Modelling Energy Savings and Environmental Benefits from Energy Policies and New Technologies

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Executive Summary

Many environmental policies are aimed at encouraging the adoption of new technologies by businesses and households. Based on engineering calculations, policy-makers often assume that there will be substantial energy savings, and therefore environmental benefits, from the adoption of products such as compact florescent light bulbs, energy-efficient models of appliances, or programmable thermostats. Since these engineering calculations typically fail to take into consideration the effects of behavioural decisions made by individual economic agents, the anticipated benefits of policies designed to encourage the use of energy-efficient technologies are often not fully realized.

In order to design effective policies, it is necessary to take into account the economic incentives faced by individual agents. Doing so clearly has important policy implications in terms of the extent of the changes that would be required to meet the energy or greenhouse gas reduction targets that might be specified under national policies or international treaties. In addition, in some cases it may mean that the policy may have to be specified in a different way, or with added dimensions, in order to meet its stated objectives. In this paper this problem is explained and illustrated through an examination of how microeconomic modelling approaches can be used to help evaluate the expected outcomes of policies once economic incentives are taken into consideration.

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1. Introduction

Technological change, especially when it involves improvements in energy efficiency, is often viewed as a harbinger of good news as far as efforts to improve environmental quality are concerned. This view underlies many policy initiatives that target the adoption of new technologies in the residential, commercial/industrial and transportation sectors. For example, as part of their overall plan to reduce primary energy consumption by 20 per cent, the top two priorities of the Action Plan for Energy Efficiency of the Commission of the European Communities, focus on (i) labeling and minimum energy performance standards for a variety of appliances ranging from boilers, water heaters, televisions, street lighting and appliances; and (ii) requirements for energy performance standards in new and renovated buildings (Commission of European Communities, 2006).

In this paper we discuss several issues related to the evaluation of the potential effectiveness of policies that focus on the adoption of new technologies. Although we draw primarily on examples from the residential sector, the general arguments and approaches apply to all sectors.

The initial evaluation of the potential for a new technology (such as compact fluorescent light bulbs, energy-efficient household appliances, or programmable thermostats, for example) to save energy, and thereby put fewer stressors on the environment, is generally based primarily on engineering calculations. These engineering calculations often provide an upper limit on the potential benefits from widespread adoption of these technologies. In practice, however, these upper limits are unlikely to be reached. This is due to the fact that behavioural decisions made by individual economic agents ultimately determine how and when these new technologies are used.

In order to design policies and evaluate their effectiveness, it is therefore necessary to take into account the economic incentives faced by individual agents. The purpose of this paper is to examine how (empirical) microeconomic modeling approaches can be used to help evaluate the expected outcomes of policies targeting the widespread adoption of new technologies as a means of reducing energy demand and/or improving environmental quality.

The structure of the remainder of this paper is as follows. In Section 2 we examine various ways in which expected energy savings from new technologies might be calculated from a mainly engineering perspective. Section 3 presents latent variable and hazard model approaches to modeling the adoption of new technologies by consumers. This is followed, in Section 4, with an examination of issues pertaining to gauging the extent of aggregate energy savings and environmental benefits that can be expected from the adoption of new technologies. These issues include rebound effects, synergies, and the roles of price and income. Section 5 concludes with an overview of the strengths and weaknesses of the various approaches to calculating expected energy and environmental benefits from the introduction of new technologies into the market place.

2. 'Engineering-based' approaches to evaluating new technologies

A common starting point for the evaluation of the energy-saving potential of a new technology is to consider the savings that would accrue if the technology were to be adopted and used with the same intensity as the technology that it replaces. For example, consider the case of a household that decides to purchase a new more efficient clothes washer. High-efficiency washing machines use almost 50 per cent less energy and 40 per cent less water than standard models. These represent the energy and water savings that would be realized in the case where behaviour remains constant before and after the purchase of a high-efficiency model. However, if the demand for clean clothes changes, the full potential energy and water savings will not be realized. A study of 98 households by Davis (2008), indicates that the demand for clean clothes increased by 5.6 per cent after the acquisition of a high-efficiency washer. Most, but not all of this increase came through an increase in the average load size. In this particular case, an engineering based evaluation may be reasonably accurate. However, this will not necessarily be the case for all technologies. Additional examples are discussed in Sorrell and Dimitropoulos (2008).

In situations where consumers have an option of whether or not to adopt a new technology, engineering information on energy use characteristics is combined with energy price estimates and capital costs or cost differentials in order to determine whether or not it makes economic sense for the technology to be purchased by the typical consumer. If the technology is economically viable, then the energy use characteristics of the new technology are used to forecast the impacts of widespread adoption on energy demand and the environment.

2.1 The life cycle cost approach

One commonly used approach that is used to determine whether or not consumers will purchase a new technology is to calculate the Life-Cycle Costs (LCC) associated with installing and using the new appliance or product. The general formula for the LCC associated with the purchase of any given product model "j" with an expected lifetime T_j, where the household faces a discount rate of r, is given by:

$$LCC_j = (Purchase\ and\ Installation\ Costs)_j + \sum_{t=0}^{T_j} \frac{(Operating\ Costs)_{jt}}{(1+r)^t}.$$

The LCC associated with a new technology is comprised of two components. There are the fixed costs related to the purchase and installation of the technology and the variable costs associated with its operation. Purchase and installation costs will vary widely across applications. For example, if a household opts to switch to the use of compact fluorescent light bulbs, this requires much smaller financial and time commitments than those associated with the replacement of an old low-efficiency furnace with a new high-efficiency model.[1]

Unlike purchase and installation costs, operating costs accrue over time. These costs will depend on a variety of factors. The most obvious factor is the cost of the energy used in the operation of the appliance or product. Expected energy costs are calculated based on the engineering specifications of the product (i.e., how much energy is used in its 'typical' operation) and the expected prices of energy. In the case where the new technology is replacing an older technology that provides the same type of services (such as light or heat or refrigeration, for example), it is generally assumed that these variable costs can be calculated based on the same intensity of use that was typical for the previous technology. A typical LCC evaluation for a high-efficiency furnace, for example, will apply forecasted electricity and natural gas prices over the expected lifetime of the furnace, assuming that the thermostat is set at the same temperature regardless of the efficiency of the furnace, in order to calculate the (expected)

[1] In North America, the term furnace, when used in a household context, refers to a central device used for heating homes. In the U.K. a similar appliance would generally be referred to as a boiler or heater.

present value of the operating costs. Thus, all savings result from the (present value of the) reduced energy use (electricity, natural gas, etc.) by the new furnace relative to its previous counterpart, less the difference in capital costs. Similarly, a typical LCC calculation for fluorescent light ballasts will assume that the lights will be operated for the same number of hours per year as when magnetic ballasts were used.

Real-world decisions, however are often more complicated. Some households will replace a furnace due to the fact that the current furnace breaks down. If the breakdown occurs during a period of inclement weather and the furnace needs to be replaced immediately, a household will not likely be able to search across various models and make a perfectly informed decision regarding which model performs best according to LCC criteria. Even the worst new model on the market will likely use less energy than the furnace that is being replaced. That is, regardless of the new model selected, energy savings will be achieved if temperature settings remain the same. Other households may replace a currently working furnace with a new more energy efficient model. These households will be better able to search over competing models.

