THE DESIRE TO ACQUIRE: FORECASTING THE EVOLUTION OF HOUSEHOLD ENERGY SERVICES

by

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ABSTRACT

People are constantly inventing and adopting new energy-using devices to make their lives more comfortable, convenient, connected, and entertaining. This study aggregates 134 energy-using household devices, not including major appliances, into categories based on the energy service they provide. By 2006, there were 43 energy-using devices in the average U.S. household that used over 4,700 kWh of electricity, natural gas, and gasoline. A fixed effects panel model was used to examine the relationship of demand for energy-using devices to energy price, household income, and the cost of these devices. This analysis finds that the elasticity of demand for these devices with respect to energy price is -0.52 with a 90% confidence interval of -1.04 to -0.01. The elasticity of demand to income is 0.52 (a 90% confidence interval of [-0.42, 1.46]. The cost of these devices was also statistically significant.

Keywords: electricity use; energy efficiency; energy-using devices; household energy consumption; residential sector; small appliances

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CHAPTER 1: INTRODUCTION

Thomas Edison once said, "we will make electricity so cheap that only the rich will burn candles" [1] (Langenberg, 1996, p. 1721). This statement has become a reality over the past century. Edison could only dream of the impact that new technology and expanding energy systems would have on the availability of cheap energy. In turn, the availability of cheap energy has lead to the invention of bigger and better ways to use this energy. People now derive an unprecedented level of comfort, convenience, and connectivity from an abundance of new technologies and household devices. In 1900, only 8% of American households were connected to electricity or telephone networks and less than 15% had a bathtub and indoor toilet (Smil, 2006). However, by the end of the century, virtually every American household was connected to the electric grid and had adopted telephones, radios, televisions, and refrigerators. The widespread adoption of energy-using devices has had a dramatic effect on human lifestyles as well as household energy consumption.

While many large appliances, such as refrigerators, clothes washers and dryers, dishwashers, and ranges/stoves, have reached household saturation in wealthy countries, people are constantly inventing and adopting new energy consuming devices. One serious consequence of the increasing penetration of household devices is the associated greenhouse gas (GHG) emissions. These emissions result from the combustion of fossil fuels to produce electricity or the direct consumption of gasoline or natural gas by devices such as lawn mowers, patio heaters, and barbeques. There are two ways to reduce the GHG emissions of these devices: reduce the emissions caused by the production of electricity or the combustion of fossil fuels, or improve the energy efficiency of the devices that use these fuels. Advocates of energy efficiency argue that the latter option can cost-effectively reduce energy consumption. However, many economists suggest that attempts to promote the adoption of more efficient devices often fail to fully realize their anticipated energy savings.

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[1] This was Thomas Edison's response to a question regarding the impact that his light bulb would have on the candle industry.

This debate is important because policy makers require accurate information to inform their decisions when it comes to addressing climate change or other issues related to modern energy systems. The purpose of this study is to examine key relationships determining the demand for new energy-using devices over the past 30 years and forecast how these relationships might help anticipate the evolution of energy demand under different policy scenarios.

Several terms used in this report require definition: *energy system, device/technology*, *energy service*, and *energy efficiency*. An *energy system* is a combination of the processes and devices that produce, supply, and consume energy within an economy. The terms *device* and *technology* are used in this report to describe any household device that uses electricity, gasoline, or natural gas. The *devices* referred to in this study do not include common household devices used for space heating, water heating, lighting, or major appliances including refrigerators, freezers, dishwashers, clothes washers, clothes dryers, and stoves/ranges. This study focuses on smaller energy-using devices since these have generally received less study but have grown to make up a substantial share of overall household energy use. Device is often used in place of the term technology because a new device may not represent a new technology, just a repackaging of an existing one. For example, a laptop computer is a re-packaging of the technology used in a desktop computer. *Energy service* refers to the service that people derive from energy-using devices, such as heat to cook food or power to mow the lawn. *Energy efficiency* refers to the amount of energy a device requires to provide a certain level or quality of service.

The first chapter of this report introduces the background research that prompted this study and a review of the rationale for the method I used. Section 1.1 describes the how energy efficient technologies can reduce GHG emissions. Section 1.2 explores the reasons why improving energy efficiency may not reduce GHG emissions. Trends in household energy consumption over the past 30 years are summarized in Section 1.3. Section 1.4 outlines different approaches to energy modelling and section 1.5 and 1.6 introduce the methods I used to analyze historical energy consumption and generate forecasts. The final section of chapter 1, section 1.7, summarizes the research objectives of this study.

