Conditional Demand Analysis Revisited:

Evaluating Residential End-Use Energy Consumption in Canada

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Executive Summary

It is often important to have information about energy consumption by end-use in a residential context, but in the absence of direct metering of each appliance, it is necessary to allocate total household energy consumption among the various end-uses using some alternative means. The method of Conditional Demand Analysis (CDA), introduced by Parti and Parti (1980) uses regression analysis to achieve this disaggregation based on information about total energy consumption and appliance holdings for different households.

Unfortunately, empirical results obtained using CDA are often disappointing, yielding negative estimates of average energy consumption for some appliances and/or implausibly large estimates for others. In this paper, the CDA method is explained and various attempts that have been made to rectify these problems by incorporating more information in CDA models are reviewed. This additional information often involves actual metering data for some appliances for some households, or diary information indicating appliance use, or multiple observations for each household such as hourly energy consumption data. Unfortunately, none of these additional sources of information is available with the 2003 Survey of Household Energy Use (SHEU03) data that are used here to estimate end-use energy consumption for Canadian households.

In this paper we modify the CDA model to incorporate additional information contained in SHEU03 concerning the scale of use of particular appliances by different households. These scale variables, which reflect such factors as the size of the house and of the household, as well as the capacity of certain appliances, differ from appliance to appliance. However, the inclusion of these scale variables does not appear to resolve the problems previously identified in empirical applications of CDA, with average electricity consumption found to be negative for several appliances. Some possible explanations for this result are investigated, including grouping of appliances so that they have a common coefficient. This helps in some cases but not others, and tests of the various groupings indicate that not all are appropriate. Alternative methods of dealing with the empirical problems encountered with CDA models require further investigation.

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1. Introduction

Determining household consumption of energy for different end-uses has long been of interest to energy economists for a variety of reasons. This type of information is important for modeling and forecasting residential energy demand, for determining the expected value and ultimate usefulness of various energy demand side management programs, as well as for determining the likely savings associated with various minimum energy performance standards that may be enacted. Of course, knowledge of the energy consumption of different appliances would also be useful to the household itself as well as for firms planning marketing strategies for specific types of appliances.

The most obvious method that could be used to determine energy consumption by end-use would involve direct metering, measuring actual energy usage by each appliance. However, due to the high cost involved, this approach has only been implemented in a limited number and type of situations. Most commonly, this method has been used in a simulated setting rather than in the context of actual functioning households. In view of the many vagaries of consumer and household behavior, it is very difficult to generalize the findings from such studies to assess likely energy consumption by end use in specific real world circumstances.

An alternative approach, introduced by Parti and Parti (1980), known as Conditional Demand Analysis (CDA) involves utilizing information on total household energy consumption and on appliance holdings by each household to determine energy end-use by appliance type. Given representative data from household surveys, it is then possible to assess likely energy consumption according to end use in a particular jurisdiction. However, the success of CDA for statistically isolating end-use energy consumption depends crucially on variation in appliance ownership, and the increasing and now very high penetration rates – which approach saturation levels for many appliances such as refrigerators – make it difficult to reliably estimate energy consumption for particular end-uses.

In this paper, we revisit CDA and consider alternative methods of dealing with many of the problems associated with its implementation, including high penetration rates, household appliance holdings that are not recorded within survey data, and the relatively frequent occurrence of negative estimates of energy consumption associated with particular end uses that have been reported in previous CDA studies. The data that are used in our analysis are from the 2003 Survey of Household Energy Use (SHEU03), and pertain to energy usage and appliance holdings by households residing in houses and residential buildings with fewer than five storeys in Canada. Over 4000 households are included in the survey, representing over 11 million households across Canada.

The plan of the remainder of this paper is as follows. In the next section the general CDA specification developed by Parti and Parti (1980) is developed and discussed. Section 3 provides a brief review of a number of empirical studies that have utilized and/or extended the basis CDA framework in various ways. Proposed additional refinements to the model are discussed in Section 4, while Section 5 describes relevant aspects of the data from SHEU03 that are used in the empirical application. Results are presented in Section 6 while the final suggestion contains a summary and suggestions for future research.

2. General CDA Model

The model devised by Parti and Parti (1980) to determine end-use consumption by appliance when only total energy consumption is observed is based on the observation that the total energy consumption by household *h*, E_h, is comprised of the sum of energy consumption in that household by each of *N* specified appliances, E_{ih} (i=1,…,N), as well as energy consumption by that household attributable to remaining (unspecified) appliances, E_{0h}:

$$(1) \qquad E_h = E_{0h} + \sum_{i=1}^{N} E_{ih} = \sum_{i=0}^{N} E_{ih} \ .$$

Of course, in any particular household, energy is only consumed by an appliance if the household actually has that appliance, so we define a dummy variable A_{ih} which equals 1 if household h has appliance i, and which equals zero otherwise:

$$(2) \qquad A_{ih} = \begin{cases} 1 \ \ if \ \ household \ h \ has \ appliance \ i \\ 0 \ \ otherwise \end{cases}$$

where A_{0h} = 1, on the basis that all households have the unspecified appliances.

It would be expected that consumption of energy by any appliance in household *h* would depend on variables such as price, income, weather, etc. To allow for this possibility, a set of *M* +1 explanatory variables, V_{jh}, $j = 0, ..., M$, is introduced, where $V_{0h} = 1$ is a constant. Parti and Parti (1980) specify that energy consumption of each appliance, including the unspecified appliances, is a linear function of these explanatory variables, so that:

$$(3) \qquad E_{ih} = \sum_{j=0}^{M} \beta_{ij} (V_{jh} A_{ih}), \quad i = 0, ..., N \ ,$$

where β_{ij} are unknown parameters. Hence:

(4) $$E_h = \sum_{i=0}^{N} \sum_{j=0}^{M} \beta_{ij} (V_{jh} A_{ih})$$

Given that $A_{0h} = 1$ and $V_{0h} = 1$, this can be written in the form:

(5) $$\begin{aligned} E_h &= \beta_{00} + \sum_{i=1}^{N} \beta_{i0} A_{ih} + \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} A_{ih}) \\ &= \beta_{00} + \sum_{i=1}^{N} \beta_{i0} A_{ih} + \sum_{j=1}^{M} \beta_{0j} V_{jh} + \sum_{i=1}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} A_{ih}) \end{aligned}.$$

If it is assumed that (3) does not hold exactly, that is, that there is a stochastic error term appended to (3), then (4) and (5) would also have an error term appended. In this context, (5) is a straightforward linear regression model, albeit with a large number of terms (1+*N*+*M*+*M***N*), where *M* is the number of explanatory variables other than the constant that are used to model the energy consumption of each appliance, and *N* is the number of appliances for which detailed household ownership information is available. Estimation of (5) would yield estimates of the β_{ij} parameters, and use of these estimates in place of the true parameter values in (3) would yield estimates of energy consumption by each appliance in each household.

Although there are likely to be a number of econometric issues that arise with estimation of (5), including a potentially high degree of collinearity among the explanatory variables, one of the key issues is that the parameter estimates do not have any direct interpretation, and it may often not be of particular interest to estimate energy consumption of each appliance in each household. Rather, it may be more relevant to know the average consumption of each appliance across households that actually have that appliance. This information could be obtained by manipulating the estimates obtained from (5), but Parti and Parti (1980) determined how it could be obtained directly by estimating a respecified version of (5).

