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**A Model of Residential Energy End-Use in Canada:
Using Conditional Demand Analysis to Suggest Policy Options for Community Energy Planners**

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Abstract

We applied Conditional Demand Analysis (CDA) to estimate the average annual energy use of various electrical and natural gas appliances, and derived energy reductions associated with certain appliance upgrades and behaviours. The raw data came from 9773 Canadian households, and comprised annual electricity and natural gas use, and responses to >600 questions on dwelling and occupant characteristics, appliances, heating and cooling equipment, and associated behaviours. Replacing an old (>10 years) refrigerator with a new one was estimated to save 100 kWh/yr; replacing an incandescent lamp with a CFL/LED lamp was estimated to save 20 kWh/yr; and upgrading an old central heating system with a new one was estimated to save 2000 kWh/yr. This latter effect was similar to that of reducing the number of walls exposed to the outside. Reducing the winter thermostat setpoint during occupied, waking hours was estimated to lower annual energy use by 200 kWh/°C-reduction, and lowering the thermostat setting overnight in winter relative to the setting during waking hours (night-time setback) was estimated to have a similar effect. This information may be used by policy-makers to optimize incentive programs, information campaigns, or other energy use change instruments.

Keywords

Residential, appliances, Canada

Research Highlights

- Conditional Demand Analysis (CDA) applied to data from 9773 Canadian households
- Energy savings associated with certain appliance upgrades estimated
- Energy savings associated with thermostat behaviours estimated
- Policy-makers can use findings to optimize incentives and information campaigns

1. Introduction

1.1 Estimating Appliance Energy Use

As part of a larger project on community energy strategies, we desired to estimate the typical annual energy use of various electrical and natural gas appliances, with the particular goal of deriving the energy reductions associated with appliance upgrades and behaviours.

There are three methods typically used to estimate the energy use of individual appliances. The first is direct sub-metering, in which an energy meter is installed on every (major) appliance in a household. The meters should be left in place to record energy use for a representative period. This process should be repeated in multiple houses, with a sample size representative of the larger population, typically several hundred, and will then yield very high quality data and energy use estimates. However, this method is also very expensive and invasive, and thus its applications have been limited [e.g. Isaacs et al., 2010; de Almeida, 2011; Parker, 2002].

A second approach is engineering estimates. In this case, the basic power draw of an appliance at the important points in its operational cycle are measured (or estimated), and this is conflated with an assumed usage pattern. The usage pattern may come from a defined standard household definition, or may be estimated by other means [NRCan, 2009]. This method has relatively low data requirements, but whereas the power measurements may be made unambiguously, the usage estimates may not accurately describe the range of possible patterns within and between real households.

The third method, and the one used in this paper, is called Conditional Demand Analysis (CDA). This is a purely statistical technique, and relies, in its simplest form, on survey data on total household energy use and appliance ownership. More sophisticated models may be derived with additional survey data on household characteristics, and householder socio-economic variables and behaviours. It is relatively inexpensive and non-invasive for householders, and was particularly attractive to us in this research because the necessary data already existed, having been collected for a different purpose. However, it also has limitations. In the following section we describe the CDA method in more detail.

1.2 Conditional Demand Analysis (CDA)

The basic CDA equation is relatively straightforward:

$$y_i = \sum_{j=1}^J UEC_{ij} N_{ij} + \varepsilon_i \quad [1]$$

where,

- y_i = annual energy use of household i (kWh)
- UEC_{ij} = annual energy use (unit energy consumption) of appliance j in household i (kWh)
- N_{ij} = number of appliance j present in household i
- ε_i = error term (kWh)

Depending on the appliance under consideration, and the survey data available, this equation may be made more sophisticated by casting UEC_{ij} as a function of climate, household characteristics, and householder socio-economic variables and behaviours. With data on a large sample of houses, this equation can then be solved using well-established regression techniques, and most prior applications have used ordinary least squares (OLS). Given that y_i and N_{ij} are known from survey data, when the regression equation is solved the unknown variables UEC_{ij} are the regression coefficients.

Of course, the estimates are dependent on the quality of the raw data, and householders might not be absolutely accurate in their responses to the survey questions, or might not interpret the questions in a universal manner. This introduces noise into the data and increases error in the estimates.

Further, regression relies on variability in the inputs. For example, if we only have data on whether a household has a refrigerator or not, since almost every modern household has a refrigerator of some kind then there is almost no variability in this input. The consequence is that it will be mathematically impossible to separate out refrigerator energy use from other end uses. The only way around this is to have additional data, such as total number of refrigerators, or refrigerator age, which introduces variability.

A third issue is intercorrelation, particularly with respect to unknown variables. For example, we might know about ownership of dishwashers, but not have data on swimming pool ownership. We can expect a positive relationship between ownership of these: higher income households will tend to have more of both. Thus the CDA estimate of dishwasher energy use may include a portion of the energy used by pools, for which we have no explicit input variable, leading to an overestimate of dishwasher energy use. The same problem can occur between known variables, if they are highly intercorrelated the mathematics of regression may not allocate energy use between them appropriately.

Despite these drawbacks, CDA is widely accepted if applied and interpreted appropriately, and end-use estimates have been shown generally to lie within the range of engineering estimates. CDA is widely used by utilities to forecast loads, and by researchers to explore energy end-use issues.