1.1 Reducing energy consumption by increasing efficiency

In the 1970s, a spike in energy prices caused by the Organization of Petroleum Exporting Countries' (OPEC) oil-embargo prompted oil-dependent nations to search for ways to reduce dependence on oil imports (Herring, 1999). A global recession in the early 1980s, coupled with the increasing opposition to and cost overruns of nuclear power plants, spurred efforts to reduce the "wasteful" use of energy (Jaccard, 2005). The development and diffusion of more energy efficient technologies and processes was believed to be a solution to these problems. Not only would improving energy efficiency reduce dependence upon foreign energy and mitigate the environmental impacts of supplying and using energy, it would save households and businesses money.

Energy efficiency proponents assert that improving the energy efficiency of devices is "generally the largest, least expensive, most benign, most quickly deployable, least visible, least understood, and most neglected way to provide energy services" (Lovins, 2005. p.1). They argue that the potential of energy efficiency to reduce consumption is increasing faster than people and businesses are implementing it. Reducing wasteful energy use and improving energy efficiency could help to avoid economic, environmental, and security costs of supplying and distributing energy (Lovins, 2005).

This type of argument is the basis for studies that suggest energy efficiency can help mitigate the impact of greenhouse gas emissions from the combustion of fossil fuels for energy. Pacala and Socolow (2004) suggest that humanity has the technical capacity to supply the world with energy until 2050 while curbing GHG emissions to mitigate the impact on rising atmospheric CO_2 concentrations. Of the 15 options presented to mitigate rising GHG emissions, they identify improvements in energy efficiency and conservation as having the "greatest potential". They suggest that pursuing efficiency improvements in space heating and cooling, water heating, lighting, and refrigeration in residential and commercial buildings alone could reduce GHG emissions by 25%. In a similar study, McKinsey (2007) proposes that out of the five clusters of options to reduce U.S. GHG emissions they present, improving the energy efficiency of buildings and appliances has the greatest potential. McKinsey (2007) suggests that these improvements, including more efficient consumer electronics and appliances, would save people money and reduce GHG emissions by up to 9% in 2030. The projections of these reports suggest that energy efficiency is a cost effective way to reduce energy consumption and associated GHG emissions.

These studies use what is known as a bottom-up approach to modelling demand for energy. Bottom-up models are typically used to estimate the technical potential and economic cost of using more energy efficient equipment to reduce energy consumption (Worrell, Ramesohl, and Boyd, 2004). These models incorporate a lot of detail on energy-using technologies including their capital cost and operating cost, which is based on how efficient they are at using energy. Including this level of detail allows modellers to examine the often higher capital cost of a more efficient technology against the long run energy savings. These models often indicate that it is in the best interests of people and businesses to use more energy efficient devices because it will save them money in the long run. However, bottom-up models of energy demand tend to underestimate the cost of using more energy efficient devices and overestimate the effectiveness of improved efficiency at reducing energy consumption.

1.2 Why increasing efficiency may not reduce energy consumption

Technologies that are more energy efficient tend not to achieve the expected reduction in energy consumption for two reasons: technologies that are more efficient either do not make good substitutes or are more useful than older technologies.

Bottom-up models tend to lead to the conclusion that people choose technologies based only on financial costs without considering differences in risk or quality of service. For example, while more efficient devices use less energy, they tend to have a higher capital cost resulting in a long payback period for this extra investment. People are much more sensitive to the initial cost of a device versus their future cost savings (Jaffe, Newell, and Stavins, 1999). Even though a compact fluorescent light bulb may save you money in the long-term, the higher capital cost makes it a riskier investment than a cheaper alternative. Also, people may be less inclined to invest in an efficient technology when it is unfamiliar: they do not know whether it will work as well as an established alternative. For example, the first generations of compact fluorescent light bulbs would often fail before the end of their expected lifetime. Additionally, a more efficient device may not be a perfect substitute for the alternative. Initially, fluorescent light bulbs were not compatible with dimmer switches and emitted a cool, unappealing white light.

Households and businesses may not embrace new and more efficient technologies for a number of reasons. However, in the past when more efficient devices have become popular, their adoption has resulted in an increase in energy consumption (Huber and Mills, 2005; Jaccard, 2005; Smil, 2008). Efficient technologies reduce the amount of energy required to provide a service (such as lighting) and, thus, reduce the cost of providing that service. This cost reduction can lead to an increase in the demand for the service, an effect referred to as rebound.