Other operating costs that may be relevant for a particular technology include those associated with maintenance and repair and with any 'hands-on' time required when using the product. Once all of the purchase, installation and operating costs have been accounted for, and an appropriate discount rate has been selected, the LCC for the new technology can be compared to those for other options. If competing technologies have different lifetimes and different replacement costs, these features must be taken into consideration in the calculation of LCC values for these different technologies.

Table 1 provides an example of LCC analysis that was undertaken by Natural Resources Canada (NRCan) to examine the potential benefits of switching from magnetic to electronic ballasts for fluorescent lighting in Canada (Canada, 2003). The final column contains the differences in the LCC for the two technologies under their base case scenario of a 7 per cent discount rate, average Canadian electricity prices (measured in constant 2001 dollars) and an expected lifetime for ballasts of 50,000 hours. Other assumptions in the calculations include (i) ballasts are used for 3,600 hours per year in commercial establishments and 4,000 hours per year in industrial establishments; (ii) a heating/cooling factor of 0.78 which is applied to the net gains due to the fact that a change in ballast type will have an impact on HVAC requirements given the differences in waste heat across the two technologies; (iii) a useful life of fluorescent lamps that depends on the model used (19,000 hours for F40T12 lamps and 11,000 hours for F96T12 and F96T12HO lamps); (iv) specific differences in energy usage characteristics across ballasts designed for inputs of 120 versus 347 volts.

Table 1: LCC Analysis of Switch to Electronic from Magnetic Ballasts in Canada

Ballast for the Operation of:	Voltage	Annual Energy Savings (kWh/year/unit)	Net Present Value of Benefits ($ 2001)
1 x F40T12 lamp (4 ft; 1.5inch diameter)	120V 347V	39 28	13.74 –6.67
2 x F40T12 lamps (4 ft; 1.5inch diameter)	120V 347V	44 35	14.81 9.50
2 x F96T12 lamps (8 ft; 1.5inch diameter)	120V 347V	49 49	7.96 -0.04
2 x F96T12HO lamps (8 ft; 1.5inch diameter)	120V 347V	119 119	24.23 10.23

Source: Canada (2003)

From Table 1 we see that in most applications considered, the differences in the LCC values for the two technologies indicate that there are net financial savings to be achieved from a switch from magnetic to electronic light ballasts. For all applications using 120V inputs, the LCC cost for the electronic ballasts are lower than for the magnetic ballasts. For the case of 347V inputs, the electronic ballasts have a lower or virtually identical LCC for three of the four situations considered. While these results would seem to suggest that in most applications a switch from a magnetic ballast to an electronic ballast is an obvious decision to make, before reaching such a conclusion it is necessary to take into account the extent to which the assumptions that underlie these calculations are likely to hold. We discuss how this uncertainty might be dealt with in a subsequent subsection.

2.2 Payback period

When making a selection among available technologies, the additional costs associated with the purchase of a more energy-efficient product must be weighed against the associated savings in energy costs. In many instances the incremental capital costs are substantial when compared to the short-term energy savings. The Payback Period is a measure of the length of time until the purchaser of the technology recoups the initial investment. It is measured as the ratio of the incremental capital cost to the annual energy savings. As is the case for computing the LCC, the calculation of energy savings to determine the Payback Period relies on engineering information on energy-usage characteristics of the product, predictions of future energy prices, and an assumption that the new technology will be used with the same intensity as the one that it is replacing. Implicit in both the LCC and Payback Period calculations, as typically performed, is the assumption that all technologies are equally reliable and have similar repair costs in the case of a malfunction.

2.3 Dealing with uncertainty in LCC calculations

When evaluating a specific new technology, values must be specified for a variety of key variables such as energy prices, discount rates, and the expected lifetime of the product. None of these values are known with certainty. Furthermore, some key variables may vary across regions and individuals. In many jurisdictions, energy prices vary across regions, while expected lifetimes of some products, such as heating and air-conditioning equipment, may be affected by local climatic conditions. Discount rates are known to vary widely across individual consumers.

This uncertainty plays a greater role in LCC calculations than it does in Payback Period calculations. Payback Period calculations are used to determine the amount of time required for the initial purchase and installation costs to be offset by the energy savings from a new technology. Since Payback Period calculations do not require the analyst to specify a discount rate or the expected lifetime of the product, fewer 'key variables' are used in these calculations. Furthermore, forecasts of future energy prices do not have to be extended as far into the future for Payback Period calculations. Given that uncertainty plays a much larger role in the case of

LCC calculations, we will limit our discussion to methods of dealing with uncertainty in LCC analysis.

Uncertainty with respect to key variables can be dealt with in a rudimentary way by checking for robustness of LCC results as the values of forecasted prices, discount rates and appliance lifetimes are altered. This can be done via discrete sensitivity analysis where one key variable is changed at a time or via scenario analysis where more than one key variable changes across the cases considered (Brent, 1996; Campbell and Brown, 2003). If the LCC for a new energy-efficient technology is lower than that for alternative technologies over what is considered to be a reasonable range of values for prices, discount rates and expected lifetimes, then the new technology would be considered to be economically viable. Two drawbacks to these methodologies are (i) only a limited set of combinations of key variables can feasibly be considered through the specification of discrete scenarios; and (ii) if the new technology has a lower LCC in some scenarios and a higher LCC in others, then the evaluation of the technology in terms of its economic viability becomes somewhat problematic.

One way to deal with both the limited scope of scenarios that can be considered and the problem of potentially uncertain outcomes that may result from a standard scenario analysis framework is to frame the problem in such a way so that an unfavourable outcome in a relatively 'likely' scenario is weighted differently from an unfavourable outcome in a relatively 'unlikely' scenario. This can be done by assigning (subjective) probability distributions to the sample spaces of key variables in order to perform continuous sensitivity analysis. This approach results in a probability distribution for LCC values, allowing for a more precise measurement of the risks associated with the introduction of new technologies.

Software such as Crystal Ball (an add-on to Microsoft Excel) can be used to perform continuous sensitivity analysis.[2] Specifications regarding the distributions of the key variables and their correlations are used as an input into Monte Carlo simulations that are used in turn to generate probability distributions for the LCC associated with a particular technology. Some recent examples of continuous sensitivity analysis can be found in applications from Canada and

[2] See documentation at http://www.crystalball.com/support/documentation/CB7%20User%20Manual.pdf.

the US (US Department of Energy (USDOE) 2000a, 2007; Lockerbie and Ryan, 2005). The USDOE studies use continuous sensitivity analysis in their assessment of water heater technologies and more recently in their LCC evaluations of dishwashers, dehumidifiers, cooktops, ovens, microwave ovens and commercial clothes washers. In a Canadian context, this approach has been used to examine the minimum efficiency performance standards associated with fluorescent light ballasts (Lockerbie and Ryan, 2005).

Table 2 provides information on one set of distributions considered by Lockerbie and Ryan (2005) for the case of a switch from a magnetic to an electronic fluorescent light ballast using 2 x F96T12 lamps and an input of 120 volts. These distributions are applied to a variety of pricing assumptions based on differences in electricity prices across regions in Canada. Summary statistics for this continuous sensitivity analysis are provided in Table 3 for Canada as a whole as well as for two of its provinces. The results illustrate the impact of changes in the values of key parameters on the results of LCC analysis. The results show that whether or not it will make economic sense for individuals to adopt a new technology can be very sensitive to the underlying assumptions regarding key parameters. In this particular case, while the sensitivity analysis indicates that the NPV is always positive in regions with high electricity prices, in areas of the country facing lower electricity prices, there is a good chance that the NPV for the switch from magnetic to electronic light ballasts will be negative.

