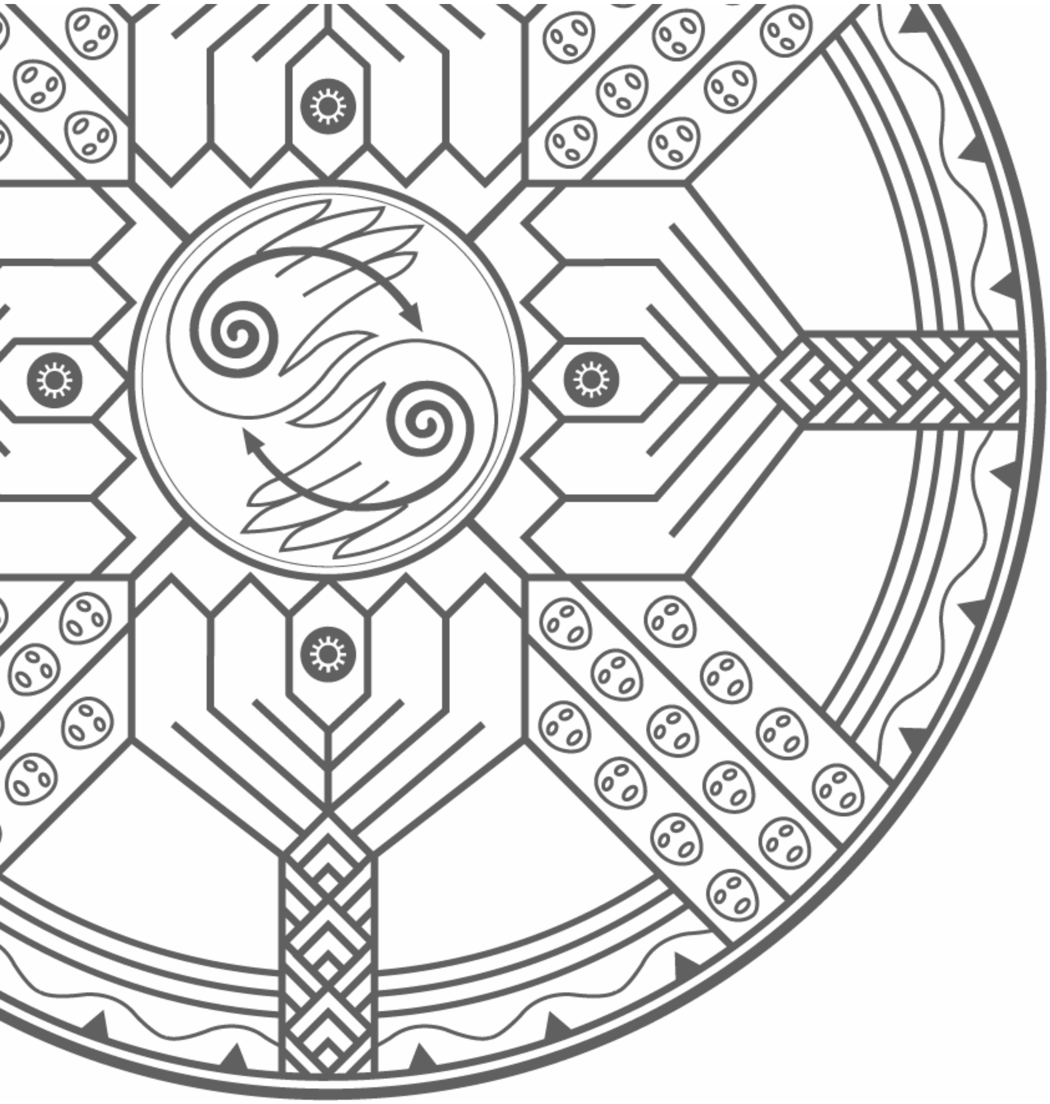

Determining Demand for Energy Services: Investigating income-driven behaviours

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Table of Contents

Abstract

Conventional residential energy demand models are concerned with estimating fuel use (for example, gas, electricity and oil) demand. In this paper, we propose a residential energy demand model that is based on the demand for energy services, namely space heating load, water heating load, and appliance and lighting load. The model is developed using Canadian household data. We estimate the demand for energy services using a two-step estimation procedure. In the first step we compute the efficiencies for furnaces and water heaters for each of the 440 households using a deterministic frontier analysis. In the second step, the estimated furnace and water heater efficiencies are used to determine the demand for energy services. Price elasticities are expressed as a linear function of income to highlight income-related behaviour. Despite limitations with the database, the results show a clear variation in behavioural responses to changes in price and in income across the income groups and energy services. Low-income households are more responsive to price and income changes than higher-income households, while all households are more responsive to price changes than income changes. Space heating load presents the strongest distributional effect with a factor two between price elasticities of the low- and high-income groups. Results also confirmed the rebound effect with respect to the efficiency of furnaces and water heaters. This effect is quite noticeable with furnace efficiency. We used the rebound effect to design a policy that could help lower-income groups cope with increases in energy prices.

1. Introduction

Conventional residential energy demand models are concerned with estimating utility (fuel) demand. However, fuel is not consumed for itself but for the services it provides. It is energy services that people demand, not fuels. For example, it is the desire to keep warm that people value and not the desire for a particular fuel or energy.

In this paper, we propose a residential energy demand model that is based on the demand for energy services, namely space heating load, water heating load, and appliance and lighting load. We apply it to Canadian household data. Price elasticity is a useful parameter that provides information on consumer behaviour with respect to changes in the price of commodities. However, unlike a majority of models that looks at the price elasticity of fuels, in this paper we focus on the price elasticity with respect to energy services and compare it with the price elasticity of utilities.

This work is part of a broader research agenda. In 2001, the International Institute for Sustainable Development, together with The Energy Resources Institute (TERI) in India, initiated research on the impacts of climate-change-driven energy policies on lower-income groups. In this phase of the project, the methodology for developing a residential energy demand model was tested using Canadian data. It is envisaged that the learning acquired in this exercise would prove useful in replicating the methodology for India where data may not be so readily available and modifications may need to be made.

Generally, lower-income Canadian households allocate a greater share of their budget to energy expenses than higher-income groups (see Table 1). It can therefore be anticipated that increases in energy prices caused by climate-change-driven energy policies will be borne disproportionately by lower-income groups. However, the magnitude of these impacts on these groups has yet to be determined within an energy demand modelling framework.

Table 1: Canadian Income Groups and their Energy Expenditures in 2000.

Group	**Income Range**	**Electricity Expenditures**	**Fuel Expenditures**	**Total Expenditures**	**Ratio of Total Energy Expenditures to Total Expenditures**
Low	< $30,180	900	851	21,564	8%
Medium	$30,180-$61,849	964	1,089	47,166	4%
High	> $61,849	1,061	1,301	95,753	2%

Source: Compiled from Statistics Canada (2001, 2002).

In order to assess these impacts, we modified the MARKAL (MARKet ALlocation) model (Fishbone and Abilock 1981)—an energy planning tool used to evaluate GHG emissions. MARKAL was developed in the late 1970s by member countries of the OECD under the guidance of the International Energy Agency (IEA) (Berger et al. 1992; Condevaux-Lanloy and Fragnière 2000; Fishbone and Abilock 1981). It is now in use in more than 35 countries (Condevaux-Lanloy and Fragnière 2000). MARKAL is a demand-driven, multi-period, partial equilibrium model. It is a dynamic optimization model that uses linear programming to find the optimal mix of fuel and technologies to meet demand for energy services, at least cost, over a pre-determined time horizon, usually between 20 to 50 years. Some MARKAL models, like the Canadian MARKAL-ED model, have demand endogenously determined through price-elastic demand functions (Loulou and Lavigne 1995).

The Canadian MARKAL-ED model requires price elasticities on energy services to determine the change in demand when there is a constraint on the system, such as a carbon constraint. Up to now, price elasticities of residential energy services in Canada have been based on price-elasticities of residential utility consumption determined for Quebec and adapted to the MARKAL model using expert judgment (Kanudia and Loulou 1999). In this paper, we go one step further by estimating price elasticities of residential energy services for the three income groups using a robust econometric approach.

2. Input and Output Energy

Residential energy end-uses can be decomposed into space heating, water heating, appliance usage and lighting. Demand for energy services is also referred to as the load, and for the residential sector, we have the space heating load, the water heating load, the appliance load and the lighting load. The load is given in Joules (J).

However, households purchase utilities such as kilowatt-hours (kWh) of electricity, litres (l) of oil, cubic metres (m^3) of natural gas, etc. These utilities are typically transformed into energy services (e.g., space heating load, water heating load, appliance load and lighting load) through conversion technologies like furnaces, space heaters and heat pumps (see Figure 1).

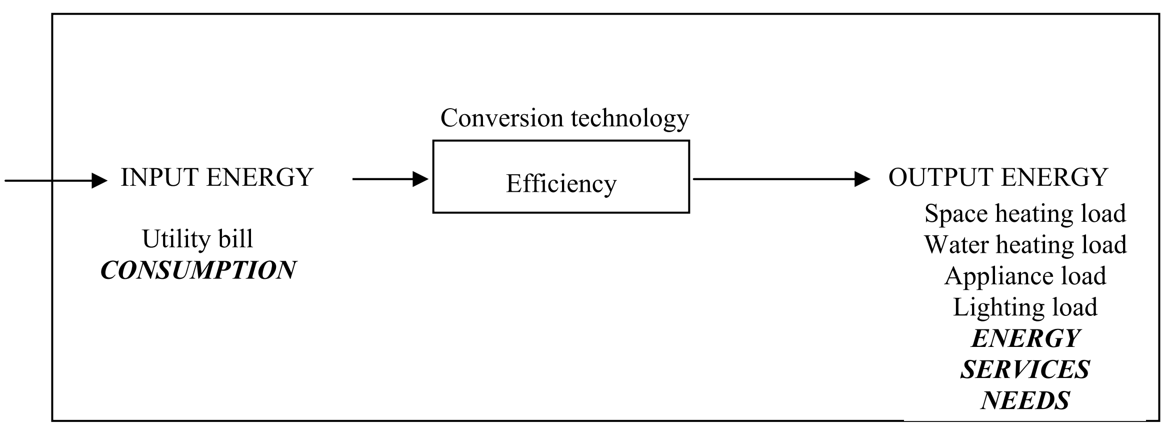

Figure 1: Relationship between input and output energy.

The appellations "input energy" and "output energy" are given with respect to the conversion technology. Input energy refers to the energy content of the utility consumption, while output energy refers to the load. The relationship between input energy and output energy, illustrated in Figure 1, can be written as follows:

$$E^{x}_{IN,j}=\frac{E^{x}_{OUT,j}}{\lambda^{x}_{k,j}} \tag{1}$$

Where:

$E^{x}_{IN,j}$: is the energy content of the utility consumption j for providing the energy service x or input energy (in Joules);

$E^{x}_{OUT,j}$: is the energy service x or output energy (in Joules); and

$\lambda^{x}_{k,j}$: is the efficiency of technology k for converting the input energy into output energy x for utility j.