At the household level, a direct rebound occurs when the demand for an energy service increases due to a decrease in its cost (Berkhout, Muskens, and Velthuijse, 2000). For example, the adoption of more efficient lights may result in households using more lights or leaving their lights on longer. In a survey of studies on the rebound effect, Greening, Greene, and Difiglio (2000) found that in response to an increase in energy efficiency, households increased their demand for space heating by 10% to 30%, space cooling by 0% to 50%, water heating by 10% to 40%, and lighting by 5% to 12%. While these results indicate some take-back of energy savings in households, greater rebound effects occur on an economy-wide scale. Some economists suggest that in some cases the rebound can actually ‘backfire’ and lead to an overall increase in energy consumption (Sorrell, 2007).

The Khazzoom-Brookes (K-B) hypothesis states that “if energy prices do not change, cost effective energy efficiency improvements will inevitably increase economy-wide energy consumption above what it would be without those improvements” (Sorrell, 2007, p. vii). This theory suggests that an improvement in efficiency will reduce the amount of energy that businesses and households require. This reduction will have two effects. First, lowered energy consumption will reduce the cost of products produced by businesses and the cost of operating household devices. These cost savings allow businesses to produce more products or increase the number of devices a household can afford to own and operate. As the price of operating that device falls, households can afford to adopt devices that use more energy. Second, a reduction in the amount of energy required by businesses and households will reduce demand for energy and lower its price. The increase in the ability of households to purchase energy-using devices and the reduced cost of energy that results from improved energy efficiency will lead to the intensification and proliferation of energy end-uses, or services (Herring, 1999). Thus, energy efficiency allows households to afford to have more devices and demand more energy services. Huber and Mills (2005) argue that “the more energy-efficient a technology grows, the faster it metastasizes and finds new applications” (p. 94). For example, the innovation of electronic devices has led to an explosion in the number of portable electronic devices available to consumers to provide new and better services.

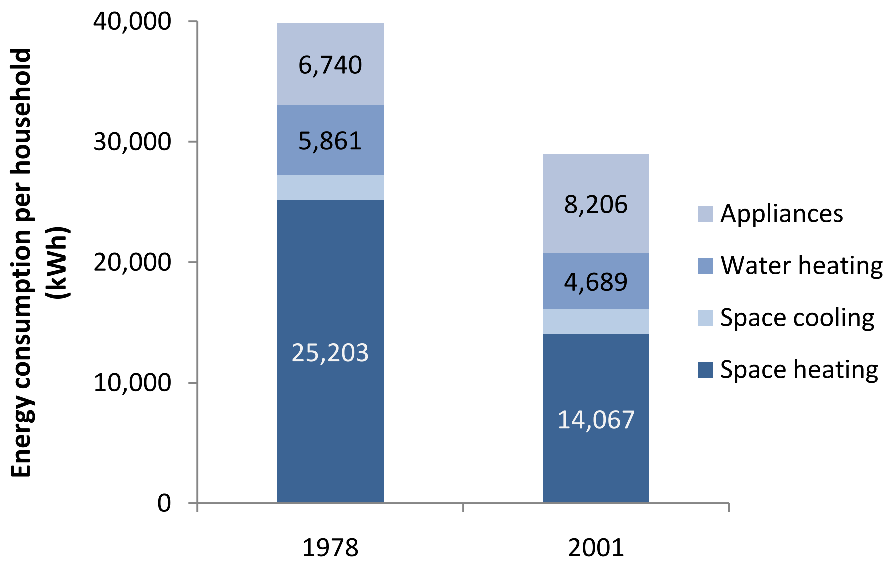
There are two reasons to be wary of the ability of efficiency to reduce energy consumption: (i) households may not find devices that are more efficient desirable; and if they do, (ii) energy savings will be offset by an increase in demand and use of these devices. Huber and Mills (2005) observe, “through all of the technological history on record so far, it [improving efficiency] has had just the opposite effect” (p. 107).