Table 2: Specifications for Continuous Sensitivity Analysis for Fluorescent Light Ballasts

Assumption	Distribution	Parameters
Discount Rate	Triangular	min=5%; max=10%; most likely=7%
Annual Usage	Normal	mean=3,600; std dev=360
Life of Ballast	Normal	mean=50,000; std dev=5,000
Lamp Life	Normal	mean=11,000; std dev=550

Table 3: Summary NPV Results Using Assumptions in Table 2

Summary Statistic	Average Prices (Canada)	High Prices (Saskatchewan)	Low Prices (Manitoba)
Mean NPV	$6.29	$12.78	-$1.10
Minimum NPV	-$2.43	$1.90	-$7.37
Maximum NPV	$15.94	$24.80	$5.83
Standard Deviation NPV	$2.53	$3.16	$1.82
% of NPV values > 0	99.6%	100.0%	26.44%

2.4 Aggregate energy savings from new technologies

LCC and/or Payback Period calculations are often used as building blocks in aggregate models of energy demand in order to determine whether or not new technologies are expected to achieve widespread adoption given current and expected prices, and if so, the implications for aggregate energy use and environmental impacts. The LCC or Payback Period calculations provide useful information for the prediction of market shares for new technologies. If these calculations indicate that there are significant economic benefits to switching technologies, then these results can be combined with information on how often individuals replace various sorts of technologies in order to forecast how quickly technologies will enter into widespread use. Once these market shares have been predicted, future energy consumption predictions are made. These energy consumption predictions are also based on engineering figures. Although the details of the aggregate modeling process are beyond the scope of this paper, LCC calculations form a portion of the underlying basis for analyzing the impacts of new technologies on energy use in a variety of studies.

As a simplified example, consider the estimation of future aggregate residential energy demand due to the use of a particular appliance, such as a dishwasher. As new households purchase energy-efficient models and other households replace older models that break down with the new models, the 'vintage' mix of dishwashers shifts over time. Given a 'typical' intensity of use for the appliance, the portion of aggregate energy demand attributable to any given appliance type 'k', such as dishwashers, where there are j=1,…, J models/vintages of dishwashers in use at any point in time, can be calculated as:

$$TEU_{kt} = \sum_{j=1}^{J} EPU_{kj} \cdot UNIT_{kjt}$$

where TEU_{kt} = Total Energy Use Attributable to Appliance k at time t

EPU_{kj} = Energy Use per unit of models of Appliance k of vintage j

$UNIT_{kjt}$ = Number of units of vintage j of Appliance k in use at time t

Detailed explanations of how these aggregate models are structured can be found in various publications such as Interlaboratory Working Group (2000) and USDOE (2007).

2.5 Other issues

In practice, LCC calculations tend to ignore all costs except for the purchase price and the energy costs associated with the 'typical' operation of a product. This can have implications for the analysis of the energy-use impacts of technologies. If the omitted portions of the installation and operating costs differ across technologies, relative LCC figures will be distorted. In such cases, results that indicate that a new technology will (will not) be widely adopted may be misleading.

Several other uncertainties beyond the 'key variables' considered in discrete and continuous sensitivity analysis, as well as many real-world complications, are not dealt with in basic engineering approaches that are used to evaluate the energy-savings potential of new technologies. Although sensitivity analysis may be used to check for robustness across prices, discount rates and expected lifetimes, there are other sources of uncertainty that remain uncaptured by these approaches. These include expected product reliability (in terms of frequency and complexity of repairs, for example) and the possibility that a new energy-efficient technology will quickly become obsolete. For example, in many countries there is currently a push for consumers to replace incandescent light bulbs with compact fluorescent lamps (CFLs). Although the capital cost of a CFL is considerably greater than for an incandescent bulb, industry and government studies have shown that this will be more than offset by the energy savings over the life of the CFL (which greatly exceeds the life of an incandescent bulb). Meanwhile, the next expected change in light bulb technology appears to be to Light Emitting Diodes (LEDs). For example, one project being conducted under the California Energy Commission's Public Interest

Energy Research (PIER) Program entitled *Lighting California's Future* is working towards creating commercially viable LED 'downlighting' systems in a residential (kitchen lighting) context (Graeber, 2007). However, it may be expected that consumers who have recently switched to CFLs will be reluctant to change again to LEDs, especially if they have stockpiled CFLs (which have a longer life than incandescent bulbs anyway). Alternatively, consumers who are aware that LEDs are more efficient than CFLs and are expected to be available soon, may be reluctant to embrace the CFL technology if they have a reasonable expectation that it will soon be obsolete.

Perceptions of reliability also matter when making a capital investment in a new technology. The more risk adverse agents are, the less likely they will be to invest in a technology that does not yet have a track record of proven reliability. Risk adverse agents may be willing to trade off the higher energy costs of an older technology that has proven to be reliable against the expected costs (based on their subjective assessment) associated with break-downs of a newer technology. For example, unlike older models, newer high efficiency furnaces have integrated ignition control systems for their electronic ignition systems. Extra components found on the high efficiency models, such as the control board, increase the number of possible parts that can fail on the furnace, providing additional perceived risk for some agents, especially when many of these components are very expensive. These perceived risks are likely to be higher when the technology is relatively new, possibly leading purchasers to view the lifetime of the furnace as being closer to the warranty period than to the stated furnace specifications. Such views would be likely to materially affect LCC and payback period calculations, and may translate into a reluctance to embrace new technologies. As mentioned above in the context of CFLs, another risk facing agents is that a new technology that they invest in may become obsolete. Given observed advances in technologies, some agents may delay investing in a more efficient product in the hope that something even better may come along.

Other factors that may come into play include increased complexity of use (for programmable thermostats, for example) and differences in non-tangibles (such as harsher light from CFL bulbs). For large appliances, the costs of installation (which may vary according to the complexity of the technology embodied in the appliance) as well as disposal of the current appliance will also be included into any calculation of the benefits and costs of changing technologies.

Even if all costs could be accurately captured, engineering-based calculations will never be able to properly capture either the true differences in LCC or Payback Periods across technologies. This is because individuals respond to prices and other aspects of the economic environment not only by deciding whether or not to purchase energy-efficient technologies but also by determining the intensity of use of appliances and products. As a household's energy bill falls after installing a more efficient furnace or air-conditioner, the household may use the extra disposable income that results in order to increase 'thermal comfort'. A high-income household may decide to purchase a new energy-efficient refrigerator and continue to use an older less efficient refrigerator as a 'beer fridge'. A low-income household may decide to repair an older energy-inefficient washing machine, while a high-income household in the same circumstances may elect to purchase a new energy-efficient model. Furthermore, the combination of technologies that is used matters. The installation of a programmable thermostat that does not function properly with a high-efficiency furnace, for example, will not lead to any energy savings for a household. In the next section we examine ways in which decisions to replace/purchase new technologies can be modeled.

3. Modeling the adoption of new technologies by consumers

Whether or not an individual agent will adopt a particular new technology depends on a variety of factors. Among these factors are the expected remaining life of the currently installed technology, replacement costs, expected energy cost savings, perceived risks with respect to reliability and repair costs, and the speed at which technology is evolving. At one end of the spectrum, there are energy-efficient alternatives, such as CFL bulbs, for which the required financial outlay is relatively small and the technology that is being replaced (incandescent bulbs) does not represent a significant previous investment. Furthermore, a consumer can easily assess the reliability of the technology and the desirability of using it on a widespread basis by trying it out (for example by using one or two CFL bulbs) before switching technologies completely.