Each conversion technology is characterized by its efficiency in converting input energy into output energy. Typical efficiency values are less than one for space heaters using natural gas and water heaters using gas or electricity.

2.1 Energy Content of the Utility Consumption

The energy content of the utility consumption depends on the fuel type. Standard values for converting the utility consumption into its energy content (or input energy) are given in Table 2. The energy content of utility consumption can therefore be expressed as follows:

$$E^{x}_{IN,j}=C_{j}U^{x}_{j} \tag{2}$$

Where:

$E^{x}_{IN,j}$: is the input energy or energy content of the utility consumption j for providing energy service x (J);

U^{x}_{j}: is the utility consumption j associated with energy service x (kWh, litres, cubic metres, etc.); and

C_{j}: is the conversion factor to establish the energy content of utility consumption j given in Table 2.

Table 2: Energy Content of Different Types of Fuels.

Type of Fuel	**Basic Unit of Input Energy**	**Energy Content**
Electricity	1 kWh	3.6 MJ
Natural gas	1 Cubic metre (m^3)	37.259 MJ
Oil	1 Litre (l)	38.524 MJ
Propane	1 Litre (l)	25.6 MJ
Wood	1 tonne (t)	13956 MJ

Source: NRCAN 1995.

2.2 Input and Output Prices

The energy expenses of a single household for a given energy service remain the same whether you consider output energy or input energy. We have:

$$P^x_{IN,j} E^x_{IN,j} = P^x_{OUT,j} E^x_{OUT,j} \tag{3}$$

Where:

$P^x_{IN,j}$: is the price of input energy for fuel consumption j;and

$P^x_{OUT,j}$: is the price of output energy for fuel consumption j.

The price of output energy is not a real price but is what people actually pay taking into consideration efficiency of the conversion technology. Substituting the output energy expressed in Equation (1) into (3), the expression of the output energy price becomes:

$$P^x_{OUT,j} \lambda^x_{k,j} E^x_{IN,j} = P^x_{IN,j} E^x_{IN,j} \tag{4}$$

$$P^x_{OUT,j} = \frac{P^x_{IN,j}}{\lambda^x_{k,j}} \tag{5}$$

The price of output energy is greater than the price of input energy by the same ratio as energy lost in the conversion process from input to output energy.

3. A Brief Survey of Econometric Models of Residential Energy Demand

We did a literature review on two fronts. The first involved a review of studies looking at energy services, end uses and income groups. The second survey focused on the key variables used by the present cadre of models in the design of residential energy demand models.

3.1 Energy Services, End Uses and Income Groups

Econometric models of energy consumption, as opposed to engineering models, permit the determination of price and income elasticities. Studies have investigated demand for output energy, the energy demand by end uses or the energy demand by different household groups. None of these studies investigated all of these aspects at once as we did. Our methodology models demand for output energy of end uses according to household income. We discriminate between energy services and end uses. End uses refers to unbundled input energy into its components (e.g., space heating, water heating, appliances and lighting) while energy services are the output energy of end uses (see Figure 1 and Equation 1).

This section reviews the literature on demand for energy services, end uses and income groups. The review is limited to energy demand models developed using microdata, i.e., data at the household level. The review shows that households respond differently to price increases according to the type of end uses, and that income groups do show a different response to price increases in their utility consumption. We therefore anticipate that households will respond differently across income groups and energy services (or end uses).

3.1.1 Demand for Energy Services

Our literature review highlighted only one study, based on household data, that dealt with demand for energy services. Schwarz and Taylor (1995) investigated the demand for comfort, expressed as the indoor temperature, and evaluated the heating energy load using an engineering expression that is a function of the difference between indoor and outdoor temperatures. Their objective was to relate the "thermostat response to changes in insulation" (Schwarz and Taylor 1995: 45). However, their approach does not relate energy need to energy consumption as defined by Equation (1).

At the sectoral (macro) level, McRae (1979) investigated the demand for output energy using a two-stage analysis of demand for fuels that determines the contribution of each fuel to the total demand for energy. To do this, he first converted physical units of fuel demand into energy content (BTU) using a standard conversion factor. Then, he converted the input energy (fuel demand expressed in BTU) into output energy (BTU) using published standard factors that "capture the relative efficiency of conversion from input to output energy of different fuels and conversion technologies in the same end-use sector" (McRae 1979: 204). However, the approach used by McRae is not satisfactory because each household's furnace and water heater typically has a different efficiency. Variations in efficiency are explained not only by the technology used—defined by the type of ignition device used and fresh air intake—but also by the frequency of servicing (Douthitt 1986; 1989).

3.1.2 End Uses

There are more studies on energy demand by end uses (input energy) than on demand for energy services (output energy). The studies we reviewed on energy services focused on the demand for space heating. Not surprisingly, these studies were performed using data from northern countries where the greatest energy consumption in the residential sector is usually attributable to space heating.

Douthitt (1986) determined the combined demand for natural gas for residential space heating and water heating in Canada. In that study, the fuel was not used for other usage except for space heating and water heating and therefore no unbundling was needed (When a specific fuel is only used for a given end use, the unbundling process is then simplified. Otherwise, the process is a non-trivial task and is prone to induce errors). Douthitt (1989) determined the demand for space heating of Canadian households. In that case, the unbundling to determine specifically the demand attributable to space heating was not performed by the author but by the Department of Energy, Mines and Resources (EMR) of Canada, and the unbundling technique is not disclosed. Haas and Biermayr (1997) developed an energy model for space heating, hot water and electric appliances of Austrian households. The authors present how they unbundled space heating consumption from water heating consumption when the same fuel is used in both. Their technique is based on a simple linear regression of the monthly energy consumption of that fuel. First, they assume that monthly water heating consumption is constant and is therefore associated to the constant parameter of the regression. Then, they assume that the monthly space heating consumption is proportional to heating degree days of that month. In another study, Leth-Pethersen and Togeby (2001) investigated space heating for apartment blocks in Denmark, heated with oil or district heating. In this study, no unbundling was carried out. Klein (1988) investigated demand for space heating by taking the difference in utility consumption during the heating months and the months when no heating is needed.

Haas and Biermayr (1997) are the only authors that investigated energy demand of a range of end-uses within the same study, permitting a comparison of price and income elasticities between end uses. Their results show that households respond differently for different end uses.

3.1.3 Income Groups

A few studies have investigated price and income elasticities for different household groups and we present their main results here. These studies show that different income groups respond differently to price increases.

Lafrance and Perron (1994) report "interesting results" by income groups but did not publish them, while Donnelly and Diesendorf (1985) introduced an aggregate energy demand with a price elasticity that varies with the income, but did not use it.

Poyer and Williams (1993) developed a model of total energy consumption and reported long-term price elasticities of -1.13 (Blacks); -0.46 (Latinos); and -2.45 (Majority), and long-term income elasticities of 0.12 (Blacks); 0.23 (Latinos); and 0.16 (Majority). Although Poyer et al. (1997) reported average energy and electricity expenditures for poor and non-poor households within each household type, Minority and Majority, they did not apply this discrimination to their results. The model developed by Poyer et al. (1997) does not provide price and income elasticities but allows the determination of impacts of price changes on economic welfare of households.

Baker et al. (1989) found that, on average, the higher-income households are less responsive than low-income groups to changes in energy prices, while their estimation of income elasticities based on microdata did not show positive values for each single household (see Table 3). However, income elasticities tend to increase, on average, toward the lower-income households.

Table 3: Price and Income Elasticities: Source Baker et al. (1999).

Elasticity	All Households	Income Level	
		Low	High
Gas-heated houses			
Income	0.115	0.139	0.012
Own price	0.20	-0.444	-0.208
Electricity-heated houses			
Income	0.131	0.177	-0.172
Own price	-0.758	-0.759	-0.684

Contrary to intuition, Nesbakken (1999), using two sets of pooled data for 1993–1995, found that the Norwegian higher-income group is more responsive to price and income changes (see Table 4). Nesbakken (1999) advances the possibility that the lower-income group is already at a low level of energy consumption and therefore cannot adjust its consumption to a price increase without discomfort.

Table 4: Price and Income Elasticities: Source Nesbakken (1999)

Elasticity	All Households	Income Level	
		Below Average	Above Average
Short-run income	0.01	0.01	0.01
Long-run income	0.20	0.18	0.22
Short-run energy price	-0.50	-0.33	-0.66

.

3.2 Designing a Residential Energy Demand Model

The objective of the exercise or study and the available data are the two key factors that determine the choice and/or design of the residential energy demand model. Some authors argue that there is no consensus on the best way to express energy demand (Poyer and Williams 1993). We argue here that it is the objectives sought, coupled with the data available, that shape the energy demand model. For example, in our case, we want to investigate the impact climate change mitigation policies will have on the demand for energy services across income groups. We therefore need to have a model that captures the demand for energy services and not the demand for fuels.

There are a number of key questions that must be answered before an energy demand model is formulated and estimated. The modeller must choose the structural form of the demand function— joint-decision models, reduced-form models, conditional-demand analysis or household production function—and its functional form—should it be linear, semi-log or a double log. The next issue to resolve is the units of analysis for the energy demand model—physical vs. thermal vs. expenditure. Prices also play a key role in determining consumer behaviour and it is important to make sure that they choose the right fuel price, whether it is the marginal or average price, as well as the price of the substitute. And last but not least, the expression of elasticities, either variable or a constant. Sections 3.2.1 to 3.2.6 look at each of these key issues, and also investigate the issue of the efficiency of the conversion technology.

3.2.1 Structural Form

We choose to consider energy models according to how energy is viewed at the household level. Demand for energy can either be considered as a final good or as an input to the household production function. In the latter case, energy can be substituted with other household goods, while in the former it is not. It is important to note that all models recognize that energy demand is a derived demand—household purchase utilities for the services they provide, not for the utilities by themselves.

Residential energy demand is determined by adding up the consumption of each equipment (space heaters, water heaters, appliances and lighting), which in turn is given by the (input) capital stock of equipment multiplied by its utilization rate. For a given household, the residential energy demand can be expressed as:

$$E_{IN,j} = \sum_k u_{k,j} A_{k,j} \tag{6}$$

Where:

$E_{IN,j}$: is the energy consumption of fuel *j* (input energy);

$u_{k,j}$: is the utilization rate of equipment *k* for fuel *j*; and

$A_{k,j}$: is the capital stock of equipment *k* that uses fuel *j*.

The double index of the utilization rate of the equipment allows for dual-fuel equipments such as electricity-oil furnaces.