Define $\overline{V}_{ij}$ as the average value of the explanatory variable V_{jh} for those households that actually have appliance i. Thus, with *H* representing the total number of households:

$$(6) \qquad \overline{V}_{ij} = \frac{\sum_{h=1}^{H} V_{jh} A_{ih}}{\sum_{h=1}^{H} A_{ih}}, \quad i = 0, ..., N; \quad j = 1, ..., M ,$$

where $\overline{V}_{i0} = 1$. Hence:

$$(7) \qquad \beta_{ij} V_{jh} A_{ih} = \beta_{ij} (V_{jh} - \overline{V}_{ij}) A_{ih} + \beta_{ij} \overline{V}_{ij} A_{ih}$$

so that in (5),

$$(8) \qquad \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} A_{ih}) = \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} - \overline{V}_{ij}) A_{ih} + \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} \overline{V}_{ij} A_{ih}$$

Next, define the average amount of energy consumed by appliance i in households with this appliance as:

$$(9) \qquad \overline{E}_{i} = \frac{\sum_{h=1}^{H} E_{ih} A_{ih}}{\sum_{h=1}^{H} A_{ih}} = \frac{\sum_{h=1}^{H} E_{ih}}{\sum_{h=1}^{H} A_{ih}}, \quad i = 0, ..., N .$$

Using (3) and (6), this can be rewritten as:

$$(10) \qquad \overline{E}_{i} = \frac{\sum_{h=1}^{H} \sum_{j=0}^{M} \beta_{ij} V_{jh} A_{ih}}{\sum_{h=1}^{H} A_{ih}} = \sum_{j=0}^{M} \beta_{ij} \overline{V}_{ij}, \quad i = 0, ..., N$$

Now since:

$$(11) \qquad \overline{E}_{i} A_{ih} = \sum_{j=0}^{M} \beta_{ij} \overline{V}_{ij} A_{ih} = \beta_{i0} A_{ih} + \sum_{j=1}^{M} \beta_{ij} \overline{V}_{ij} A_{ih}$$

it follows that:

$$(12) \qquad \sum_{i=0}^{N} \bar{E}_i A_{ih} = \sum_{i=0}^{N} \beta_{i0} A_{ih} + \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} \bar{V}_{ij} A_{ih}$$

Therefore,

$$(13) \qquad \sum_{i=0}^{N} \bar{E}_i A_{ih} - \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} \bar{V}_{ij} A_{ih} = \beta_{00} + \sum_{i=1}^{N} \beta_{i0} A_{ih}$$

Substituting (13) and (8) into (5) now yields:

$$(14) \qquad \begin{aligned} E_h &= \sum_{i=0}^{N} \bar{E}_i A_{ih} + \sum_{i=0}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} - \bar{V}_{ij}) A_{ih} \\ &= \bar{E}_0 + \sum_{i=1}^{N} \bar{E}_i A_{ih} + \sum_{j=1}^{M} \beta_{0j} (V_{jh} - \bar{V}_{0j}) + \sum_{i=1}^{N} \sum_{j=1}^{M} \beta_{ij} (V_{jh} - \bar{V}_{ij}) A_{ih} \end{aligned}$$

With an error term appended, this is again in the form of a linear regression model, where the explanatory variables are the appliance ownership dummy variables (A_{ih}), the variables $(V_{jh} - \bar{V}_{0j})$ which reflect the difference between the value of the jth explanatory variable for the hth household (V_{jh}) and its average value over all households ($\bar{V}_{0j}$), and interaction terms $(V_{jh} - \bar{V}_{ij})A_{ih}$ which for each appliance type i, are either the difference between the value of the jth explanatory variable for the hth household (V_{jh}) and its average value over all households with that appliance ($\bar{V}_{ij}$), or zero if the household does not have that particular appliance.

A particularly attractive feature of (14) is that the estimated coefficients on the appliance ownership dummy variables are estimates of $\bar{E}_i$, the average consumption of energy attributable to each specified appliance (for households that have that appliance), while the intercept is an estimate of $\bar{E}_0$, which is average energy consumption by unspecified appliances that are owned by all households. Since these measures are all estimated directly, estimated standard errors are obtained directly and confidence intervals can be readily calculated.

Empirically, there are a number of problems with estimation of (14). First, there are just as many coefficients in (14) as in the original specification in (5), and although multicollinearity may have been alleviated to some degree by the respecification, in practice it is generally a major problem with either model formulation. The model requires some households to have certain appliances and not others, so that A_{ih} is not a constant, but as penetration rates for any appliance approach saturation, estimation will become problematic. Of course, if *all* households have a particular appliance, this appliance would simply become part of the set of unspecified appliances, and specific end-use energy consumption for that appliance would not be estimated separately.

Perhaps the most important consideration with estimation of (14) is that the interpretation of the coefficients only makes sense if the estimated coefficients on the appliance ownership dummy variables are positive. Typically, this is not the case. In the Parti and Parti (1980) application there are relatively few negative coefficients, although this may – at least in part – stem from a number of parametric restrictions that they introduce.

3. Previous CDA Applications and Modifications

A number of studies have utilized the CDA framework and/or have modified it in various ways in an attempt to deal with some of the empirical problems, such as negative coefficients on the appliance dummy variables, which taken at face value would indicate that compared to not using them, on average use of these appliances saves energy.

Bartels and Fiebig (1990) note that CDA is an indirect approach to the estimation of end-use loads and that problems of negative or technically implausible large estimates arise primarily because ownership of appliances among households in the sample is not sufficiently heterogeneous. The natural solution to this is to supplement the analysis with various additional sources of information. Aigner, Sorooshian and Kerwin (1984) jointly estimate CDA equations for each of the 24 hours in a day, while Caves et al (1987) propose a Bayesian approach for combining end-use profiles produced by engineering models with CDA. Larsen and Nesbakken (2002) compare the numerical results from engineering models of household end use energy consumption and CDA, and find that both have drawbacks, although they note that those associated with the engineering approach would be difficult to eliminate. As Bartels and Fiebig (1990) note, a problem with engineering models is that they ignore individual behaviour which would be expected to be important in the context of household energy use.

An alternative method of incorporating additional information into the analysis is to combine direct metering data, gathered on a selection of appliances for a sub-sample of households used in the CDA analysis, with the CDA analysis itself – Bartels and Fiebig (1996) even analyze which particular end uses (appliances) should be individually metered. The approach used by

Bartels and Fiebig (1990) to combine direct metering data and CDA follows from the reformulation of the CDA model into a random coefficients framework, as developed in Fiebig, Bartels, and Aigner (1991). As these latter authors note, an additional byproduct of the random coefficients approach is that it provides for a structure for the heteroskedasticity that is frequently observed in CDA studies. In their application they also have available diary information for a subset of households that provides frequency-of-use information for a number of appliances which can be incorporated in the CDA to improve precision. Unfortunately, in many cases – such as with the SHEU03 data used here – neither partial metering data, nor diary information, nor hourly household energy consumption data, is available.

In a Canadian context, Lacroix (2004) – using separate survey data for 1989, 1994, and 1999 – and Bernard and Lacroix (2005) apply CDA to data from Quebec and again find evidence of large and in some cases negative estimated coefficients. They investigate whether there is evidence of heteroskedasticity – which they find – as well as whether the model is too restrictive in its imposition of uniform electricity consumption among households for the same use. Using 1999 data, Lacroix and Bernard (2005) find that the uniformity hypothesis is not rejected except for electric water heating, a result they attribute to the very high saturation rate of electric water heating for households that use electricity as their main source of energy for space heating.

4. Further Model Refinements

In the absence of additional information in the form of usage diaries, or direct metering, or repeated measures of energy consumption for each household – such as on an hourly basis – the analysis is necessarily limited to the aggregate data contained in the survey, which in the case of SHEU03 refers to the calendar year 2003. Despite this limitation, there is considerable information contained in the survey that may help alleviate some of the problems typically encountered in CDA studies. As Fiebig, Bartels and Aigner (1991) note, there are two important sources of variation that are typically ignored in CDA studies – variation in the intensity of use of a particular appliance among households, and the fact that the dummy variables used in the general model indicate the presence or absence of the appliance but do not allow for variations in size or capacity. However, some information available in SHEU03 may allow these factors to be incorporated in the analysis, as we detail below.

In terms of empirical implementation, a key issue with the specification in (5) or (14) concerns the determination of the explanatory variables in (3), V_{jh}, $j = 0, ..., M$, that explain energy use by each appliance in household *h*. In their empirical analysis, Parti and Parti (1980) include several variables in a rather *ad hoc* way with very little explanation or justification. Given that the sum of the equations for energy consumption by each appliance yields the total energy consumption equation, it would be expected that variables that are typically included in aggregate energy demand equations for the residential sector would appear here – specifically price, income and weather variables. Of course, every variable need not appear in the set of explanatory variables for each appliance, as weather would affect energy demand for heating and cooling but might be expected to have little or no effect on energy demand for microwaves, for example. Similarly, an increase in the price of energy might induce a change in a thermostat setting, thereby affecting demand for energy for heating and/or cooling, but in the short run it is unlikely to affect energy demand for refrigerators or freezers, although of course in the long run such a price increase may induce a change to more energy efficient models of these appliances.

In addition to these explanatory variables, when examining energy demand for individual appliances it is also necessary to take account of scale effects. A household with a larger house would be expected to use more energy for heating, while a larger household might be expected to have a larger energy requirement for a clothes washer, for example, either because they wash more loads or because they have a larger washer that uses more energy. Of course the particular variables that best capture these scale effects are likely to differ for each appliance. House area and temperature variables may be appropriate for heating and cooling energy, while household size may be better for the unspecified appliances. In addition to these general scale effects, there may be specific scale effects that arise from differences across households in terms of appliance size or capacity. Where available, this appliance size or capacity information would also be appropriate to incorporate into the empirical analysis.