1.3 Trends in household energy consumption

Increasing demand for energy-using devices is also a function of falling energy prices and rising incomes. In 1900, the cost of one kWh of electricity in US cities was $0.15 ($3.25 in U.S. 2000 dollars) (Smil, 2006). By the year 2000, the cost of the same amount of electricity had fallen to $0.06. Over the same period, the average manufacturing hourly wage rose from $4 to $13.90 (U.S. 2000 dollars), making electricity roughly 190 times more affordable (Smil, 2006). Combined with a doubling to tripling in the average efficiency of lights and appliances, in 2000 one unit of electricity in the U.S. could provide 200 to 600 times more energy service than a century earlier (Smil, 2003). In a similar study, Fouquet and Pearson (2006) found that improvements in lighting technology, fuels, and infrastructure coupled with a 15 fold increase in GDP from the year 1800 to 2000 allowed people in the U.K. to enjoy 25,000 times more artificial light.

Falling capital and operating costs have contributed to an explosion in the number of energy-using household devices. In 2006, the residential sector used 21% of all energy consumed in the U.S. and was responsible for 20% of total GHG emissions (Energy Information Administration (EIA), 2009). However, from 1978 to 2001, only one category of household energy consumption grew: household appliances. Figure 1 shows that appliance energy consumption increased 22% per household over this period (Laurence, 2002).

Figure 1: U.S. household energy consumption, weather adjusted

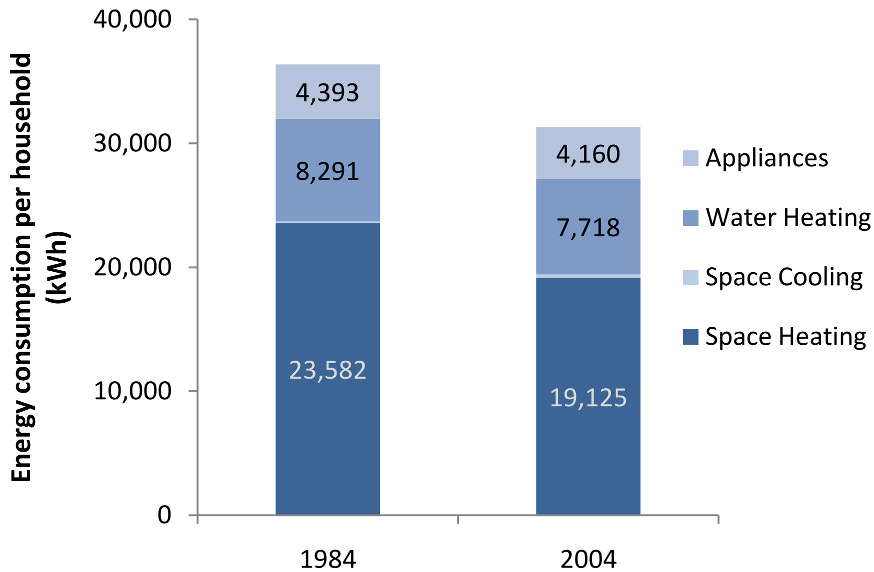


Source: Created from data contained in Laurence (2002).

Contrary to appliances, the energy consumption of space heating, space cooling, and water heating fell from 1978 to 2001.

The trends in household energy consumption are similar in Canada. From 1984 to 2004, the amount of energy consumed for space and water heating in Canada decreased (Natural Resources Canada (NRCan), 2005). In contrast to the U.S., Figure 2 shows that total energy consumption of appliances decreased slightly from 1984 to 2004 (NRCan, 2005).

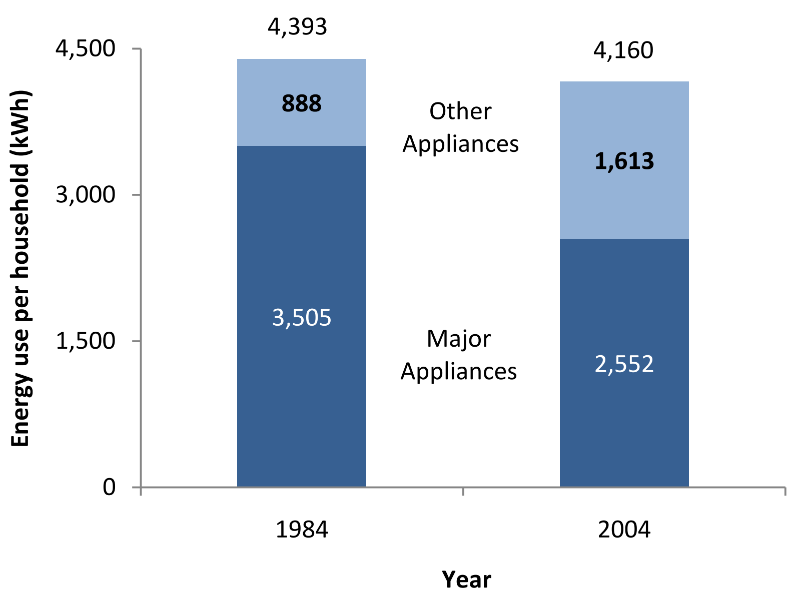
Figure 2: Canadian household energy consumption, weather adjusted



Source: Created from data contained in Natural Resources Canada (2005).