Depending on how Equation (6) is solved, the energy demand model can be joint-decision models or discrete-continuous models, reduced-form models or conditional-demand analysis. Equation (6) can also be solved within the framework of the household production function.

The joint-decision models or discrete-continuous models closely reflect energy demand as a joint decision of the choice of equipment (discrete decision) and the utilization rate of the equipment (continuous decision). In that case, the energy demand model is a two-level model (Bohi and Zimmerman, 1984):

$$\begin{aligned} A_j &= g(P_j, P_s, P_k, Y, X) \\ u_j &= f(P_j, Y, Z) \end{aligned} \tag{7}$$

Where

A_j: is the demand for equipment that uses fuel *j*;

u_j: is the utilization rate of equipment for fuel *j*;

P_j, P_s: are the price of the fuel *j*, and the price of alternative fuel *s*, respectively;

P_k: is the price of equipment *k*;

Y: is the household income; and

X, Z: are other socio-economic and structural variables (e.g., equipment and dwelling characteristics).

This approach was used by Nesbakken (1999); Halvorsen and Larsen (2001); Dubin and McFadden (1984); Bernard et al. (1996); and Hausman (1979). However, this approach is data intensive and can be computer intensive as well.

Reduced-form models are also named "conditional-demand" models because energy demand is conditional on the stock of appliances and/or technologies. Reduced-form models collapse the Equation system (7) that describes the equipment stock and the utilization rate into a single equation (Bohi and Zimmerman, 1984):

$$E_{IN,j}=h(P_j,P_s,Y,X,Z,A_j) \tag{8}$$

Price of equipment is a determinant of the capital stock of equipment but not directly of energy consumption, and is therefore not included in Equation (8). Static models assume the stock of appliances is fixed. Dynamic models are built using time series, but we did not review them specifically. This approach has been widely used over the years and for a variety of fuels (Branch 1993; Wills 1981; Green et al. 1986; Micklewright 1989; Douthitt 1986 and 1989; Poyer et al. 1993 and 1997; Lee and Singh 1994; Haas and Biermayr 1997; and Leth-Peterson and Togeby 2001).

Conditional analysis unbundles the energy demand into unit energy consumption (UEC) of a given appliance or end use. It is based on "conditional-demand" models but conditional analysis does not provide price elasticities. It was introduced by Parti and Parti (1980) and used by Fiebig et al. (1991), Lafrance and Perron (1994) and Tiedemann (1997).

Energy demand can also be modelled within the framework of household production function. To enable the substitution of energy with non-energy goods, energy demand is expressed by an equation, such as a reduced-form model, within a system of equations that describes the household production function. Such models were used by Flaig 1990, Klein (1988) and Quigley (1984).

3.2.2 Energy Units

When performing energy demand analysis simultaneously on different fuels, the question of the energy units arises. Energy can either be expressed in terms of physical units (kilowatt-hours, litres, etc.), monetary units (expenditure) or thermal units (Joules or thermal equivalent units such as oil equivalent). Thermal units are based on the calorific factor of the fuel, i.e., the amount of energy released if it were burned with perfect efficiency (Turvey and Nobay 1965). Besides electricity, there is no single value for the energy content of carbon-based fuels. Furthermore, when aggregating different fuels using time series data, Bernard et al. (1987) show that the total energy consumption expressed in thermal units can decrease over time when, in reality, total energy consumption does not (when expressed in other units). Turvey and Nobay (1965) had shown a similar effect. Turvey and Nobay (1965) argued that monetary units, expressed through expenditures, should be used when aggregating fuel consumption of different types to compare market shares. As they conclude: "An economic phenomenon deserves an economic approach" (Turvey and Nobay 1965: 791).

This difficulty disappears when analyzing a single fuel. Many econometric analysis of energy demand have been carried out in physical units (Bernard et al. 1996, Branch 1993, Douthitt 1986, Halvorsen and Larsen 2001, Wills 1981). When aggregating different fuels, some authors used kWh equivalents (Dubin and McFadden 1984, Leth-Petersen and Togeby 2001), energy content (Douthitt 1986, Douthitt 1989, Poyer and Williams 1993, Poyer et al. 1997), or used monetary units (Micklewright 1989, Quigley 1984). Green constructed energy consumption by dividing expenditures by price (Green et al. 1986). Once again, the selection of units to carry an energy demand analysis is conditional on the availability of the data and the objective of the study.

3.2.3 Efficiency of Conversion Technologies

Although efficiency is one of the key factors that determine utility consumption (Douthitt 1986, 1989) as shown in Equation (1), it is seldom taken into consideration in an energy demand model.

Models in which efficiencies of the conversion technology were considered are all space heating demand models, although water heating is also conditioned by the efficiency of the water heater. Douthitt (1986, 1989) determined the demand for space heating of Canadian households. In 1986, he used a proxy for the furnace efficiency. If the furnace had been replaced or serviced in the current year, then the value of the dummy variable would be one. Otherwise, it would be zero. Haas and Biermayr (1997) developed an energy model for energy end uses of Austrian households that included the efficiency of the furnace. Because the same conversion technology not only provides space heating but also hot water, Haas and Biermayr included the efficiency value of the space heating equipment in their energy demand model for hot water. Leth-Pethersen and Togeby (2001) investigated space heating in apartment blocks of Denmark whose energy model is conditional on the energy carrier type (oil or district heating). The coefficient of the energy carrier type parameter is expressed as the sum of an average value (over all apartment buildings) and an unobserved random component that allows for specific efficiency levels of heating systems.

The efficiency of conversion technologies can lead to a rebound effect that was first identified by Khazzoom (1980). The rebound effect can be described as an increase in demand for energy services that is caused by efficiency improvement, thus reducing conservation gains (Khazzoom 1980; Haas and Biermayr 1997; and Schwarz and Taylor 1995). This effect is also called the "feedback effect" or "takeback effect." A typical example to illustrate the rebound effect is car travel demand that is usually expressed in passenger-mile. If a car's efficiency doubles, one would think that half as much fuel is necessary to meet the car travel demand, as Equation (1) shows. A parallel (and also valid) approach is to consider that you can now travel twice as far for the same cost as before which is equivalent to saying that the price of gas has halved (Khazzoom 1987). If the price elasticity in car travel is non-zero, meaning that the car owner responds to a price change, then his demand in car travel will increase. An increased efficiency can therefore increase the demand in output energy! The same logic can be applied to space heating and hot water. If the efficiency of the furnace increases, the household may increase its average indoor temperature. The household can now increase its indoor temperature without increasing its utility bill when comparing with the heating costs before changing the furnace. Schwarz and Taylor (1995) showed that improved insulation leads to higher indoor temperature setting across various climates and house sizes.

Berndt and Watkins (1986) overlooked the rebound effect in their study. They made a plea for price and income elasticities to be determined on fuel consumption (input energy) rather than on the energy load or requirement (output energy). Their main argument is that econometric analysis of input energy captures the effect of the conversion technology (and hence its efficiency), but not output energy. We show below that output energy can also capture the efficiency of the conversion technology.

Let us start with the expression of output energy written as follows:

$$E_{OUT,k,j} = u_{k,j} W_{k,j} \tag{9}$$

which is derived from comparing Equation (6) to (1). According to Berndt and Watkins (1986), the only way to capture the impact of the conversion technology efficiency is to model energy demand using input energy. Clearly, this comes from the fact that the utilization rate, as expressed by Equation (7), does not depend on efficiency. We argue otherwise. From the description of Khazzoom (1980) and results from Schwarz and Taylor (1995) already discussed above, one would rather express the utilization rate as:

$$u_{k,j} = g(P_j, Y, Z, \lambda_{k,j}) \tag{10}$$

This equation expresses the level of usage of a technology and how the efficiency of the conversion technology can influence it. In particular, the above expression permits the rebound effect. Similarly, one could also write:

$$u_{k,j} = g(P_{OUT,k,j}, Y, Z) \tag{11}$$

where the utilization rate depends on the output price. In this approach, the efficiency of the conversion technology is taken into account in the definition of the output price.

3.2.4 Average vs. Marginal Utility Prices

Authors have invariably used average or marginal utility prices in their energy demand models. Supporters of marginal and average prices have developed their own set of arguments. Standard economic theory is developed on marginal pricing and, as such, most econometric models of energy demand are based on marginal utility pricing. Marginal utility prices were used by Douthitt (1986, 1989), Hausman (1979) and Wills (1981). A small number of authors did look at marginal pricing under a multi-block tariff. Under an increasing multi-block tariff, average and marginal prices increase with increasing utility consumption. Taylor (1975) had recommended usage of marginal prices in conjunction with average prices in an energy demand model. Nordin (1976) modified Taylor's approach and showed that marginal prices should be used in conjunction with a lump sum payment before purchasing all utility units at the marginal price. Later, Barnes (1982) operationalized Nordin's approach. The procedure was applied by Douthitt (1986, 1989).

However, some authors argue that consumers facing utility bills react not to the marginal price of utilities but to their bill as a whole, and thus to the average price of the bill (Branch 1993 and Green et al. 1986). Average utility prices were used by Branch (1993), Green et al. (1986) and Nesbakken (1999). For convenient reasons, average prices substitute for marginal prices (Garcia-Cerutti 2000 and Douthitt 1989 for oil), while others used consumer or retailed price index (Baker et al. 1989 and Micklewright 1989). Green et al. (1986) used lagged average prices to avoid simultaneity and identification problems. In that case, he had already used current average prices to determine the quantity of electricity and natural gas demanded by dividing utility expenditures by average utility price.

3.2.5 Variable Price Elasticities

Most residential energy demand models are based on constant price elasticities. However, Betancourt (1981) introduced variable price elasticities in residential energy demand modelling. He investigated four models of variable elasticities, one of which was dependent on previous electricity prices, heating degree-days and cooling degree-days. Betancourt's calculation of variable price elasticity was later corrected by Donnelly and Diesendorf (1985) who demonstrated that prices need to be normalized when using a price elasticity function of lagged price. Although Donnelly and Diesendorf (1985) introduced price elasticities as a function of income, they have not tested it in their empirical example on Australian data.

Since then, variable elasticities have been used in residential energy demand by various authors. Micklewright (1989) allowed price and income elasticities to depend on "whether central heating is present and how it is powered, while the effect of income is in addition allowed to vary with housing tenure" (mortgage paid, free rent, tenant, etc.). Wills (1981) showed that price elasticity (electricity) increases with the size of owned appliance stock. Douthitt (1989) determined that consumers facing higher than average fuel prices present a greater responsiveness to price changes than consumers facing lower than average fuel prices. Poyer and Williams (1993) use the price elasticity specification as in Betancourt (1981), and showed that price elasticities vary with cooling and heating degree-days. Furthermore, they also showed that income elasticity is a function of household size.

