioned studies utilized household level data and average price.

The elasticities of adults and children on total electricity use are 0.20439 and 0.04756, respectively. This suggests that changes in the number of adults present has a markedly higher effect on electricity use than do changes in the number of children. This result has been previously demonstrated by Hirst, Goeltz, and Carney (1982).

The effect of winter season weather varied substantially between electrically heated and non-electrically heated homes. The SQFT*HDD (household size - heating degree day interaction) elasticity for electrically heated homes was 1.15571, while non-electrically heated homes display an elasticity of 0.17506.

While most studies include some measure of weather in the demand model, few studies present weather elasticities. Those studies providing elasticities generally do not disaggregate electrically heated and non-electrically heated homes. As such, the elasticity reported in most studies would be an average and inapplicable to the current study.

One study however, Hartman and Werth (1981) did disaggregate electric heat using a conditional demand methodology and state-level data. The study presents a HDD elasticity of 0.88 for electrically heated homes. This compares favorably to the results of the present study.

The final elasticity to examine is that of the appliance stock. The calculated elasticity is 0.35783 and is similar to the elasticity reported by Wilder and Willenborg (1975). Table 5-1 presents the results of the winter demand model estimation.

2. Summer Season

All estimated coefficients are significant at the 5% level, with the exceptions of price and income. Price is significant at the 10% level. Real household income, while

Table 5-1. Winter OLS AVP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	144.70999	21.15020	6.842	.0000
APPL	116.87585	12.39391	9.430	.0000
AVP	-44429.71745	4460.25624	-9.961	.0000
CHILD	59.92907	14.07305	4.258	.0000
RINCOME	-5.01682E-03	4.06137E-03	-1.235	.2170
SQFTHDD1	9.882021E-04	2.37995E-05	41.522	.0000
SQFTHDD2	1.289808E-04	1.58967E-05	8.114	.0000
(Constant)	926.37448	131.85845	7.026	.0000
R Square	.76700			

exhibiting the expected sign, fails to display significance at the 20% level.

The own-price elasticity of -0.21969 is well bounded by the estimates of previous studies. This elasticity is also well below the price elasticity exhibited in the previous winter equation, suggesting that summer electricity usage is less price elastic than is winter usage.

Because the price of electricity declines with increasing electricity consumption in winter months, the winter own-price elasticity may be overstated. This study will address this issue in later analyses.

The elasticities of adults and children are 0.21792 and 0.02996, respectively. These elasticities are very similar to those obtained in the winter season analysis.

The summer season weather measure (household size and cooling degree day interaction) for homes with air conditioning yields an elasticity of 0.55710. Those homes without air conditioning are less sensitive to weather and home size, and exhibit an elasticity of 0.12586. When compared to Hartman and Werth (1981), the elasticity for air conditioned homes appears reasonable. The study does not provide an elasticity estimate for non-air conditioned homes.

The elasticity estimate of the effects of the appliance stock is 0.35226. This summer season elasticity is nearly identical to that estimated for the winter season. Table 5-2

Table 5-2. Summer OLS AVP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	163.69430	27.71962	5.905	.0000
APPL	122.07406	15.64386	7.803	.0000
AVP	-12268.77046	6801.82059	-1.804	.0716
CHILD	40.05273	18.42743	2.174	.0300
RINCOME	3.241501E-03	5.39965E-03	.600	.5485
SQFTCDD1	1.299460E-03	5.12916E-05	25.335	.0000
SQFTCDD2	3.945904E-04	1.06680E-04	3.699	.0002
(Constant)	175.88728	204.87672	.859	.3909
R Square	.55227			

displays the summer demand model estimation results.

3. Transitional Season

All estimated coefficients in the transitional season model are significant at the 1% level, with the exception of income which is significant at the 20% level.

The estimated own-price elasticity for the months of the transitional season is -0.98566. This is somewhat higher than the own-price elasticity exhibited during the winter months, and may be overstated due to the decreasing block pricing in effect during the transitional months.

The income elasticity of 0.08071 is well within the results of previous studies. The elasticities related to adults and children are 0.30644 and 0.06851, respectively. These are again very similar to those reported for the preceding two models. The appliance elasticity is 0.67164 and is considerably higher than that derived from either of the two preceding models. The estimation results are presented in Table 5-3.

4. Discussion

The relative explanatory power of the models decreases substantially from winter to summer season (R-squares of 0.76700 and 0.55227, respectively). This reduction in R-square from winter to summer is largely related to the greater explanatory power of winter weather over summer weather. The two SQFTHDD terms in the winter model account

Table 5-3. Transitional OLS AVP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	148.99242	28.73872	5.184	.0000
APPL	150.64939	15.85583	9.501	.0000
AVP	-38597.75560	7433.29541	-5.193	.0000
CHILD	59.29107	19.16702	3.093	.0021
RINCOME	7.549329E-03	5.49046E-03	1.375	.1699
(Constant)	793.57561	214.15807	3.706	.0002
R Square	.37257			

for over 0.61 of the model R-square. The corresponding terms in the summer model account for only 0.45 of the model's R-square. Thus, winter weather provides a greater explanation of the variability of electricity use than does summer weather.

The transitional season model provides the least explanatory power with an R-square of 0.37257. The nature of the weather effect terms in the winter and summer models (weather - household square footage) may provide some explanatory power related to household size, a measure totally lacking in the transitional season model. Therefore, the addition of a size term (SQFT) to the transitional season model may help the explanatory power and make the model more comparable with the summer and winter models. The results of this estimation are presented in Table 5-4.

The R-square of the transitional season model containing a SQFT term increased to 0.43299, and SQFT is significant at the 1% level. This provides an elasticity of 0.31920 associated with household size. Other elasticities calculated from this model are: own-price (-1.02427), adults (0.27330), children (0.05964), and appliance stock (0.61850). All estimated coefficients are significant at the 1% level, except income, which fails significance at the 20% level but does achieve a positive sign.

Table 5-4. Alternative transitional OLS AVP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	132.88014	27.46061	4.839	.0000
APPL	138.73131	15.19784	9.128	.0000
AVP	-41853.55343	7091.87609	-5.902	.0000
CHILD	51.60806	18.27954	2.823	.0050
RINCOME	2.827503E-03	5.27397E-03	.536	.5922
SQFT	.16306	.02458	6.634	.0000
(Constant)	707.49446	204.24433	3.464	.0006
R Square	.43299			

This demonstrated relationship between household size and electricity use, in the absence of weather, suggests that the winter and summer weather terms may overestimate actual weather sensitivity by failing to exclude changes in electricity usage primarily related to dwelling size. The interpretation of the dwelling size measure in the equation is, in all likelihood, a secondary measure of the appliance stock.

All three seasons share similarity in appliance stock, number of adults, and number of children coefficient estimates. The marginal effect of an additional adult is approximately 150 kWh per month, other things equal. The marginal effects of an additional appliance is approximately 120 kWh per month. The marginal effect of one additional child is approximately 60 kWh per month. This suggests that the pooling of all months, allowing for differential price and weather effects will be appropriate and more efficient than three separate estimations. The estimated coefficients for the above factors are not significantly different by season at the 5% level.

The pooled model provides substantially the same results presented in the three individual models. All estimated coefficients are significant at the 1% level, except for summer average price (10% level), real income, and the transitional season dummy. The pooled model estimation results are presented in Table 5-5.

Winter and transitional season estimated coefficients are nearly identical and provide similar own-price elasticities (-0.75036 and -0.78298, respectively). Summer own-price elasticity is -0.22022, slightly larger than reported for the summer model. Other elasticities are substantially unchanged from the separate models.

Overall, the pooled model provides increased efficiency without imposing any undesirable restrictions. The number of individual parameters estimated could be further reduced by combining winter and transitional price into "non-summer" average price, as winter and transitional season coefficients are not significantly different at the 5% level.

The relative lack of significance of household income in the above models may result from several factors. For example, income is a determinant in not only the utilization of the appliance stock, but also in the level of the appliance stock. Thus, an appliance stock equation may help reveal the true effect of income on electricity usage.

Another possible explanation centers around the measure of income used in this and other studies. Consumption decisions may not be based on current income, but rather on expected or permanent income. Therefore, a measure of household wealth may provide a superior explanatory measure.

Table 5-5. Pooled OLS AVP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	152.06513	14.83779	10.249	.0000
APPL	125.16254	8.49359	14.736	.0000
AVPST	-12298.37387	6302.24751	-1.951	.0511
AVPTT	-43445.55184	9143.06041	-4.752	.0000
AVPWT	-43004.05820	4372.33296	-9.835	.0000
CHILD	53.22613	9.87572	5.390	.0000
RINCOME	-1.20874E-04	2.85991E-03	-.042	.9663
SQFTCDD1	1.302353E-03	4.68781E-05	27.782	.0000
SQFTCDD2	3.900515E-04	9.61225E-05	4.058	.0001
SQFTHDD1	9.781303E-04	2.29754E-05	42.573	.0000
SQFTHDD2	1.241753E-04	1.56006E-05	7.960	.0000
SUMMER	-609.22570	198.42454	-3.070	.0022
TRANS	278.97938	240.58996	1.160	.2463
(Constant)	813.82139	117.44866	6.929	.0000
R Square	.69743			

B. OLS Marginal Price Total Demand Models

In order to investigate the use of marginal price in place of average price, the above equations (equations (1), (5), and (9) of Chapter III) were re-estimated using the real marginal price of electricity as the price measure.

Overall, both estimated coefficients and explanatory power are very similar to the average price estimations. This result was reasonably expected, as the utility tariff provides only one declining block structure in its rates (a two-part tariff), and average prices are necessarily similar to marginal prices.

Also, only all-electric households, those with electric heat, purchase electricity from the two block rate schedule (non-summer only). All consumers in the sample purchase pay a fixed monthly service charge, and state and local taxes (where applicable).

Appendix A provides the detailed results of the marginal price model estimations.

C. 2SLS Average Price Total Demand Models

The two-stage least squares models utilize equations (1) and (2), (5) and (6), and (9) and (10) of Chapter III. This method is used to estimate a price function, and purge the price variable, average price, of correlation with the residuals in the demand equations. The 2SLS models are estimated for the winter, summer, and transitional seasons.

Because no multi-block pricing occurs in the summer months, it is unlikely that the 2SLS estimation should have any significant effect on the summer model. During the transitional and winter seasons, average price and energy use are inherently negatively related due to the two-part tariff faced by electrically heated households. Thus, the literature suggests that own-price elasticities for these seasons should be lessened using the 2SLS method.

For computational ease on a microcomputer, 2SLS estimations are prepared using two passes of OLS. Appendix B provides the results of the first stage price instrument estimation for winter, summer, and the transitional season. In general, the R-square values for the models approximately 0.60 for the winter and summer seasons, and 0.40 for the transitional season.

Appendix C provides the estimations of the formulated price models, equations (2), (6), and (10) of Chapter III. R-square values are similar to those reported above, and most coefficient estimates are significant at the 1% level. Additionally, all parameter estimates are of the expected sign: rate increase dummy > 0, franchise fee dummy > 0, preferential electric heating rate dummy < 0, electricity use > 0.

The second stage of the 2SLS models entailed estimating equations (1), (5), and (9) of Chapter III using the predicted values of the average price from the first stage. The detailed results of these three estimations are presented in Appendix D. The explanatory power of these models is very similar to that of the OLS estimations using average price.