Despite the overall decrease in appliance energy consumption, Figure 3 indicates a doubling in the energy consumption of "other appliances".

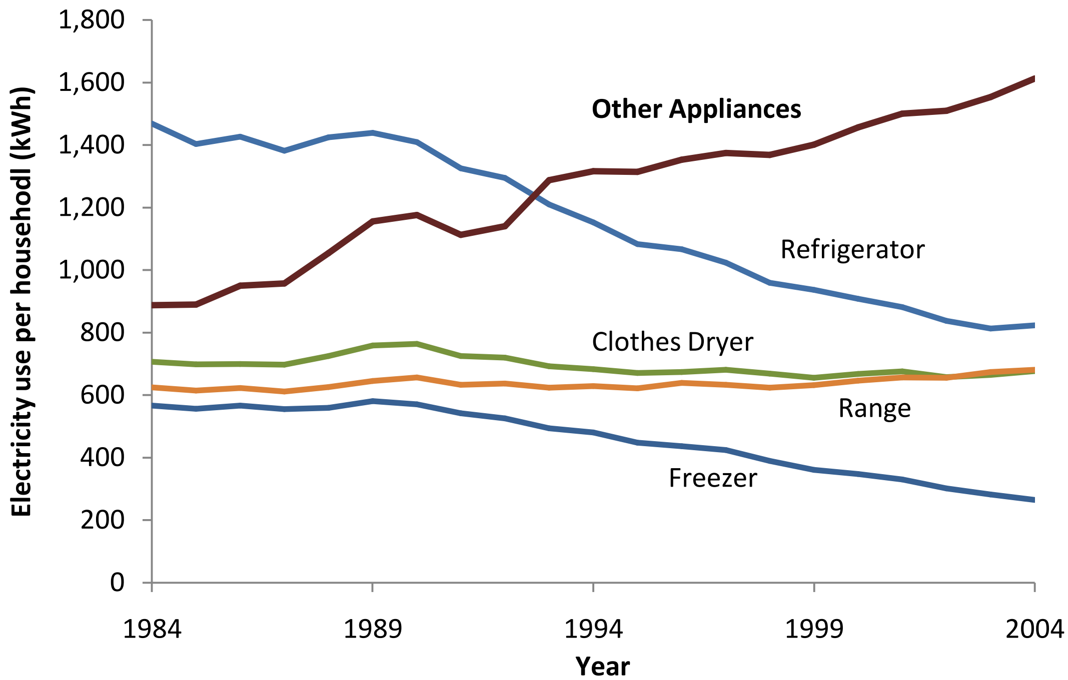
Figure 3: Canadian household appliance energy use



Source: Created from data contained in Natural Resources Canada (2005).

“Major appliances” includes refrigerators, freezers, dishwashers, clothes washers, clothes dryers, and ranges but does not include hot water use. NRCan (2005) defines “other appliances” as televisions, VCRs, DVD players, radios, computers, and toasters. Figure 4 shows the average household electricity consumption of these “other appliances” and several major appliances over the past 20 years. As the electricity consumption of refrigerators and freezers has fallen and clothes dryers and ranges have remained similar, the electricity consumption of “other appliances” has risen steadily since 1984.

Figure 4: Annual electricity consumption of Canadian household appliances



Source: Created from data contained in Natural Resources Canada (2005).

The “other appliances” category includes televisions, VCRs, DVD players, radios, computers, and toasters (NRCan, 2005).

The adoption of many new devices by households over the past two decades has offset gains made in the energy efficiency of major appliances. From 1990 to 2005, improvements in the efficiency of major appliances reduced their electricity consumption by 17% (NRCan, 2007). However, over the same period, the increase in penetration of other minor appliances (including televisions, VCRs, DVDs, stereo systems, and personal computers) resulted in a three percent increase in total appliance electricity consumption (NRCan, 2007).