Although a linear functional form is used in (3) to relate energy demand for a particular appliance to the set of explanatory variables, the explanatory variables themselves need not be linear. Aggregate energy demand equations are often expressed in log-log form, or at least frequently involve the logarithms of prices and income, and while the need to sum individual appliance energy demands to obtain aggregate energy demand (going from (3) to (4)) rules out the use of logarithms of E_{ih}, the explanatory variables themselves could certainly be in logarithmic form. Parti and Parti (1980) do not consider this type of specification in their empirical application, although they do include a number of multiplicative explanatory variables. For example, for air conditioning their explanatory variables include house area as well as house area separately multiplied by the energy price, by income, and by a temperature-type measure. Interestingly, the energy price and income do not appear to be included in the set of explanatory variables except in this multiplicative form. This makes these appliance energy demand equations fundamentally different from an aggregate energy demand equation where the energy price and income would generally appear separately. Nevertheless, the rationale for including price and income in multiplicative form is generally appealing as an increase in the energy price might be expected to have a different effect on energy demand for heating in a house with a larger heated area than in a smaller house.

A more general specification that would allow price and income to have direct as well as multiplicative effects would be to replace (3) with (15):

$$E_{ih} = \sum_{j=0}^{M} \beta_{ij} (V_{jh} A_{ih}) = (\gamma_{i0} + \sum_{l=1}^{L} \gamma_{il} W_{lh})(1 + \sum_{p=1}^{P} \delta_{ip} X_{ph}) A_{ih}, \quad i = 0, ..., N, \tag{15}$$

where W_{lh} would include the types of economic variables that generally appear in energy demand equations, such as prices and income, while X_{ph} would include scale variables that are appropriate to each appliance, as discussed above. The formulation in (15) has a similar structure to scale effects that have been previously employed in consumer demand equations using household data (see Pollak and Wales, 1992) to reflect the changes in consumption associated with the presence of a larger number of “equivalent adults” in the household. In our empirical work we consider the use of (15) as well as a simpler specification where the explanatory variables in V_{jh} simply include the economic variables (W_{lh}) and the scale variables (X_{ph}), without any interactions between them.

5. Data and Application

The data that are used in our empirical application are from the 2003 Survey of Household Energy Use (SHEU03), a cross-section survey of Canadian households that has been conducted periodically by Statistics Canada on behalf of Natural Resources Canada. Survey respondents supplied detailed responses to questions about appliance holdings, house characteristics, and total energy consumption by fuel type. In addition, limited information on demographic and socio-economic characteristics was also collected. The 2003 survey involved 4551 households although complete information is not available on all variables for all respondents. In particular, many respondents did not have energy consumption data available and/or were not prepared to allow this information to be obtained from their utility supplier. In addition, many households did not report income, or reported it only in specified ranges – in such cases the midpoints of the ranges were used – while other households provided no information on other variables included in the empirical analysis here, such as indoor temperature setting, dwelling age, etc.

Energy price information is not collected as part of SHEU03, which necessitated obtaining detailed monthly electricity price information for each jurisdiction in Canada for 2003. Many of these prices change at various times throughout the year, but SHEU03 only contains annual energy usage information, or in some cases, separate energy usage data for the 2003 heating and cooling seasons. To determine a marginal electricity price for 2003, monthly marginal electricity prices were weighted based on average monthly shares of electricity consumption for the period

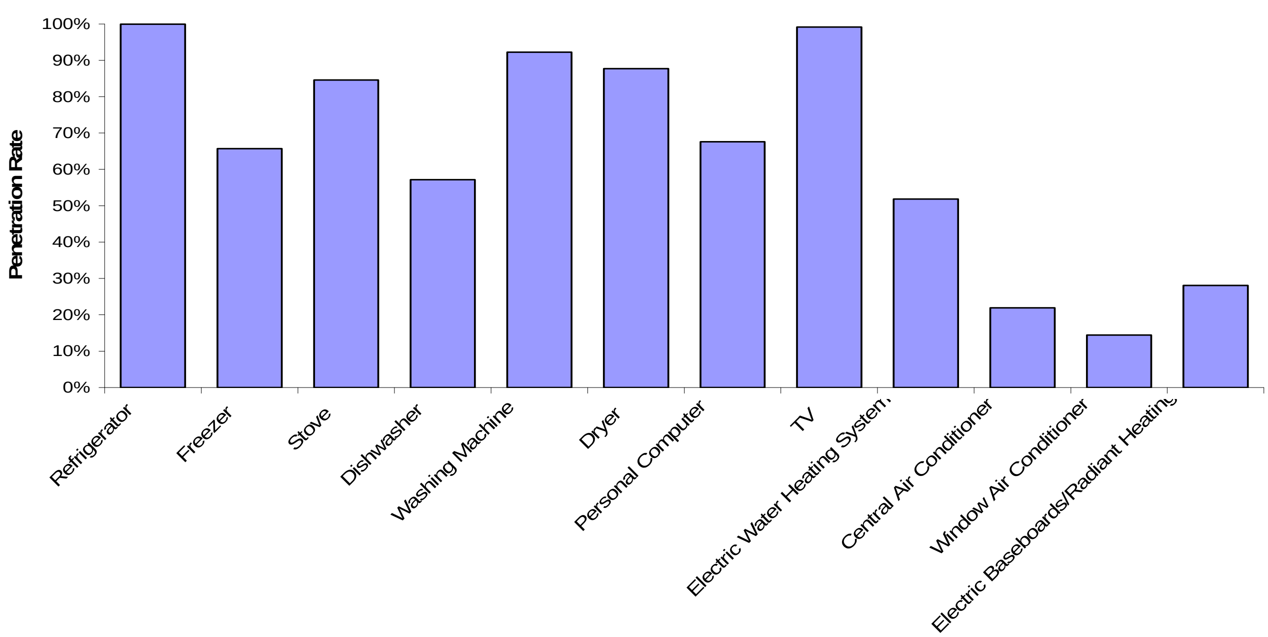
1996-2001 for each province, which are available in Statistics Canada's electronic database, CANSIM. Provincial consumption data of this type are not available since 2001, but a plot of the monthly electricity consumption shares over the 1996-2001 period reveals that the seasonal pattern is remarkably stable. Once these annual prices were obtained for each jurisdiction, and appropriate taxes for each jurisdiction were included, they were matched to each observation in SHEU03 based on forward sorting area (part of the postal code) information, or where this was not available, by province. In the latter case, electricity prices for each jurisdiction within a province were averaged to obtain the annual provincial electricity price. In jurisdictions where electricity had a block pricing system, the block that matched a household's monthly consumption (based on disaggregating annual consumption using the provincial monthly consumption shares) was used.[1]

Consistency of the electricity prices for each observation was checked by calculating the ratio of annual electricity expenditures (calculated as marginal price times consumption) to household income. Approximately 96% of the sample spent less than 10% of their income on electricity, with the vast majority spending less than 2.5% of their income this way. In our empirical work, households where reported electricity consumption exceeded 25% of their income were omitted. In addition, households that consumed less than 2000 kWh of electricity were also omitted as the approximate annual electricity consumption from even the most energy efficient refrigerator, washing machine, drier, and range (all of these appliances being present in most households in the sample) would exceed this amount.

[1] Further details concerning the construction of electricity prices are contained in Appendix 1.

The remaining sample comprises 3874 households. Details of the appliances that are included in the analysis, as well as the proportion of households with the specified appliance (penetration rates) and relevant scale variables are provided in Table 1. Penetration rates for selected appliances are shown in Figure 1.

Figure 1: Penetration Rate for Major Appliances



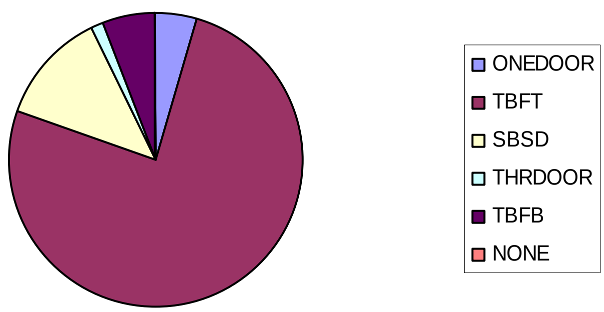
As Figure 1 and Table 1 show, there are a number of appliances with very high penetration rates, particularly refrigerators, televisions, and incandescent lights, which are present in almost all households. This proved to cause problems in estimation mainly for refrigerators, and in an attempt to alleviate this problem, refrigerators were separated into five types – one door, two doors with the freezer on the bottom, two doors with the freezer on the top, side-by-side doors, and three doors.