3.2.6 Fuel Substitution

Some energy models include the price of one or many substitute fuel(s). It was not possible to do so in our model because our database is not homogeneous with respect to the availability of gas. There are some regions in Canada, especially in the eastern provinces, where natural gas is not available. This is usually circumvented by specifying an energy model for each case, one electricity demand model for regions where gas is available and one where gas is not available (Douthitt 1989).

4. Demand for Energy Services Using Frontier Analysis

The challenge we faced was to develop a methodology that could estimate price elasticities across income groups on output energy, but with only data on input energy available. Surveys track input energy, not output energy. Furthermore, the critical data for moving from input energy to output energy is through the conversion technologies and their respective efficiencies. However, these data are not reliable for two reasons. First, efficiency was surveyed for the furnace only, and second, each household reported what they thought the efficiency of their furnace was by selecting an efficiency range.

To circumvent unreliable efficiency values of furnaces and unobserved values for water heaters, we developed a methodology based on a two-step process. The first step determines the efficiency of gas furnaces and electric and gas hot water heaters using the deterministic frontier analysis described below. The second step then goes on to use a standard econometric regression exercise but using the efficiency values from the first step.

The methodology we develop here to model energy demand services has the following key features:

1) It models demand for energy services—space heating, hot water, and a combination of appliances and lighting—using a double log static reduced form.
2) It uses thermal units (Joules) because our database contains data on energy consumption, not on energy expenditures. Because we are not using time series data but cross-sectional data, the difficulty noted in the previous section does not apply to our work.
3) It explicitly considers efficiency of furnaces and water heaters.
4) It determines these efficiencies using a deterministic frontier analysis. In our energy model, the efficiency of the conversion technology is incorporated in the expression of the output energy by multiplying input energy values by the efficiency of the conversion technology, because output energy values are unobserved. By doing so, our approach is consistent considering the feedback effect of efficiency on demand for energy services.
5) It used average provincial utility prices because we cannot associate a specific pricing schedule to each household, as the exact location of each household was not public information. In some Canadian provinces, pricing schedules can vary from one region to another or from one locality to another.
6) It does not use prices of substitute energy sources because, in some provinces, the two situations co-exist, i.e., gas is available in some regions within a given province while it is not in others, and our database does not discriminate at the regional level.
7) It expresses price elasticity as a linear function of income. We will determine if different income groups show different responses to price changes.

4.1 A Frontier Analysis to Determine Efficiency

The efficiency is given by the following equation, which follows from Equation (1):

$$\ln \lambda_i^x = \ln E_{OUT,i}^x - \ln E_{IN,i}^x \tag{12}$$

The output energy is smaller than or, at the limit, equal to the input energy. Therefore, $\ln \lambda_k \leq 0$.

The efficiency is determined by minimizing the difference between the output energy and the input energy for each household *i*:

$$\begin{aligned} &\underset{\lambda_i^x, a_0, a_1, \Lambda}{\text{Min}} \sum_i \left(\ln E_{OUT,i}^x - \ln E_{IN,i}^x\right)^2 \\ &\text{subject to:} \quad \ln E_{OUT,i}^x \leq \ln E_{IN,i}^x \\ &\qquad\qquad\qquad E_{OUT,i}^x > 0 \\ &\qquad\qquad\qquad \lambda_i^x > 0 \\ &\text{defining:} \quad \ln \lambda_i^x = \ln E_{OUT,i}^x - \ln E_{IN,i}^x \end{aligned} \tag{13}$$

where output energy is given by Equations (14) and (15) and the input energy is data. A non-linear optimization program (GAMS) is used to solve the problem in which the coefficients of the output energy and the efficiency values are simultaneously estimated for a given energy service. We do not solve for the efficiency for appliances and lighting services and electric space heaters as these are assumed to be 100 per cent. Instead we only solve for efficiency of water heaters (electricity and natural gas) and natural gas space heaters.

The system is first solved for hot water. Output energy is given by Equation (15), input energy is given by the billing data (disaggregated and converted into Joules) and the price of output energy is substituted with Equation (5). Then the system is solved for space heating services substituting Equation (14) for output energy and again Equation (5) for the price of output energy, and using the corresponding billing data for input energy. In this way, we estimated the efficiency value for each household in our dataset that is needed for the second step whereby, we estimate the actual energy service demand equation.

4.2 Econometric Model of Output Energy

Our econometric model of output energy is based on a reduced-form model. The functional form we chose is the double log because it allows direct reading of price. Income elasticities have a more complex expression because price elasticities also vary according to income. For simplicity reasons, and to be consistent with the disaggregation of the billing data by energy services, the energy services related to appliances and lighting have been combined into a single energy service.

The equations below show the variables that are selected in the final model where only the statistically significant parameters are kept. We didn't include lagged prices because the simple correlation coefficient between price and its lag is found to be 0.997 (that is likely to cause a severe multicollinearity problem).

$$
\begin{aligned}
\ln E_{OUT,i}^{SH} = a_0^{SH} &+ \left(a_1^{SH} + a_3^{SH} \ln Y_i\right) \ln P_{OUT,i} \\
&+ \frac{b_1^{SH}}{1+\exp(-b_3^{SH} Y)} \\
&+ c_1^{SH} \ln HDD_i + c_2^{SH} \ln T_i \\
&+ d_1^{SH} \ln A_i + d_2^{SH} H_i^B + d_3^{SH} \ln N_i^S \\
&+ d_4^{SH} \ln N_i^{Do} + d_5^{SH} \ln N_i^{Wi} + d_6^{SH} N_i^{Sk} \\
&+ e^{SH} \ln \lambda_i^{SH} \\
&+ f_1^{SH} \ln E_{OUT,i}^{HW} + f_2^{SH} \ln E_{OUT,i}^{AL}
\end{aligned}
\tag{14}
$$

$$
\begin{aligned}
\ln E_{OUT,i}^{HW} = a_0^{HW} &+ \left(a_1^{HW} + a_3^{HW} \ln Y_i\right) \ln P_{OUT,i} \\
&+ \frac{b_1^{HW}}{1+\exp(-b_3^{HW} Y)} + b_2^{HW} \ln HHS_i \\
&+ c_1^{WH} \ln T_i \\
&+ d_1^{HW} \ln A_i + d_2^{HW} \ln N_i^S + d_3^{HW} N_i^{Dw} + d_4^{HW} N_i^{Wa} \\
&+ e_1^{HW} \ln C_i^{Tk} + e_2^{HW} N_i^A \\
&+ f^{HW} \ln \lambda_i^{HW}
\end{aligned}
\tag{15}
$$

$$
\begin{aligned}
\ln E_{OUT,i}^{AL} = a_0^{AL} &+ \left(a_1^{AL} + a_3^{AL} \ln Y_i\right) \ln P_{OUT,i} \\
&+ \frac{b_1^{AL}}{1+\exp(-b_3^{AL} Y)} + b_2^{AL} \ln HHS_i \\
&+ c_2 I_i^{HB} + c_4^{AL} N_i^{DW} + c_6^{AL} N_i^{Dr} \\
&+ d_1^{AL} I_i^{Fz} + d_2^{AL} N_i^{FF} + d_3^{AL} N_i^{NFF} \\
&+ e_1^{AL} A_i^R + e_2^{AL} I_i^{Ck} + e_3^{AL} \ln N_i^{Li} + e_4^{AL} I_i^{Ac} + e_5^{AL} I_i^{FuF}
\end{aligned}
\tag{16}
$$

where:

^{x} : indexes the energy service. *SH*: space heating, *HW*: hot water, *AL*: appliances and lighting;

$E_{OUT,i}^x$: is the output energy of energy service x for household i in Joules;

$a_j^x, \ldots, e_j^x$: are the coefficients j for the energy service x;

$P_{OUT,i}^x$: is the price of output energy that provides energy service x in the current year, t;

Y_i : is the income of household i;

HHS_i : is the household size of household i;

HDD_i : is the average heating degree-days of the province where household i is located;

T_i : is the average indoor temperature for household i;

T_i^{Gd} : is the average ground temperature of the province where household i is located;

A_i : is the floor area of house i;

B_i : is the basement area of house i;

H_i^B : is the heated basement area of house i;

I_i^{HB} : is the heated basement index of house i (1=yes; 0=no);

N_i^S : is the number of storeys in house i;

N_i^{Do} : is the number of doors in house i;

N_i^{Wi} : is the number of windows in house i;

N_i^{Sk} : is the number of sky windows in house i;

N_i^{Dw} : is the number of dishwasher loads for household i;

N_i^{Wa} : is the number of washer loads for household i;

N_i^{Dr} : is the number of dryer loads for household i;

N_i^A : is the number of aerators in house i;

I_i^{Fz} : is the freezer index for house i (1=yes; 0=no);

N_i^{FF} : is the number of frost-free refrigerators in house i (1=yes; 0=no);

N_i^{NFF} : is the number of non-frost-free refrigerators in house i (1=yes; 0=no);

A_i^R : is the age of the range in house i;

N_i^{Li} : is the number of light bulbs in house i;

I_i^{Ti} : is the hot water tank insulation index for house i (1=yes; 0=no);

I_i^{Ck} : is the cooktop index for house i (1=yes; 0=no);

I_i^{Ac} : is the air conditioning index for house i (1=yes; 0=no);

I_i^{FuF} : is the furnace fan index for house i (1=yes; 0=no); and

λ_i^x : is the efficiency of the furnace (x=SH) or of the water heater (x=WH).

The inclusion of water heating, appliances and lighting into the expression for space heating translates the heat gained through loss mechanisms from water heating, appliances and lighting. As a consequence, the expressions of output energy for hot water, appliances and lighting must be solved before the output energy for space heating can be estimated.

The price of output energy can be expressed in terms of input energy and is given by Equation (5). We obtain a system of equations that can be solved one at a time, where the equation for space heating is solved last.

4.3 Econometric Model of Input Energy

The analytical expressions for input and output energy are the same, except for the price of energy. The expressions of input energy (space heating, water heating, and appliances and lighting) are the same as given by Equations (14) to (16) where input energy is used instead of the output energy. However, the hot water consumption and the appliance and lighting consumption do not contribute to input energy, only output energy, and the corresponding parameter coefficients were set to zero.

4.4 Price and Income Elasticity

Price elasticities are computed from the formula $\partial \ln E_{OUT}^{x} / \partial \ln P_{Out}$ for x = space heating (SH), hot water (HW), and appliance and lighting (AL) in Equations (14) to (16). Price elasticities are thus simply the coefficient of the price parameter. Price elasticity is given by:

$$\varepsilon_{P,i}^{x} = a_1^x + a_3^x \ln Y_i \tag{17}$$

where $\varepsilon_{P,i}^{x}$ is the price elasticity of energy service x and for household i.