1.3 Prior CDA Studies

In this section we provide brief descriptions of other applications of CDA in similar circumstances. It would be impractical to list all of the individual variables, interactions, and UECs for each of the studies, nevertheless, these were considered in constructing our models. Aydinalp-Koksal & Ugursal [2008] applied CDA to an earlier vintage of the national Canadian dataset that we used in our analysis, although electricity and natural gas energy use data was available for only 2050 and 1012 households, respectively. Tiedemann [2007] used CDA on data from 791 households in British Columbia to develop a model of electricity use. Lafrance & Perron [1994] used CDA to study the change in major energy end-uses in Quebec using three large samples of households (42000, 24000, and 46000) five years apart. Larsen & Nesbakken [2004] developed a model for electricity use in Norway using data from 1453 households. Berg & McGrath [1988] reviewed several older studies of electricity use in US locations, and in particular a study from Florida with data from 7059 households. Similarly, Sebold & Parris [1989] reviewed 30 separate US CDA studies conducted in the 1980s, and Lawrence & Parti [1984] reviewed 15 separate US CDA studies conducted prior to these, with sample sizes typically of several thousand households. Aigner et al. [1984] used 15-minute whole-house electricity data from 80-132 households for the month of August for three consecutive years, combined with survey data, to estimate daily load profiles for individual appliances. It is also noteworthy that the well-established US RECS (Residential Energy Consumption Survey) uses CDA to generate individual end-use estimates [Battles, 1994]. The results of these studies are summarized in the Discussion section for comparison to our own results.

A review of these sources quickly reveals that there is no standard set of variables used as predictors in the regression equation. In each study the surveys were very or subtly different. The list of appliances that respondents were asked to report on varied, as did the properties of these appliances, and the behaviours that householders employed. Nevertheless, there were some common themes in the studies, and we used these to inform our choice of model variables, along with knowledge of engineering principles. Still, the final choice of variables involves some exploratory work including/excluding variables and interpreting the result. Our choices were limited by the content of the survey that provided our data, a survey that we did not play a role in designing.

2. Methods & Procedures

2.1 Survey Data

Our raw data came from the 2007 administration of the Households and the Environment Survey (HES) [StatCan, 2009]. The target group was a geographically representative sample from across Canada (excluding northern territories, Indian reserves, and households of armed forces personnel). Respondents from 21690 households completed the survey via telephone interview. The survey consisted of more than 300 questions on dwelling and occupant characteristics, energy use, water, fertilizers and pesticides, recycling and composting, indoor environment and air quality, and transportation and gasoline use. In addition, in 2007, NRCan partnered with StatCan to administer a supplementary questionnaire on Energy Use (EUS) [StatCan, 2010]. This survey was administered in paper form to all HES households; complete data were obtained from 9773 households. The EUS consisted of more than 300 questions on dwelling and occupant characteristics, household appliances, and HVAC equipment. The EUS also obtained energy use data; data for electricity and gas were monthly and were obtained, in most cases, directly from the utility (with the householder's permission).

2.2 Climate Data

For household energy use related to space heating and cooling, we introduced a dependency on local climate data. The standard indices used in CDA, and in building energy studies more generally [ASHRAE, 2009, Ch. 14], are heating-degree-days (HDD) and cooling-degree days (CDD), typically to a base temperature of 18 °C (considered the typical outdoor temperature at which there is a transition from space heating to space cooling)¹. Equations are shown below:

$$HDD18_k = \sum_{d=1 \text{ to } 365}^{if \bar{T}_{kd} < 18} 18 - \bar{T}_{kd} \quad [2]$$

$$CDD18_k = \sum_{d=1 \text{ to } 365}^{if \bar{T}_{kd} > 18} \bar{T}_{kd} - 18 \quad [3]$$

where,

¹ Prior studies have used various base temperatures, including 18 °C, and there is recognition that there is a wide range of appropriate base temperatures between buildings, depending on their specific construction and operational characteristics. Nevertheless, for large building populations where specific characteristics are not known, 18°C persists in being the most common choice for base temperature, and HDD and CDD to this base are the most widely available in published climate data.

$HDD18_k$	=	heating degree days, base 18 °C in location k
$CDD18_k$	=	cooling degree days, base 18 °C in location k
$\bar{T}_{kd}$	=	average outdoor temperature in location k on day d (°C)

In our dataset, the geographical information for each household was limited to census metropolitan area (CMA, an urban area with a population of 100,000 or more), province, and the first three letters of the postcode. We used data from Environment Canada from 2007 to calculate HDD18 and CDD18 for each CMA. Households with a valid CMA code (N=4663) were assigned the climate data for that CMA. For the remainder we looked next at the postcode, and assigned the climate data for a representative CMA with the same postcode first character. For households that did not provide postcode data (N=820) we assigned the climate data for a representative CMA in the same province. Climate data and geographical assignments are shown in Appendix A.

2.3 Data Cleaning

Our general approach was to remove, or cap, extreme values for the major variables in the model. In common with prior work in this area, we considered univariate outliers only. For electrical energy use, we dropped cases where reported household energy use was more than 4 s.d. from the mean; we also decided that households with energy use of <1000 kWh/yr represented low outliers. We also dropped cases where reported dwelling age, total household income, number of occupants, and dwelling floor area were each more than 4 s.d. from the mean; we also determined that dwellings with a floor area of <400 ft² represented low outliers. Finally, we dropped cases where reported weeks in the year the dwelling was occupied was more than 3 s.d. from the mean². Table 1 summarizes descriptive statistics for the variables described above in the raw data; mean values following the collective removal of these outliers, and listwise removal of missing values, are shown alongside model results below. Data from the national census indicated national median/mean household income before tax was \$53,634/\$69,548, and the mean number of occupants per private dwelling was 2.5 [StatCan, 2006]. Based on these metrics our starting sample appears representative of Canadian households generally. However, the results tables indicate that the final model samples were weighted towards households with higher incomes. We also note that the proportion of single-family detached dwellings in our

² We have typically used 3 s.d. as an outlier criterion in other kinds of work [e.g. Veitch et al., 2007]. In this case we were concerned that excluding outliers on multiple variables with this criterion would erode the sample size too much, so we chose a more liberal criterion for most variables. We retained the 3 s.d. criterion for the absence variable because a more liberal criterion created a minimum value for absence that we judged to be too low.

sample was higher than for Canadian households generally. These biases were likely due to self-selection in the voluntary EUS process.