The principal finding of the 2SLS estimation is the marked decrease in winter season own-price elasticity. The elasticity estimate fell from -0.74668 (OLS) to -0.14224 (2SLS). A slight increase in elasticities is seen for both the summer and transitional periods. All other elasticities remained very stable throughout the OLS average price, marginal price, and 2SLS estimations.

D. OLS Average Price Total Demand Models in Double Log Specification

Equations (3), (7), and (11) of Chapter III were estimated using OLS. The resulting regression coefficients are interpreted as constant elasticities.

1. Winter Season

All estimated coefficients in the winter season model are significant at the 1% level and of the previously discussed expected sign, with the exception of real income. The displayed price elasticity is -0.79389, very similar to the -0.74668 calculated from the linear specification. The income elasticity is 0.02056 and significant at the 35% level. It is similar to that estimated by Garbacz (1983) and somewhat lower than the results reported by Acton, Mitchell, and Sohlberg (1980). Both studies utilized some form of disaggregate data.

The estimated coefficients (and elasticities) for the effects of adults and children are 0.29973 and 0.01745, respectively. These elasticities are very similar to those from the linear specification described above. The appliance stock elasticity of 0.07730 is lower than that calculated from the linear specification.

The weather measure elasticities for electrically heated and non-electrically heated homes are 0.44273 and 0.37350, respectively. These are again substantially different than those obtained using the linear specification. Electrically heated homes under the prior model displayed an elastic relationship with household electricity use (elasticity of 1.15571). The assumption of constant elasticity inherent in the double log specification may account for the large differences in estimated elasticities.

The results of the winter season double log estimation are presented in Table 5-6.

2. Summer Season

All summer season model coefficients are significant at approximately the 10% level or better, with the notable exception of the appliance stock measure. The appliance stock measure displays the appropriate positive relationship, but fails to achieve significance at the 50% level. Additionally, the appliance stock elasticity is extremely small,

Table 5-6. Winter OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.29973	.03447	8.695	.0000
APPL	.07730	.01110	6.964	.0000
AVP	-.79389	.07600	-10.445	.0000
CHILD	.01745	2.48520E-03	7.022	.0000
RINCOME	.02056	.02100	.979	.3277
SQFTHDD1	.44273	.02188	20.234	.0000
SQFTHDD2	.37350	.02166	17.244	.0000
(Constant)	-2.12407	.44148	-4.811	.0000
R Square	.72595			

less than 0.01. One possible explanation for this result is that space conditioning accounts for a major part of the variability in summer season electricity usage, and appliance stock effects may be subsumed into the cooling degree day - square footage terms of the model.

Price elasticity is -0.21900, very similar to that reported earlier. The income elasticity is 0.07819, well within the findings of other studies. The elasticities of adults and children are also similar to previous findings in this study.

Similar to the winter season findings, the summer season weather measure variables provide much different elasticity estimates in the double log specification. Air conditioned households' weather elasticity is 0.40583, approximately two-thirds of that displayed in previous models. Elasticity for non-air conditioned homes is 0.36284, or three times that displayed in the linear specification.

Table 5-7 provides the regression results for the summer season model.

3. Transitional Season

The double log specification results for the transitional season are very similar to the results previously described for the linear specification. All estimated coefficients are significant at the 1% level, and most constant elasticities are very similar to those previously described.

Table 5-7. Summer OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.29559	.04834	6.115	.0000
APPL	7.282426E-03	.01602	.455	.6495
AVP	-.21900	.13959	-1.569	.1171
CHILD	6.606817E-03	3.49445E-03	1.891	.0590
RINCOME	.07819	.03011	2.597	.0096
SQFTCDD1	.40583	.02373	17.103	.0000
SQFTCDD2	.36284	.02427	14.953	.0000
(Constant)	.22274	.64637	.345	.7305
R Square	.47111			

Own-price elasticity is -1.40336, indicating an elastic response to price changes, as compared to a near unit elastic response under the previous average price specifications. Income elasticity is 0.12724, still rather inelastic.

Elasticities for the adults and children measures are similar to those previous results also. The appliance measure elasticity is 0.13750. This result is lower than previously reported for the transitional season, but similar to the double log results for summer and winter seasons. The results of this estimation are presented in Table 5-8.

4. Discussion

As with the results previously discussed for average price models, the explanatory power of the models decreases from winter to the transitional season. The R-squares for the winter, summer, and transitional season models are 0.72595, 0.4711, and 0.33441, respectively.

Own-price elasticities in the double log specification are very similar in magnitude to those reported from the linear specifications. Additionally, the differential effects of adults and children on electricity consumption also share a similar pattern with previous findings.

In an attempt to improve the explanatory power of the transitional season model a household size measure (SQFT) was added and the model was re-estimated. The R-square increases to 0.38658, and all coefficients are significant at the

Table 5-8. Transitional OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.35433	.07439	4.763	.0000
APPL	.13750	.02390	5.752	.0000
AVP	-1.40336	.20368	-6.890	.0000
CHILD	.01972	5.42258E-03	3.636	.0003
RINCOME	.12724	.04556	2.793	.0055
(Constant)	-.06282	.82494	-.076	.9393
R Square	.33441			

5% level. The elasticity for household size is 0.34511 and is similar to the weather variable elasticities reported for summer and winter seasons. Table 5-9 presents the results of this regression.

This result suggests that the multiplicative nature of a linear in logarithms specification may require a different weather measure than that used in the previous linear models. By including both household size (SQFT) and weather measures (CDD or HDD), the usage effect of weather and household size on electricity consumption may be better captured.

Preliminary winter season model estimations provide a household size elasticity of 0.41449 with HDD elasticities of 0.45813 and 0.31365 for electrically heated and non-electrically heated homes. Summer results show a SQFT elasticity of 0.49500 with CDD elasticities of 0.35992 and 0.26719 for air conditioned and non-air conditioned homes. Winter and summer season estimation results are presented in Tables 5-10 and 5-11, respectively.

E. OLS Marginal Price Total Demand Models in Double Log Specification

As reported for the linear specification models, the use of marginal price impacts little change on the estimated equations or elasticities. In general, all elasticities and estimated coefficient significance levels remain relatively unchanged by use of marginal price. One noted exception is

Table 5-9. Alternative transitional OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.27089	.07288	3.717	.0002
APPL	.11256	.02336	4.819	.0000
AVP	-1.46118	.19602	-7.454	.0000
CHILD	.01764	5.22386E-03	3.376	.0008
RINCOME	.10022	.04402	2.277	.0233
SQFT	.34511	.05824	5.926	.0000
(Constant)	-2.52197	.89494	-2.818	.0051
R Square	.38658			

Table 5-10. Alternative winter OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.29521	.03473	8.501	.0000
APPL	.07554	.01121	6.741	.0000
AVP	-.79312	.07685	-10.321	.0000
CHILD	.01715	2.49423E-03	6.876	.0000
HDD1	.45813	.03415	13.415	.0000
HDD2	.31365	.03443	9.111	.0000
RINCOME	.01830	.02108	.868	.3854
SQFT	.41449	.02815	14.722	.0000
(Constant)	-1.99446	.45487	-4.385	.0000
R Square	.72510			

Table 5-11. Alternative summer OLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.27208	.04886	5.569	.0000
APPL	1.467835E-03	.01614	.091	.9276
AVP	-.24306	.13957	-1.741	.0820
CDD1	.35992	.02990	12.039	.0000
CDD2	.26719	.03075	8.690	.0000
CHILD	5.992349E-03	3.49812E-03	1.713	.0871
RINCOME	.07737	.03010	2.570	.0103
SQFT	.49500	.03950	12.533	.0000
(Constant)	-.24595	.65823	-.374	.7088
R Square	.47222			

the somewhat smaller magnitude (absolute value) of price elasticities using the marginal price variable. Elasticity estimates are reduced by 10 to 20% over those reported in the average price estimations.

Model results for the marginal price estimations appear in Appendix E.

F. 2SLS Average Price Total Demand Models in Double Log Specification

The results of the two-stage least squares regressions for the double log specifications closely resemble the results of the 2SLS runs for the linear specifications. The winter 2SLS regression provided a significantly reduced price elasticity of -0.13718, compared to the OLS elasticity of -0.79389. This result was also observed from the 2SLS estimation under the linear specification. Again, all other estimated elasticities remained generally unchanged. Table 5-12 presents the results of the winter season estimation.

The summer season model provides a slightly greater price elasticity than reported by OLS (-0.24182 versus -0.21900), however these are not significantly different at the 5% level. All other estimated coefficients were nearly identical to the OLS estimations. Summer season estimation results appear in Table 5-13.

Table 5-12. Winter 2SLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.32591	.03609	9.031	.0000
APHATW	-.13718	.11733	-1.169	.2426
APPL	.08032	.01157	6.940	.0000
CHILD	.01681	2.59121E-03	6.487	.0000
RINCOME	.04330	.02209	1.960	.0502
SQFTHDD1	.43809	.02281	19.207	.0000
SQFTHDD2	.35847	.02266	15.820	.0000
(Constant)	.29686	.55992	.530	.5961
R Square	.70240			

Table 5-13. Summer 2SLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.29531	.04838	6.104	.0000
APHATS	-.24182	.18061	-1.339	.1810
APPL	7.348248E-03	.01603	.459	.6467
CHILD	6.596777E-03	3.49622E-03	1.887	.0595
RINCOME	.07798	.03014	2.587	.0098
SQFTCDD1	.40597	.02375	17.094	.0000
SQFTCDD2	.36302	.02429	14.944	.0000
(Constant)	.13965	.76950	.181	.8560
R Square	.47068			

Results for the transitional season 2SLS model were also very similar to its linear counterpart. All estimated coefficients were similar in significance and magnitude to the OLS regression results. Table 5-14 displays the results of the transitional season estimation.

G. Alternative Appliance Stock Measure

The alternative, weighted by usage appliance stock measure, APPL1, was used to estimate OLS average price, marginal price, and 2SLS models. No significant changes were observed in estimated model coefficients. This suggests that the simple sum appliance measure is equally as useful as the weighted average measure. Model results are not presented, and are available from the author.

H. Conditional Demand Models

Two conditional demand models are estimated, both of the form of equation (24) of Chapter III. The first model to be discussed uses real average price as the price measure, while the second utilizes the real marginal price of electricity.

Of the four price measures included in the model (electric spaceheat, air conditioning, common effect appliances, and residual usage), three are negative. The price term for winter space heating and common effect appliances achieve significance at the 20% level. The associated own-price elasticities, as well as all other estimated elasticities, will be discussed in the following section.

Table 5-14. Transitional 2SLS AVP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.35503	.07706	4.607	.0000
APHATT	-1.36478	.32590	-4.188	.0000
APPL	.13780	.02480	5.557	.0000
CHILD	.01978	5.62225E-03	3.518	.0005
RINCOME	.12809	.04743	2.701	.0072
(Constant)	.07366	1.22531	.060	.9521
R Square	.28824			

Three of the four estimated income coefficients are positive, with the positive coefficients failing significance at the 20% level. Only the negatively signed income term associated with winter space heating achieved significance. The negative sign of this coefficient is not as hypothesized from consumer theory or previous studies.