The expression of price elasticity is a linear function of income. Price elasticity is determined for each household, according to its level of income and, as a result, all households with the same income level will share the same price elasticity.

Similarly, income elasticities are computed from the formula $\partial \ln E_{OUT}^{x} / \partial \ln Y$ for x = space heating (SH), hot water (HW), and appliance and lighting (AL) in Equations (14) to (16).

5. Data

5.1 Description of the Database

The Canadian Residential Energy End-use Data and Analysis Centre (CREEDAC), based at Dalhousie University at the time of this study, provided the database on behalf of Statistics Canada. This database is a combination of four sources of data: the 1993 Survey of Household Energy Use (SHEU 1993); the Energy Statistics Handbook published by Statistics Canada; the Electric Power Statistics; and the Canadian Economic Observer (CREEDAC 1999).

The SHEU 1993, carried out by Statistics Canada, contains demographic and dwelling data on 10,982 Canadian households (CREEDAC 1999). Access to actual energy metering was granted through respondent’s permission. The other three data sources, the

Energy Statistics Handbook; Electric Power Statistics; and the Canadian Economic Observer, were used to compile provincial (average) energy prices for electricity, natural gas and oil in 1993 and 1992. Long-term heating degree-days were supplied by CREEDAC.

The database we received is a subset of the SHEU 1993. It only contained data on low-rise single family dwellings, including single detached and attached dwellings, that accepted to disclose their annual energy billing over the year 1993 and that use the same fuel for space heating and water heating (CREEDAC 1999). There are 8,767 low-rise single-family dwellings in SHEU 1993, out of which some 2,529 accepted to disclose their annual utility consumption. CREEDAC removed the following households: (1) households with incomplete energy billing, i.e., for less than 12 months; (2) households that do not use the same fuel for supplemental and main space heating when supplemental space heating is used; and (3) households that do not use the same fuel for space heating and water heating. Twenty-two oil-, 249 natural-gas- and 320 electric-heated households passed the screening process. Finally, CREEDAC removed the 22 oil-heated households because they were from the same province. That left 569 households in the sub-dataset we received.

We then applied our own screening process to remove households with missing data entries. Because the dataset was getting smaller rather rapidly, we changed the entries related to refrigerators and freezers. In the CREEDAC sub-dataset, the age and size of the first two refrigerators and the age and size of the freezer are given. These entries are not always complete and many parameters were missing. Some respondents had entered the second refrigerator without specifying the first refrigerator, or they had given the age of the freezer but not its size. Therefore, to reduce the number of household entries to be removed, we determined for each entry the number of frost-free refrigerators, non-frost-free refrigerators and freezers. The other missing parameters that resulted in discarding households were the number of doors and windows and the gross income. The final dataset we used had 440 households—188 natural-gas-heated households and 252 electricity-heated households—from seven provinces (Newfoundland, New Brunswick, Ontario, Manitoba, Saskatchewan, Alberta and British Columbia). There were no household entries from Prince Edward Island, Nova Scotia and Quebec.

The final dataset we used for our analysis has the following variables: household index; space and water heating fuel; household gross income (mid-value of a range); energy consumption for space heating in Joules (constructed from billing data); energy consumption for hot water in Joules (constructed from billing data); energy consumption for appliances and lighting in Joules (constructed from billing data); provincial average of electricity price in 1993 and 1992 ($/Joules); provincial average of natural gas price in 1993 and 1992 ($/Joules); household size; ground temperature; heating degree days; average indoor temperature during the heating season (constructed); number of storeys; heated floor area; number of doors; number of windows; number of skylights; number of frost-free refrigerators; number of non-frost-free refrigerators; number of freezers; age of stove or oven; presence of electric cooktop; presence of air conditioner (constructed); number of lights; presence of furnace fan; annual number of dryer loads (constructed);

annual number of annual dishwasher loads (constructed); annual number of annual washer loads (constructed); capacity of hot water tank; presence of hot water tank insulation and number of aerators and low-flow shower heads. It also had the efficiency of the space heating equipment (mid-value of a range).

As noted above, some of the variables in the database we received were constructed (CREEDAC 1999). The utility consumption by end-use has already been converted into their energy content using the values given in Table 2. Utility prices were also converted into prices per Joule using Table 2. Furthermore, the billing data have already been disaggregated into space heating, domestic hot water, and appliances and lighting. However, we re-did the disaggregation of the billing data for electricity-heated houses into end uses using a methodology that induced a variation in the ratio of appliances and lighting consumption to hot water consumption. This is the subject of Section 5.3. Average indoor temperature during the heating season is obtained by time-averaging the temperature setting in the daytime (6 a.m.–6 p.m.), evening (6 p.m.–10 p.m.) and night (10 p.m.–6 a.m.). In the database we received, data were given on the usage of air conditioners (number of hours). It soon became evident that these data were not correct. We therefore transformed the data into an index identifying the presence of air conditioners. Weekly number of dryer and washer loads was for summer and winter. Annual values were obtained by adding winter and summer values after having multiplied each one by 26 weeks. The weekly dishwasher loads were transformed into annual dishwasher loads by multiplying the weekly value by 52. As stated earlier, the number of frost-free and non-frost-free refrigerators was constructed from the database we received.

The SHEU93 does provide efficiency values, but only for furnaces. However, efficiency values of furnaces are not reliable because surveyed households were asked to select a range of efficiency within which they think their furnace lies. As a result, the final dataset contains no data on efficiency of furnaces and water heaters.

5.2 Disaggregation of the Utility Bill for Natural-gas-heated Houses

The disaggregation of the billing data of houses heated with natural gas was straightforward because the houses found in this category use natural gas for space heating and for hot water. The electricity bill directly corresponds to appliances and lighting. During the summer months (July and August), space heating is usually not required. As such, the average consumption of July and August provides the average consumption to supply the hot water throughout the year. Space heating is thus taken as the remainder of the natural gas bill once the yearly consumption for hot water is subtracted from it.

5.3 Disaggregation of the Utility Bill for Electricity-heated Houses

In electricity-heated houses, electricity supplies all three energy services: space heating, hot water, and appliances and lighting. While the disaggregation of the electricity bill into space heating was straightforward, it was not such a straightforward exercise to discriminate between hot water and appliances and lighting.

The determination of the consumption related to space heating follows the same approach as the one used for natural-gas-heated houses. There is no space heating during the summer months of July and August. This leaves the hot water and appliance and lighting consumptions in those months. If the household uses air conditioning during the summer months, then the "shoulder" months (June and September) are used. The consumption for hot water and appliances and lighting over the whole year is simply six times the electricity consumption for the two summer or shoulder months. Space heating is then the difference between the annual electricity bill and the yearly consumption for hot water and appliances and lighting.

$$E_{IN,i}^{AL\&HW} = 6X(household \quad electricity \quad consumption \quad of \quad summer / shoulder \quad months) \tag{18}$$

$$E_{IN,i}^{SH} = annual\ household\ electricity\ bill - E_{IN,i}^{AL\&HW} \tag{19}$$

To discriminate between hot water and appliances and lighting, CREEDAC assumed that *all* houses have the same ratio between their appliance and lighting load and their hot water load. This is a strong assumption. The detail of the method used by CREEDAC to discriminate between hot water and appliances and lighting is available in CREEDAC (1999).

We preferred to discriminate between appliance and lighting consumption and hot water consumption by using a ratio of the two derived from an engineering model, HOT 2000 (CREEDAC 2001). CREEDAC computed space heating, appliance and lighting, and hot water consumptions for all the houses found in the database using the same model. The individual values obtained are sometimes very far from observed consumption as it can be monitored on natural-gas-heated houses whereas the electricity consumption only applies to appliance and lighting. However, we believe that the ratio between the appliance and lighting consumption and hot water consumption is representative. This ratio is given by:

$$\frac{E_{IN,el,i}^{AL}}{E_{IN,el,i}^{HW}} = R_i \qquad \forall i \tag{20}$$

Knowing that:

$$E_{IN,el,i}^{AL\&HW} = E_{IN,el,i}^{AL} + E_{IN,el,i_i}^{HW} \qquad \forall i \tag{21}$$

and substituting Equation (20) into (21), we can then easily unbundle energy consumption for appliance and lighting (AL) and hot water (HW).

5.4 Determination of the Income Groups

The households are split into three income groups—lower-, middle-, and higher-income households. We use "terciles," where all income groups contain the same number of households. The range in income that defines each group is presented in Table 1. The estimated number of households in each group is 3,899,787.

The income groups were determined using the 2000 household spending survey (Statistics Canada 2001). This survey is processed in two separate datasets, one on household expenditures and the other on equipment. Statistics Canada (2001) performed the categorization of income groups based on the household equipment dataset whose reference period is December 31, 2000 while the household expenditure reference period is January 1 to December 31, 2000. It results in a slightly different number of reporting households, but the difference is considered marginal. For quintiles, Statistics Canada (2002) reported differences of less than $1,500 in income ranges.

In Table 1, we note that there is a clear difference in energy expenditure patterns among the three income groups. Energy expenditures were determined using the 2000 household equipment and spending survey (Statistics Canada 2002).

5.5 Analysis of the Database in Light of Income Groups

Some insight can be gained by looking at the database parameters by income group. Table 5 presents average values of the variables within each income group.

We note that the lower-income group uses the least energy overall (20 per cent less than the higher-income group), but has the biggest share of space heating, although they have smaller houses with the least-heated basement area, doors and windows. Furthermore, the sample seems to live in a warmer climate (in 1993) as revealed by the lower value of heating degree-days. However, that group has the highest annual average indoor temperature and faces slightly bigger energy prices because they use more electricity for space and water heating. Such a negative correlation between income and indoor temperature was also observed by Schwarz and Taylor (1995). This would be worth investigating as it raises the question if it is related to a physical explanation (older house where there is more draft) or to human behaviour.

On the other hand, the lower-income group has the smallest share of energy consumption on appliances and lighting. But this can be explained by the fact that they either don't own a dishwasher, washing machine and dryer, or they own these appliances but use them less. They may also have fewer light bulbs in their house, their range may be older and they may use air conditioners less.

The share of hot water in terms of energy consumption is about the same from one group to the other.

Table 5: Database Parameters by Income Group.