Table 1. Descriptive statistics for entire sample. Refer to glossary for variable descriptions.

	ELECTRICITY (kWh)	NGAS (kWh)	HAGE (yrs)	INCOME (x1000 \$)	NOCC	FLOOR_AREA (x 1000 ft ²) ^a
N	9773	9773	9303	8946	9553	9773
Mean	12312	12291	36.6	67.6	2.40	2.11
Std. Deviation	8412	15145	25.7	61.8	1.23	1.02
Median	9897	0	32	52.0	2	2.02
Minimum	14	0	0	0	1	0.17
Maximum	61434	102251	207	3000.0	14	8.20

^a Canada is officially metric, but Canadian house sizes are almost universally quoted in ft², and it therefore made sense in our context to conduct analysis and reporting in these terms; 1000 ft² = 92.9 m², and our sample mean of 2110 ft² = 196m².

2.4 Model Development

We followed the process outlined in Aydinalp-Koksal & Ugursal [2008] by first considering logical approaches to modelling individual appliance categories from engineering principles and the data available. Then we combined these categories together into final models, by delivered energy (fuel) type, and tested variations and options on these. For brevity, we do not describe the development and variations of all model options, but will describe the terms in the final models when discussing the results. In general, space heating/cooling appliances were interacted with climate and house size data, and some other appliances were interacted with data on number of occupants, or usage. We included separate terms for both old (>10 years) and new versions of the same appliance (where data permitted)³, as well as additional estimates for the heat loss associated with having all (four) walls exposed to the outside, and for various thermostat behaviours applied to central heating systems.

After finalizing the electricity model we developed a natural gas model that followed the same form. This aided in comparing the models and interpreting the policy guidance derived from the model outputs, and we reasoned that energy use models should be robust in form where the end uses are identical. There are far fewer appliances that use natural gas, but some, particularly those for space and

³ For some appliances, respondents were asked to indicate whether it was Energy Star rated. After exploration, we chose not to further divide new appliances into Energy Star and non-Energy Star types. The sample sizes in some of these categories were very low, and we were concerned about the accuracy of Energy Star recognition and reporting by the respondents.

water heating, are large users. Outliers were determined in an identical way as for the electricity models, except that we did not exclude very low values of natural gas use: very low use of natural gas is legitimate as many households have few gas appliances.

The dataset did contain information on the use of other fuels, including oil, propane, and wood. These fuels collectively represent only a minor part of total residential energy use nationally (although they are important in some provinces). In principal, similar models could have been developed for these fuels, however, project scope did not allow us to pursue this.

3. Results

3.1 Electricity Model

Table 2 shows the output table for the final model (we used SPSS v. 19). The complex model was statistically significant and explains 53 % of the variance in annual electricity use. All of the terms in the final model are statistically significant contributors to the model (using our usual $\alpha=0.05$ criterion), with two exceptions, as described below. The values in the column labelled “B” are the coefficient estimates of interest, from which UECs can be derived. An N preceding an independent variable name (see glossary for variable definitions) indicates that it represents the number of such appliances reported for the household, and therefore can have a value greater than 1. Independent variable names not preceded by an N indicate whether at least one appliance was owned, and therefore can have a maximum value of 1; in these cases, ownership of more than one such appliance would be very rare.

Table 3 shows mean values for each of the principal variables included in the model, and only for the cases included in the model.

Table 2. Output of regression model for electricity use (complex). The final column shows the resulting UEC estimate for the associated appliance or behaviour shown in bold type.

N=4536, $R^2_{adj}=.525$, $F_{25}=201.6$	Unstandardized Coefficients		Sig.	UEC (kWh/yr)
	B	Std. Error		
(Constant)	2101.7	479.9	.000	
DISHWASHERByDWLDS	123.7	41.4	.003	458
NFRIDGE_NEWByNOCC	258.7	45.3	.000	660
NFRIDGE_OLDByNOCC	301.2	56.0	.000	768
NFREEZER	558.2	157.2	.000	558
NCOOKING_ELECTRIC_NEW	424.6	172.3	.014	425
NCOOKING_ELECTRIC_OLD	508.5	177.7	.004	509
NLAUNDRY_ELECTRIC	1022.9	193.9	.000	1023
NTELEVISION	218.9	102.6	.033	219
NOTHER_APPLIANCES	98.8	23.0	.000	99
NLIGHTING_INEFF_MISS	450.5	244.7	.066	
NLIGHTING_INEFF_NONMISS	25.7	7.4	.001	599
HOTWATER_ELECTRIC_MISS	912.8	269.4	.001	
HOTWATER_ELECTRIC_NEW_NONMISSByNOCC	1506.3	123.4	.000	4891
HOTWATER_ELECTRIC_OLD_NONMISSByNOCC	1265.0	154.7	.000	4275
HOTWATER_ELECTRIC_NONMISSByDWLDS	283.7	79.1	.000	
MSH_ELEC_CENTRAL_NEWByHDDByFLOOR_AREA	325.9	56.8	.000	3111
MSH_ELEC_CENTRAL_OLDByHDDByFLOOR_AREA	532.6	40.3	.000	5085
MSH_ELEC_ROOM_NEWByHDDByFLOOR_AREA	963.0	52.9	.000	9194
MSH_ELEC_ROOM_OLDByHDDByFLOOR_AREA	853.6	33.1	.000	8149
SSH_ELECByHDDByFLOOR_AREA	80.8	21.0	.000	771
MSH_ELECByFOURWALLSEXPByHDDByFLOOR_AREA	109.8	32.0	.001	1048
MSH_ELEC_CENTRALByWIN_TEMPByHDDByFLOOR_AREA	29.0	17.4	.096	277
MSH_ELEC_CENTRALByWIN_SETBACKByHDDByFLOOR_AREA	-40.8	15.0	.007	-390
CACByCDDByFLOOR_AREA	695.3	214.5	.001	323
NWACByCDDByFLOOR_AREA	853.2	241.8	.000	396