Part of the explanation for increasing energy consumption is that many of the devices now considered household necessities were rare or did not exist in 1978: cordless telephones, large-screen TVs, microwave ovens, personal computers, telephone answering machines, VCRs, and DVD players (Laurence, 2002). Additionally, many new devices require the use of DC adapters and feature remote control stand-by modes that consume electricity even when the device is not turned on (Laurence, 2002). Falling costs of new devices and rising incomes have also allowed the adoption of devices that previously only affluent households could afford.

As efficiency improves, incomes rise, and the price of energy remains low, people will continue to adopt energy-using devices to make their lives more convenient and comfortable. It is ironic that as sustainable design and energy conservation have become mainstream concepts in the residential sector, households are incorporating heated and air conditioned garages, heated patios, heated walkways and driveways to melt snow and ice, a second laundry in the master bedroom, and sauna and steam showers (Eviston, 2007). Living space is also expanding outside of the home with the addition of outdoor grills, refrigerators, and televisions, natural gas powered mosquito catchers, patio heaters and perhaps someday patio chillers; a new luxury hotel in Dubai cools the sand on its beach and there are proposals to install chillers to “waft” a cool breeze over the beach (Leake, 2008). Further, over the past 30 years, the number of electronic devices in use has exploded from a handful of devices to 20 to 30 per household (International Energy Agency (IEA), 2009). The cost of supplying energy for electronic devices worldwide is expected to rise from $80 billion in 2008 to $200 billion by 2030 (IEA, 2009).

This proliferation of new energy-using devices is offsetting to some degree improvements in efficiency. While the data presented in this section identify the impact of new technologies on residential energy consumption, policy makers require informative tools to help design effective policies to reduce GHG emissions and address climate change. Simulation models are one tool that policy makers can use to evaluate the effectiveness of various policy alternatives. The next sections of this chapter will explore existing modelling approaches and how the growing energy consumption of these devices might be modeled.

1.4 Energy modelling

Models designed to emulate how the economy interacts with energy systems fall into two broad categories, top-down and bottom-up (Worrell et al., 2004). While the objective of both of these types of models is to estimate the impact that policies may have on households and businesses, their approaches are fundamentally different. The main difference between these approaches is the level of technological detail used to represent the energy system (Böhringer & Rutherford, 2008).

Bottom-up models are comprised of a database of technologies that are available to provide a given energy service, such as space heating. Once a desired level of service is set, these technologies are ranked based on the life-cycle cost of providing that energy service. This life-cycle cost includes the capital cost and the operating cost of the technology discounted to the present using a social discount rate. The cost of providing the desired amount of energy service is the sum of the life-cycle costs of the technologies required to supply the service. However, these simple calculations do not account for barriers to energy efficiency and the rebound effects that occur with an increase in efficiency. Therefore, these models tend to underestimate the economic cost of climate change policies and overestimate the amount these policies will reduce greenhouse gas emissions (Jaccard, Nyboer, Bataille, and Sadownik, 2003).

Top-down energy models are different from bottom-up models because they use production functions instead of individual technologies to estimate the demand for energy and the cost of supplying it. As demand for a commodity, such as electricity, increases, so does its cost. Because these models have the ability to simulate the interaction between different economic sectors, they can show the impact that policies may have on different sectors.

Two parameters are used in top-down models to represent the evolution of technology in the economy: elasticities of substitution (ESUB), and an autonomous rate of energy efficiency improvement (AEEI). ESUB indicates the ability of one input (capital, labour, energy, materials) or energy source (coal, oil, gas, renewables) to substitute for another (Jaccard et al., 2003). The AEEI represents the non-price induced evolution of technologies to provide more service using less energy (Jaccard and Bailie, 1996): such as the development of refrigerators with more insulation and better compressors that use less electricity. Top-down models are more representative of the true cost of climate change policies because the production functions, ESUB, and AEEI are estimated from real market behaviour (Jaccard et al., 2003). However, reliance on data from real market behaviours also limits top-down models. Because there is limited data on these parameters, many simplifying assumptions must be made which reduces the accuracy of the top-down model forecasts (Böhringer, 1998). In top-down models, the ESUB function determines the ability of an economy to adapt to a policy whereas bottom-up models use a database of available technologies. This lack of technological detail tends to make top-down models overestimate the cost of climate change policies and does not allow the modelling of technology-specific policies. The relative strengths and weaknesses of each modelling approach have resulted in the development of hybrid energy-economy models in an attempt to capture their respective strengths.