At the other end of the spectrum there are technologies that are costly to evaluate and install. A new furnace, for example, requires an initial time investment in order to obtain information about which available models and features may be appropriate for any particular building. Price information is relatively difficult to obtain, as typically quotes must be gathered via visits from representatives of specialized firms that do not have retail outlets. Installation is costly in terms of time and inconvenience. And there may be uncertainty as to whether or not other related pieces of equipment (such as programmable thermostats) will function properly with a particular new model. Some households may replace a furnace that is still functioning properly due to the perceived energy savings that can be obtained. However, given the initial investment cost of the currently used model, many households will wait until the useful life of the current appliance is deemed to be over.

A particular household's assessment of the desirability of adopting a new technology will likely depend on a variety of socioeconomic factors. Standard demand theory predicts that as household income increases and access to credit markets improves, earlier adoption of relatively expensive energy-savings technologies such as new furnaces becomes more likely. The demand for energy-saving technologies is also expected to be inversely related to the purchase price of the technology and positively related to the prices of the required energy inputs such as electricity and/or natural gas. As family size increases, the demand for services such as refrigeration, clean clothes and lighting are likely to increase. With more people in a household and more intensive use of technologies there will likely be an increase in the number of lighting fixtures in use at any given time, for example. Furthermore, appliances may break down earlier and therefore require earlier replacement. In summary, household income, prices, family size and composition and other factors, including building characteristics, are liable to affect the decision regarding whether (and when) to adopt a new technology. An understanding of the how these factors play into the decision-making process, both qualitatively and quantitatively, can be useful to policy makers who are interested in increasing the uptake of these technologies.

An understanding of these factors is useful for aggregate models of residential energy consumption that rely on estimates of the rate at which technology will be adopted. Given that initial LCC or Payback Period analyses indicate that new technologies are economically viable, assumptions about the rates at which such technologies can be expected to be adopted are often based on (i) 'survival' or 'retirement' curves that are used to model how quickly or slowly households tend to replace old technologies with new ones; and/or (ii) latent variable models of the technology replacement decisions made by households. In this section we will examine ways in which detailed microeconomic data can be used to examine the issue of appliance replacement, with a focus on the potential impacts of household socioeconomic characteristics on the decision to retire an old appliance and replace it with a newer more energy-efficient model.

3.1 Appliance retirement and hazard models

In analyzing appliance purchase decisions, it is useful to distinguish between 'new' households that are purchasing a particular appliance for the first time, and 'existing' households, that is, those households that already have an existing model of the appliance in question, although possibly one that does not embody recent technological or energy efficiency improvements that are incorporated in new models. Whereas 'new' households have a relatively straightforward choice regarding which products to purchase, the decisions made by 'existing' households are more complex. The former group can simply look at LCC or Payback Periods, for example, when selecting among technologies, and though these calculations will vary across households because of differences in key variables such as price expectations, discount rates, and even credit constraints, their decision is a relatively simple – select the technology with the most favourable LCC or Payback Period. For 'existing' households, the decision is more complex since they must also decide 'when/if' to purchase a new appliance to replace the one already in use.

Appliance retirement rates (the proportion of the current stock of appliances in the economy that will be replaced by new appliances) can be estimated somewhat crudely on the basis of information on aggregate appliance shipments and available information on expected product lifetimes.[3] While calculations of this type provide a rough estimate of *what* is happening in terms of appliance replacement, they do not provide any information about *why* it is

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[3] For detailed information on how shipment information can be used to estimate rates of replacement of appliances in the residential sector see, for example, USDOE (2007).

happening, and therefore whether this rate might be expected to persist, or how it might be influenced by various socioeconomic factors. This can have important implications for assessing the rate and extent to which new technology will be dispersed, and energy efficiencies realized. For example, suppose that shipment and product lifetime information suggests that 20 per cent of a particular type of appliance is replaced each year. This might be viewed as indicating that a new model embodying energy-efficiency characteristics would completely replace the stock of existing models within 5 years. However, a household's decision to replace (or retire) existing appliances depends on income as well as a variety of other socio-economic factors, and ignoring this information is likely to result in completely unreliable estimates. To incorporate the effects of these and other factors, a different type of approach is needed.

Hazard models, also referred to as 'duration' or 'survival' models, can be useful for exploring how factors such as income and household size affect the decision of when to replace an appliance. In these models, the length of time a piece of equipment (such as an appliance or a furnace) is kept by a household, which in most cases also represents the length of time that will elapse before any new technology may potentially be adopted by that household, can be modeled as a function of the household's socioeconomic characteristics. These hazard models obviously have greater data requirements than the method described earlier. Specifically, in addition to information on the socioeconomic characteristics of households, detailed individual household-level data is also required on (i) the length of ownership of previous appliances that have been replaced, and (ii) the length of ownership of appliances that are still in use. Applications of hazard models to household survey data include examinations of replacement of space heating and central air-conditioning units in the US (Fernandez, 2001) and for a variety of household appliances in Canada (Young, 2008a).

The basic set-up of these models is quite straightforward. The length of time that an appliance is used by a household before it is 'retired', denoted as t, is considered to be a random variable with a corresponding 'survival function', $S(t)$. This survival function defines the probability that an appliance will be used for *at least t years* before it is retired (either due to failure or to a decision by a household to 'retire' a still-functioning appliance). Generally, the survival function is expressed in terms of a cumulative distribution function (CDF) for t, denoted

F(*t*). By definition, *F*(*t*) indicates the probability that the appliance will be retired *before time t*. Since an appliance can only be used for *at least t years* if it was not retired *before time t*, it must be the case that: $S(t) = 1\text{-}F(t)$.

These models can also be expressed in terms of what are referred to as the hazard rates. The 'hazard rate' provides a measure of the likelihood that an appliance will be retired at age *t*, given that it has survived to an age of at least *t*. The hazard rate, $h(t)$, is defined as $f(t)/(1\text{-}F(t))$, where $f(t)$ is the probability density function (PDF) corresponding to $F(t)$. Given the relationship between $S(t)$, $f(t)$, $F(t)$, and $h(t)$, the specification of any one of these functions is sufficient. The choice is often made based on the desired shape of the hazard function.

Studies based on household level data in the US and Canada indicate that, for most appliances, empirical hazard functions are upward sloping, or exhibit positive duration dependence (Fernandez 2001, Young 2008a)[4]. That is, conditional on having 'survived' up to age t, the likelihood that an appliance will be retired at age t, increases with t. In these instances, a 'Weibull' specification can be used since it always generates a hazard function that changes monotonically with t (Greene, 2008). Occasionally, empirical hazards for appliances have other shapes. Such is the case for dishwashers in Canada, for example, where the empirical hazard is hill-shaped. In these cases, a log-normal or a log-logistic specification will be more appropriate, since their hazard functions are hill-shaped. Figures 1 and 2 depict the empirical hazards for dishwashers and clothes washers for Canada based on the 2003 Survey of Household Energy Use (SHEU03).