Table 3. Mean values for variables and cases used in regression model for electricity use (complex).

	Mean		Mean
ELECTRICITY (kWh/yr)	12412.5	NTELEVISION	2.08
HAGE	34.1	NOTHER_APPLIANCES	11.2
INCOME (x1000\$)	73.6	NLIGHTING	35.1
NOCC	2.55	NLIGHTING_INEFF	23.3
FLOOR_AREA (x1000 ft ²)	2.21	HOTWATER_ELECTRIC	0.391
POSTSEC_EDU	0.833	HOTWATER_ELECTRIC_NEW	0.303
DWELTYPE	0.229	HOTWATER_ELECTRIC_OLD	0.088
HDD (x1000)	4.32	MSH_ELEC_CENTRAL_NEW	0.028
CDD (x1000)	0.21	MSH_ELEC_CENTRAL_OLD	0.060
DISHWASHER	0.788	MSH_ELEC_ROOM_NEW	0.039
DWLDS	3.7	MSH_ELEC_ROOM_OLD	0.150
NFRIDGE_NEW	0.994	SSH_ELEC	0.182
NFRIDGE_OLD	0.412	FOURWALLSEXP	0.455
NFREEZER	0.838	WIN_TEMP	-0.417
NCOOKING_ELECTRIC_NEW	0.669	WIN_SETBACK	2.00
NCOOKING_ELECTRIC_OLD	0.404	CAC	0.358
NLAUNDRY_ELECTRIC	1.83	NWAC	0.21
CWLDS	4.75		

In cases where an appliance variable is interacted with another variable, one obtains the UEC estimate for the appliance by multiplying the value in the “B” column by the mean value of the interaction variable(s). For example, dishwasher ownership is interacted with number of dishwasher loads per week, so UEC estimate for mean dishwasher energy use is $123.7 \times 3.7 = 458$ kWh/yr. Similarly, number of refrigerators was interacted with number of household occupants. The number of occupants is a common interaction variable in prior cited studies. Some authors have found that non-linear expressions for number of occupants worked better, with the increase in energy use per additional occupant declining as the number of occupants increases (e.g. square-root or logarithmic variants [e.g. Manitoba Hydro, 2011; Tiedemann, 2007]). We tried these, but saw little benefit. For lighting, the UEC is the estimated energy use per lamp, multiplied by the average number of lamps per house.

The three electric cooking appliances (stove, cooktop, and oven) were combined into a single electric cooking variable, as cooktop and oven ownership was extremely small. Stove ownership was very high, but the combined variable, which had a maximum value of 3, introduced enough variability into the cooking-related appliance variable. Similarly we combined clothes washers and dryers into a single variable. Ownership of washers and dryers was very high, and adding them to the model as separate variables introduced destabilizing effects, as might be expected; Tiedemann [2007] had a combined laundry appliance variable for a CDA model for BC, Canada, presumably for similar reasons. We also combined ownership of a variety of smaller appliances into a single “other” variable. This included microwaves, computers, monitors, TV entertainment devices, audio equipment, phones, and watercoolers. In this case, the value in the “B” column represents the mean use of any one of these appliances, we cannot distinguish among them with this model.

For water heating, we included variables to separately account for the usage by the dishwasher, dependent on dishwasher loads, and usage for other purposes (e.g. hygiene), dependent on number of occupants. The total energy use estimate for water heaters is the sum of these components.

Main space heating was interacted with both heating-degree-days and household floor area (as a correlate for wall area), as suggested by heat loss theory. We used separate variables for households with central space heat and room-level space heat, to parallel the obvious similar separation for air conditioning. Central space heating included hot air, hot water boiler, and heat pump systems; room-level space heat included baseboards and radiant heat systems. Supplemental electric space included use of any of supplementary electric baseboards, portable heaters, electric fireplace, supplementary radiant floor heating, or supplementary electric furnace was indicated.