Parameter	Income Group		
	Low	Medium	High
Number of households*	150	200	90
Household size	2.5	3.3	3.5
Income	$19,000	$44,000	$82,000
Number of electricity-heated houses*	94	111	47
Number of gas-heated houses*	56	89	43
Percentage of gas-heated houses*	37%	45%	48%
Energy Consumption			
Appliances and lighting	24 GJ	31 GJ	37 GJ
Water heating	25 GJ	30 GJ	33 GJ
Space heating	70 GJ	72 GJ	79 GJ
Total	119 GJ	133 GJ	149 GJ
Percentage of appliance and lighting*	20%	23%	25%
Percentage of water heating*	21%	23%	22%
Percentage of space heating*	59%	54%	53%
Characteristics related to location of house			
Percentage of houses in eastern provinces (Ontario and Maritimes)	55%	44%	35%
Percentage of houses in the prairies	44%	52%	57%
Percentage of houses in BC	1%	4%	8%
Energy price in 1993 (SH and HW)	11.5	10.6	10.2
Electricity price in 1993 (AL)	15.7	15.4	15.1
Heating degree days	5,283 HDD	5,374 HDD	5,573 HDD
Ground temperature	6.7	6.6	6.4
Characteristics of house			
Floor area of house	100	117	134
Number of storeys	1.2	1.3	1.3
Area of heated basement	38	50	60
Number of doors	2.4	2.7	2.9
Number of windows	9.9	10.5	12.8
Number of sky windows	0	0.1	0.1
Size of hot water tank	182	186	201
Index for hot water tank insulation	0.19	0.10	0.08
Characteristics of appliances			
Number of frost-free refrigerators	0.8	1.1	1.1
Number of non-frost-free refrigerators	0.4	0.2	0.2
Index for freezer	0.8	0.9	0.8
Age of range	10.2	9.5	8.6
Index for cooktop	0.06	0.11	0.11
Index for air conditioning	0.1	0.2	0.3
Number of lights	26	38	48
Index for furnace fan	0.9	0.9	1.0
Household behaviour			
Annual average of indoor temperature	19.7	19.4	18.9
Number of washer loads per year	279	353	387
Number of dryer loads per year	209	274	339
Number of dishwasher loads per year	64	152	229

Source: CREEDAC (2001).

Note: All values are average values unless specified by *.

6. Results

The methodology we used to estimate the demand for energy services is a two-step process. First, efficiency of water heaters and furnaces for each of the 440 households is determined using the frontier analysis. Second, the demand for energy services is estimated using an econometric model. The results from these two steps are presented in Sections 6.1 and 6.2, respectively. Section 6.3 then goes on to discuss price and income elasticities for energy services and energy consumption.

6.1 Results from the Frontier Analysis: Efficiency of Furnaces and Water Heaters

In this section we report on the results from the deterministic frontier analysis model (Equation 13) that was used to calculate the efficiency of water heaters (electric and gas) and furnaces (gas).

Table 6 presents average efficiency values of water heater and furnaces for the whole dataset and by income groups. It also compares the results with typical energy efficiency values of Canadian conversion technologies as reported by CREEDAC (1997, 1999).

Table 6: Efficiency of Conversion Technologies.
* Values set by hypothesis

Conversion Technology	Income Group		
	Low	**Medium**	**High**
Water heater			
Electricity	0.91	0.89	0.86
Gas	0.29	0.30	0.30
Overall average	0.68	0.63	0.59
Other source [1] – electricity		0.83	
– gas		0.55	
Space heating			
Electricity*	1.00	1.00	1.00
Gas	0.86	0.87	0.89
Overall average	0.947	0.954	0.953
Other source [2] – gas		0.69	
*Appliances and lighting**	1.00	1.00	1.00

Note: [1]: CREEDAC 1999; [2]: CREEDAC 1997.

An interesting feature about the frontier analysis model is its ability to pick up the difference between gas- and electricity-fired water heaters. Using this model, we are able to show that electricity-fired water heaters generally have higher energy efficiency compared to gas-fired water heaters as observed by CREEDAC (1999).

Although the values of electricity-fired water heaters we obtained are of the same order of magnitude as typical electricity-fired water heaters, the values of gas-fired water heaters and gas-fired space heaters are off by 25 and 30 points, respectively. We speculate that this difference might be due to a scaling effect. Let us recall that a single energy price is given for each province, without any consideration for regional differences (Sections 4 and 5.1). Output prices are expressed in terms of input prices and efficiency values in Equations (14) or (15) for the determination of efficiency values. Therefore, input price and efficiency share the same parameter that is estimated in the regression. And, as a consequence, a relationship between input price and efficiency will result. When closely looking at average values of efficiency of water heaters and space heaters, they do show a relationship to level of gas prices, confirming the existence of the relationship between level of prices and efficiency values. This is shown in Table 7. And, in the case of gas-fired water heaters, efficiency of these is determined with those of electricity-fired water heaters that have a much larger energy price (factor 2).

Table 7: Regional Differences in Efficiency Values and Energy Prices.

Province	1993 Gas Price ($/GJ)	1993 Electricity Price ($/GJ)	Efficiency		
			Water Heater – Gas	Water Heater – Electricity	Space Heater – Gas
AB	3.4	--	0.24	n/a	0.70
SK	4.3	--	0.27	n/a	0.80
BC	5.1	12.8	0.31	0.76	0.95
MB	5.4	13.1	0.34	0.78	0.999

6.2 Estimation of Energy Services Demand

Tables 8 and 9 summarize the estimated demand for energy services for the three income groups. The results show that lower-income households use less energy service than higher-income households. The estimated demand for water heating load is quite low, compared to the appliance and lighting load and to the water heating consumption, in compliance with the low efficiency values of the water heaters.

Table 8: Estimated Demand for Energy Services (in GJ)

Group	Appliance and Lighting	Water Heating	Space Heating
Low	24	13	64
Medium	31	15	67
High	37	16	74
Average	30	15	67

Table 9: Shares of Estimated Energy Services in Output Energy

Group	Appliance and Lighting	Water Heating	Space Heating
Low	24%	14%	62%
Medium	28%	14%	58%
High	29%	13%	58%
Average	27%	14%	59%

Table 10 compares the adjusted R^2 of all regressions performed. The results indicate each of the four regressions account for less than 50 percent of the variation in energy output. A better fit would probably be obtained if we could better unbundle the three energy services—space heating, hot water, and appliances and lighting—or if some key variables, such as the number of children in a household (usually contributes to an increased demand in space heating and hot water) and the number of persons that stay in the house all day (also contributes to an increase of all house services needed) could have been included. These variables were however not available in the database we used.

Table 10: Comparison of the Adjusted R^2 of Regression Analysis on Output Energy.

Appliances and lighting	0.49
Hot water	0.41
Space heating with contribution from hot water and space heating	0.41
Space heating alone	0.40

6.2.1 Appliances and Lighting

Table 11 presents the estimates of the parameters for appliance and lighting. All coefficients of the "physical" parameters are of the correct sign. Energy consumption of appliances and lighting increases with household size, basement heated (resulting in the use of basement by household members), number of dishwasher and dryer loads, the use of a freezer, number of refrigerators, the age of the range, the use of a cooktop, the use of air conditioning, the number of lights, and the use of a furnace fan.

Table 11: Regression Results for Appliances and Lighting.

Parameter	Coefficient	Standard Error	t-statistic
Constant / Intercept	3.12	0.39	8.04
a_1 - Constant in elasticity function	-0.81	0.25	-3.27
a_3 - Ln(Income) * Ln(Output price)	0.11	0.06	2.01
b_1 - Constant in income function	1.32	0.82	1.61
b_3	-0.03	0.01	-2.74
Household size	0.04	0.01	3.10
Heated basement index	0.05	0.03	1.61
Number of dishwasher loads per year	0.20E-03	0.10E-03	1.97
Number of dryer loads per year	0.28E-03	0.95E-04	2.92
Freezer index	0.10	0.04	2.42
Number of frost=free refrigerators	0.22	0.05	4.72
Number of non-frost-free refrigerators	0.11	0.04	2.69
Age of range	0.55E-2	0.25E-2	2.18
Cooktop index	0.12	0.06	1.98
Air conditioning index	0.20	0.04	4.99
Number of light bulbs	0.51	0.10	4.85
Furnace fan index	0.13	0.06	2.16
R^2	0.49		

6.2.2 Water Heating

Table 12 presents the estimates of the parameters for water heating. All coefficients of the "physical" parameters are of the correct sign. Energy needed for water heating increases with the household size, the house temperature, the floor area (increased piping), the number of dishwasher and washer loads, the efficiency of the hot water heater and the capacity of the hot water tank. Results have shown little sensitivity to the household income in the hot water load. Households only marginally adjust their hot water load following a change in their income. This is reflected in the income elasticity of hot water energy load as it is presented in Section 6.3.1.

There are two approaches to explain the positive correlation between indoor temperature and hot water needs. First, there is usually a positive correlation between household size and indoor temperature. Elderly members and/or young children require an increased indoor temperature (Schwarz and Taylor 1995) and a greater household size can be a sign of the presence of these members. Because of the positive correlation between household size and hot water needs, and between household size and indoor temperature, the resulting correlation between indoor temperature and hot water needs is also positive. Second, we can also speculate that an increased indoor temperature is a proxy for human lpresence through the day. As a result, with an increased presence in the house during the day, hot water needs increase.

An increased efficiency leads to an increase in the hot water load. This may be caused by the rebound effect and is investigated in Section 6.3.2.

Table 12: Regression Results for Water Heating.

Parameter	Estimate	Standard Error	t-statistic
Constant	2.76	0.31	8.97
a_1 - Constant in elasticity function	-0.46	0.09	-4.94
a_3 - Ln(Income) * Ln(Output price)	0.03	0.01	2.70
Efficiency of hot water heater	0.24	0.04	6.81
Household size	0.10	0.02	6.45
House temperature	0.02	0.84E-02	2.17
Floor area	0.83E-03	0.43E-03	1.93
Number of dishwasher loads per year	0.22E-03	0.11E-03	2.11
Number of washer loads per year	0.30E-03	0.96E-04	3.15
Hot water tank capacity	0.75E-03	0.53E-03	1.41
R^2	0.41		

6.2.3 Space Heating

Table 13 presents the estimates of the parameters for space heating. Two cases were investigated: with and without the contribution of hot water and appliance and lighting to the space-heating load.

All coefficients of the "physical" parameters are of the correct sign. Energy needed for space heating increases with efficiency of the space heater (similar case to hot water heating), heating degree days (a colder climate), the indoor temperature, the number of storeys, the floor area, and the number of doors and windows. Energy needed for space heating decreases with the heated basement area (the basement usually acts as an insulator, and we can speculate that temperature of basements is maintained at a lower setting than the rest of the house, and the effect of insulation is greater than the extra energy used to heat the basement), the number of sky windows (we speculate that the better angle with respect to sun than standard windows explains the positive correlation), the hot water load, and the appliance and lighting load.

The loads of hot water and appliance and lighting do contribute to space heating through heat loss, and therefore reduces the space heating load. For example, heat is lost to the house when cooking. It is a similar process for hot water heating, lighting and other appliances.

Table 13: Regression Results for Space Heating with Contribution from Hot Water and Appliances and Lighting.