Mathematically, the Weibull, log-normal and log-logisitic specifications are most compactly expressed in terms of their survival functions (Greene, 2008):

Weibull: $S(t) = \exp[(-\lambda t)^p]$;

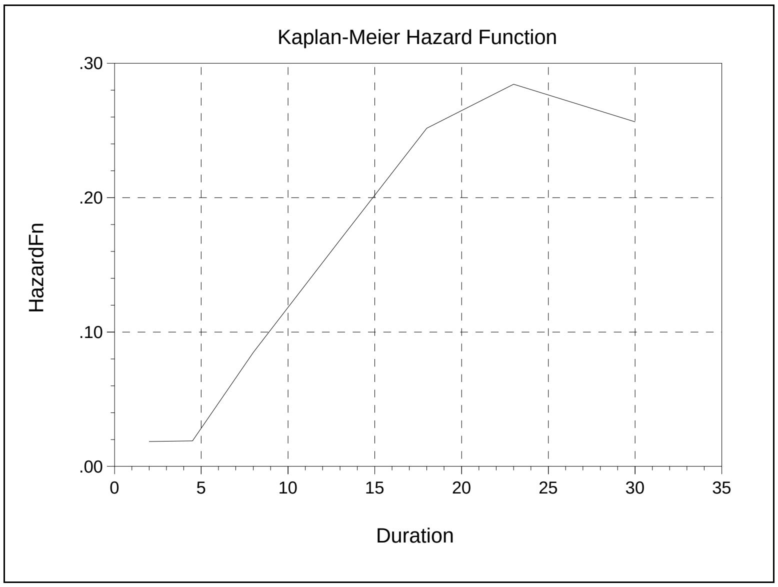
log-normal: $S(t) = \Phi[-p\ln(\lambda t)]$ where Φ represents the standard normal CDF ;

log-logistic: $S(t) = 1/[1+ (\lambda t)^p]$.

[4] An empirical hazard is based on 'actuarial' Life Tables constructed from the data and does not include the impacts of any socioeconomic factors. See, for example, Greene (2002).

For any of these specifications, the survival function depends on two basic parameters. One is a scale parameter (p) and the other is a location parameter (λ). The impacts of household characteristics are introduced by allowing the location parameter for household i, λ_i, to be a function of a vector of characteristics corresponding to that household (x_i): $\lambda_i = \exp[-x_i'\beta]$.[5]

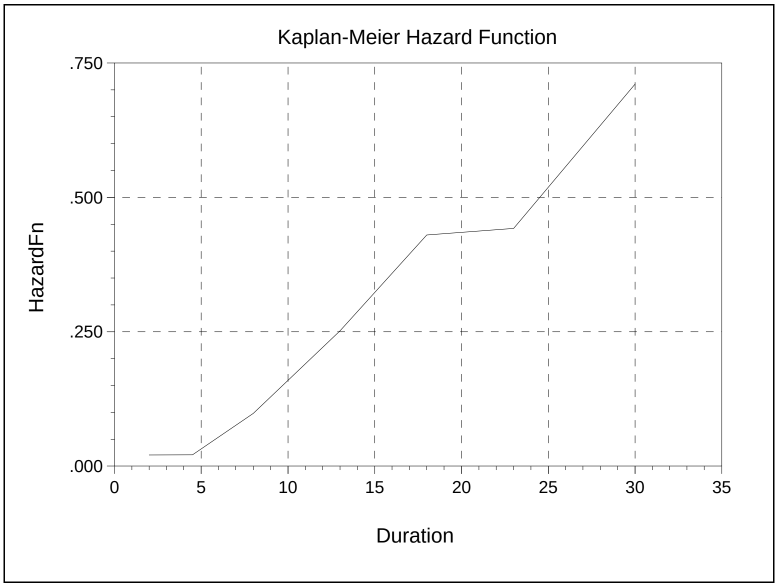
Figure 1: Empirical (Kaplan-Meier) Hazard Function for Dishwashers



Source: Young (2008a)

[5] Given that the socioeconomic characteristics enter into the model via the location parameter, the effects of individual characteristics on the expected length of time that an appliance will remain in use are not given directly by the parameters (β). Rather, as shown by Greene (2008), for a Weibull hazard $E[t \mid x_i] = \exp(x_i'\beta)\,\Gamma[(1/p)+1]$, where $\Gamma[.]$ is the gamma function. For a log-logistic or log-normal hazard $E[\ln(t) \mid x_i] = x_i'\beta$ E[ln(t) | x_i] = x_i'β.

Figure 2: Empirical (Kaplan-Meier) Hazard Function for Clothes Washers



Source: Young (2008a)

Results from Canadian household level data examined in Young (2008a) indicate that the impact of various socioeconomic factors on appliance replacement varies across appliance types. While household size (and often the number of children in the household), which might be expected to affect the intensity of use for certain appliances, matters for most appliances considered (freezers, dishwashers, clothes washers and clothes dryers), the only appliance that had replacement rates which were income-sensitive were clothes washers. Table 4 summarizes the results in this study. The +/- signs indicate the direction of the impact of a particular factor on the length of time that an appliance remains in household use. For example, income (which was incorporated into the models via a set of dummy variables for various income ranges) shows a significant negative relationship with the length of time that a household will keep a clothes washer. This means that higher income families will tend to replace clothes washers earlier than those in lower income brackets.

Table 4: Significant factors in parametric survival models

Appliance	Significant covariates
Refrigerator	Residence is owner-occupied (+)
Freezer	Residence is a mobile home (−), Residence is in an urban area (+), Number of individuals in the household (−), number of children in the household (+)
Dishwasher	Residence is owner-occupied (−), Number of individuals in the household (−)
Clothes washer	Income (−), Residence is in an urban area urban (+), Number of individuals in the household (−), Number of children in the household (+)
Dryer	Residence has somebody at home during the day (+), Number of individuals in the household (−)

Source: Young (2008a)

It is interesting to note that in the SHEU03 dataset used in this study, survey respondents were asked whether or not an appliance was still in working condition when replaced. Although many refrigerators were still in working order when replaced, this was not the case for clothes washers. The fact that clothes washer replacement rates are income-sensitive may be due to the subjective nature of appliance 'failure.' When deciding whether or not to replace a broken-down appliance, agents will take into account the cost of repair to correct the apparent 'failure.' While a high income household may opt to replace a failed but repairable appliance, a lower income household may prefer to pay a repair bill that requires a smaller cash outlay than would be required for a replacement purchase. The fact that replacement rates for other appliances were not income-sensitive in the Canadian duration models may be due to the fact many factors vary across appliances, including the costs and feasibility of repairs, the retail price of the appliance, and the expected post-repair lifetime of the appliance.

3.2 Latent variable models: logit/probit analysis

Another approach to modeling appliance replacement is to examine the factors that determine whether a household will purchase a particular technology. It is assumed that the decision to purchase a clothes washer, for example, will depend on a variety of factors including the age of any appliance currently in use, market conditions, socioeconomic characteristics of individual households and the attributes/features of new appliances (some of which are considered in standard LCC or Payback Period analysis).