Jaccard (2002) suggests that energy-economy models are more accurate and useful to policy makers when they incorporate three key components: technological explicitness, behavioural realism, and macroeconomic feedbacks. A technologically explicit model, with a database of available technologies, can take into account the ability of policies to influence the rates of technological innovation and change. Models should also be behaviourally realistic; they should reflect the way that people's choices influence energy consumption. Finally, energy models should incorporate the interactions, or feedbacks, that would occur between economic sectors and energy systems due to the application of different climate change policies.

The CIMS model, developed at the School of Resource and Environmental Management (REM) at Simon Fraser University, is a hybrid model that combines the strengths of top-down and bottom-up modelling approaches. Similar to bottom-up models, CIMS incorporates a database of energy production and end-use technologies and tracks the flow of energy from where it is produced to where it is used. However, CIMS uses a number of variables to simulate behavioural realism. These variables can be modified to simulate the consumer's sensitivity to the costs of new technologies: capital costs, the non-financial "intangible" costs of using a new technology, and the desirability of a new technology compared to an older one. CIMS has also made some steps towards incorporating economic feedbacks, similar to top-down models, that simulate the attractiveness and costs associated with substituting one type of energy or technology for another (Bataille, Jaccard, Nyboer, and Rivers, 2006). As a result, CIMS is a technologically explicit model that incorporates behavioural realism and some economic feedbacks.

However, due to its technological explicitness, CIMS tends not to capture the evolution in demand for energy services. CIMS uses a database of technologies to meet the forecast demand of energy services. Once the characteristics of the technologies in this database are set, they do not change over the course of the simulation period. However, people's desire for comfort and convenience, entertainment and connectivity is made possible by increasing incomes, cheap energy, and falling costs of an energy evolving and expanding array of energy-using devices. This evolution, or innovation, of the technology can drastically change the characteristics of a device and cause some to be adopted more rapidly and extensively than forecasters ever envisioned. For example, in 1953 IBM developed a "small" computer that they thought would be useful for business applications and projected that there would be a need for only 250 machines for the entire U.S. (Ceruzzi, 2006). According to the analysis in this study, there were over 250 million personal computers[2] being used in U.S. households in 2006. Over the past 50 years, computers have evolved to provide services beyond the specialized applications demanded by researchers and businesses and become an essential part of people's lives. This study examines trends in the evolution of technologies and in an attempt to capture trends that are difficult to portray in technologically explicit, hybrid energy-economy models, such as CIMS.

The modelling of climate change policies requires models to forecast technological change over extended periods: up to 2050 and beyond (Worrell et al.,

2 Including desktop, laptop, and palm and pocket computers.

2004). However, after 10 to 20 years the household devices listed in the model will have changed dramatically. Using broader categories of energy-using devices, instead of individual technologies, to model energy demand may more accurately portray how these devices change over time.

The evidence presented in this chapter showed the continuing growth in energy-using household devices. It is important for policy makers to be aware of these trends when designing policies to combat climate change. Therefore, the goal of this study is to develop a model of the relationships driving demand for these devices and use it to estimate their demand for the next 30 years. The methods used are intended to address some of the shortcomings of conventional bottom-up energy modelling.

People's increasing demand for energy-using devices is tied to their desire for the service that they provide. Therefore, this study examined the relationships in the evolution energy-using devices by grouping them based on several considerations including the type of service they provide, a literature review of demand for different kinds of devices, and the data available to probe these relationships.

Burwell and Swezey (1990) were among the first authors to examine trends in the penetration of energy-using devices as a function of their service. They observed that the adoption of successive generations of entertainment devices from radios, to black-and-white TVs, to colour TVs and VCRs tended to proceed rapidly and follow an s-shaped household penetration curve. Conversely, labour saving devices, such as vacuum cleaners and dishwashers, were adopted at a slower pace and exhibited a less dramatic, linear increase in household penetration.

The concept of energy service modelling continued to evolve with Nordhaus' (1997) study of the demand for artificial light. He concluded that the evolution of lighting technology caused a substantial decrease in the price of light resulting in a dramatic increase in its use. He estimated that modern, efficient light bulbs allowed people to use 9 to 16 times more light than they could otherwise afford due to lower energy prices and higher incomes. New technologies can radically improve the service that a device provides and make that service more desirable. Fouquet (2008) expands this type of analysis to heat, power, and light in order to examine the impact that technology, often more efficient technology, has on reducing the cost and increasing the desirability of an energy service. He finds that new technologies tend to expand the use of a given energy service because they provide a better service than previous generations. It follows that examining the evolution of the technologies used to provide energy services may reveal useful insights into how and why people use energy.