Both weather measures, summer season and winter season, are highly significant and positively related to electricity use. In addition, common block coefficients for children and adults are positive and highly significant.

The constant terms, representing appliance equation intercept terms, are in general significant at the 5% level. In the following section dealing with the conditional deviation specification of the model, appliance constant magnitudes will be evaluated. The results of the average price conditional demand estimation appear in Table 5-15.

Results for the conditional demand equation estimated using the real marginal price measure are largely the same as reported above. Appendix G presents the results of this estimation.

I. Conditional Demand Models in Deviation Form

As demonstrated in Chapter III, when the conditional demand equation is estimated in conditional deviation form, the resulting appliance intercept terms are interpreted as

Table 5-15. AVP conditional demand estimation

Variable	B	SE B	T	Sig T
A6CDD	1.329589E-03	4.85350E-05	27.394	.0000
A6P	-3306.41651	8153.87433	-.406	.6851
A6Y	1.659526E-04	6.30488E-03	.026	.9790
A8HDD	8.455454E-04	3.19211E-05	26.489	.0000
A8P	-103891.0590	9088.22314	-11.431	.0000
A8Y	-.02659	7.53306E-03	-3.529	.0004
AVP	858.34905	7063.18285	.122	.9033
COM1AD	51.14709	3.57639	14.301	.0000
COM1AVP	-2862.12477	1830.60460	-1.563	.1181
COM1CH	14.56248	2.50751	5.808	.0000
COM1Y	1.218658E-03	1.59827E-03	.762	.4458
DEHUM	-205.46137	54.14181	-3.795	.0002
DUMACS	-111.99249	230.64340	-.486	.6273
DUMHW	2527.82305	232.43300	10.875	.0000
DW	55.22934	61.46083	.899	.3689
EDRYER	127.23563	56.08006	2.269	.0234
ERANGE	-99.83787	55.36113	-1.803	.0714
FREEZ	43.11140	55.11828	.782	.4342
MWAVE	218.35353	55.74216	3.917	.0001
RINCOME	5.968073E-03	6.24042E-03	.956	.3390
SUMMER	111.18532	49.27309	2.257	.0241
TRANS	87.39236	32.54526	2.685	.0073
(Constant)	440.99942	193.24650	2.282	.0226
R Square	.72108			

average appliance electricity usage. Both average price and marginal price models are re-estimated in conditional deviation form.

1. Estimated Appliance Electricity Use

Of primary interest in the conditional demand model in deviation form are the estimated unit energy consumptions (UECs) of the various specified appliance. These estimated UECs appear in Table 5-16.

Estimated UECs from the average price and marginal price specifications are very similar, with the exception of winter season space heating estimates. Using a marginal price measure substantially reduces the estimated electricity use by space heating.

The average electricity use through dehumidifiers and electric ranges is negative, suggesting that the model suffers from omitted variable bias or specification error. While published estimates of dehumidifier usage are not available, a range of 50 to 200 kWh per month is suggested by engineering methods. Parti and Parti (1980) reports estimated electric range use of 60 kWh per month. Because both appliances represent a small share of total household electricity usage (3-5%), it is not surprising that isolating their UECs is difficult. Many studies in the field hypothesize that conditional demand analysis best estimates the UECs of larger electricity using appliances.

Table 5-16. Estimated appliance usages

APPLIANCE	AVP	MP
AIR CONDITIONING	630.7709	665.6957
CLOTHES DRYERS	211.9511	203.4252
COOKING RANGES	-59.9930	-50.0671
DEHUMIDIFIERS	-105.333	-109.979
DISHWASHERS	59.35568	53.97865
ELECTRIC HEATING	1554.857	1156.837
FREEZERS	122.7518	118.5025
MICROWAVE OVENS	286.5973	278.9768
RESIDUAL USE	576.0204	613.7649

The estimated UEC for dishwashers in this study is approximately 3 kWh per day. Because dishwashers are a luxury good, they may serve as a proxy for an array of other appliances, and thus bias the UEC upward. In a 1979 study, the Midwest Research Institute (MRI) reports a metered estimate of the dishwasher UEC of 0.41 kWh per day.

MRI reports a UEC for electric clothes drying of 2.83 kWh per day, while this study finds the UEC to be in excess of 6 kWh per day. While the current study is substantially higher, the MRI study is based on a national sample. Thus, the differing temperatures and humidity of Iowa may require a greater drying time and electricity consumption for clothes dryers.

The estimated UEC of food freezers in the current study is slightly over 3 kWh per day. This compares very favorably with MRIs estimate of 3.68 kWh per day.

As with dishwashers, microwave ovens may be considered a luxury good, and thus be a proxy for other electricity using appliances. This study finds a UEC of over 9 kWh per day for microwave ovens. Assuming a 1 kW microwave oven in use for 1 hour per day, a maximum UEC of 1 kWh per day is expected. The present study estimate is clearly biased upward.

The estimated UEC for summer air conditioning use is slightly over 20 kWh per day in the current study. This is approximately twice that estimated by MRI. Due to the unusually hot summer of 1983 (included in the present sample), and the more humid Iowa climate, the estimated UEC seems reasonable.

With the exception of the UEC for electric space heat, the average price and marginal price specifications agree closely. However, the space heating UEC ranges from over 50 kWh per day (average price model) to slightly under 40 kWh per day (marginal price model). One reason for this discrepancy is the greater degree of simultaneity between average price and electricity use. Thus, the average price based estimate may be biased upwards. Utility records indicate that electrically heated houses use from 1200 to 1600 additional kWh per month than do non-electrically heated homes in the winter. While this usage may not be entirely attributable to electric heating, it does suggest that the estimated UECs from this study are reasonable.

Appendix H provides the details of the conditional demand estimations in deviation form.

2. Estimated Elasticities

Table 5-17 presents selected elasticities from the conditional demand models. These elasticities are calculated at the conditional mean of the independent variables, and utilize the estimated appliance UECs when the estimated UECs are non-negative. Results are reported for both average and marginal price based models.

Table 5-17. Estimated elasticities

PRICE	MP	AVP
AIR CONDITIONING	0.075073	-0.13772
CLOTHES DRYERS	-0.12539	-0.31755
COOKING RANGES	0.525405	1.148431
ELECTRIC HEATING	-0.78019	-1.32548
FREEZERS	-0.22389	-0.56028
MICROWAVE OVENS	-0.09482	-0.23947
RESIDUAL	-0.71023	0.036231
INCOME		
AIR CONDITIONING	0.001880	0.002818
CLOTHES DRYERS	0.086095	0.060155
COOKING RANGES	-0.35986	-0.21863
ELECTRIC HEATING	-0.05122	-0.19057
FREEZERS	0.147962	0.103986
MICROWAVE OVENS	0.067641	0.047933
RESIDUAL	0.075765	0.104102
WEATHER		
AIR CONDITIONING	1.230986	1.312157
ELECTRIC HEATING	1.144342	0.870386

The overall price and income elasticities are calculated as the consumption-weighted summation of the individual appliance elasticities. Using the marginal price measure of electricity price, the calculated winter price elasticity is -0.62171, while the summer price elasticity is -0.26811. For the corresponding average price based model, winter own-price elasticity is -0.85940, and summer own-price elasticity is -0.19207. These own-price elasticities are very similar to those obtained using the total household electricity demand methodology.

The estimated income elasticity for the marginal price based models is 0.025 for winter and 0.065 for summer months. Using the average price based models, winter income elasticity is -0.060 and summer elasticity is 0.065. These elasticities, including the improbable negative relationship, are again similar to those estimated using the total demand models.

3. Discussion

The results of the conditional demand estimations suggest that bias from omitted variables may be substantial. The nonsensical, negative UECs and the overestimated UECs provide evidence of the need for more complete inventories of household appliances.

Specification error may also have a role in the results of the conditional demand estimations. The common effect appliances (dishwashers, electric ranges, microwave ovens, clothes dryers, food freezers, and dehumidifiers) were all constrained to have the same price, income, and household size effects. It is reasonable to assume that if the assumption of identical effects is incorrect, the resulting estimates will be biased.

The most likely incorrect constraint on the common effect appliances is that of identical use effects by children and adults. In order to investigate this hypothesis, the deviation form equations were re-estimated omitting the common effect interaction with children and adults. Since this may impose an additional bias due to the omitted variables, the results will not be entirely conclusive.

The estimation shows no substantial change in the estimated coefficient UECs, and supports the inference that model specification error (due to the constrained adults and children effects) is not substantial for the common effect appliances. Appendix I reports the estimated models.

VI. MODEL ANALYSES AND APPLICATIONS

This chapter focuses on two major issues: inspection of the statistical properties of selected models and applying the estimated models to specific public utility and PUC concerns.

A. Model Parameter Stability

Because of the pooled (cross sectional, time series) nature of the data used in this study, an examination of the applicability of the pooling is desired. Specifically, the investigation centers on whether or not the model parameters are the same for both years of sample data. The Chow test for stability is utilized to test this hypothesis for each seasonal model.

The 2SLS models are deemed to be theoretically superior to the single equation models, based both on the literature and the estimated model parameters. The stability test will be conducted on the three seasonal 2SLS demand models in the linear specification. Due to extreme multicollinearity the double log models are not tested.

The first stage price models are also not tested, as the underlying price mechanism is known to have changed at the end of the first year of the sample data. The price models are constructed to account for the price increase in the utility tariff. The resulting parameter stability tests are conditional on the assumption of price parameter stability.

The Chow test F-values for winter, summer, and transitional season linear models are 1.56 (7,1246), 1.54 (7,825), and 3.17 (5,410), respectively. The transitional season F-value suggests a very significant difference in the parameters from the first sample year to the second. The summer and winter season F-values suggest less strongly (significant at the 15% level) that those seasonal model parameters are also different between sample years.

Because the transitional season model has the lowest explanatory power and fewest parameters, it is possible that one or more omitted variables may explain differences between years. None of the differential slope terms in the transitional model are significant at the 20% level. However, the differential intercept suggests that the overall level of electricity usage changed by approximately 300 kWh between estimation years.

Closer examination of the differential slopes of the winter estimation reveals that weather effects are less in the second year of the data. Additionally, the effect of adults on electricity consumption is also lower in the second year. These results are also observed for the summer estimation. This may suggest that weather effects require a more thorough modeling treatment, such as the use of explicit temperature measures and a more complex weather activity specification.

While model stability appears to be questionable, the magnitude of the instability is relatively low. For example, the slopes of the estimated weather effects vary by only 10-20% between sample years. The reduction in electricity use by adults is approximately 75 kWh per month per adult, or less than 10% of total electricity use.

B. Backcasting

To investigate the predictive ability of the estimated total demand models, each model will be used to predict historic electricity consumption within the sample period. Because utility and PUC forecasts are made by consumer class (residential, commercial, industrial, etc.) the mean predicted values will be examined. Individual, household-level forecasts are generally not of interest.

For each of the 24 sample months, the predicted consumption was calculated for average price, marginal price, and 2SLS based linear and double log models. Each model's backcasts were evaluated by squaring and summing the monthly deviations from actual usage.