Parameter	Estimate	Standard Error	t-statistic
Constant	3.90	0.38	10.23
a_1 - Constant in elasticity function	-0.76	0.16	-4.85
a_3 - Ln(Income) * Ln(Output price)	0.11	0.04	2.93
b_1 - Constant in income function	1.19	0.52	2.28
b_3	-0.04	0.01	-3.38
Furnace efficiency	0.44	0.15	2.92
Heating degree days	0.87E-04	0.21E-04	4.09
Indoor temperature	0.02	0.82E-02	2.95
Number of storeys	0.07	0.04	1.63
Floor area	0.14E-02	0.46E-03	3.15
Heated basement area	-0.78E-03	0.33E-03	-2.37
Number of doors	0.03	0.02	1.45
Number of windows	0.02	0.39E-2	5.52
Number of sky windows	-0.06	0.05	-1.11
Contribution of hot water	-0.20	0.08	-2.39
Contribution of appliances and lighting	-0.03	0.09	-0.37
R^2	0.41		

When the contribution of hot water and appliance and lighting is overlooked, the household size becomes a statistically significant factor. Results are shown in Table 14. Parameter values and signs stay the same compared to the case where predicted values of hot water and space heating are used as regressors. Our results show that the space heating load slightly decreases with the number of persons living in the house. One would think that with an increased household size, doors would be opened more often. However, results suggest that internal heat gain from human beings contributes more to the space heating than human behaviour.

Table 14: Regression Results for Space Heating Without the Contribution from Hot Water and Appliances and Lighting.

Parameter	Estimate	Standard Error	t-statistic
Constant	3.55	0.28	12.67
a_1 - Constant in elasticity function	-0.81	0.15	-5.48
a_3 - Ln(Income) * Ln(Output price)	0.12	0.04	3.03
b_1 - Constant in income function	1.40	0.51	2.71
b_3	-0.04	0.01	-3.76
Furnace efficiency	0.48	0.15	3.27
Heating degree days	0.81E-04	0.21E-04	3.82
Indoor temperature	0.02	0.81E-02	2.42
Number of storeys	0.07	0.04	1.76
Floor area	0.11E-02	0.44E-03	2.51
Heated basement area	-0.80E-03	0.32E-03	-2.50
Number of doors	0.02	0.02	1.33
Number of windows	0.02	0.39E-2	5.24
Number of sky windows	-0.06	0.05	-1.18
Household size	-0.02	0.01	-1.91
R^2	0.40		

Once again, we observe potential rebound effect with respect to an increased efficiency of the furnace, and it will be further investigated in Section 6.3.2. Elasticity of the conversion technology is even greater for space heating than for water heating. There is thus more room to enhance space heating needs than hot water.

6.3 Results for Energy Services Demand

When using inter-country cross-sectional data, the computed elasticities are interpreted as long-term elasticities. According to Griffin (1996), elasticities estimated using cross-section data or pooled data are substantially larger and this difference is persistent, thus reflecting long-term capital stock adjustment. Such interpretation of elasticities results was used by Green et al. (1986) and Wills (1981).

Results show that responses to price and income changes vary according to income, as well as for energy services and end uses. Low-income households are more responsive to price and income changes than higher-income households. Space heating load presents the strongest distributional effect with a factor two between price elasticities of the lower and higher-income groups.

Tables 15 and 16 present price and income elasticities, calculated for each energy service and for each income group.

Table 15: Price Elasticities – Output Energy.

Group	Appliance and Lighting	Water Heating	Space Heating With HW and AL	Space Heating Without HW and AL
Low	-0.49	-0.38	-0.43	-0.47
Medium	-0.39	-0.36	-0.33	-0.37
High	-0.32	-0.34	-0.25	-0.29
Simple average*	-0.40	-0.36	-0.34	-0.38
Sample average**	-0.41	-0.36	-0.35	-0.39

* Simple average: performed over the three income groups;
**Sample average: performed over the 440 households

Not only do income groups respond differently to a price increase for a given energy service, but they respond differently for different energy services.

The low-income group always presents the greatest behavioural response to price changes for any given type of energy services, and the high-income group the smallest. This can be explained by the pattern of energy expenditures across income groups. The budget share of energy expenditures of the low-income group is four times the one of the high-income group (see Table 1). As a result, a variation in energy prices will impact the budget of low-income households more than higher-income households, and the low-income group will reasonably be more sensitive to variation in energy prices than higher-income groups.

The space heating load presents the greatest variation of price elasticities across income groups with almost a factor two between the elasticity of the low- and the high-income groups. Two factors can explain this large difference: the pattern of the space heating load and that of output energy prices across income groups. First, the low-income group presents the greatest share of the space heating needs at 62 per cent of all its energy needs, that is four points above the share of higher-income groups (see Table 9), even though the low- income group has smaller energy needs in absolute terms than other groups (see Table 8). Coupled with their budget constraint (see Table 1), the low-income group is thus more sensitive to variation of (output) energy prices. Second, Douthitt (1989) showed that price elasticities increase (in absolute terms) with the level of energy prices. The low-income group faces greater output energy prices than other groups, except in regards to hot water for which there is almost no variation (see Table 16), and the spread of energy prices is greatest for space heating with a difference of some 13 per cent in energy prices that the low- and high- income groups face. The pattern of energy prices, as suggested by Douthitt (1989), is reflected in the price elasticities we obtained.

Table 16: Output Energy Prices ($/GJ).

Group	Appliance and Lighting	Water Heating	Space Heating
Low	15.7	16.8	11.8
Medium	15.4	16.8	10.9
High	15.1	16.9	10.4
Simple average*	15.4	16.8	11.3
Sample average**	15.4	16.8	11.1

* Simple average: performed over the three income groups;
**Sample average: performed over the 440 households

Although the low-income group is more sensitive to energy prices, especially for space heating, and that its space heating need is smaller than other groups, the low-income group has room for energy-conserving behaviour as they set their indoor temperature, on average, to a higher value than other groups (see Table 5). However, results tend to indicate that lowering the indoor temperature only has a small impact on the overall space heating load of the household (see Tables 13 and 14).

By focusing on the high-income group, the spread of price elasticities for the space heating load can be explained by other means. The high-income group sets its indoor temperature to a lower value than other income groups, on average (see Table 5), and are thus more resistant to further reducing their indoor temperature. Coupled with the fact that their energy expenditures only represent a small fraction of their total expenditures, they are less sensitive to increases of energy prices.

Finally, price elasticities of the space heating load are smaller when the contribution of appliances, lighting and hot water is taken into account. In that case, variations in output energy prices, which can be due to a utility price increase or a change in the furnace efficiency, do not impact as much the household's energy needs because of the contribution of appliances, lighting and hot water to the space heating load.

Table 17: Income Elasticities – Output Energy.

Group	Appliance & Lighting	Water Heating	Space Heating With AL and HW	Space Heating Without HW and AL
Low	0.32	0.08	0.28	0.29
Medium	0.31	0.08	0.27	0.27
High	0.30	0.08	0.26	0.26
Simple Average*	0.31	0.08	0.27	0.27
Sample Average**	0.31	0.07	0.27	0.28

* Simple average: performed over the three income groups;
**Sample average: performed over the 440 households

As in the case of price elasticities, the low-income group shows the greatest response to a change in income. However, the most striking result is the fact that there is almost no variation of price elasticities across income groups and none at all in the case of water heating. Furthermore, water heating has a really small elasticity, of two orders of magnitude smaller than space heating and appliances and lighting. Patterns of water heating usage are almost insensitive to changes in income. The income elasticity is the greatest for appliances and lighting. This can be explained by a combination of behavioural (usage) and ownership (e.g., buying a dishwasher) patterns.

Comparison with other studies is not possible for output energy as we have none to compare with. However, we also estimated demands for input energy, and these results are compared with other studies. It is the subject of the next section.

6.4 Results on Input Energy and Comparison with Other Studies

Price and income elasticities were also computed on input energy. The regression has the same expression as output energy given in Equations (14) to (16). However, the hot water consumption and the appliance and lighting consumption do not contribute to input energy, and the corresponding parameter coefficients were set to zero. Regression results are presented in Tables 18 and 19. Regression results for appliances and lighting are not shown because they are exactly the same as the results obtained for output energy. This is because we used a single efficiency value (100 per cent) for all of the 440 households for that end use.

The price and income elasticities for the three end uses are given in Tables 20 and 21.

Table 18: Regression Results for Water Heating.

Parameter	Estimate	Standard Error	t-statistic
Constant	2.77	0.31	9.04
a_1 - Constant in elasticity function	-0.50	0.10	-5.18
a_3 - Ln(Income) * Ln(Output price)	0.04	0.01	3.12
Efficiency of hot water heater	-0.40	0.09	-4.16
Household size	0.10	0.02	6.42
House temperature	0.02	0.84E-02	2.24
Floor area	0.79E-03	0.43E-03	1.85
Number of dishwasher loads per year	0.22E-03	0.11E-03	2.06
Number of washer loads per year	0.30E-03	0.96E-04	3.17
Hot water tank capacity	0.69E-03	0.53E-03	1.30

Table 19: Regression Results for Space Heating Without the Contribution from Hot Water and Appliances and Lighting.

Parameter	Estimate	Standard Error	t-statistic
Constant	3.56	0.28	12.70
a_1 - Constant in elasticity function	-0.76	0.13	-5.76
a_3 - Ln(Income) * Ln(Output price)	0.11	0.03	3.06
b_1 - Constant in income function	1.22	0.45	2.69
b_3	-0.03	0.01	-3.21
Furnace efficiency	-0.15	0.17	-0.87
Household size	-0.02	0.01	-1.90
Heating degree days	0.81E-04	0.21E-04	3.83
Indoor temperature	0.02	0.81E-02	2.45
Number of storeys	0.07	0.04	1.79
Floor area	0.11E-02	0.44E-03	2.52
Heated basement area	-0.81E-03	0.32E-03	-2.50
Number of doors	0.02	0.02	1.32
Number of windows	0.02	0.39E-2	5.22
Number of sky windows	-0.06	0.05	-1.19

The regression results for hot water and appliances and lighting are almost identical to the ones obtained for output energy. But looking closely at the results, we see that the coefficient of furnace or water heater efficiency is negative, while it is positive when the regression is performed on output energy. When upgrading a furnace or water heater, households will increase their usage of hot water or their space heating load (output energy), but at the same time they will decrease their energy consumption associated to the given usage. In other words, the decrease in energy consumption will not be fully met because households tend to increase the usage of energy services. This is the rebound effect.

Price elasticities for appliance and lighting energy consumption are the same when determined for the load, simply because the efficiency is 100 per cent for each household.

For hot water and space heating consumption, price elasticities based on input energy present a greater value than the price elasticities based on output energy.