A common approach to modeling this type of decision from an applied microeconomic perspective is to consider a latent or unobserved variable model having the form:

$$Y_i^* = x_i'\beta + \varepsilon_i$$

where: $$Y_i = \begin{cases} 1 \ if \ Y_i^* > 0 \\ 0 \ if \ Y_i^* \leq 0 \end{cases}.$$

In this formulation, Y_i^* is an unobservable (latent) measure of the 'desirability' of purchasing a new energy-efficient technology for the i^{th} household. This unobserved 'desirability' will, in general, be a function of the characteristics of the new technology (relative to other available options) and the socioeconomic characteristics of the household, as measured by variables contained in the vector x_i. Once this 'desirability' reaches a certain threshold, the household will purchase the technology. Although the latent variable is unobservable, the outcome of the decision of whether or not to purchase a new technology is observed. This decision is captured empirically through the binary variable Y_i which takes a value of 1 in the case where a household purchases the technology and 0 otherwise. For symmetric distributions of the random error term (ε), this model can be rewritten as:

$$\begin{aligned} E(Y \mid x_i) = \text{Prob}\ (Y_i = 1 \mid x_i) = \text{Prob}(Y_i^*>0 \mid x_i) &= \text{Prob}(x_i'\beta+\varepsilon_i>0 \mid x_i) \\ &= \text{Prob}(\varepsilon_i> -x_i'\beta \mid x_i) \\ &= 1 - \text{Prob}(\varepsilon_{i<} -x_i'\beta \mid x_i) \\ &= 1 - F(-x_i'\beta) \end{aligned}$$

where F(.) is the CDF of ε. In practice, either a normal or logistic CDF is generally used, resulting in either a 'probit' or 'logit' model.

One recent example of the use of a latent variable approach to the adoption of new energy efficient technologies can be found in USDOE (2000b). This particular study examines clothes washer ownership and replacements in the US. At any point in time, a household that owns a washing machine may find itself in one of three situations: (1) the current appliance is functioning properly; (2) the current appliance is in need of repair; or (3) the current appliance has failed and is beyond repair. In the first case, with the introduction of new energy-efficient technologies, a household who owns a functioning washing machine faces the decision of whether or not to replace their current appliance. In the second case, the household must decide whether or not to repair, purchase a new appliance or purchase a used appliance. In the third case, the household must decide whether or not to replace the failed appliance with a new or used model. In this study, the decisions are modeled as a function of the relative prices of the various options, features of the appliances, income and interest rates. The logit results indicate that appliance price is a major driving force behind the purchase decision. Another recent application, discussed in detail in Section 4 below, uses a probit specification to examine the determinants of a household's decision to install and use a programmable thermostat.

Logit and probit models were also used in a recent study of the factors associated with the decision by many households to keep a secondary 'beer' fridge in the home in Canada (Young 2008b). This phenomenon can lead to an increase in energy use instead of a decrease as many households purchase a new energy efficient refrigerator and then continue to use an older inefficient model, thereby creating an increase in refrigeration capacity for the household. Controlling for a variety of socio-economic characteristics of the household and for the type of residence, income was found to be a significant driver behind this decision. Compared with the base group of households with annual incomes below $20,000 (Cdn), those in the ($20,000 to $39,999) and ($40,000 to $59,000) ranges had about 10 per cent higher probability of using a secondary refrigerator, while households with annual incomes of $80,000 or more had about a 15 per cent higher probability.

Other ways in which the economic behaviour of individuals can affect the energy savings available from the introduction of new technologies are discussed in the next section.

4. Aggregate energy savings potential and economic behaviour

Once a new energy-efficient technology has been purchased, its impact on energy use and the environment depends on how it is used. Engineering studies show that both control strategies and the features of the physical environment in which a technology are used can be important considerations. For example, 'exergy-efficient' space heating technologies (such as embedded coils in floors) require a well-insulated building shell if they are going to be capable of providing sufficient heat in a living or work space (Ala-Juusela, 2003).[6] The importance of well-insulated building materials is also relevant for other heating and cooling technologies. Indoor climate control effectiveness will be affected by a variety of factors including the location of the building, the level of comfort required, the number of occupants and the periods of occupancy, the physical characteristics of the building (such as roof and wall types), and the activities undertaken in the building (Monts and Blisset, 1981). The fact that some technologies will only provide energy savings in the presence of other physical features of a building illustrates that 'synergies' matter, that is, in many cases, a combination of factors is necessary for energy efficiency gains to be realized.

For given technologies and 'building envelope' configurations, engineering studies show that variations in operational strategies can lead to substantial differences in energy use. For example, Becker and Paciuk (2002) examine pre-cooling and ventilation strategies for office buildings in a warm climate. They find that altering strategies can have significant impacts on peak-load energy demand, with the appropriate strategy depending on the specific features of a building. In another recent study, Canbay et al (2004) explain how altering control schemes can be a cost-effective method of reducing energy use for a given HVAC system. These authors demonstrate that a 22 per cent energy saving could be achieved in a shopping center in Turkey through an adjustment in HVAC control strategies.

While these engineering studies could be viewed as indicating that human factors play at least some role in determining realized energy savings associated with energy efficient

[6] Exergy is defined as a combination of energy quantity (which is conserved according to the first law of thermodynamics) and energy quality (which is consumed according to the second law of thermodynamics). See Ala-Juusela (2003) for further details on exergy efficiency.

technologies, in general these types of studies do not tend to consider the specific role, or generally the importance, of human behaviour in affecting realized energy savings. Similarly, the roles of economic (and possibly other) considerations in affecting human behaviour, and hence realized energy savings, are also typically not examined in any detail, if at all. In such circumstances, the expected energy savings associated with a new energy-efficient technology may often appear to be overstated, or at least may not be fully realized in the periods following its adoption. Yet in many cases, by modeling the adoption decision and energy use to take account of human behaviour, it may be possible to indicate the extent to which this non-realization of energy savings is likely to occur, and perhaps more importantly, to identify the factors associated with this so that policies can be adopted that might mitigate these effects.

Consider, for example, the situation where a new technology, Technology B, becomes available, where Technology B uses 20 per cent less energy than Technology A. Based on this information, it might be argued that if all individuals using Technology A could only be convinced/required to switch to Technology B, aggregate energy savings amounting to 20 per cent of energy usage by those currently using Technology A could be achieved.[7] Of course there are a number of reasons why this might not occur and indeed, even if it did occur, might not be desirable. First, as in this scenario, and as is often the case, there is no mention of the cost of switching technologies; that is, no NPV or LCC calculation, or payback period – even assuming no change in behaviour by those who switch from Technology A to Technology B. Second, as is discussed elsewhere in this volume, there may often be a change in behaviour associated with the adoption of new technology, resulting in rebound effects. To use a simple example, the installation of new energy-efficient windows or increased insulation in a house might mean that energy use in that house actually increases as rooms that were previously too cold to be used effectively, and in which space heating was not utilized because it was found to be ineffective, may now be heated effectively and utilized to a greater extent. Third, the technology may not be utilized correctly, or at least effectively, so that even abstracting from changes in behaviour, expected energy savings are not realized. Finally, there may be particular characteristics of those who adopt the new technology, or at least possibly among the early adopters, that result in energy savings being less than what would be expected. For example, suppose that a particular

[7] See, for example, Sekhar and Toon (1998, p.315).

technology – such as energy-efficient lighting – is only adopted by those who could be considered to be "energy-aware". Thus, this group includes people that turn lights off when rooms are unoccupied, and who used the previously most energy-efficient technology. As a result, realized energy-savings associated with the adoption of the new lighting technology might prove to be much smaller than expected. In the following, based on Ryan and Cherniwchan (2007), we provide an empirical illustration of these latter two effects in the context of Canadian households, some of whom use programmable thermostats (PT) to control their space heating requirements.