For main space heating, we included an additional variable with an interaction that coded for a household with all (four) walls exposed to the outside; this included mobile homes, and single detached houses without an attached garage. For central main space heating systems we included additional variables with interactions related to thermostat behaviour. The first related to reported thermostat setting (in Celsius) in the winter when someone was at home and awake. We took the reported value and subtracted 21 (the median value) to represent a deviation from median behaviour. The second related to reported thermostat night-time setback behaviour, which was the reported thermostat setting in the winter when someone was at home and awake minus the thermostat setting in the winter during the night. Note that although the interaction related to thermostat setting was not statistically significant it was retained because: it was a useful counterpoint to the setback interaction variable; its

inclusion improved the rest of the model; its coefficient is reasonable; although our practice is to use $\alpha=0.05$, authors of some prior CDA studies have accepted variables with values of $p<0.1$ [e.g. Aydinalp-Koksal & Ugursal, 2008; Lafrance & Perron, 1994]; and, the equivalent term was significant in the gas model.

Freezers and laundry appliances were not divided into new and old categories as this did not help with model stability, and because manufacturers' data suggested [NRCan, 2011a] little change in energy use per new freezer over the past 20 years. Air-conditioning appliances were not divided into new and old for reasons related to model stability.

Note that we included two specific variables that coded for missing data. For most variables, we took a conservative approach and excluded cases with a missing value on any of the input variables from the analyses. However, for two variables (certain lighting types, and water heater fuel type) the number of missing values was quite large and, in combination with the removal of outliers, reduced the sample size by up to two-thirds. For these we employed the missing indicator method. For example, if there are missing data for a variable X , one creates a new dummy variable X_MISS . If a household had missing data for variable X then X is recoded to 0, and X_MISS is coded as 1; if a household had non-missing data for X then X is unchanged, and X_MISS is coded as 0. X_MISS is then included as a predictor in the regression equation. This approach preserves cases, but it is conceptually unappealing in that the dummy variable has no real-world meaning, although one would hope that its coefficient estimate approximates the average energy use for households with non-missing data. This method might not be attractive in all applications [van der Heijden et al., 2006], but it has been used to advantage in prior CDA analyses [Bartels & Fiebig, 2000; Manitoba Hydro, 2011].

For lighting, the variables related to efficient lighting (fluorescent) were not statistically significant and were thus dropped from the model, whereas the inefficient lighting variable (incandescent) was retained. Fluorescent technologies are typically four to five times more efficient than incandescent technologies, and thus the mean energy use of a single fluorescent lamp would be too small to be resolved by the model. The missing dummy code variable for inefficient lighting was retained, despite having a $p>0.05$, because dropping it would mean cutting the overall sample size substantially and thus compromising other end-use estimates.

3.2 Natural Gas Model

The gas model had the same form as the electricity model, with some small deviations. We included an additional missing data dummy code, because there were households that had a relatively high gas use (our criterion was 10000 kWh/yr) but reported not using natural gas as their main space heating fuel. We reasoned that such high gas use would be very difficult to achieve without using gas for space heat. We did not have other data that would allow us to confidently recode the main space heating fuel as gas, so we chose to recode the data with a missing dummy code instead. This substantially increased the variability explained by the model. We included a separate variable for clothes dryer; gas washers do not exist, and gas dryers are rare, and thus the universal ownership problem with electric laundry appliances did not apply here. Dryers were not divided into new and old categories to parallel the decision made in the electricity model with regard to laundry appliances.

Table 4 shows the output table for the final model. This model is statistically significant and explains 79 % of the variance in annual gas use. All of the terms in the final model are statistically-significant contributors to the model, with two exceptions: the term for interaction of water heating and dishwasher loads, and the term for supplemental space heat. We left these in to maintain parallelism with the electricity model. Table 5 shows descriptive statistics for each of the variables included in the model, and only for the cases included in the model.

Table 4. Output of regression model for gas use (complex). The final column shows the resulting UEC estimate for the associated appliance or behaviour shown in bold type.

N=5158, R ² _{adj} =.792, F ₁₄ =1404	Unstandardized Coefficients		Sig.	UEC (kWh/yr)
	B	Std. Error		
(Constant)	965.6	134.3	.000	
NCOOKING_GAS_NEW	1715.2	406.3	.000	1715
NCOOKING_GAS_OLD	1970.0	619.1	.001	1970
DRYER_GAS	1353.2	496.6	.006	1353
HOTWATER_GAS_MISS	1076.4	274.1	.000	
HOTWATER_GAS_NEW_NONMISSByNOCC	1601.4	129.4	.000	4210
HOTWATER_GAS_OLD_NONMISSByNOCC	1638.3	158.0	.000	4302
HOTWATER_GAS_NONMISSByDWLDS	56.1	70.3	.425	
MSH_GAS_NEWByHDDByFLOOR_AREA	1853.9	35.9	.000	17702
MSH_GAS_OLDByHDDByFLOOR_AREA	2049.6	37.7	.000	19570
SSH_GASByHDDByFLOOR_AREA	21.3	25.7	.407	
MSH_GASByFOURWALLSEXPByHDDByFLOOR_AREA	270.8	30.0	.000	2586
MSH_GASByWIN_TEMPByHDDByFLOOR_AREA	22.0	10.3	.033	210

MSH_GASByWIN_SETBACKByHDDByFLOOR_AREA	-22.8	8.8	.009	-218
NGAS_HEAT_MISS	21202.5	412.9	.000	

Table 5. Mean values for variables and cases used in regression model for gas use (complex).