Berndt and Watkins (1986) observed the same results using Canadian time series data. An intuitive explanation is that households do not adjust as much their energy needs; these are "more" inelastic than energy consumption. Let us consider space heating. There is a minimum space heating load needed, especially for households living in cold climate, and as a result, households will not *a priori* want to reduce their indoor temperature setting. The mathematical explanation is the scaling effect: if the independent parameter is greater, then its coefficient is smaller. Prices in terms of input energy are smaller than prices in terms of output energy, when efficiency is smaller than the unit as Equation (5) shows, resulting in greater price elasticity.

Table 20: Price Elasticities – Input Energy.

Group	Appliance and Lighting	Water Heating	Space Heating Without HW and AL
Low	-0.49	-0.39	-0.51
Medium	-0.39	-0.36	-0.41
High	-0.32	-0.33	-0.34
Simple average*	-0.40	-0.36	-0.43
Sample average**	-0.41	-0.36	-0.43

* Simple average: performed over the three income groups;
**Sample average: performed over the 440 households

Income elasticities on input energy present the same features as price elasticities obtained on output energy, both in magnitude and sign.

Table 21: Income Elasticities – Input Energy.

Group	Appliance and Lighting	Water Heating	Space Heating Without HW and AL
Low	0.32	0.08	0.27
Medium	0.31	0.09	0.26
High	0.30	0.08	0.25
Simple average*	0.31	0.08	0.26
Sample average**	0.31	0.08	0.26

* Simple average: performed over the three income groups;
**Sample average: performed over the 440 households

Comparison with other studies is made using our results on input energy.

Haas and Biermayr (1997) investigated energy demand by end uses of Austrian households. They reported long-term price elasticity for space heating (-0.84) and appliances (-0.40). It is worth noting here that we decided against including lagged prices because of high degree of multicollinearity between price and lagged price (the sample correlation is 0.997). The price elasticity for appliances is of the same order of magnitude than our value. However, the price elasticity for space heating they found is much larger than ours (-0.46, on average). They also obtained income elasticities for space heating (0.12), appliance and lighting (0.14), and water heating (0.21). The differences in price and income elasticities observed between their study and ours might be explained by the fact that the differences in heating season in Austria and Canada and by differences in energy prices. They also reported a rebound effect.

Using a Quebec database, Bernard (2000) determined price and income elasticities using a two-level model. At the higher level, the total residential energy demand for Quebec is determined in Joules. At the lower level, the market share of each fuel is calculated and feeds into the higher level. Description of the model is found in Arsenault (Arsenault et al. 1995). The long-term price elasticity value they report is -0.73 (short-term value is -0.25) and their long-term income elasticity is 0.35 (short-term value is 0.13). The elasticity values Bernard (2000) estimated are larger than our values. The data we used are for a single year but are cross-sectional (seven Canadian provinces excluding Quebec), while the data used by Bernard (2000) are a time series but for a single province.

7. Policy Implications

Our results show that the three income groups respond differently to an energy policy, with the lower-income group being more responsive to changes in prices and income than other income groups. These results are in conformity with Douthitt's (1989) hypothesis that lower-income groups are more responsive to price and income changes than the higher- and middle-income groups. In particular, our results suggest that the lower-income group is more likely to change its needs for energy services and energy consumption based on a change in energy prices than any other income group. This is especially true for space heating that accounts for some 60 per cent of energy needs. However, from a climate change perspective, a price increase may not be the best policy as the group that will respond most favourably is the group that will have the least impact in terms of quantity reduction.

From a social perspective, the greater price elasticity of lower-income groups invokes the need to target the lower-income group to help it adjust to any increase in energy price. The difference of response to price and income changes leads to the fact that policy options will not have the same impact. In turn, we will look at a lump-sum payment (subsidy), a subsidy targeted at the purchase of a more efficient furnace and a subsidy targeted at utility pricing.

7.1 Subsidies

Subsidies in the form of a lump-sum payment have been used in the past to alleviate the impact of a price increase to lower-income groups. This is possible because price and income elasticities are of opposite signs. In Canada, a lump sum payment of CDN$125 was awarded to all low-income individuals or CDN$250 for low-income families by the federal government in 2000 as a result of the increase of energy prices. Low-income families were determined on the basis of the previous year's income declaration. However, all eligible households received the payment without discrimination.

7.2 Targeted Subsidies: More Efficient Furnaces

An alternative is to design subsidies targeted to the purchase of a more efficient gas furnace for lower-income groups. Our results show that lower-income groups hold less efficient furnaces (Table 6). With a subsidy for efficient furnaces, we take advantage of the rebound effect: the more efficient furnace will increase the output energy used for space heating, but still decreasing total energy consumption. With an elasticity of 0.44, the more efficient furnace contributes toward mitigating the impact of an energy price increase on the lower-income group. That way, we insure that lower-income households conserve the same level of energy needs in space heating without a major impact of their heating costs. Higher-income groups can always afford the purchase of a more efficient furnace because their purchasing power is simply greater. Policies designed to reduce energy demand might be more effective by upgrading furnaces.

Our database did not allow us to investigate energy policies targeted at dwelling insulation the same way we did for efficiency of gas furnaces. This might allow policy-makers to also help lower-income groups that use electric space heaters to cope with an energy price increase.

7.3 Targeted Subsidies: Utility Price

Direct subsidies on the utility price could also be applied. We are not suggesting a (universal) lifeline pricing scheme that does not discriminate between households as implemented in Armenia during part of 1997 (Kaiser 2000). We suggest targeting specifically the lower-income households. In universal lifeline tariffs, all households benefit from the pricing scheme, including the higher-income groups. Targeted lifeline schemes, on the other hand, focus on specific households. Such schemes have existed in the U.S., and are combined with other welfare programs (Poyer et al. 1997). Only lower-income households that use a space heating fuel whose price has increased will be compensated.

It is generally accepted that subsidies should be used on a temporary, not on a permanent basis. One could easily design an energy policy package that comprises a temporary subsidy on utility prices with a time frame implemented for the installation of more efficient gas furnaces.

7.4 Policy Relevance to India

In this section, we shall explore whether the results for Canada can be used as a guide for policy-makers in India. Let us begin by identifying the similarities and differences between the two countries with respect to energy sources and services. The main differences will be the type of energy services in demand.

In Canada, the main energy service in demand is space heating, while in India, the main energy services in demand are cooking and space heating. The next difference will be the fuel mix that is used to provide the energy services. In Canada, the main fuels are electricity and gas (some 80 per cent of residential market share) and the degree of substitutability among the various fuels is limited in the short term. In India, a variety of fuels are used including electricity, gas, kerosene, wood and charcoal. The degree of substitutability among the fuels varies and is more highly correlated with income than it is in Canada. For example, a high-income family in India would not substitute their electricity- or gas-run cooking stove for a wood or charcoal cook stove if the price of electricity or gas increases. However, the low-income groups may not have an option but to switch to cheaper alternatives if the price of electricity or gas were to increase.

The main similarity between the two countries is the behaviour of the middle- and high-income groups with respect to price changes. For example, the willingness to pay for energy services may be similar for the middle- and high-income groups in both countries. Furthermore, the penetration of appliances like refrigerators, dishwashers and hot water heaters is higher in the middle- and high-income groups in India. If this is the case, then the possibility of implementing a differentiated price system may be an option in India whereby the high-income groups pay a higher price than the middle-income groups which, in turn, pay a higher price than the low-income groups. The only drawback of this system in India is the transaction costs that may rise from implementing a differentiated pricing system. Maddock and Castaño (1991) demonstrated that a complex five-block pricing system, differentiated according to the quality of the neighbourhood, was successfully implemented in Medellin, Colombia. This is an alternative to household-targeted pricing based on the hypothesis that higher-income families do live in better neighbourhoods.

The other alternative is to increase the prices across all income groups but to then have a subsidized technology program that targets the middle- and low-income groups. The technology subsidy was shown in the Canadian case to be more progressive than a price increase and more efficient than a lump-sum payment. This result should also hold for India considering the similarities and differences discussed above.

It will be necessary for Indian policy-makers to address the energy sector in the near future. In India, electricity prices are currently highly subsidized. In 1996–97 the gap between cost and price was estimated at 21 per cent for electricity (Etienne 2000). The removal of these subsidies will impact all households, particularly low-income households. It is therefore imperative that policy-makers implement a pricing structure that is not regressive, but at the same time efficient. A combination of a price increase coupled with rebates and support for the purchase of efficient technologies directed at the poor is a step in the right direction.

8. Conclusion

Attention was given to estimating the demand for residential energy services, consistent with our future use of the MARKAL model. We developed a unique methodology based on deterministic frontier analysis to establish efficiency of furnaces and water heaters for individual households. We were then able to include these efficiencies into a standard econometric regression of the different energy services and end uses. Demand for energy services and corresponding price and income elasticities were computed for each of the 440 households in the dataset.

Our results show a clear variation in behavioural responses to changes in price and in income across the income groups and energy services. Low-income households are more responsive to price and income changes than higher-income households, and all households are more responsive to price changes than income changes, as well as for energy services and end uses. Space heating load presents the strongest distributional effect with a factor two between price elasticities of the low- and high-income groups. Results also confirmed the rebound effect with respect to efficiency of furnaces and water heaters. This effect is quite noticeable with furnace efficiency. We used the rebound effect to design a policy that could help lower-income groups cope with increases in energy prices. This study clearly demonstrates the usefulness of the frontier analysis methodology to determine price and income elasticities on output energy.

This study did not take into account regional differences in price elasticities. For one, our dataset did not cover all provinces of Canada. In a country such as Canada where we can observe large variations of heating degree days between the coldest and warmest provincial climates, one could anticipate variation in price elasticity according to climate. Households living in colder climates are anticipated to show greater price responsiveness. Regional or provincial differences can be taken into account in a linear function of the price elasticity in the same line as household income. This is left to others to show.

With the World Summit on Sustainable Development having called for improved access to reliable and affordable energy services (Johannesburg 2002), this study contributes to a better understanding of the effect of price and income elasticities on energy services. Although the study was performed on Canadian data, the methodology can be easily expanded to developing country data when available. The focus on energy services is expected to increase in the coming years and will translate into an enhanced understanding of demand for energy services as opposed to utility consumption. This study highlights the need for a better understanding of the energy sector in developing countries in terms of energy services.

8.1 Future Development in Econometric Energy Demand Modelling

Dahl (1993) recommends that extensive work be done to address current models as opposed to developing new ones. We argue that the choice of demand model depends on the dataset available and the objective sought. Benchmarking of energy demand models based on the same (dummy or real) database would be the only way to address performance of the different models in terms of the results of price and income elasticities. This has been partially performed by some authors (Donnelly and Diesendorf 1985 and Halvorsen and Larsen 2001) but never as a full-scale exercise. Benchmarking has been an ongoing activity in scientific fields and could be a way forward in energy demand modelling.

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