TABLE 1: Details of the Appliance Variables used in the Analysis

Variable	Description	Penetration Rate	Scale variable(s)
ONEDOOR	Single door refrigerator	0.05	household size, size
TBFT	Top and bottom refrigerator with freezer on top	0.76	household size, size
SBSD	Side by side door refrigerator	0.12	household size, size
THRDOOR	Three door refrigerator	0.01	household size, size
TBFB	Top and bottom refrigerator with freezer on bottom	0.06	household size, size
TWOREF	=1 if more than one refrigerator; 0 otherwise.	0.30	household size, size
TOPFZ	Top opening freezer	0.57	household size, size
FRONTFZ	Front opening freezer	0.09	household size, size
STOVE	Stove	0.85	frequency of use
OVEN	Oven	0.07	frequency of use
MICWAVE	Microwave	0.95	frequency of use
COMPDW	Compact dishwasher	0.02	annual loads
SDDW	Standard dishwasher	0.55	annual loads
AUTOWM	Automatic washer	0.90	size, annual loads
WDWM	Washer/dryer combination washer	0.02	size, annual loads
OTHWM	Other type of washer	0.00	size, annual loads
DRYER	Clothes dryer	0.88	size, annual loads
PC	Personal computer	0.68	annual hours of use
TV	Television	0.99	annual hours of use
VCR	VCR	0.85	annual hours of use
DVD	DVD player	0.54	annual hours of use
VGAME	Video game system	0.29	
STEREO	Component stereo system	0.59	annual hours of use
PSTEREO	Compact and portable stereo system	0.62	annual hours of use
SATDISH	Satellite dish	0.27	
EPHONE	Telephone that requires an electrical outlet	0.90	
AMACHINE	Answering machine	0.40	
VENTILA	Central ventilation system	0.11	
POOLHEAT	Pool heater	0.01	
WCOOLER	Water cooler	0.16	
CEILFAN	Ceiling fan	0.59	annual hours of use
HWATER	=1 if electricity is used to heat water	0.52	household size
CENAIR	Central air conditioning system	0.22	area, annual hours of use
WINAIR	Window air conditioner	0.14	area, annual hours of use
FURFAN	Furnace fan	0.54	
BASNRAD	Electric baseboard and radiant heating equipment	0.28	house age, area, HDD
NFURAIR	Electric furnace with forced air	0.08	house age, area, HDD
HALOGEN	Halogen light bulb	0.47	number of bulbs
CFLUORES	Compact fluorescent light	0.32	number of bulbs
OFLUORES	Other fluorescent light	0.58	number of bulbs
INCAND	Incandescent light bulb	0.99	number of bulbs

The distribution of the different types of refrigerators across households is shown in Figure 2. Of course, since each household has one of the models, it is necessary to omit one of the refrigerator categories when estimating the model. However, in contrast to the case with a standard regression model, the results are not invariant to the particular model that is omitted.

Figure 2: Distribution of Different Types of Refrigerators



An alternative approach is to relegate refrigerators to the group of unspecified appliances, but to include an appliance category defined as “more than one refrigerator”. As Table 1 shows, some 30% of the households in the sample have more than one refrigerator. In our empirical work we utilize both these approaches – including four of the five categories of (main) refrigerator, and then omitting refrigerators as a separate appliance but including the “more than one refrigerator” appliance category.

6. Empirical Findings

Results obtained when the model in (15) is estimated using these different refrigerator appliance specifications are presented in Table 2. The dependent variable in these estimations is total household electricity consumption in kWh. This variable ranges between 2,005 kWh and 169,720 kWh, with average consumption of 13,882 kWh. The results in Table 2 are based on the model in which the scale variables are simply included along with the electricity price and income as explanatory variables for all appliances as well as the natural gas price for stoves, ovens, hot water, and the two electric heating variables, with no interactions between the scale variables and these economic variables. Due to space limitations, only the average energy consumption values and their estimated standard errors are shown in Table 2. These are the coefficients on the appliance dummy variables in (15) as well as the constant term in (15) which represents electricity consumption by the unspecified appliances.

As can be seen in Table 2, a number of the estimated coefficients are negative, and in some cases these negative values are significantly different from zero. The pattern of signs and significance on the different types of refrigerators differs noticeably depending on which model is omitted. For example, in column (2) when TBFT models are omitted (relegated to the unspecified category), the estimated average shares for the other types of refrigerators are all positive, although only the SBSD model is significant at the 10% level or higher. Despite these changes, for the other appliances in the model the differences in the refrigerator variables that are included in the model have very little effect. Generally the same appliances have significant coefficients under each specification, with the magnitudes of these coefficients being similar, even in the final column where the refrigerator variable indicates the presence of more than one refrigerator.

TABLE 2: AVERAGE ENERGY USE ESTIMATES BY APPLIANCE - NO INTERACTION TERMS

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ONEDOOR	-	2155.90	557.75	844.48	658.94	-
	-	(2040)	(2315)	(3215)	(2588)	-
TBFT	-2626.90	-	-1582.00	-968.23	-1669.70	-
	(2383)	-	(1173)	(2627)	(1646)	-
SBSD	-2175.20	2153.60 †	-	1406.30	106.41	-
	(3583)	(1263)	-	(2993)	(1965)	-
THRDOOR	-1416.80	1896.50	-98.02	-	329.66	-
	(3936)	(2961)	(3147)	-	(3356)	-
TBFB	-2714.50	1436.60	-758.28	315.55	-	-
	(3578)	(1690)	(2005)	(3185)	-	-
TWOREF	-	-	-	-	-	-607.51
						(2155)
TOPFZ	1779.00 **	1773.00 **	1767.80 **	1752.60 **	1765.50 **	1611.70 *
	(658)	(660)	(658)	(659)	(658)	(675)
FRONTFZ	3263.40 *	3259.90 *	3141.60 *	3213.50 *	3239.10 *	3457.30 *
	(1362)	(1349)	(1346)	(1348)	(1352)	(1485)
STOVE	-110.43	-120.80	-105.08	-93.10	-109.95	157.36
	(751)	(754)	(751)	(752)	(753)	(735)
OVEN	1817.10 †	1796.00 †	1829.90 †	1826.50 †	1808.70 †	1995.60 †
	(989)	(990)	(988)	(988)	(988)	(967)
MICWAVE	487.49	517.97	492.12	483.15	500.53	307.68
	(871)	(868)	(870)	(872)	(873)	(872)
COMPDW	346.34	382.68	384.61	362.45	351.72	393.50
	(1250)	(1264)	(1249)	(1248)	(1250)	(1239)
SDDW	88.84	67.55	90.60	104.05	90.19	157.40
	(290)	(291)	(290)	(289)	(290)	(290)
AUTOWM	2249.80 †	2395.40 †	2263.00 †	2260.10 †	2225.60 †	2650.00 *
	(1307)	(1313)	(1309)	(1311)	(1311)	(1252)
WDWM	2223.00	2350.50	2191.00	2259.10	2227.60	2722.70 †
	(1509)	(1516)	(1509)	(1510)	(1509)	(1484)
OTHWM	2648.80	2903.70	2642.90	2674.50	2593.10	3021.50
	(2168)	(2179)	(2167)	(2170)	(2168)	(2276)
DRYER	-280.43	-282.81	-304.74	-294.46	-257.52	-566.98
	(856)	(851)	(854)	(859)	(855)	(797)
PC	1120.40 **	1115.20 **	1115.70 **	1103.50 **	1109.40 **	1073.30 *
	(428)	(428)	(427)	(427)	(428)	(428)
TV	860.93	888.10	922.69	873.60	868.90	822.79
	(1195)	(1196)	(1198)	(1195)	(1192)	(1266)
VCR	688.95	670.44	676.25	682.13	695.81	593.17
	(507)	(505)	(509)	(507)	(506)	(486)
DVD	-225.87	-225.50	-216.30	-224.74	-231.29	-207.86
	(390)	(390)	(390)	(390)	(390)	(398)