The model with the best predictive ability using the above criterion is the 2SLS model in linear specification. This model's backcast deviation from actual usage is 41% of the next best backcasting model, the average price based model in linear form. All linear models out perform their double log counterparts by at least a factor of 2, compared by this squared deviation method. Figures 6-1, 6-2, and 6-3 present backcast plots of the linear, log, and 2SLS models.

C. Weather Normalization

Utility rate-making is a complex and cost-based process. One of the crucial steps in calculating prospective utility rates involves distributing historical utility costs across historical electricity sales (Iowa methodology). Because sales vary substantially with weather, weather normalization is used to remove the changes in electricity use due to weather.

Many methods are used to accomplish this end, however few are model-based. Most involve determining weather sensitive sales, and multiplying by a ratio of normal degree days to observed degree days. This provides an implicit unit elasticity of weather sensitive sales with respect to degree days. As observed in the analysis of conditional demand models, this may not necessarily provide an accurate adjustment.

If all weather sensitive sales in the residential sector are related to heating and cooling systems, the conditional demand analysis suggests a range of applicable elasticities. For residential customers using air conditioning, the elasticity range suggested is 1.23 to 1.31. Thus, a unit elasticity adjustment may fail to sufficiently sterilize electricity sales of weather effects due to air conditioning.

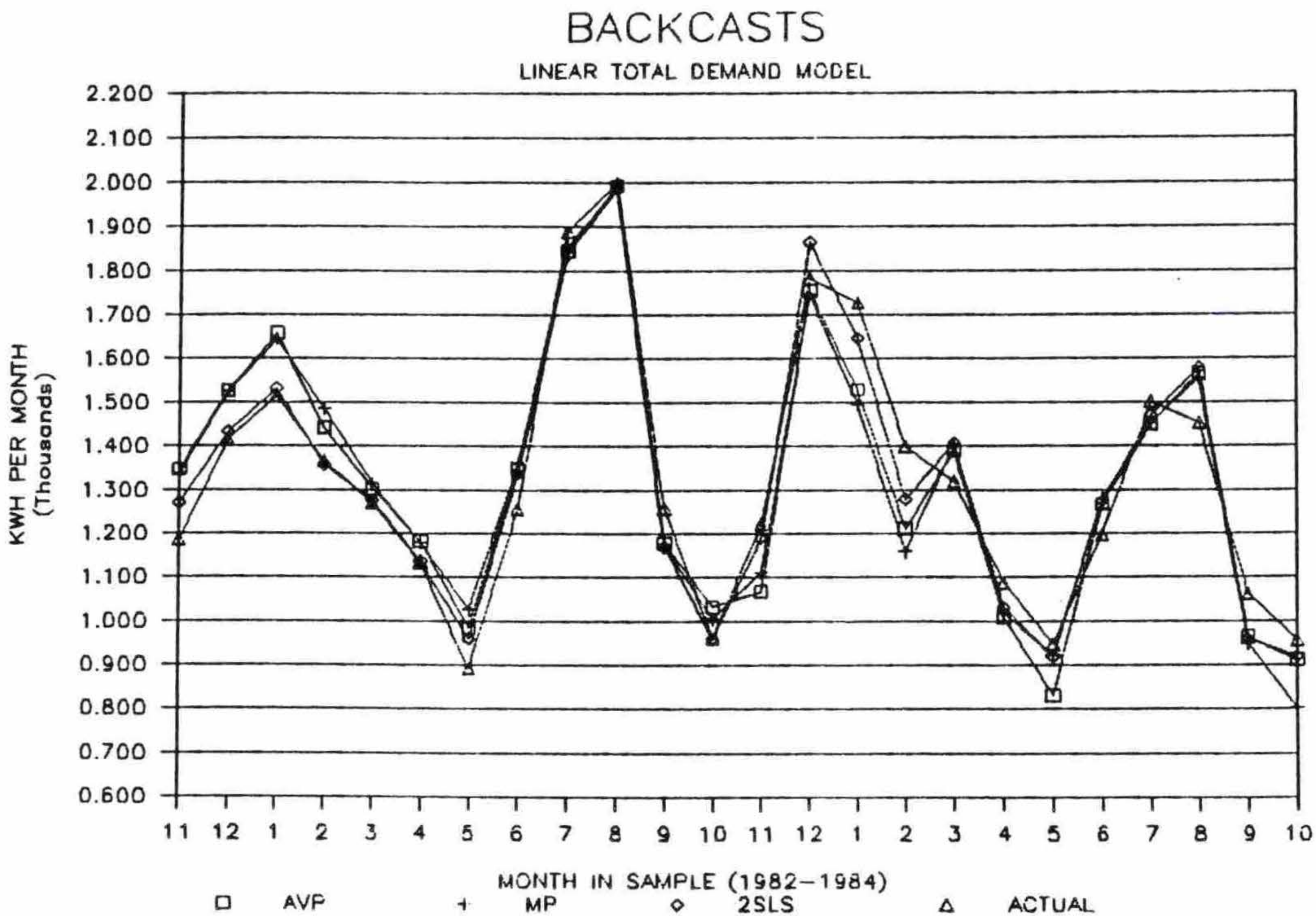

Figure 6-1. Linear total demand model backcasts

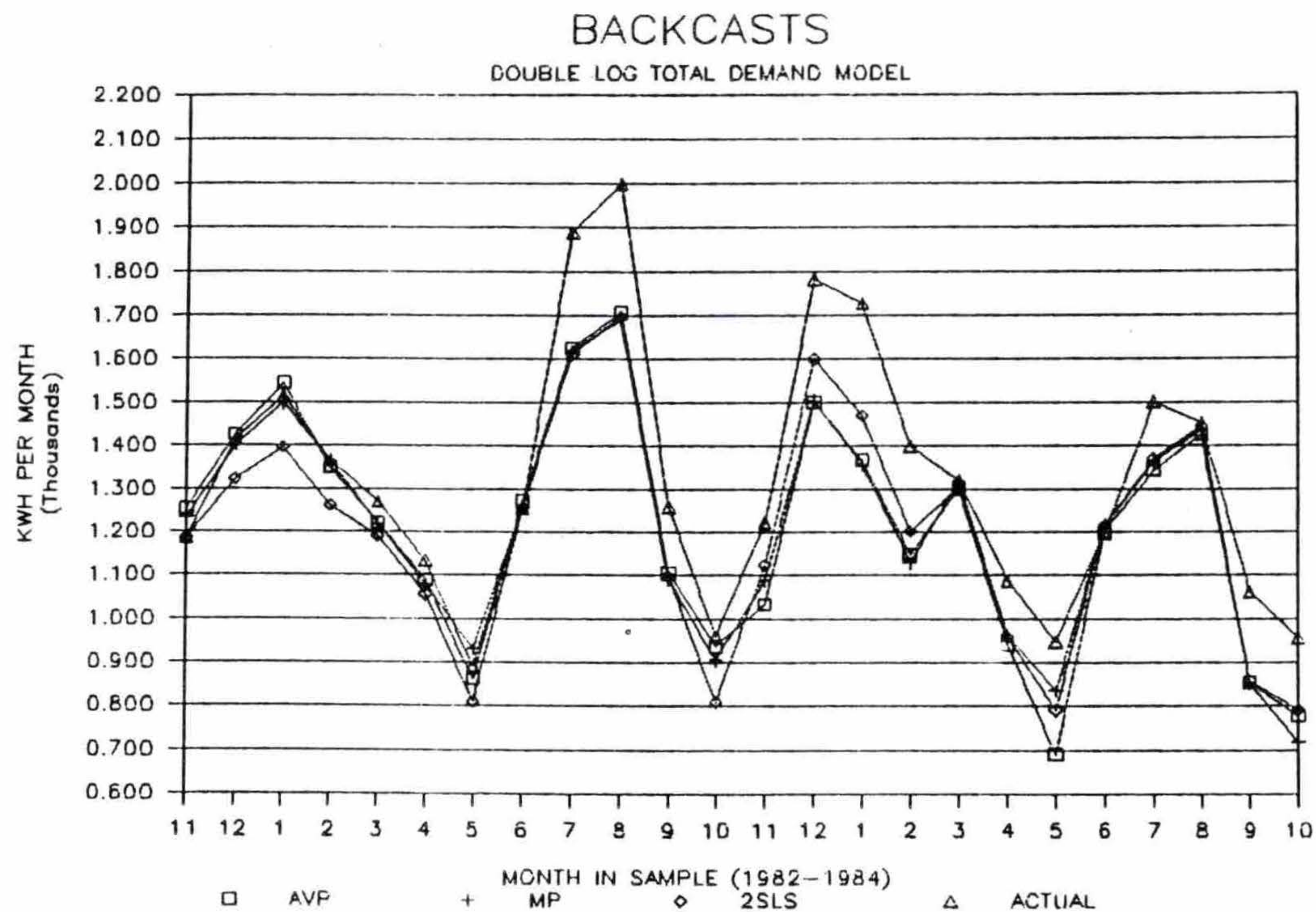

Figure 6-2. Double log total demand model backcasts

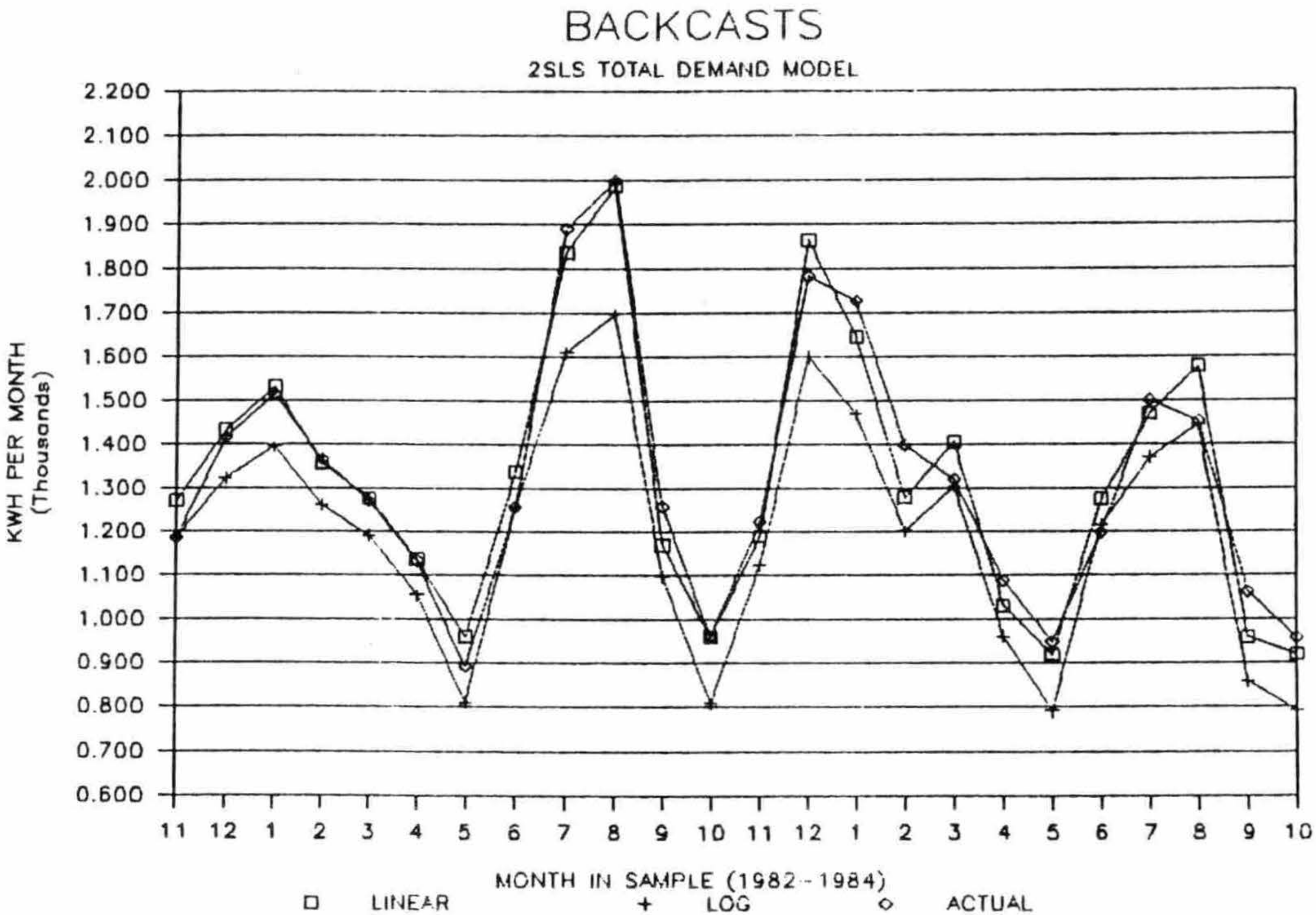

Figure 6-3. 2SLS total demand model backcasts

The conditional demand models suggest that the unit elastic adjustment may be appropriate for electrically heated residential sales. The elasticity range from the average price and marginal price based models is 0.87 to 1.14.