A programmable thermostat (PT) is a temperature sensitive switch that controls a furnace (and/or air-conditioner) by adjusting the temperature setting to preset levels for prescribed periods, such as when the home is unoccupied during working hours, or when a lower (higher) ambient temperature is less of a comfort concern, such as during the night (day). Estimates of the savings that can be obtained by using the features of a PT vary, but are generally quite large. Claims of the amount of estimated savings that can result from using such a device range from as much as 2 per cent of the home heating bill for each degree Celsius (1.8 degrees Fahrenheit) that the thermostat is set lower at night[8] to approximately $150 (US) of annual energy costs assuming a typical, single-family home with an 8 hour daytime setback and a 10 hour nighttime setback of 8°F in winter and 4°F in summer.[9] Further, these claimed savings apparently can be achieved quite inexpensively. According to cost and savings information provided on the US home energy saver website, an Energy Star PT has an incremental cost of $107 and generates annual bill savings of $29, so that the simple payback period is just 3.7 years.[10] In Canada, PTs are readily available at an even lower cost, and in view of the greater space heating requirements in Canada, the payback period would be considerably less. According to the US home energy saver website, the annual rate of return after-tax for such a device is calculated at 30 per cent, rating it 4th best out of 10 energy efficiency measures that were considered, and well in excess of the 16 per cent average rate of return on investment for all 10 measures.

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[8] Natural Resources Canada, "Heating with Electricity", http://www.oee.nrcan.gc.ca/publications/infosource/pub/home/heating_with_electricity_chapter3.cfm?text=N&printview=N

[9] U.S. Department of Energy, "Programmable Thermostats – Proper Use Guidelines", http://www.energystar.gov/index.cfm?c=thermostats.pr_thermostats_guidelines

[10] http://hes.lbl.gov/hes/profitable_dat.html.

In view of their low purchase and retrofit cost, and the apparently large energy savings that they are claimed to be able to generate, it might be expected that programmable thermostats would have been widely adopted in the Canadian residential sector. In fact, since per-capita residential end-use energy consumption in Canada, influenced by such factors as climate, efficiencies of space and hot water heating equipment, and housing characteristics, is primarily (57 per cent) required for space heating purposes,[11] this would appear to be an ideal setting for PT use. Yet, such is not the case. In the 2003 Canadian Survey of Household Energy Use (SHEU03), only 28.6 per cent of households had a PT, an increase from 14.6 per cent in 1997, and this percentage varied quite noticeably across different regions. Of course, one possible explanation for the relatively low uptake of PTs is that the claimed energy savings are not typically realized. To assess whether there is empirical evidence that installing and using a programmable thermostat actually reduces energy consumption, we combine the latent variable modeling approach presented in the previous section with an energy demand model in which the endogeneity of the decision to utilize a PT is incorporated.

Estimation of a simple energy demand equation for 1496 households in SHEU03 who use natural gas for their primary form of space heating – households for which a PT is likely to be most effective – controlling for prices of natural gas and electricity, region, income, education, household size, house age, yields a coefficient estimate of -6.6 (which is significant at a 5 per cent level) on a binary (dummy) variable reflecting the presence of a PT. This indicates that a household that has a PT will, holding these other factors constant, have total energy consumption that is lower by 6.6 gigajoules, which represents approximately 4 per cent of energy consumption for these households. While at first glance this estimate appears to confirm the energy-saving claims for a PT, a problem with this approach is that it has not taken account of the fact that homeowners choose whether to have a PT, and indeed – as we discuss later – whether to use it effectively. Failure to take account of this endogeneity of the dummy variable results in a biased estimator. This problem has been considered widely in the so-called treatment effect literature, and a variety of approaches for dealing with this have been considered.[12] Here we focus on a two-step procedure analogous to a sample-selectivity type correction that might be used if we

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[11] Natural Resources Canada, "Energy Efficiency Trends in Canada, 1990 to 2004", http://oee.nrcan.gc.ca/Publications/statistics/trends06/index.cfm

[12] See, for example, Greene (2008).

were to focus only on an endogenously selected subsample.

Here we represent the energy demand equation as:

$$C_i = x_i'\beta + \delta\, PT_i + \varepsilon_i$$

where C_i refers to energy consumption, x_i is a vector of explanatory variables for the i^{th} household, PT_i is a dummy variable that equals 1 if household i has a PT and equals zero otherwise, and the coefficient δ on this dummy variable is the parameter of interest. Since PT_i is endogenous it can be modeled in terms of a latent or unobserved variable where:

$$PT_i^* = z_i'\beta + e_i$$

where: $$PT_i = \begin{cases} 1 \; if \;\; PT_i^* > 0 \\ 0 \; if \;\; PT_i^* \le 0 \end{cases}.$$

Here PT_i^* is an unobservable (latent) measure of the 'desirability' of having a PT for the i^{th} household which depends on z_i, a vector of characteristics pertaining to the i^{th} house and household. As shown by Greene (2008), among others, under the assumption that the error terms are normally distributed,

$$E(C_i \mid PT_i = 1) = x_i'\beta + \gamma + a\, IMR_i$$
$$E(C_i \mid PT_i = 0) = x_i'\beta + a\, IMR_i$$

where $$IMR_i = \begin{cases} \phi(z_i'\gamma)/\Phi(z_i'\gamma) \;\; \text{if} \;\; PT_i = 1 \\ \phi(-z_i'\gamma)/(1-\Phi(z_i'\gamma)) \;\; \text{if} \;\; PT_i = 0 \end{cases},$$

and where $\phi(.)$ is the standard normal pdf and $\Phi(.)$ is the standard normal cdf.

Thus, estimation of the originally specified energy demand equation can be viewed as resulting in a biased estimator because the IMR_i variable is omitted. This can be resolved by including IMR_i as an additional explanatory variable in the energy demand equation, that is, by estimating:

$$C_i = x_i'\beta + \gamma\, PT_i + a\, IMR_i + \varepsilon_i$$

Of course, IMR_i is unknown since it depends on the parameter vector γ. Hence the two-step procedure involves first estimating a probit model of the decision to have a PT and using the estimated parameters to calculate an estimated IMR_i variable, and then including this estimated variable in the energy demand equation. In addition, the standard errors of this final model need to be adjusted to take account of the generated regressor, IMR_i, that has been included.

Estimation of the probit model as the first-step of this two-step process using the SHEU03 data reveals that the probability of having a PT is significantly increased for those with higher education, higher income, a forced air furnace, central air conditioning, recently-replaced windows, or one or more energy-efficiency improvements in the last two years, while it is significantly decreased for those with older houses. Overall, the probit model correctly predicts the presence or absence of a PT in 67 per cent of the 1496 households that use natural gas for their primary form of space heating. Inclusion of the generated IMR from this estimation in the energy demand equation results in a coefficient estimate on the PT dummy variable of -0.6, which is no longer significant even at a 10 per cent level of significance. Thus, once the endogeneity of the decision to have a PT is taken into account, it is seen that having this device does not significantly reduce energy consumption. A similar result is obtained if, as outlined in Greene (2002), instead of including the IMR variable, the predicted probabilities from the probit model are used as an instrument for the PT variable.

There are several possible explanations for this result. First, it may be the case that households that install PTs are the same ones that in the absence of a PT would manually turn the thermostat down at night, up in the morning when they rise, down when they leave for work, and up again when they return home from work in the evening. In such cases, the presence of a PT makes it easier to control the temperature in different periods to reduce energy consumption but it does not actually result in a reduction in energy consumption relative to the level that would be achieved anyway.