VGAME	-748.31 * (353)	-752.04 * (352)	-747.96 * (353)	-743.26 * (354)	-741.64 * (353)	-715.76 * (353)
STEREO	101.05 (332)	77.83 (334)	110.21 (332)	102.06 (332)	78.16 (332)	83.28 (339)
PSTEREO	382.76 (309)	378.19 (309)	392.59 (310)	385.25 (309)	384.03 (309)	407.46 (308)
SATDISH	107.41 (338)	103.88 (340)	100.86 (340)	102.57 (338)	110.22 (338)	61.35 (341)
EPHONE	-872.00 (697)	-879.27 (699)	-865.55 (700)	-872.16 (698)	-900.65 (695)	-874.98 (691)
AMACHINE	-692.39 * (307)	-681.96 * (307)	-673.22 * (307)	-690.58 * (307)	-688.84 * (306)	-740.84 * (313)
VENTILA	342.68 (575)	343.31 (578)	336.66 (575)	346.54 (575)	343.07 (574)	342.04 (596)
POOLHEAT	4405.80 ** (1607)	4479.50 ** (1609)	4476.20 ** (1609)	4198.30 ** (1586)	4332.70 ** (1603)	4363.40 ** (1653)
WCOOLER	645.36 † (378)	645.71 † (378)	622.08 (380)	638.13 † (378)	641.68 † (378)	530.11 (380)
CEILFAN	141.66 (289)	164.26 (289)	126.21 (290)	152.83 (291)	146.62 (289)	154.77 (294)
HWATER	4694.90 ** (740)	4664.60 ** (741)	4682.60 ** (739)	4707.90 ** (740)	4706.60 ** (740)	4330.60 ** (725)
CENAIR	1804.70 ** (443)	1821.10 ** (442)	1791.10 ** (443)	1808.10 ** (444)	1819.10 ** (443)	1866.70 ** (411)
WINAIR	209.08 (481)	185.23 (484)	214.53 (481)	206.64 (480)	220.16 (480)	335.40 (486)
FURFAN	-3245.90 ** (503)	-3228.00 ** (503)	-3226.50 ** (502)	-3237.80 ** (503)	-3242.80 ** (504)	-2969.40 ** (486)
BASNRAD	5200.70 ** (546)	5216.70 ** (545)	5201.10 ** (546)	5196.10 ** (548)	5191.90 ** (546)	5287.60 ** (550)
NFURAIR	5225.70 ** (699)	5205.90 ** (700)	5242.50 ** (699)	5224.40 ** (699)	5229.40 ** (698)	5051.10 ** (727)
HALOGEN	-173.86 (324)	-141.93 (324)	-161.92 (324)	-171.24 (324)	-178.26 (323)	-279.72 (324)
CFLUORES	411.06 (323)	408.67 (322)	419.21 (323)	399.03 (322)	408.29 (323)	411.83 (321)
OFLUORES	272.83 (310)	284.12 (309)	283.33 (310)	277.24 (310)	265.63 (310)	215.86 (314)
INCAND	-2381.50 (1555)	-2398.60 (1554)	-2315.10 (1556)	-2361.40 (1554)	-2485.40 (1540)	-3011.00 * (1512)
UNSPECIFIED [CONSTANT]	9176.00 ** (2716)	7947.60 ** (2449)	8703.30 ** (2469)	9044.50 ** (2784)	9041.00 ** (2463)	8670.10 ** (2433)
R^2	0.4958	0.4952	0.4955	0.4956	0.4956	0.4915

Notes: **, * and † indicate significance at the 1%, 5%, and 10% levels, respectively.
Estimated standard errors are based on a heteroskedasticity consistent covariance matrix estimator.

In terms of the results in Table 2, appliances having significant positive electricity consumption across the different specifications include top opening freezers, front opening freezers, ovens, automatic washers, personal computers, pool heaters, water coolers, electric hot water heaters, central air conditioning systems, electric baseboard and radiant heating equipment, and electric furnaces with forced air. However, answering machines, video game consoles, and furnace fans all have significant negative coefficients. Taken literally this would mean that these appliances reduce electricity consumption on average. It is likely that these negative coefficients reflect some omitted factors pertaining to households that have these appliances and lower energy consumption. In addition this may be due to variation across households in the components of the group of unspecified appliances, a factor which is not incorporated in the model.

Next, the model was re-estimated with the interaction terms included, that is, using the specification in (15) rather than in (3). Results for this specification are provided in Table 3. In general these results are similar to those in Table 2, although there are some noticeable differences. In particular, compared to the Table 2 results described above, in Table 3 portable stereos, compact fluorescent lights, and washer/dryer combination washers now have positive and significant coefficients whereas top and front opening freezers no longer have significant coefficients. There are also now some significant coefficients for some of the different types of refrigerators in some specifications, but there is no general pattern across the different specifications. Unfortunately, use of the more general model specification in (15) did not resolve any of the significant negative coefficients found with the simpler specification, with answering machines, video game consoles, and furnace fans all still having significant negative coefficients.

TABLE 3: AVERAGE ENERGY USE ESTIMATES BY APPLIANCE - INCLUDING INTERACTION TERMS

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ONEDOOR	- -	-3786.30 (2330)	-6690.70 ** (2038)	-7872.40 * (3894)	-467.00 (2468)	- -
TBFT	538.76 (1209)	- -	-209.23 (685)	-1594.00 (1560)	4779.90 ** (1297)	- -
SBSD	734.78 (2324)	-2814.10 (2456)	- -	-3060.60 (2795)	1258.20 (4088)	- -
THRDOOR	2587.90 (3783)	4098.70 (5349)	1842.00 (4265)	- -	8028.30 (6848)	- -
TBFB	-5532.60 ** (1516)	-4315.80 (4408)	-5254.60 (3612)	-8100.90 † (4537)	- -	- -
TWOREF	- -	- -	- -	- -	- -	3590.90 (3506)
TOPFZ	835.59 † (496)	617.81 (550)	973.32 † (533)	801.20 (551)	732.99 (556)	689.27 (493)
FRONTFZ	-795.99 (1154)	465.17 (813)	371.00 (814)	48.08 (988)	391.68 (830)	3117.50 (4951)
STOVE	-122.33 (650)	53.46 (675)	102.45 (659)	55.38 (664)	37.17 (662)	85.07 (661)
OVEN	2074.60 * (963)	2170.00 * (958)	2155.20 * (951)	2120.80 * (933)	2124.90 * (948)	2152.10 * (968)
MICWAVE	721.03 (741)	756.48 (690)	670.30 (685)	723.81 (704)	591.09 (684)	408.18 (671)
COMPDW	471.81 (1142)	482.36 (1162)	442.93 (1160)	418.58 (1180)	463.12 (1164)	458.37 (1158)
SDDW	63.51 (272)	52.64 (271)	89.91 (271)	85.57 (270)	85.68 (273)	124.36 (272)
AUTOWM	2422.60 * (982)	2829.00 ** (1000)	2576.90 * (1029)	2661.20 ** (1036)	2645.40 ** (1012)	2227.60 * (1089)
WDWM	2359.00 † (1323)	2611.90 * (1293)	2359.90 † (1286)	2484.40 † (1299)	2524.70 * (1288)	2371.10 † (1372)
OTHWM	2905.50 (2099)	2960.00 (2115)	2560.00 (2064)	2406.00 (2049)	2746.40 (2118)	3052.90 (2232)
DRYER	-536.45 (705)	-641.83 (680)	-518.32 (692)	-660.51 (696)	-586.06 (698)	-321.89 (698)
PC	1025.30 * (403)	1018.80 * (399)	1019.30 * (401)	1037.90 ** (400)	1060.40 ** (407)	1076.10 ** (406)
TV	1872.30 (1168)	1649.50 (1141)	1780.30 (1146)	1841.40 (1147)	1606.50 (1154)	1405.90 (1154)
VCR	443.76 (446)	486.34 (443)	452.22 (448)	447.33 (446)	471.85 (441)	415.85 (446)
DVD	-113.85 (386)	-150.93 (371)	-208.12 (370)	-201.44 (370)	-209.16 (371)	-221.83 (375)