The previously estimated total demand models provide an alternative method to adjusting weather effects from residential sales. By predicting historical sales using 30-year normal degree days, weather effects can be removed without the need for isolating the fraction of sales which are weather sensitive.

The model based approach provides an average weather normalized electricity use per customer of 1271 kWh per month over the sample period. This compares with actual customer electricity use of 1325 kWh per month. Using the unit elastic methodology described above, weather normalized customer sales would also be 1271 kWh per customer.

This result suggests that the unit elastic methodology may well provide sufficient correction for the effects of weather. However, the model based approach provides a more theoretically appealing, and defensible methodology.

D. CDD Elasticity of Electrically Heated Homes

Electrically heated homes are thought to be constructed to a higher thermal integrity than are natural gas heated homes. If this is the case, then the cooling degree day effects of these "all-electric" dwellings should be significantly less than for other air conditioned houses. In order to test this hypothesis, a model was estimated allowing for differential weather effects between these two types of homes.

Table 6-1 presents the results of the model estimation. Because no multistage tariff is present in the summer, the real average price of electricity was chosen as the price measure. This is further supported empirically by the results of the 2SLS estimations of summer household electricity demand reported previously.

An F-test of the restricted and unrestricted models yields a highly significant F-value of 33.3 (1,831). The negative coefficient of SQFTCDDH (SQFTCDD1 * DUMH) suggests that electrically heated homes do have some physical superiority over other air conditioned homes. This may be in the form of better/more insulation or more efficient cooling equipment.

It is interesting to note that electrically heated homes have an average summer electricity usage of 1511 kWh per month, while air conditioned, non-electrically heated homes have an average summer use of 1656 kWh per month. This difference is significant at the 5% level.

E. Weatherization Effects

The utility survey included a question regarding weatherization activities. Because it solicited only a yes

Table 6-1. Summer CDD elasticity analysis

Variable	B	SE B	T	Sig T
ADULTS	159.74141	27.20527	5.872	.0000
APPL	152.22850	16.21371	9.389	.0000
AVP	-11867.20028	6673.85527	-1.778	.0757
CHILD	39.91319	18.07978	2.208	.0275
RINCOME	3.155007E-03	5.29780E-03	.596	.5517
SQFTCDD1	1.354978E-03	5.12351E-05	26.446	.0000
SQFTCDD2	3.938733E-04	1.04667E-04	3.763	.0002
SQFTCDDH	-4.12645E-04	7.15021E-05	-5.771	.0000
(Constant)	89.21105	201.57168	.443	.6582
R Square	.56952			

or no response, no information exists about the specific activities undertaken. Thus, the variable WEATHER (1 if weatherization, 0 otherwise) provides only a broad measure of weatherization.

In order to investigate whether weatherization provides significant reductions in household electricity usage several models will be estimated. It is not immediately apparent what sign of the estimated coefficient of WEATHER will carry. If high electricity consumption is a factor in the weatherization decision, then those households which have been weatherized may have reduced their individual consumption, but not relative to the remainder of households. A better method of analysis would entail collecting pre and post weatherization electricity consumption data.

As an effort to control for the above situation, the variable YEAR (year house was built) will also be entered into the model estimation. Because older homes tend to be less well insulated and thus greater consumers of electricity for space conditioning, YEAR is hypothesized to be positively related to electricity use. By controlling for dwelling vintage, some of the effects of the relative reduction of usage attributable to weatherization may be mitigated.

Another issue in weatherization relates to human behavior. If those households that weatherize also make lifestyle changes to reduce electricity use, then the portion of the effect attributable to physical improvements can not be isolated from behavioral adaptation.

To investigate this issue, a model will be formulated for the transitional season. This season is assumed to use require no space conditioning, and any weatherization effects apparent would tend to be behavioral rather than physical changes.

Table 6-2 provides the estimation results. The estimated coefficient of YEAR is negative and significant at the 10% level, indicating that newer homes consume marginally less electricity. The weatherization measure is not significantly different from zero, suggesting that this weatherization measure is not reflecting a lifestyle adaptation which reduces electricity usage.

The summer season model was also estimated including the variable YEAR, and WAC (WEATHER*DUMAC). The measure of weatherization is used since the effect weatherization is only applicable to those dwellings with space conditioning. The results of the estimation appear in Table 6-3.

The estimated coefficient of YEAR is again negative and is significant at the 15% level. WAC is negative and highly significant, suggesting that other things equal, weatherized dwellings have an average electricity savings of approximately 300 kWh per month in the air conditioning season.

Table 6-2. Transitional weatherization analysis

Variable	B	SE B	T	Sig T
ADULTS	145.37291	28.89951	5.030	.0000
APPL	154.84051	15.98095	9.689	.0000
AVP	-40827.43120	7504.40010	-5.440	.0000
CHILD	61.98145	19.51523	3.176	.0016
RINCOME	.01108	5.82730E-03	1.901	.0581
WEATHER	-21.03758	45.49207	-.462	.6440
YEAR	-1.73745	.89554	-1.940	.0530
(Constant)	4199.51323	1762.09001	2.383	.0176
R Square	.37876			

Table 6-3. Summer weatherization analysis

Variable	B	SE B	T	Sig T
ADULTS	166.24620	27.11924	6.130	.0000
APPL	133.71805	15.41915	8.672	.0000
AVP	-12082.19173	6646.82802	-1.818	.0695
CHILD	70.52681	18.57228	3.797	.0002
RINCOME	8.322111E-04	5.63457E-03	.148	.8826
SQFTCDD1	1.299466E-03	5.04141E-05	25.776	.0000
SQFTCDD2	1.945098E-04	1.08867E-04	1.787	.0744
WAC	-289.78201	45.48650	-6.371	.0000
YEAR	-1.28062	.84968	-1.507	.1321
(Constant)	2731.50359	1661.95579	1.644	.1006
R Square	.57464			

A similar analysis was conducted for the winter season, except the weatherization effect was allowed to vary between electrically heated and non-electrically heated households. Thus, the variables WNOHEAT (WEATHER*(1-DUMH)) and WHEAT (WEATHER*DUMH) are used. This estimation is presented in Table 6-4.

The effect of the year the dwelling was built is negative and highly significant. The effect of weatherization on electrically heated homes is negative and not significantly different from zero. The effect of weatherization on non-electrically heated homes is negative and significant at the 1% level. Because electricity usage of electrically heated homes is much more weather sensitive than are non-electrically heated homes, this result is somewhat puzzling. It may be the case that electrically heated homes, for the reasons cited previously, do not display relative reductions in usage attributable to weatherization.

These results cautiously suggest that weatherization activities provide the greatest electricity reduction in the summer season. Additionally, some weatherization savings are also observed in the winter season, at least by dwellings without electric heat. As previously suggested, a better weatherization analysis would utilize pre and post activity consumption data, and perhaps some measure of the weatherization activity taken.

Table 6-4. Winter weatherization analysis

Variable	B	SE B	T	Sig T
ADULTS	145.91261	21.23925	6.870	.0000
APPL	118.09020	12.45971	9.478	.0000
AVP	-45556.33413	4450.71554	-10.236	.0000
CHILD	66.03892	14.37723	4.593	.0000
RINCOME	5.371367E-04	4.34418E-03	.124	.9016
SQFTHDD1	9.774354E-04	2.61330E-05	37.402	.0000
SQFTHDD2	1.196889E-04	1.62062E-05	7.385	.0000
WHEAT	-1.35155	54.64987	-.025	.9803
WNOHEAT	-110.29570	39.99097	-2.758	.0059
YEAR	-2.47020	.68424	-3.610	.0003
(Constant)	5750.49662	1340.41557	4.290	.0000
R Square	.77086			

F. Forecasting

The 2SLS model in linear specification provided the best backcasting of historical usages, and will be used to analyze forecasting ability. The 12 month period from May 1987 to April 1988 will be forecasted and appropriate confidence intervals prepared.

The first stage price equation will be utilized to prepare the price forecasts. The prices will be adjusted by the ratio of average model estimation period CPI to forecast month CPI to adjust for inflationary changes. Actual weather, as measured by degree days will be used for the weather measure. Because no additional income data are available, real income level is held constant for the forecasts. All additional independent variables will be also held constant.

The results of the forecast and corresponding 95% confidence intervals are displayed in Figure 6-4 and Table 6-5. Evident from the figure, the forecast confidence intervals are greatest during the transitional months. This occurs due to the relatively low R-square of the period model. Summer and winter intervals are approximately equal.