	Mean		Mean
NGAS (kWh/yr)	11676.9	HOTWATER_GAS_NEW	0.281
HAGE	34.4	HOTWATER_GAS_OLD	0.099
INCOME (x1000\$)	70.8	MSH_GAS_NEW	0.192
NOCC	2.5	MSH_GAS_OLD	0.172
FLOOR_AREA (x1000 ft ²)	2.19	SSH_GAS	0.14
POSTSEC_EDU	0.819	FOURWALLSEXP	0.488
DWELTYPE	0.229	WIN_TEMP	-0.441
HDD (x1000)	4.36	WIN_SETBACK	1.99
DWLDS	3.68		
NCOOKING_GAS_NEW	0.054		
NCOOKING_GAS_OLD	0.02		
DRYER_GAS	0.045		
CWLDS	4.68		

4. Discussion

4.1 Comparison of UECs to Other Sources

For electric appliances, there are several studies to which we can compare our results. Table 6 summarizes the UECs for each appliance type from prior CDA studies, sub-metering, and engineering estimates, and compares them to values derived from our analysis. Note that previous work did not consider the age effects or behaviours that we addressed in our more complex model.

In addition to the values in Table 6, we can generate additional, simplified estimates for comparison. For example a 120 W TV [CNET, 2010] on for 4 hrs/day uses 175 kWh/yr. For lighting, the most common single lamp type in residences is probably the 60W incandescent [Navigant, 2002, Appendix D]. Single fluorescent lamps are usually <30W, but single halogen lamps may be 25W or 50W, and can be as high as 150W. The most commonly used lamps are on ~3 hrs/day, but a reasonable average might be 1 hr/day [Gaffney et al., 2010; Navigant, 2002 Appendix D]. These assumptions yield an average use per lamp of 18.3 kWh/yr. Sub-metering of 12 residential a/c units in southern Ontario, representing a CDD

above the average for our sample, showed an average energy use for cooling of 520 kWh/yr [Saldanha & Beausoleil-Morrison, 2012].

For gas appliances, we were not able to find citable studies to which we can compare our results. However, we were given the results of a CDA gas analysis from a large Canadian utility [Manitoba Hydro, 2011]. For gas cooking, our estimate is substantially higher than that for electric cooking, but is substantially lower than the value provided by Manitoba Hydro (2752 kWh/yr). For gas dryers, our estimate is substantially higher than that for a single electric laundry appliance, but this may be partially explained by the lower efficiency of delivered energy from gas compared to electric. Our estimate is in good agreement with the value provided by Manitoba Hydro (1799 kWh/yr). For gas water heating, our estimate is similar to our estimate for electric water heating, and is a somewhat lower than the value provided by Manitoba Hydro (5335 kWh/yr). For main space heating, an estimate derived from the value provided by Manitoba Hydro (inputting the same average house size as in our sample, and assuming a mid-efficiency furnace) was 26900 kWh/yr. Substituting the HDD18 value for Winnipeg into our estimate yielded a value of ~25000 kWh/yr.

Overall, our UEC estimates are in good agreement with the range of values from prior studies, and form a better complete set than any single prior study. The only major exception was for central electric heating. But note that for Canada as a whole this type of main space heating is rare, and the single most common main space heating type in Canada is natural gas.

Table 6. Comparison of our UEC estimates for electric appliances to those from prior CDA studies.

End Use	Newsham & Donnelly [2012] (New/Old if applicable)	Tiedemann [2007]	Bartels & Fiebig [2000]	Lafrance & Perron ^a [1994]	Bernard & Lacroix [2005]	Battles [1994]	Berg & McGrath [1988]	Sebold & Parris [1989]	Lawrence & Parti [1984]	Engineering Est./sub-metered ^b
	Canada	BC, Canada	NSW, Australia	QC, Canada	QC, Canada	Bonneville Power, USA	Florida, USA	Northern Illinois, USA	Bonneville Power, USA	
Primary Space Heat		5037	993	10658		6182	744	10140	12534	6300-7900
<i>Water heating</i>	3111/5085			13975	13894					
<i>Hot air</i>				12642						
<i>Heat pump</i>				9966						
<i>Baseboard</i>	9194/8149			9873	8935					5300
Suppl. Space Heat	771	2310	426	1286	1323					850
Central a/c	323	346	~200-1000		1963		4440	1810	2672	1200-2500
Room a/c	396	207					2184	490	526	500-1300
Water Heater	4891/4275	3186	~4000-5500		3401	4161	~1500	~4000	4625	2800-4700
Refrigerator	660/768	1112	~1400		988	1172	1536	1400	1668	600-2200
Freezer	558		648		689		1296	1150	288	400-1800
Cooking	425/509	721					564	310	1799	550-2000
<i>Stove</i>			554							
<i>Cooktop</i>			302							
<i>Oven</i>			297							
<i>Microwave</i>			67				204	280		80-200
Dishwasher	458	38	492					~70	2562	200-600
Clothes Washer	1023	648	119						1135	500-900
Clothes Dryer							756	1170	2059	200-1100
Lighting Total	599 ^c	1937	1005							730-2100
TV	219	878	157				276			150-500
Computer		656								200

^a single family dwelling sub-sample only; ^b where multiple values were reported, we chose UECs with climate dependence from climates closest to Canada;

^c for incandescent and halogen only

4.2 Informing Potential Policy Actions

Our results provide estimates for the policy-maker on the potential energy savings associated with various actions, information which may then be used to optimize incentive programs or other instruments. Table 7 summarizes the appliance substitutions, behaviours and other choices with their energy effects as estimated in our models and rounded for ease of interpretation. In this table we highlight only those effects that appear to be reliable⁴.

Table 7. Summary of potential energy saving actions and behaviours, for policy consideration.