VGAME	-819.47 * (337)	-733.63 * (339)	-772.52 * (340)	-732.99 * (337)	-693.42 * (339)	-693.30 * (334)
STEREO	136.54 (322)	125.12 (322)	140.28 (322)	123.69 (323)	94.90 (320)	110.41 (325)
PSTEREO	573.13 † (295)	531.15 † (295)	544.95 † (294)	560.18 † (296)	529.40 † (295)	540.15 † (296)
SATDISH	83.76 (333)	81.91 (337)	67.06 (340)	86.44 (336)	105.69 (336)	83.37 (341)
EPHONE	-478.13 (630)	-387.47 (619)	-394.20 (618)	-453.12 (615)	-456.31 (618)	-360.19 (619)
AMACHINE	-844.15 ** (303)	-831.64 ** (303)	-832.64 ** (302)	-831.67 ** (295)	-833.32 ** (299)	-852.16 ** (304)
VENTILA	671.10 (558)	616.69 (554)	693.15 (554)	621.25 (554)	656.49 (555)	633.39 (569)
POOLHEAT	4990.20 ** (1526)	5197.50 ** (1546)	5265.20 ** (1511)	4988.60 ** (1467)	5246.20 ** (1529)	4937.80 ** (1545)
WCOOLER	660.32 † (377)	739.84 * (373)	684.25 † (374)	666.57 † (374)	714.88 † (373)	616.35 (379)
CEILFAN	370.50 (296)	414.11 (295)	347.68 (296)	335.19 (294)	381.10 (294)	350.10 (300)
HWATER	4849.70 ** (756)	4178.20 ** (882)	4459.60 ** (816)	4493.60 ** (771)	4493.30 ** (803)	4358.10 ** (625)
CENAIR	2103.40 ** (416)	2139.20 ** (413)	2079.90 ** (418)	2064.70 ** (418)	2161.30 ** (420)	1949.50 ** (401)
WINAIR	338.01 (459)	323.52 (461)	333.29 (458)	299.80 (457)	349.86 (457)	449.12 (470)
FURFAN	-3138.60 ** (451)	-3176.70 ** (457)	-3218.80 ** (457)	-3234.20 ** (453)	-3228.40 ** (459)	-3145.40 ** (458)
BASNRAD	5203.40 ** (526)	5178.90 ** (523)	5152.40 ** (522)	5235.10 ** (522)	5239.30 ** (526)	5252.50 ** (529)
NFURAIR	4706.60 ** (608)	4651.80 ** (606)	4669.30 ** (610)	4707.00 ** (607)	4749.00 ** (619)	4574.30 ** (631)
HALOGEN	-122.80 (312)	-130.43 (303)	-169.58 (302)	-169.43 (303)	-146.77 (301)	-300.92 (309)
CFLUORES	628.11 * (312)	575.59 † (308)	588.12 † (311)	557.81 † (307)	594.47 † (309)	619.23 * (310)
OFLUORES	434.75 (311)	462.06 (306)	431.65 (308)	430.93 (303)	383.65 (305)	325.40 (306)
INCAND	-2261.50 (1618)	-2115.60 (1615)	-2134.00 (1635)	-2191.30 (1630)	-2251.60 (1613)	-2652.00 (1624)
CONSTANT	6948.60 ** (2308)	5434.00 * (2202)	6350.40 ** (2232)	6813.90 ** (2609)	6633.20 ** (2202)	6893.60 ** (2205)
R^2	0.5057	0.5056	0.5070	0.5089	0.5070	0.5023

Notes: **, * and † indicate significance at the 1%, 5%, and 10% levels, respectively.
Estimated standard errors are based on a heteroskedasticity consistent covariance matrix estimator.

One of the possible explanations for the significant negative estimates that are still evident for some appliances in Table 3 may be the large number of appliances that are explicitly included in the model. In order to investigate whether this is the case, a number of tests were run testing whether subsets of appliances had common coefficients. The groupings that were used and the test results are shown below in Table 4.

TABLE 4: TESTS OF EQUALITY OF COEFFICIENTS ON SUBSETS OF APPLIANCES

Grouping	Variables	(1)	(2)	(3)	(4)	(5)	(6)
Freezers	TOPFZ FRONTFZ	0.176	0.870	0.516	0.494	0.721	0.386
Cooking Appliances	STOVE OVEN MICWAVE	0.011	0.015	0.016	0.012	0.014	0.000
Dishwashers	COMPDW SDDW	0.720	0.711	0.760	0.777	0.746	0.722
Washing Machines	AUTOWM WDWM OTHWM	0.972	0.976	0.980	0.981	0.992	0.935
Entertainment and Office Equipment excluding computers	TV VCR DVD VGAME STEREO PSTEREO SATDISH EPHONE AMACHINE	0.008	0.017	0.013	0.013	0.021	0.005
Air Conditioning	CENAIR WINAIR	0.002	0.001	0.002	0.002	0.001	0.000
Heating Equipment	BASNRAD NFURAIR	0.526	0.501	0.536	0.499	0.536	0.273
Lighting	HALOGEN CFLUORES OFLUORES INCAND	0.152	0.183	0.164	0.167	0.163	0.021
All 8 tests jointly		0.001	0.002	0.002	0.002	0.002	0.000

Notes: Values in the Table are p-values for the specified test. For example, a p-value less than 0.05 indicates rejection of the test of equality of coefficients at a 5% significance level.

As the p-values in the first row of Table 4 show, for all six specifications, the hypothesis that the two types of freezers have the same coefficients cannot be rejected at a 5% level of significance, as all p-values exceed 0.05. Similar results are obtained for the groupings for dishwashers, washing machines, heating equipment and lighting. However, the hypothesis of common coefficients is rejected for the other three groupings – cooking appliances, entertainment and office excluding computers, and air conditioning. Interestingly, if video game consoles and answering machines are excluded from the entertainment category, the hypothesis of common coefficients would not be rejected for this category case either.

To examine the effect of grouping the appliances in the categories listed in Table 4, two additional estimations were performed. In the first, only the groupings where the hypothesis was not rejected – freezers, dishwashers, washing machines, heating equipment and lighting – were imposed. Thus, top-opening and front-opening freezers were replaced with a single freezer variable, the two types of dishwashers were replaced with a single dishwasher variable, etc. In the second case, the cooking and entertainment groupings were also imposed, but in view of the importance of space heating in residential energy consumption, the heating equipment category was not imposed. The coefficient estimates for these two estimations are reported in Table 5 along with the coefficient estimates from the model with no groupings – column (1) of Table 3 – which is reproduced here as column (A). To simplify the presentation in this table, results are only provided for the case where the omitted refrigerator category is single-door refrigerators (column (1) in the previous tables of results). Also, standard errors are omitted, but coefficients that are significant at a 5% level of significance or better are shaded.