Seven of the 12 monthly average uses are contained within the 95% confidence interval. Of the 5 months with usage outside the confidence interval, 3 vary by less than 35 kWh from observed usage. The remaining two months, May and

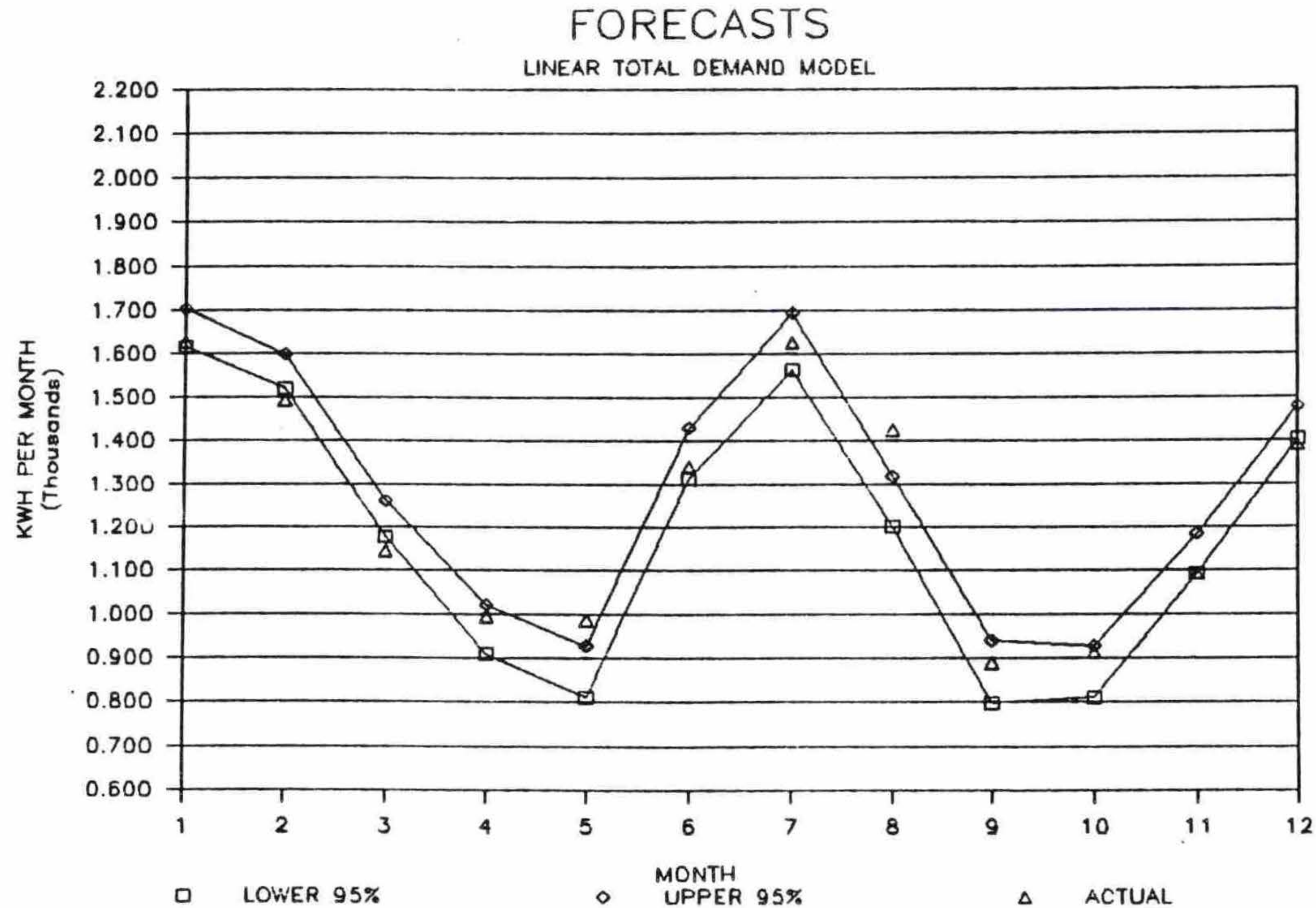

Figure 6-4. Linear total demand model forecasts

Table 6-5. Forecasted electricity use

	95% CI LOWER	FORECAST	95% CI UPPER
JANUARY	1617.720	1660.76	1703.799
FEBRUARY	1520.585	1559.88	1599.165
MARCH	1177.119	1218.96	1260.792
APRIL	909.5538	965.70	1021.849
MAY	811.2192	869.50	927.7736
JUNE	1314.046	1372.44	1430.841
JULY	1563.938	1629.30	1694.667
AUGUST	1200.556	1258.75	1316.947
SEPTEMBER	798.7395	869.25	939.7670
OCTOBER	811.2192	869.50	927.7736
NOVEMBER	1092.623	1138.25	1183.873
DECEMBER	1403.529	1440.90	1478.273

August, show the largest deviation between forecast and actual. August, with fewer CDD than June, achieved greater electricity usage than June. This result was unexpected and can not be accounted for.

May usage was also higher than expected, possibly due to weather effects not accounted for in the transitional season model. Cooling degree days for May were 121, compared to a 30 year average of 66 CDD. As a result, some households may have utilized air conditioning systems. On an annual basis, the average forecasted electricity use was 1238 kWh, compared to the observed use of 1244 kWh.

VII. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

Several interesting issues have emerged from the numerous model estimations undertaken in this study. Those issues to be discussed are: the effects of varied functional form in the estimations, the selection and modeling of the price measure, implications of the estimated elasticities, and the use of conditional demand analysis.

1. Functional Form

Ordinary least squares was used to estimate demand models with both linear (level) and double log models. While the estimated models have been shown to display certain similarities, some significant deviations also occurred. Backcasts using the linear models consistently out performed backcasts from the double log models in terms of accuracy. Visual analysis of the backcasts suggests that the linearization caused by the log transformation may be inappropriate.

Figure 6-2 reveals that double log backcasts fail to capture the peaks of electricity use. Because these peaks are largely related to weather effects, it may be the case that double log models do not capture the effect of weather on electricity use.

The linear specification models proved superior in both overall and "peak and valley" backcasting. This statement gains support from Figure 6-1. When used to forecast the mean electricity use of the sample from May 1987 to April 1988, the linear model performed well. This lends further support to the linear specification, at least for forecasting use.

In terms of estimated parameters, the log models tended to display a positive, significant income effect. This result is suggested both by consumer theory and previous studies. The effect of income in the linear specification models was consistently negligible. Other elasticity differences were also observed using the linear and log specifications and will be discussed later in this chapter.

While neither model specification is clearly superior, their differences and similarities do highlight the need to closely examine modeling objectives. If forecasting is the primary objective, minimizing forecast error, while preserving the essence of relevant theory is a suitable goal. A model with good explanatory power and significant parameters may fail to provide good forecasts. Alternatively, a model which provides excellent forecasts, may not always yield satisfying estimates of structural parameters, such as demand determinant elasticities.

2. Price Measures and Models

This study examined three alternative methods of specifying electricity prices, average price (OLS), average price (2SLS model), and marginal price. Average price was calculated ex post from billing and consumption data, while marginal price was determined from the utility tariff. The selection of the best measure of price has long been argued, and was previously discussed in this paper. The results of this research support the model-based, 2SLS approach to price measurement and estimation of demand models.

The decreasing block pricing of electricity during the winter and transitional seasons provides an inherently negative relationship between price and use. This relationship, when left uncorrected, provided own price elasticity estimates in the range of unity. The use of a price equation and two stage least squares for estimation reduced winter price elasticities substantially. It is thought that this results from the correction of the negative bias in decreasing block pricing.

The results of this study are applicable outside the utility industry. Many products, from insurance coverage to consumer goods, are sold with "quantity" discounts. When modeling the demand for these goods, both average price (or marginal price) and a model based price measure should be investigated. The overstatement of own price elasticity can severely overstate sales increases (or decreases) due to product price adjustments.

3. Estimated Elasticities

Numerous elasticities were estimated in this study, including own price, income, summer weather, winter weather, household size, and appliance stock elasticities. The magnitude and reasonableness of each elasticity was discussed previously in the context of the estimated model. However, several issues warrant further discussion. Additionally, many elasticities have specific implications for regulatory and utility activities.

Own price elasticity has been estimated to be in the range of -0.1 to -0.3 for summer and winter months, and approximately unit elastic in the transitional season. This suggests, other things equal, that price increases will substantially increase total revenue. Further, the determination of rates based solely on historic sales and revenue requirements will under-collect total revenue. Regulators and utilities should take own price elasticity into account when setting prospective rates.

The magnitude of income elasticity is less clear from this study, however it appears to be bracketed between zero and 0.10 for summer and winter months (transitional month elasticity is somewhat greater). Additionally, increases in income may lead to increases in the household appliance level. The effect of increases in the appliance stock (as well as appliance replacement) may increase or decrease electricity use. For example, the purchase of a microwave oven may reduce the electricity used by an electric range more than by a one-to-one relationship. Additionally, new appliances tend to be more energy efficient, and hence consume less electricity with comparable utilization.

Utility planners should not ignore the effects of income level changes when planning for future generating capacity. It is presently unclear what the magnitude and direction of income effects will be in the long run, however research can be undertaken to monitor changes in both appliance efficiencies and holdings.

Summer weather elasticity estimates range between 0.40 and 0.60 for air conditioned homes in the current study. For the winter season, the estimated range is much greater, from 0.40 to 1.20, double log and linear models, respectively. This leaves open a substantial amount of latitude in pursuing weather normalization of electricity sales. As demonstrated previously, the often used unit elastic adjustment of weather sensitive sales provides good results with this study's data. Weather normalization is an important part of utility ratemaking and model-based adjustments should be analyzed prior to accepting the common adjustment method.

A substantial difference between the consumption effects of children and adults has also been demonstrated. As household profiles change, and specifically as the Iowa population ages, the ratio of adults to children may increase. This suggests that household electricity use may rise if adult children live with parents, or aging parents live with their children. As with appliances and efficiencies, utility planners should monitor trends in household size and composition.

The final elasticity to examine is that of the appliance stock. As discussed above, this relationship may be very dynamic due to changes in appliance efficiencies. At present, the estimated elasticity is approximately 0.30 to 0.60 when measured by the simple summation of appliances from the specified list.

4. Conditional Demand Analysis

The results of the conditional demand analysis are mixed, but overall encouraging. This method of analysis appears best suited for large electricity using appliances, such as space conditioning. It did provide some other reasonable use estimates for freezers and electric dryers. Most smaller appliances yielded unrealistically high, or negative, estimated electricity usage.

Overall price and income elasticities are consistent with total demand models, however the lack of significance and incorrect signs are observed. Weather effect elasticities are also very comparable to those estimated using other methods.

While the conditional demand model was used with mixed success, it has a substantial cost advantage over direct metering, with an approximate fixed cost of $1000 and $10 monthly per household. If successful, conditional demand analysis can economically provide average appliance use estimates and help isolate demand determinant relationships.

B. Recommendations

1. Data

As with most studies utilizing secondary data, this study suffered at times from failing to have enough precise and relevant measures of all variables. Income and age of household head were coded as ranges, and thus precise measures of these potentially critical variables were not available. Weatherization was a binary indicator of weatherization activity and failed to elucidate the action taken. Additionally, only one observation of household demographics and appliances was available for analysis.

If any of these variables changed over the two year estimation period, the resulting inaccuracies would bias the estimated parameters. It is nearly certain that nominal income increased over the period, and the lack of significance of income in some estimations may be a result of this factor.

For the purposes of both econometric studies and load research (the initial purpose of the data collection), all data should be collected in actual values instead of coded ranges. From a practical standpoint this may reduce the likelihood of survey response, and thus several tests should be conducted to jointly optimize survey response rates and data quality. The surveys should be readministered periodically to determine what changes are occurring in the sample households.

This study utilized 24 months of data observations on 105 households. Most conditional demand studies are conducted on samples in excess of 1000 households. A sample size in the thousands of households is also common for other micro-level modeling efforts. The increase in sample size provides for more precise parameter estimates, smaller forecast errors, and additional flexibility in modeling (especially sub-populations). If replicated at a future date, the results from the methods and models of this study may be improved by using a larger sample size.

2. Policy

As stated in the introduction to this study, econometric methods can aid legislators, regulators, and public utilities to achieve their desired goals. While the goals they pursue are diverse, this study has demonstrated the flexibility of econometric modeling of residential electricity demand.