Appliance / End use	Action	Energy saving (kWh/yr)	Common Policy Option
Refrigerator	Replace Old with New	100	Incentive and free disposal [e.g. Hydro Ottawa, 2012a]
Electric Cooking Equipment	Replace Old with New	100	Incentive and free disposal ^a
Lighting	Replace incandescent with CFL (or LED)	20/lamp	Incentive [e.g. Hydro Ottawa, 2012b] ^b
Electric Main Space Heating	Replace Old Central system with New	2000	Incentive and free disposal ^c
Gas Main Space Heating	Replace Old system with New	2000	Incentive and free disposal
Electric Main Space Heating	Reduce number of walls exposed to exterior	1000	Zoning
Gas Main Space Heating	Reduce number of walls exposed to exterior	2500	Zoning
Gas Main Space Heating	Lower thermostat during waking period	200 /°C reduction	Information campaign ^d
Electric Main Space Heating	Night-time thermostat setback in winter	400/°C setback	Incentive for programmable thermostat, and information campaign
Gas Main Space Heating	Night-time thermostat setback in winter	200/°C setback	Incentive for programmable thermostat, and information campaign

^a The model also suggests savings by replacing old gas cooking appliances with new appliances, but the standard error of these estimates was very large

^b A reasonable estimate of energy saving associated with replacing an inefficient lamp (incandescent) with an efficient one (fluorescent, or LED) may be based on the efficacy difference, which is typically 4-5x better for efficient lamps

^c The model also suggests substantial savings from replacing room-level heating with a central system, this is an unlikely option in renovation, but could be a reasonable requirement for new build

^d The model suggested a similar saving for houses with electric main space heating, but the effect was not statistically-significant at the 0.05 level ($p=.096$)

⁴ Note that although the new/old estimates by appliance type are statistically significant effects, generally in the expected direction and have a plausible magnitude, in most cases there is overlap of standard errors. The larger the overlap, the less confidence we can have that the differences are genuine and not just due to chance.

Note that although the UEC estimate for central electric heating was somewhat low, the saving associated with replacing an old central heating system with a new one was ~2000 kWh/yr whether the fuel type was electricity or natural gas. Note that the reduction in UEC in going from an old to a new gas furnace is similar to the effect that might be expected with improvements in furnace efficiencies from low to mid, or from mid to high [CMHC, 2011]. The effect of having four walls exposed scales approximately with the UEC for heating by fuel. There is no obvious reason why the effect of setting back the thermostat at night would differ by heating system fuel type. A conservative estimate might be 200/°C for both fuel types, about the same as the effect of increasing thermostat setting during daytime, occupied hours.

It is interesting to compare the magnitude of energy saving estimates. For example, there has been considerable effort invested in lamp replacement programs, and even looming legislation [NRCan, 2011b]. However, one would have to replace 20 lamps to save the same energy as the mean night-time thermostat setback of 2 °C. If the setback is achieved via the installation of a programmable thermostat (of course, one can also realise the saving with diligent manual actions), it can then be used for other energy-savings actions, such as automated demand response [Newsham et al., 2011]. On the other hand, replacing five lamps may be far easier than replacing a refrigerator or electric cooking equipment. Nevertheless, there might be other reasons to pursue one action over another, for example, replacing an old refrigerator might prevent CFC leakage.

Our analysis also highlights actions that seem less likely to save energy. For example, our results suggest that new electric water heaters use more energy than older models. This could be due to error in the model, or because water heating correlates with another variable not represented in the model, or because newer water heaters tend to be larger than older ones; we cannot distinguish between these possibilities with the data we have. Also, we see a substantial improvement in energy use for newer central electric heating systems but not for room-based systems. Room-level systems are essentially resistance heaters, and there is little improvement in heating efficiency possible with newer models. Central systems also include fans, pumps, boilers, compressors, etc., which are capable of substantial improvement over time. In fact, the estimate for newer room-based systems is a little higher than for older systems, this may be because newer systems tend to be in newer dwellings, which tend to be bigger and thus have a greater volume to heat.

5. Conclusions

Our results suggest that Conditional Demand Analysis (CDA) is a useful adjunct to sub-metering and engineering calculations for estimating the typical annual energy use of various electrical and gas appliances. Further, estimates of the energy reduction effect of appliance upgrades and some behaviours may be derived. These estimates might help to identify incentives and policies most likely to be cost-effective.

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Glossary

Here we provide definitions of the basic variables used in the overall energy models and ownership models. Interactions of these variables are also used in the energy models.