TABLE 5: AVERAGE ENERGY USE ESTIMATES BY APPLIANCE FOR MODELS WITH GROUPINGS – INCLUDING INTERACTION TERMS

<table>
<tr><th></th><th>Variable</th><th>(A)</th><th>(B)</th><th>(C)</th></tr>
<tr><td rowspan="6"></td><td>ONEDOOR</td><td>-</td><td></td><td></td></tr>
<tr><td>TBFT</td><td>538.76</td><td>92.29</td><td>2045.50</td></tr>
<tr><td>SBSD</td><td>734.78</td><td>384.64</td><td>1208.50</td></tr>
<tr><td>THRDOOR</td><td>2587.90</td><td>4504.70</td><td>8020.30</td></tr>
<tr><td>TBFB</td><td>-5532.60</td><td>-6352.30</td><td>-5682.70</td></tr>
<tr><td>TWOREF</td><td></td><td></td><td></td></tr>
<tr><td rowspan="2">Freezers</td><td>TOPFZ</td><td>835.59</td><td rowspan="2">1273.70</td><td rowspan="2">1690.30</td></tr>
<tr><td>FRONTFZ</td><td>-795.99</td></tr>
<tr><td rowspan="3">Cooking Appliances</td><td>STOVE</td><td>-122.33</td><td>-292.85</td><td rowspan="3">183.63</td></tr>
<tr><td>OVEN</td><td>2074.60</td><td>1959.10</td></tr>
<tr><td>MICWAVE</td><td>721.03</td><td>622.11</td></tr>
<tr><td rowspan="2">Dishwashers</td><td>COMPDW</td><td>471.81</td><td rowspan="2">142.14</td><td rowspan="2">-75.42</td></tr>
<tr><td>SDDW</td><td>63.51</td></tr>
<tr><td rowspan="3">Washing Machines</td><td>AUTOWM</td><td>2422.60</td><td rowspan="3">2765.70</td><td rowspan="3">3163.60</td></tr>
<tr><td>WDWM</td><td>2359.00</td></tr>
<tr><td>OTHWM</td><td>2905.50</td></tr>
<tr><td rowspan="2"></td><td>DRYER</td><td>-536.45</td><td>-693.35</td><td>-794.21</td></tr>
<tr><td>PC</td><td>1025.30</td><td>1063.00</td><td>999.94</td></tr>
<tr><td rowspan="9">Entertainment and Office Equipment excluding Computers</td><td>TV</td><td>1872.30</td><td>1778.50</td><td rowspan="9">-3.29</td></tr>
<tr><td>VCR</td><td>443.76</td><td>386.42</td></tr>
<tr><td>DVD</td><td>-113.85</td><td>-38.73</td></tr>
<tr><td>VGAME</td><td>-819.47</td><td>-961.29</td></tr>
<tr><td>STEREO</td><td>136.54</td><td>173.88</td></tr>
<tr><td>PSTEREO</td><td>573.13</td><td>517.76</td></tr>
<tr><td>SATDISH</td><td>83.76</td><td>45.79</td></tr>
<tr><td>EPHONE</td><td>-478.13</td><td>-579.50</td></tr>
<tr><td>AMACHINE</td><td>-844.15</td><td>-853.08</td></tr>
<tr><td rowspan="5"></td><td>VENTILA</td><td>671.10</td><td>434.49</td><td>612.61</td></tr>
<tr><td>POOLHEAT</td><td>4990.20</td><td>4991.10</td><td>4526.50</td></tr>
<tr><td>WCOOLER</td><td>660.32</td><td>658.50</td><td>680.62</td></tr>
<tr><td>CEILFAN</td><td>370.50</td><td>404.10</td><td>472.58</td></tr>
<tr><td>HWATER</td><td>4849.70</td><td>3814.90</td><td>4207.20</td></tr>
<tr><td rowspan="2">Air Conditioning</td><td>CENAIR</td><td>2103.40</td><td>2184.60</td><td>2159.70</td></tr>
<tr><td>WINAIR</td><td>338.01</td><td>392.95</td><td>447.48</td></tr>
<tr><td></td><td>FURFAN</td><td>-3138.60</td><td>-3642.90</td><td>-3315.80</td></tr>
<tr><td rowspan="2">Heating Equipment</td><td>BASNRAD</td><td>5203.40</td><td rowspan="2">4931.40</td><td>5030.10</td></tr>
<tr><td>NFURAIR</td><td>4706.60</td><td>4608.70</td></tr>
<tr><td rowspan="4">Lighting</td><td>HALOGEN</td><td>-122.80</td><td rowspan="4">42.44</td><td rowspan="4">47.17</td></tr>
<tr><td>CFLUORES</td><td>628.11</td></tr>
<tr><td>OFLUORES</td><td>434.75</td></tr>
<tr><td>INCAND</td><td>-2261.50</td></tr>
<tr><td></td><td>CONSTANT</td><td>6948.60</td><td>4630.60</td><td>5489.40</td></tr>
</table>

Note: Shaded cells contain coefficients that are significant at a 5% level or higher.

As can be seen from Table 5, with the groupings freezers now have a positive and significant coefficient, while the washing machines category retains the positive and significant coefficients that previously applied only to automatic washers. However, with the grouping, cooking appliances are not significant even though ovens had a positive and significant coefficient previously. This likely reflects the result in Table 4 rejecting the constancy of coefficients for appliances in this group. Grouping the entertainment appliances removes the problem of the negative and significant coefficients for answering machines and video game consoles, since the coefficient for the entertainment group as a whole is now very small and insignificant, but as shown in Table 4, the restriction that all appliances in this category have the same coefficient is rejected. The only other notable change with the grouping results compared to those in column (A) is that the lighting group now has a relatively small positive but significant coefficient.

Overall, the grouping of appliances does not resolve the problem of significant negative coefficients for some appliances, although it does help for others. However, where the test of equality of coefficients for appliances within a particular group is rejected (as is evident for some groupings in Table 4), it is not appropriate to group the appliances anyway even if this would eliminate the significant negative coefficients that previously existed for some of the appliances in that group. Rather, these negative coefficients should be viewed as indicating that the model specification is not rich enough, or the data does not have sufficient variation, to be able to realistically estimate end-use energy consumption.

7. Summary and Conclusions

It is often of interest to have information about energy consumption by end-use in a residential context, but in the absence of direct metering of each appliance in a house, it is necessary to allocate total household energy consumption among the various end-uses using some alternative means. The method of Conditional Demand Analysis (CDA), introduced by Parti and Parti (1980) uses regression analysis to achieve this disaggregation based on information about total energy consumption and appliance holdings. Unfortunately, the empirical results with this method are often disappointing, yielding negative estimates of average energy consumption for some appliances and/or implausibly large estimates for others. Various attempts have been made to rectify these problems by incorporating more information in the models. This additional information often involves actual metering data for some appliances for some households, or diary information indicating appliance use, or multiple observations for each household such as energy consumption data for each hour. Unfortunately, none of these additional sources of information is available with the SHEU03 survey data.

In this paper we consider utilizing additional information contained in the survey concerning the scale of use of particular appliances by different households. These scale variables, which reflect such factors as the size of the house and of the household, as well as the capacity of certain appliances, differ from appliance to appliance. Unfortunately, the inclusion of these variables in our application using Canadian household survey data for 2003 does not appear to resolve the problems previously identified in empirical applications of CDA. In particular, for several appliances, average electricity consumption is negative. There are a number of possible explanations for this result and some of them are investigated here. Specifically, various sets of appliances are grouped together so that they have a common coefficient. In some cases this helps resolve the negative and significant coefficients obtained in the ungrouped estimation, but in others it does not. In any event, tests of the various groupings indicate that while some are appropriate, others are not, and proceeding with the groupings in these latter cases is likely to be counterproductive – even if the negative and significant coefficients no longer appear, the resulting estimates are biased and inconsistent.

In subsequent work it is planned to evaluate other methods that might be used to alleviate the empirical problems encountered with CDA, possibly by relegating more appliances to the unspecified category but allowing this category to have a different coefficient across different types of households. However, to a large extent such an approach – like the aggregation of appliances considered here – defeats the main purpose of the analysis which is to allocate total energy consumption to the different appliances. Explicitly including only those appliances that have positive average consumption values and relegating the remainder to the unspecified category fails to take account of appliance holding information that is contained in the sample data and makes the unspecified appliance category a very non-homogeneous mix with no useful interpretation. Possibly the solution to this dilemma will require the specification of more realistic models of energy consumption that will allow for greater differences across households in appliance use. For now, this remains an inviting topic for future research.

References

Aigner, D.J., C. Sorooshian, and P. Kerwin (1984), "Conditional Demand Analysis for Estimating Residential End-Use Load Profiles", *The Energy Journa*l, 5:3, 81-97.

Bartels, R. and D.G. Fiebig (1990), "Integrating Direct Metering and Conditional Demand Analysis for Estimating End-Use Loads", *The Energy Journal*, 11:4, 79-97.

Bartels, R. and D.G. Fiebig (1996), "Metering and Modelling Residential End-use Electricity Load Curves", *Journal of Forecasting*, 15, 415-426.

Bernard, J-T. and G. Lacroix (2005), "Conditional Demand Analysis: Tests for Homoskedasticity and Uniformity", Mimeo, GREEN, Department of Economics, Laval University, June.

Caves, D.W., J.A. Herriges, K.E. Train and R.J. Windle (1987), "A Bayesian Approach to Combing Conditional Demand and Engineering Models of Electricity Usage", *Review of Economics and Statistics*, 69, 438-448.

Fiebig, D.G., R. Bartels, and D.J. Aigner (1991), "A Random Coefficient Approach to the Estimation of Residential End-Use Load Profiles", *Journal of Econometrics*, 50, 297-327.

Halvorsen, R. (1975), "Residential Demand for Electric Energy", *Review of Economics and Statistics*, 57, 12-18.

Lacroix, G. (2004), "Analyse Conditionnelle de la Demande Appliquée au Secteur Résidentiel Québécois en 1989, 1994 et 1999", unpublished MA project, Department of Economics, Laval University, December.

Larsen, B.M. and R. Nesbakken (2002), "How to Quantify Electricity End-use Consumption", Discussion Paper No. 346, Research Department, Statistics Norway.

Parti, M. and C. Parti (1980), "The Total and Appliance-Specific Conditional Demand for Electricity in the Household Sector", *The Bell Journal of Economics*, 11:1, 309-321.

Pollak, R.A. and T.J Wales (1992), *Demand System Estimation and Specification*, New York: Oxford University Press.

Taylor, L.D. (1975), "The Demand for Electricity: A Survey", *The RAND Journal of Economics*, 6:1, 74-110.