Conditional demand analysis, despite its somewhat lackluster performance, holds the potential to help define lifeline electricity usage and rates for legislators. This study's analysis of weatherization effects also demonstrates the ability of econometric models to isolate conservation effects and assist in energy policy planning. The own-price elasticity estimates can assist in projecting the possible effects caused by the rate shock of nuclear plant additions.

Regulators are charged with enforcing statutes and overseeing utility operations. Both total household and conditional demand models can provide information to aid in this pursuit. As the primary reviewers of utility forecasts and methodologies, regulators can use the forecasting methodology demonstrated in this study to project utility sales. The weather normalization procedures can assist in sterilizing the effects of weather from historic sales, thus providing a base sales figure for rate design. Conditional demand holds the potential to provide end use estimates and forecasts for various appliances. Coupled with forecasted appliance saturations, these forecasts can provide a better picture of future consumer demand.

Public utilities, as the public trustee in charge of supplying adequate energy, are concerned with planning for plant additions and preparing suitable energy management policies, among a host of other concerns. The forecasting and analysis methodology provided in this study can assist in preparing accurate forecasts of future electricity use. The various estimations of space conditioning elasticities provides a format to analyze the demand effects of abnormal weather. Finally, conditional demand analysis may help utilities to better recognize the contributions of changes in the appliance stock to electricity demand.

Ours is an information-based society, rich with evolving data collection and analysis systems. The use of econometric modeling can assist us in using our information resources to the fullest extent in our search for understanding the residential demand for electricity.

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X. APPENDIX A: OLS MP LINEAR ESTIMATIONS

Table A-1. Winter OLS MP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	130.39597	21.21895	6.145	.0000
APPL	106.74628	12.54775	8.507	.0000
CHILD	61.13765	14.04529	4.353	.0000
RINCOME	-6.00499E-04	4.04207E-03	-.149	.8819
RMP	-49169.80564	4821.71502	-10.198	.0000
SQFTHDD1	9.151885E-04	2.62358E-05	34.883	.0000
SQFTHDD2	1.481033E-04	1.64738E-05	8.990	.0000
(Constant)	962.01654	132.54316	7.258	.0000
R Square	.76782			

Table A-2. Summer OLS MP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	165.29661	27.72418	5.962	.0000
APPL	123.23300	15.64081	7.879	.0000
CHILD	40.98270	18.43026	2.224	.0264
RINCOME	3.530857E-03	5.40094E-03	.654	.5135
RMP	-14140.84320	8874.70618	-1.593	.1115
SQFTCDD1	1.287541E-03	5.17828E-05	24.864	.0000
SQFTCDD2	3.725425E-04	1.06972E-04	3.483	.0005
(Constant)	204.60600	243.62723	.840	.4012
R Square	.55188			

Table A-3. Transitional OLS MP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	105.69800	25.97709	4.069	.0001
APPL	98.53350	15.02063	6.560	.0000
CHILD	57.12564	17.07821	3.345	.0009
RINCOME	8.978093E-03	4.89049E-03	1.836	.0671
RMP	-53840.31293	4551.82382	-11.828	.0000
(Constant)	1294.44732	149.97125	8.631	.0000
R Square	.50051			

Table A-4. Alternative transitional OLS MP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	85.70390	24.15713	3.548	.0004
APPL	82.76511	14.02660	5.901	.0000
CHILD	48.77233	15.83560	3.080	.0022
RINCOME	3.927201E-03	4.56553E-03	.860	.3902
RMP	-57072.79050	4229.86095	-13.493	.0000
SQFT	.17927	.02136	8.392	.0000
(Constant)	1196.67186	139.27254	8.592	.0000
R Square	.57328			

Table A-5. Pooled OLS MP linear estimation

Variable	B	SE B	T	Sig T
ADULTS	138.61848	14.71983	9.417	.0000
APPL	111.53626	8.53317	13.071	.0000
CHILD	53.89020	9.75197	5.526	.0000
RINCOME	2.284392E-03	2.81948E-03	.810	.4179
RMPST	-14002.72131	8130.73989	-1.722	.0852
RMPTT	-52499.52874	5826.93681	-9.010	.0000
RMPWT	-48398.92825	4656.48804	-10.394	.0000
SQFTCDD1	1.296910E-03	4.67391E-05	27.748	.0000
SQFTCDD2	3.544615E-04	9.51808E-05	3.724	.0002
SQFTHDD1	9.104817E-04	2.54309E-05	35.802	.0000
SQFTHDD2	1.451865E-04	1.59770E-05	9.087	.0000
SUMMER	-598.01681	234.57739	-2.549	.0109
TRANS	324.10364	158.77863	2.041	.0413
(Constant)	894.98474	115.83256	7.727	.0000
R Square	.70471			

XI. APPENDIX B: LINEAR 2SLS FIRST STAGE PRICE ESTIMATIONS

Table B-1. Winter linear 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-1.93817E-04	1.01894E-04	-1.902	.0574
APPL	-3.31613E-04	5.98133E-05	-5.544	.0000
CHILD	-8.92299E-05	6.78474E-05	-1.315	.1887
DUMFEE	-9.90389E-05	1.67850E-04	-.590	.5553
DUMGEN	4.491580E-03	1.53103E-04	29.337	.0000
DUMRATE	-2.29199E-03	3.37254E-04	-6.796	.0000
RINCOME	-5.60352E-08	1.95840E-08	-2.861	.0043
SQFTHDD1	-8.25314E-10	1.59473E-10	-5.175	.0000
SQFTHDD2	4.880019E-10	8.45443E-11	5.772	.0000
(Constant)	.02397	3.48933E-04	68.704	.0000
R Square	.61365			

Table B-2. Summer linear 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-1.46930E-04	9.19388E-05	-1.598	.1104
APPL	-1.06567E-04	5.35382E-05	-1.990	.0469
CHILD	-8.17959E-05	6.11155E-05	-1.338	.1811
DUMFEE	-8.47865E-05	1.51285E-04	-.560	.5753
DUMGEN	4.733864E-03	1.40674E-04	33.651	.0000
RINCOME	-2.72379E-08	1.79627E-08	-1.516	.1298
SQFTCDD1	1.442748E-09	1.79503E-10	8.037	.0000
SQFTCDD2	2.371023E-09	3.58105E-10	6.621	.0000
(Constant)	.02420	3.27857E-04	73.798	.0000
R Square	.58061			

Table B-3. Transitional linear 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-2.47569E-04	1.49516E-04	-1.656	.0985
APPL	-1.63135E-04	8.66212E-05	-1.883	.0604
CHILD	-1.91919E-04	9.97211E-05	-1.925	.0550
DUMFEE	3.911131E-05	2.43478E-04	.161	.8725
DUMGEN	3.165035E-03	2.22859E-04	14.202	.0000
DUMRATE	-1.82514E-03	2.60605E-04	-7.003	.0000
RINCOME	-3.64825E-08	2.85926E-08	-1.276	.2027
(Constant)	.02441	4.94322E-04	49.384	.0000
R Square	.42050			

XII. APPENDIX C: 2SLS LINEAR PRICE MODEL ESTIMATIONS

Table C-1. Winter linear price model estimation

Variable	B	SE B	T	Sig T
DUMFEE	5.102279E-05	1.60555E-04	.318	.7507
DUMGEN	4.660943E-03	1.48016E-04	31.489	.0000
DUMRATE	-2.66427E-03	2.29364E-04	-11.616	.0000
NORMUSE	-1.30452E-06	9.33428E-08	-13.976	.0000
(Constant)	.02348	1.56154E-04	150.387	.0000
R Square	.63095			

Table C-2. Summer linear price model estimation

Variable	B	SE B	T	Sig T
DUMFEE	1.661497E-04	1.49481E-04	1.112	.2667
DUMGEN	4.478470E-03	1.45345E-04	30.813	.0000
NORMUSE	1.527139E-07	8.21602E-08	1.859	.0634
(Constant)	.02385	1.71575E-04	139.016	.0000
R Square	.53513			

Table C-3. Transitional linear price model estimation

Variable	B	SE B	T	Sig T
DUMFEE	6.231296E-05	2.37324E-04	.263	.7930
DUMGEN	3.199002E-03	2.18662E-04	14.630	.0000
DUMRATE	-1.29160E-03	2.78354E-04	-4.640	.0000
NORMUSE	-1.31152E-06	2.33941E-07	-5.606	.0000
(Constant)	.02370	2.69195E-04	88.054	.0000
R Square	.43849			

XIII. APPENDIX D: 2SLS LINEAR DEMAND MODEL ESTIMATIONS

Table D-1. Winter 2SLS linear demand model estimation

Variable	B	SE B	T	Sig T
ADULTS	152.20998	21.98901	6.922	.0000
APPL	131.54356	13.05666	10.075	.0000
AVPHATW	-8463.48685	7126.50869	-1.188	.2352
CHILD	63.13334	14.61983	4.318	.0000
RINCOME	-2.33574E-03	4.23616E-03	-.551	.5815
SQFTHDD1	1.030747E-03	2.55280E-05	40.377	.0000
SQFTHDD2	9.164808E-05	1.74367E-05	5.256	.0000
(Constant)	10.58182	194.33564	.054	.9566
R Square	.74882			

Table D-2. Summer 2SLS linear demand model estimation

Variable	B	SE B	T	Sig T
ADULTS	163.28548	27.72429	5.890	.0000
APPL	121.73698	15.65040	7.779	.0000
AVPHATS	-16363.93877	8954.52979	-1.827	.0680
CHILD	39.78792	18.43033	2.159	.0311
RINCOME	3.171507E-03	5.40029E-03	.587	.5572
SQFTCDD1	1.299732E-03	5.12904E-05	25.341	.0000
SQFTCDD2	3.973722E-04	1.06748E-04	3.723	.0002
(Constant)	286.71008	258.48380	1.109	.2677
R Square	.55231			

Table D-3. Transitional 2SLS linear demand model estimation

Variable	B	SE B	T	Sig T
ADULTS	147.56550	29.30304	5.036	.0000
APPL	148.57687	16.49389	9.008	.0000
AVPHATT	-44245.12435	12232.79612	-3.617	.0003
CHILD	58.29180	19.55028	2.982	.0030
RINCOME	7.305670E-03	5.59440E-03	1.306	.1923
(Constant)	942.18372	333.87122	2.822	.0050
R Square	.35218			

XIV. APPENDIX E: OLS MP DOUBLE LOG ESTIMATIONS

Table E-1. Winter OLS MP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.27736	.03525	7.869	.0000
APPL	.07181	.01127	6.375	.0000
CHILD	.01581	2.51367E-03	6.288	.0000
RINCOME	.05477	.02108	2.598	.0095
RMP	-.67635	.07597	-8.902	.0000
SQFTHDD1	.42810	.02214	19.335	.0000
SQFTHDD2	.36887	.02188	16.856	.0000
(Constant)	-1.94512	.46290	-4.202	.0000
R Square	.71981			

Table E-2. Summer OLS MP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.29884	.04838	6.177	.0000
APPL	6.775681E-03	.01603	.423	.6727
CHILD	6.715259E-03	3.49829E-03	1.920	.0553
RINCOME	.08038	.03012	2.669	.0078
RMP	-.10928	.17294	-.632	.5276
SQFTCDD1	.40205	.02403	16.728	.0000
SQFTCDD2	.35872	.02457	14.602	.0000
(Constant)	.64696	.71327	.907	.3647
R Square	.46980			