A second explanation may be that the households that have a PT do not use it properly, or at least not effectively. In such cases, knowing that a household possesses a PT might simply mean that the thermostat that is present in the household *could* be programmed, but that it is simply being used in place of a regular thermostat in exactly the same way – as an on/off switch that maintains the internal temperature of the house at a specified level throughout each day. In such cases, little – if any – energy savings would be expected to be attributable to the household having a PT. The extent to which this might be the case can be examined in the SHEU03 dataset as respondents who had a PT were also asked if they programmed it. Of those with PTs, 26.8 per cent stated that they did not program it. On this basis, although 28.6 per cent of survey respondents possessed PTs, only 21 per cent possessed a PT and claimed to utilize its features by actually programming it.

Of course, claiming to program a thermostat is not actually the same as programming it effectively, in the sense of having different settings on the thermostat at different times of the day. To elicit this information, SHEU03 respondents were also asked what temperature setting they use for different periods – day, evening, and night – during the heating season. In many cases, the settings are the same in two or even three of these periods. Almost 38 per cent of all households (over 20 per cent of whom have a PT) had the same temperature setting for all three periods, while only 23.5 per cent either had different settings for all three periods or at least different settings for the daytime and evening periods. Of course there can be many explanations for this result, including the presence of someone in the home during the day – for example, in households in SHEU03 that set the daytime and evening temperatures the same, over 70 per cent had the house occupied during daytime hours, while in 75 per cent of houses with the same daytime and nighttime temperature setting, no-one was at home during the day. Anecdotal evidence suggests that the decision to maintain the same temperature setting throughout the day even when no person is at home may also be due to a desire to keep pets warm while their owners are away.

There are, of course, a number of other possible explanations, including the possibility of rebound effects if automation of the process of changing temperature in different periods via a PT might mean that the temperature is set higher during some periods than would otherwise be the case as householders no longer have to worry about the extra energy consumed in a subsequent period if they forget to reset the thermostat manually. Regardless of the particular explanation, the key finding from this analysis is that the energy savings that are expected from technology may not be achieved once human behaviour is taken into account.

5. Strengths and weaknesses of various approaches

Commonly held expectations that improvements in the energy-efficiency properties of widely used technologies will lead to a lower demand for energy may not always be borne out in practice. Simply looking at engineering features when predicting the expected impacts of the introduction of new technologies can be misleading. This is because the decisions made by the (potential) users of these technologies are affected by a variety of factors such as income, prices, the age of any currently installed technology, etc. As a result, although engineering studies play an important role in the evaluation of new technologies, they need to be supplemented by studies of the decision-making processes of households and firms.

In practice, many models of aggregate energy demand, such as those used in Europe and North America, make attempts to incorporate human behaviour and the impacts of socio-economic factors when they examine the impacts of energy-saving technological improvements on overall energy demand. In the absence of household-level data on which to model decisions related to the uptake and intensity of use for these new technologies, attempts to accurately capture behavioural decisions can take a variety of forms. For instance, in their models of energy demand in the European Union, Mantzos *et al* (2003) use a much higher discount rate for the investment decisions of households (17.5 per cent) than for other agents in the economy (12 per cent for industry and 8 per cent for utilities). One rationale for the higher discount rate is simply that it reflects differences in access to credit markets across households and firms. On a practical level, use of a higher discount rate for households may simply help to 'track' the energy-use behaviour of households in that it slows down their adoption of new technologies within the model, resulting in better overall tracking of historical residential energy demand. Other factors that enter into play in the European Union model of Mantzos *et al* (2003) include the size and number of households, the size of homes, income levels, and 'climatic and cultural' conditions.

Unfortunately, human behaviour is neither as easy to model nor as easy to observe as the engineering characteristics of technologies embodied in durable goods such as household appliances or transportation equipment. As a result, there is a tendency to focus on Net Present Value and Payback Period analysis since this is much easier to implement once the necessary data related to energy use and prices are obtained. Furthermore, all of the required calculations for these types of analyses can be performed on a spreadsheet. However, these approaches tend to ignore all costs except for the purchase price and energy costs associated with the 'typical' operation of the product. In addition, although there are methods available for dealing with some of the uncertainties associated with the key variables used in these analyses, other sources of uncertainty, particularly those associated with human perceptions and behaviour, cannot readily be taken into account. Further, the fact that individuals ultimately determine the intensity of use of appliances and products, and respond to prices and other aspects of their economic environment in making these decisions, means that the final energy savings associated with any product or appliance embodying a more energy-efficient technology are unlikely to match predictions based on engineering specifications. Consequently, standard NPV and LCC calculations are unlikely to accurately reflect the true costs and benefits of these products or appliances.

While these drawbacks of the NPV and LCC analyses can be rectified to some extent using the micro-econometric modeling approaches outlined in Sections 3 and 4, these methods require extensive individual-level data if they are to be implemented. Survival or duration models, for example, require detailed individual household-level data. Information on the period of ownership of previous appliances that have been replaced, and on the period of ownership of appliances that are still in use, needs to be combined with details regarding the socioeconomic characteristics of households in order to explore the factors that determine how long a household keeps an appliance before considering the purchase of a new more energy efficient model. Appropriate data sets are not collected on a frequent basis, and may not be sufficiently detailed in any case, or sufficiently accurate – depending on how the information is collected , and results from any given country or time period are not necessarily representative of what may occur in another jurisdiction at another time.

In terms of modeling and analysis of the adoption decision for products or appliances embodying energy-efficient technologies, similar data requirements apply. In this case, as well as characteristics pertaining to the house and household for both adopters and non-adopters, necessary information includes energy consumption for these two types of households, ideally with enough information to account for those factors that, even in the absence of the technology adoption, would cause energy consumption to differ for different households. For this type of analysis it is necessary to model the decision to adopt as well as the relationship between energy consumption and the adoption choice that was made. As the results reported here for programmable thermostats demonstrate, the apparent energy savings from the new technology are not necessarily realized once the endogeneity of the decision to adopt is taken into account in the estimation procedure. Of course, different results will be obtained in different circumstances, so it is not possible to generalize and claim that the anticipated energy savings from new technology will never be (fully) realized. Rather, the message is that it is not obvious from a cursory examination of the data, or even from a simple regression analysis, that more energy-efficient products actually result in a reduction in energy consumption. What is clear, however, is that the energy savings that could hypothetically be achieved from new technologies are, in general, unlikely to be fully realized once human behaviour is taken into account. Thus, while advances in technology have the potential to have an impact the on the demand for primary energy, policy makers in particular need to be aware of the role of human decision-making when assessing the extent to which energy-efficiency programs or policies that are introduced are likely to achieve their objectives.

Finally, it is worth noting that in this report we have focused on the demand side of energy-efficient technologies, and have discussed how consumer reactions to prices, etc., may limit the extent of energy efficiency gains that are achieved from new technology. An implicit assumption here is that if there are more energy-efficient products that can be produced, they will be produced and made available for purchase to consumers. However, even if mandated minimum efficiency performance standards are imposed on production, this does not guarantee that the products embodying such standards will actually be produced and marketed. Manufacturers have to be able to recover standards-induced costs through higher prices, and already concerns have been raised that such is apparently not necessarily the case, particularly for appliances such as dishwashers and dehumidifiers.[13] Indeed, if the increases in costs associated with energy-efficient products are too high, an option for consumers in such situations is to repair rather than replace existing appliances. Although this aspect of consumer choice was considered here, the interaction between this choice and production decisions, which is also likely to affect the extent to which energy-efficient technologies penetrate the marketplace, remains as an interesting area for further research.

[13] See Chapter 12, 'Preliminary Manufacturer Impact Analysis' in USDOE(2007).

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