Appendix 1: Determination of Electricity Prices

Since the SHEU03 survey did not collect any information regarding the electricity prices that the households faced in the year 2003, nor did it collect any electricity (or any other energy source) expenditure figures which would have allowed the calculation of the average electricity price (as expenditure/consumption), it is necessary to obtain pricing information from other sources. CBEEDAC has been collecting electricity prices for different jurisdictions in Canada for the past few years and some of those prices will be used here.

Several steps have been taken in order to come up with the pricing information for all the observations, with the entire process necessitating several assumptions and approximations which are detailed below.

1. The electricity price that is used is an after-tax marginal price. The rationale for using the marginal price instead of the average price arises from the block-pricing structure of retail electricity. We expect that most consumers will be concerned with the (marginal) price that they will pay for the next kWh of electricity rather than the average price (applicable to all kWh) that they will know only when they subsequently receive their monthly bill. Support for such an approach is provided by Halvorsen (1975) and Taylor (1975), among others.

2. Since electricity is typically billed monthly, in view of the block pricing structure we require information on monthly electricity consumption in order to determine the relevant

price for each month. The simple average could be used for monthly electricity consumption (annual consumption divided by 12), but this approach is very likely to be inaccurate since households may consume more electricity per month in the heating season compared to the cooling season, or vice versa. Alternatively, since consumption is available separately for the heating and the cooling season, consumption for each of these two periods could be divided by the number of months in the relevant period. However, it is unlikely that consumption at the start and end of the heating (cooling) season is the same as in the coldest (warmest) months. In view of these considerations, we obtain monthly electricity consumption by multiplying annual electricity consumption by the "monthly to annual electricity sales ratio" for each month. These ratios are based on average monthly shares of electricity consumption for the period 1996-2001 for each province, which are available in Statistics Canada's electronic database, CANSIM. Provincial consumption data of this type are not available since 2001, but a plot of the monthly electricity consumption shares over the 1996-2001 period reveals that the seasonal pattern is remarkably stable. Using this information, monthly consumption is obtained as :

$$ME_i = AE * w_i$$

where: ME_i is electricity consumption in the ith month

AE is annual electricity consumption

w_i is the "monthly to annual electricity sales ratio" for month i.

Once ME_i has been determined, the price for month i, P_i, can be obtained from the corresponding price schedule that the household faces for that month given their level of monthly consumption.

3. Once the marginal electricity price has been obtained for each month, relevant taxes are included and then an annual price for each jurisdiction is calculated by weighting the monthly prices using the same weights as described previously.

4. For those CMA's/UC's where information concerning the electricity supplier was not available, we assume the largest/closest suppliers are used. This assumption applies to the following locations:

CMA/UC	ID	#obs	Assumed Supplier
Summerside	33	8	Maritime Electric
Sydney	34	51	Nova Scotia Power
New Glasgow	36	16	
Truro	37	10	
Bathurst	38	9	New Brunswick Power
Chatham – Newcastle	39	14	
Edmundston	42	7	
Setp-Iles	43	6	Quebec Hydro
Baie-Comeau	44	8	
Rimouski	46	12	
Sherbrooke	47	14	
Rouyn-Noranda	48	11	
Cornwall	49	11	Cornwall is served by two suppliers: Cornwall Electric and Hydro One. (http://www.city.cornwall.on.ca/main.cfm?PageName=Electricity&Parent=Business) Since we don't have the 2003 rate for Cornwall Electric, we will use the adjacent CMA, which is Ottawa as the approximation.

5. There was no pricing information for electricity suppliers in certain CMA/UC's. in these cases we use the adjacent suppliers' prices as an approximation. Impacted CMA's/UC's include the following:

Province	CMA/UC	ID	# obs	Supplier	Adjacent supplier
Ontario	Kingston	50	8	Utilities Kingston	Toronto Hydro
	Peterborough	51	6	Peterborough Utilities Service	Toronto Hydro
	Oshawa	23	20	Oshawa Power	Toronto Hydro
	Guelph	52	7	Guelph Hydro	Kitchener Wilmot Hydro
	Brantford	53	14	Brantford Power Inc.	Kitchener Wilmot Hydro
	Sarnia-Clearwater	54	7		London Hydro
	Sault Ste. Maie	55	5	Great Lake Power	Greater Sudbury Hydro
	North Bay	56	5	North Bay Hydro	Greater Sudbury Hydro
	St. Catharines	11	19	St. Catharines Hydro	Hamilton Hydro
	Thunder Bay	15	7	Thunder Bay Hydro	Greater Sudbury Hydro
Alberta	Medicine Hat	61	26	Potential Suppliers: ATCO, City of Medicine Hat Electric Utilities, and TransAlta Utilities	City of Medicine Hat Electric Utilities
	Grande Prairie	63	13	Direct Energy Regulated Service/ATCO Electric	ATCO
	Fort McMurray	64	10	ATCO Electric	ATCO

6. In order to assign price information to each household in SHEU03 it is crucial to know the location of the household so that the corresponding electricity supplier and hence price can be determined. For observations located in a CMA this is not a problem, as the supplier for each CMA can generally be determined. However, for non-CMA observations it is necessary to try to track down where these households are located and assign the appropriate prices to them. For certain provinces, there was only one major/sole electricity supplier, in which case the precise location of the household within

the province was not of importance. Such provinces include Newfoundland and Labrador, Prince Edward Island, Nova Scotia, Quebec, Manitoba and British Columbia. However, for the provinces of Ontario, Saskatchewan, and Alberta, where there was more than one electricity supplier, a different approach is required. Essentially the allocation of households to electricity suppliers was based on forward sorting area (FSA) (part of the postal code) information, or where this was not available, by province. For Ontario, we used the price from the nearest CMA/UC as the relevant price. Detailed assignments are shown in the following table:

Area (according to the FSA Map from Canada Post)	CMA/UC/FSA	Assigned to
Eastern Ontario	Peterborough, K0K, K0M, K9A, and K9V	Toronto Hydro
	Belleville, Kingston, Brockville, Cornwall, K0B, K0C, K0J, K0E, K0G, K6A, K7C, K7S K7V and K8V	Ottawa Hydro
Central Ontario	St. Catharines, Niagara Falls, Welland, Burlington, L0S, L2A, L3M, and L0R	Hamilton
	Oshawa, Barrie, L0A, L0B, L0E, L0K, L0M, L1A, L3V, L4R, L9L, L9M, L9S and L9Y	Toronto Hydro
Southwestern Ontario	Stratford, Woodstock, Brantford, Guelph, Cambridge, N0A, N0B, N0C, N0E, N0G, N0H, N0K, N1A, N1M, N1N, N2Z, N3B, N3W, N3Y, N4K, N4L, N4N, and N4W.	Kitchener Wilmot Hydro
	Sarnia, St. Thomas, N0J, N0L, N0M, N0N, N4B, N4G, N4X, N5C, N5L, N7A, N7G, and N8A.	London Hydro
	Chatham, N0P, N9Y	Edwin Hydro (Windsor)
Northern Ontario	North Bay, Thunder Bay, Sault Ste Marie, Timmins, P0B, P0C, P0J, P0K, P0L, P0M, P0N, P0S, P0X, P1L, P1P, P2A, P2N, P5A, P5N, P9A, and P9N	Greater Sudbury Hydro

For Saskatchewan, we assume that Sask Power supplied the whole province except Saskatoon.

For Alberta, we assume that ENMAX supplied Calgary, Red Deer, Lethbridge and their surrounding areas; EPCOR supplied Edmonton, Ponoka, Southern and Central Alberta through Fortis Alberta; City of Medicine Hat Utilities supplied the city of Medicine Hat; and ATCO supplied the rest of the province. Detailed assignments are as follows:

CMA/UC/FSA		Assigned to
Calgary, Red Deer, Lethbridge		ENMAX
Edmonton		EPCOR
Fortis Alberta	T0B, T0C, T0K, T0L, T1G, T1L, T1M, T1P, T1R, T1S, T1W, T4G, T4L, T4J, T4V, T7A, T7E, T7N, T7P, T7V, T9A, T9S, T9W.	
Ponoka –T4J		
Northwest Alberta	Grande Prairie, T0H, T8S.	
Northeast Alberta	Fort McMurray, T9M, T9N.	
Southeast Alberta	Lloydminster, T0J, T9C, T9X.	ATCO

For non-CMA/UC observations that did not have an FSA code in Saskatchewan, we assign the prices from Sask Power rather than taking the average of the prices of Sask Power and Saskatoon Electric. For the non-CMA/UC observations that also did not have an FSA code in Ontario and Alberta, we use the average provincial rates as an approximation.

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