Table E-3. Transitional OLS MP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.27541	.06769	4.069	.0001
APPL	.11324	.02175	5.207	.0000
CHILD	.01515	4.92366E-03	3.076	.0022
RINCOME	.11342	.04114	2.757	.0061
RMP	-1.12533	.09161	-12.284	.0000
(Constant)	1.00108	.48245	2.075	.0386
R Square	.45628			

Table E-4. Alternative transitional OLS MP double log estimation

Variable	B	SE B	T	Sig T
ADULTS	.19373	.06580	2.944	.0034
APPL	.08893	.02109	4.218	.0000
CHILD	.01313	4.70775E-03	2.789	.0055
RINCOME	.08777	.03945	2.225	.0266
RMP	-1.13705	.08742	-13.007	.0000
SQFT	.33757	.05219	6.468	.0000
(Constant)	-1.24494	.57658	-2.159	.0314
R Square	.50629			

XV. APPENDIX F:

DOUBLE LOG 2SLS FIRST STAGE PRICE ESTIMATIONS

Table F-1. Winter double log 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-.03301	9.45040E-03	-3.493	.0005
APPL	-3.60474E-03	3.07803E-03	-1.171	.2418
CHILD	8.626291E-04	6.82925E-04	1.263	.2068
DUMFEE	-5.92245E-04	6.86792E-03	-.086	.9313
DUMGEN	.19380	6.21422E-03	31.186	.0000
DUMRATE	1.58530	.18034	8.791	.0000
RINCOME	-.03416	5.72439E-03	-5.968	.0000
SQFTHDD1	-.09124	.01077	-8.474	.0000
SQFTHDD2	.03630	7.10786E-03	5.107	.0000
(Constant)	-3.98519	.10780	-36.970	.0000
R Square	.65652			

Table F-2. Summer double log 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-.02036	7.62650E-03	-2.670	.0077
APPL	1.041688E-03	2.58043E-03	.404	.6865
CHILD	-6.13992E-04	5.50712E-04	-1.115	.2652
DUMFEE	-4.76300E-04	5.46009E-03	-.087	.9305
DUMGEN	.18220	5.18748E-03	35.123	.0000
RINCOME	-.01116	4.75781E-03	-2.346	.0192
SQFTCDD1	.04062	3.90335E-03	10.407	.0000
SQFTCDD2	.04253	3.97343E-03	10.703	.0000
(Constant)	-4.15835	.06463	-64.344	.0000
R Square	.60202			

Table F-3. Transitional double log 2SLS first stage estimation

Variable	B	SE B	T	Sig T
ADULTS	-.02845	.01378	-2.064	.0396
APPL	-2.85161E-03	4.46721E-03	-.638	.5236
CHILD	-8.42611E-04	1.00383E-03	-.839	.4017
DUMFEE	5.859400E-03	9.97307E-03	.588	.5572
DUMGEN	.13369	9.10744E-03	14.679	.0000
DUMRATE	-.08730	.01031	-8.469	.0000
RINCOME	-.01551	8.39925E-03	-1.847	.0655
(Constant)	-3.63314	.07467	-48.656	.0000
R Square	.44053			

XVI. APPENDIX G: MP CONDITIONAL DEMAND MODEL ESTIMATION

Variable	B	SE B	T	Sig T
A6CDD	1.316403E-03	5.12319E-05	25.695	.0000
A6MP	1983.85468	6453.92986	.307	.7586
A6Y	1.168523E-04	6.41182E-03	.018	.9855
A8HDD	8.271085E-04	3.29185E-05	25.126	.0000
A8MP	-59922.63944	7454.08596	-8.039	.0000
A8Y	-5.31719E-03	7.60028E-03	-.700	.4842
COM1AD	41.14991	3.64544	11.288	.0000
COM1CH	13.43086	2.53953	5.289	.0000
COM1MP	-1208.08656	1794.94091	-.673	.5010
COM1Y	1.674003E-03	1.60678E-03	1.042	.2976
DEHUM	-224.91995	50.27119	-4.474	.0000
DUMACS	-227.83905	170.24075	-1.338	.1809
DUMHW	826.29800	152.78781	5.408	.0000
DW	4.80008	60.66204	.079	.9369
EDRYER	104.04717	51.70397	2.012	.0443
ERANGE	-117.14541	54.90768	-2.133	.0330
FREEZ	14.61758	52.20234	.280	.7795
MWAVE	194.45399	51.49858	3.776	.0002
RINCOME	4.628191E-03	6.23375E-03	.742	.4579
RMP	-19549.01846	8312.09737	-2.352	.0188
SUMMER	128.56570	49.88481	2.577	.0100
TRANS	30.78835	34.42350	.894	.3712
(Constant)	942.25625	206.37112	4.566	.0000
R Square	.71381			

XVII. APPENDIX H: CONDITIONAL DEMAND DEVIATION ESTIMATIONS

Table H-1. AVP conditional demand model deviation estimation

Variable	B	SE B	T	Sig T
CA6CDD	1.329589E-03	4.85350E-05	27.394	.0000
CA6P	-3306.41554	8153.87437	-.406	.6851
CA6Y	1.659538E-04	6.30488E-03	.026	.9790
CA8HDD	8.455454E-04	3.19211E-05	26.489	.0000
CA8P	-103891.0578	9088.22319	-11.431	.0000
CA8Y	-.02659	7.53306E-03	-3.529	.0004
CAVP	858.34907	7063.18288	.122	.9033
CCOM1AD	51.14709	3.57639	14.301	.0000
CCOM1AVP	-2862.12502	1830.60461	-1.563	.1181
CCOM1CH	14.56248	2.50751	5.808	.0000
CCOM1Y	1.218658E-03	1.59827E-03	.762	.4458
CRINCOME	5.968073E-03	6.24042E-03	.956	.3390
DEHUM	-141.88193	22.36149	-6.345	.0000
DUMACS	630.58367	51.23760	12.307	.0000
DUMHW	1523.91281	42.98408	35.453	.0000
DW	114.53923	33.93771	3.375	.0007
EDRYER	191.95844	24.74048	7.759	.0000
ERANGE	-42.27634	29.16793	-1.449	.1473
FREEZ	104.06470	22.76821	4.571	.0000
MWAVE	279.19112	26.59599	10.497	.0000
SUMMER	111.18532	49.27309	2.257	.0241
TRANS	87.39234	32.54526	2.685	.0073
(Constant)	521.83453	34.49952	15.126	.0000
R Square	.72108			

Table H-2. MP conditional demand model deviation estimation

Variable	B	SE B	T	Sig T
CA6CDD	1.316403E-03	5.12319E-05	25.695	.0000
CA6MP	1983.85453	6453.92990	.307	.7586
CA6Y	1.168536E-04	6.41182E-03	.018	.9855
CA8HDD	8.271085E-04	3.29185E-05	25.126	.0000
CA8MP	-59922.63743	7454.08600	-8.039	.0000
CA8Y	-5.31719E-03	7.60028E-03	-.700	.4842
CCOM1AD	41.14991	3.64544	11.288	.0000
CCOM1CH	13.43086	2.53953	5.289	.0000
CCOM1MP	-1208.08679	1794.94092	-.673	.5010
CCOM1Y	1.674002E-03	1.60678E-03	1.042	.2976
CRINCOME	4.628192E-03	6.23375E-03	.742	.4579
CRMP	-19549.01895	8312.09741	-2.352	.0188
DEHUM	-135.32474	22.71342	-5.958	.0000
DUMACS	642.85132	56.31283	11.416	.0000
DUMHW	1188.30849	47.02864	25.268	.0000
DW	91.30945	34.78150	2.625	.0087
EDRYER	194.21836	25.05528	7.752	.0000
ERANGE	-32.48653	29.60660	-1.097	.2726
FREEZ	101.74059	23.08404	4.407	.0000
MWAVE	281.93108	27.02765	10.431	.0000
SUMMER	128.56569	49.88481	2.577	.0100
TRANS	30.78833	34.42350	.894	.3712
(Constant)	552.84117	36.27661	15.240	.0000
R Square	.71381			

XVIII. APPENDIX I: CONDITIONAL DEMAND MODEL BIAS ANALYSIS

Table I-1. AVP conditional demand model bias analysis

Variable	B	SE B	T	Sig T
CA6CDD	1.347178E-03	5.06555E-05	26.595	.0000
CA6P	-3919.07440	8514.45126	-.460	.6454
CA6Y	-2.21100E-03	6.58179E-03	-.336	.7370
CA8HDD	8.675293E-04	3.32986E-05	26.053	.0000
CA8P	-98095.93768	9481.18942	-10.346	.0000
CA8Y	-.03351	7.84984E-03	-4.269	.0000
CAVP	-3830.89509	7363.69350	-.520	.6029
CCOM1AVP	-1498.88579	1907.00023	-.786	.4319
CCOM1Y	6.168058E-04	1.66823E-03	.370	.7116
CRINCOME	.01206	6.49089E-03	1.858	.0634
DEHUM	-105.33384	23.15967	-4.548	.0000
DUMACS	630.77098	53.50343	11.789	.0000
DUMHW	1554.85769	44.79690	34.709	.0000
DW	59.35688	35.10107	1.691	.0910
EDRYER	211.95114	25.70641	8.245	.0000
ERANGE	-59.99303	30.07900	-1.995	.0462
FREEZ	122.75181	23.71915	5.175	.0000
MWAVE	286.59731	27.71219	10.342	.0000
SUMMER	117.84243	51.44860	2.290	.0221
TRANS	95.97684	33.97699	2.825	.0048
(Constant)	520.74348	35.98106	14.473	.0000
R Square	.69561			

Table I-2. MP conditional demand model bias analysis

Variable	B	SE B	T	Sig T
CA6CDD	1.334629E-03	5.26719E-05	25.339	.0000
CA6MP	4682.29766	6635.66703	.706	.4805
CA6Y	-6.53400E-04	6.59584E-03	-.099	.9211
CA8HDD	8.338485E-04	3.38604E-05	24.626	.0000
CA8MP	-64806.01414	7655.59953	-8.465	.0000
CA8Y	-.01284	7.79272E-03	-1.647	.0996
CCOM1MP	-2256.47490	1842.80375	-1.224	.2209
CCOM1Y	6.134634E-04	1.65056E-03	.372	.7102
CRINCOME	.01180	6.37830E-03	1.850	.0645
CRMP	-19072.23735	8547.71343	-2.231	.0258
DEHUM	-109.97989	23.21684	-4.737	.0000
DUMACS	665.69572	57.89863	11.498	.0000
DUMHW	1156.83797	48.30643	23.948	.0000
DW	53.97865	35.53179	1.519	.1288
EDRYER	203.42520	25.67477	7.923	.0000
ERANGE	-50.06715	30.06848	-1.665	.0960
FREEZ	118.50257	23.69028	5.002	.0000
MWAVE	278.97686	27.76211	10.049	.0000
SUMMER	129.33657	51.31977	2.520	.0118
TRANS	25.66171	35.41111	.725	.4687
(Constant)	566.37581	37.26701	15.198	.0000
R Square	.69686			