CAC	Dummy code for ownership of central air conditioning
CDD	Number of cooling degree days (base 18 °C) (x1000)
CWLDS	Number of clotheswasher loads per week
DISHWASHER	Dummy code for dishwasher ownership (for all ownership dummy codes 1=ownership; 0=no ownership)
DRYER_GAS	Dummy code for ownership of gas clothes dryer
DWELTYPE	Type of dwelling (0=single-family detached; 1=other)
DWLDS	Number of dishwasher loads per week
ELECTRICITY	Total annual electricity use for dwelling (kWh/yr)
FLOOR_AREA	Total dwelling floor area, including finished basement (x 1000 ft ²)
FOURWALLSEXP	Dummy code indicating if dwelling had all walls exposed to the exterior climate (1=mobile homes and single detached houses without attached garages; 0=all other)
HAGE	Age of dwelling (years)
HDD	Number of heating degree days (base 18 °C) (x1000)
HOTWATER_ELECTRIC_MISS	Dummy code for missing data in water heater fuel type
HOTWATER_ELECTRIC_NEW_NONMISS	Dummy code for an electric water heater ≤ 10 years old
HOTWATER_ELECTRIC_NONMISS	Dummy code for ownership of an electric water heater (missing data coded as 0)
HOTWATER_ELECTRIC_OLD_NONMISS	Dummy code for an electric water heater > 10 years old
HOTWATER_GAS	Dummy code for ownership of a gas water heater
HOTWATER_GAS_MISS	Dummy code for missing data in water heater fuel type
HOTWATER_GAS_NEW_NONMISS	Dummy code for a gas water heater ≤ 10 years old
HOTWATER_GAS_NONMISS	Dummy code for ownership of a gas water heater (missing data coded as 0)
HOTWATER_GAS_OLD_NONMISS	Dummy code for a gas water heater > 10 years old
INCOME	Total household income, before tax (x1000 \$)
MSH_ELEC	Dummy code for ownership of electric main space heating
MSH_ELEC_CENTRAL	Dummy code for ownership of centralized electric main space heating (including furnace, boiler, heat pump)
MSH_ELEC_CENTRAL_NEW	Dummy code for centralized electric main space heating ≤ 10 years old
MSH_ELEC_CENTRAL_OLD	Dummy code for centralized electric main space heating > 10 years old
MSH_ELEC_ROOM	Dummy code for ownership of room-level electric main space heating (including baseboards, radiant)
MSH_ELEC_ROOM_NEW	Dummy code for room-level electric main space heating ≤ 10 years old
MSH_ELEC_ROOM_OLD	Dummy code for room-level electric main space heating > 10 years old

	years old
MSH_GAS	Dummy code for ownership of gas main space heating
MSH_GAS_NEW	Dummy code for gas main space heating ≤ 10 years old
MSH_GAS_OLD	Dummy code for gas main space heating > 10 years old
NCOOKING_ELECTRIC_NEW	Number of electric cooking appliances ≤ 10 years old
NCOOKING_ELECTRIC_OLD	Number of electric cooking appliances > 10 years old
NCOOKING_GAS_NEW	Number of gas cooking appliances ≤ 10 years old
NCOOKING_GAS_OLD	Number of gas cooking appliances > 10 years old
NFREEZER	Number of stand-alone freezers in dwelling
NFRIDGE_NEW	Number of refrigerators in dwelling that were ≤ 10 years old
NFRIDGE_OLD	Number of refrigerators in dwelling that were > 10 years old
NGAS	Total annual natural gas use for dwelling (kWh/yr)
NGAS_HEAT_MISS	Dummy code for dwellings with >10000 kWh/yr of natural gas use, but no reported gas main space heating
NLAUNDRY_ELECTRIC	Total number of electric laundry appliances (including clothes washers and dryers) in dwelling
NLIGHTING	Total number of lamps (including incandescent, halogen, regular fluorescent, and compact fluorescent) in dwelling
NLIGHTING_INEFF	Total number of inefficient lamps (including incandescent, halogen) in dwelling
NLIGHTING_INEFF_MISS	Dummy code for missing data in inefficient lamp types (1=missing; 0=non missing)
NLIGHTING_INEFF_NONMISS	Total number of inefficient lamps (including incandescent, halogen) in dwelling (where 0 indicates a dwelling with missing data)
NOCC	Number of household occupants
NOTHER_APPLIANCES	Total number of small appliances (including computers, microwaves, home theatres, DVD players, VCRs, stereos, portable stereos, water coolers, computer monitors, printers, TV set-top boxes, game consoles, and phones) in dwelling
NTELEVISION	Total number of televisions in dwelling
NWAC	Total number of portable (window) air conditioners in dwelling
POSTSEC_EDU	Dummy code for at least some post-secondary education (1) vs. high-school diploma or less (0)
SSH_ELEC	Dummy code for supplementary electric space heating
SSH_GAS	Dummy code for supplementary gas space heating
WIN_SETBACK	Thermostat setting in winter when the occupants are present and awake minus setting at night during sleep ($^{\circ}\text{C}$)
WIN_TEMP	Thermostat setting in winter when the occupants are present and awake minus 21 ($^{\circ}\text{C}$)

Appendix A

Table A1. Canadian cities classified as a census metropolitan area (CMA), along with 2007 climate metrics. Cities whose climate data was used to represent a given postcode or province are also shown.

CMA Code	City	Postcode Representative	Province Representative	HDD18	CDD18
001	St. John's	A	NL	4783	56
205	Halifax	B	NS	4403	118
305	Moncton	C, E	NB, PE	4768	133
310	Saint John			4846	35
408	Saguenay			5461	49
421	Quebec	G		5022	121
433	Sherbrooke			5108	102
442	Trois-Rivieres			4804	194
462	Montreal	H, J	QC	4341	289
505	Ottawa-Gatineau	K		4453	256
521	Kingston			4096	281
529	Peterborough			4415	180
532	Oshawa			4203	268
535	Toronto	L, M	ON	3458	453
537	Hamilton			3866	336
539	St. Catharines			3362	422
541	Kitchener			4180	220
543	Brantford			3896	341
550	Guelph			4238	191
555	London	N		3827	310
559	Windsor			3256	614
568	Barrie			4583	144
580	Greater Sudbury	P		5031	175
595	Thunder Bay			5449	91
602	Winnipeg	R	MB	5717	205
705	Regina	S	SK	5604	187
725	Saskatoon			5825	133
825	Calgary	T	AB	4873	69
835	Edmonton			5060	139
915	Kelowna			3851	137
932	Abbotsford			2878	84
933	Vancouver	V	BC	2880	50
935	Victoria			2980	34