1.5 Econometric analysis

In this study, I used econometric analysis to test for relationships in the demand for energy-using devices and several explanatory variables. Three economic variables were of particular interest: the price of energy, household income, and the cost of these devices.

Policies aimed at reducing GHG emission may increase the price of energy. This study examined the influence of the price of energy on demand for household devices. The influence of income on demand for devices was also tested. As expected, demand for household devices tends to increase as household incomes rise (McCollough, 2007; U.S. DOE, 2008). One study found an average elasticity of demand to income of 0.55 when they analyzed the sales of 10 energy-using consumer products. The elasticity of product sales to income ranged from a minimum of 0.09 for clothes dryers to a maximum of 1.26 for electric blankets (Golder and Tellis, 1998). The final economic variable examined in this study was the capital cost of the different type of devices. When trying to market a product, the capital cost has a large effect on sales (Golder and Tellis, 1998). This study examined the impact that each of these explanatory variables has had on the demand for devices over the past 30 years.

1.6 Research objectives

Cheap energy, rising incomes, and falling product costs have all contributed to people’s increasing demand for energy-using devices to make their homes more comfortable, convenient, connected, and entertaining. The objective of this study is to examine the relationship between several explanatory variables and the demand for new energy-using devices and forecast how these relationships might help anticipate the evolution of energy demand in the future. This study used data gathered on the adoption of energy-using household devices over the past 30 years to pursue the following objectives:

- Estimate the saturation and energy consumption of household devices not currently included in the CIMS model.
- Aggregate these devices into categories to estimate historical relationships in demand and energy intensity as a function of energy price, income, capital cost, and other relevant influencing factors.
- Use these historical relationships to forecast the energy consumption and GHG emissions of these devices for the next 30 years.

The remainder of this report will discuss the methods used and the results of this study. The methods used to determine the household penetration and energy consumption of devices, to aggregate them into service categories, to analyze the observed trends, and to forecasts future household energy consumption are described in Chapter 2. Chapter 3 presents and discusses the results of this study and compares the results to other studies. The final chapter of this report summarizes the findings of this study and provides recommendations for further research.

CHAPTER 2: METHODS

This chapter outlines the methodological approach I used to estimate how the adoption of energy-using household devices is influenced by several variables. Section 2.1 describes how data collected on the shipment and saturation of household devices were used to calculate household penetration of energy-using devices over the past 30 years. Section 2.2 describes how these devices were organized into categories. Section 2.3 describes the how the energy consumption and GHG emissions were calculated for each device and fuel type. Section 2.4 describes the econometric analysis performed in this study. Finally, section 2.6 outlines how the forecast of device penetration and energy consumption were generated and how uncertainty was incorporated into this study.

2.1 Household device penetration

This study began with estimating household device penetration over the past 30 years. Stocks of household devices were estimated using a combination of household saturation and shipment data collected from 1976 to 2006 (including an initial stock of devices in 1975). Saturation data specified the percentage of households using a particular device, and shipment data included the number of devices shipped, or sold, in the U.S. in any given year. The majority of the data from before 1995 were derived from a study conducted by the Lawrence Berkeley National Laboratory (Sanchez, Koomey, Moezzi, Meier, and Huber, 1998) and from the Global Marketing Information Database (GMID) (2008). From 1995 onwards, the majority of the data were obtained from annual reports produced by Appliance Magazine (2005a, 2005b, 2007a, 2007b) on the saturation and shipment of devices in the U.S. When both saturation and shipment data were available for a device, shipment data were used because the saturation of household goods does not indicate the number of devices per home, only the number of homes who have at least one.

In total, I collected data on 134 individual household devices such as televisions, home stereos, coffee makers, microwaves, compact refrigerators, and security systems. A more complete description of the devices included in this study is presented later in this chapter, and a complete list is contained in appendix A. This study did not include major household energy consumption categories already integrated into the CIMS model: space heating, water heating, lighting, or major appliances including refrigerators, freezers, dishwashers, clothes washers, clothes dryers, and stoves/ranges. However, there was one device included in this study that is also included in CIMS: air conditioners. Air conditioners were included in this study to illustrate the changing energy intensity of the air conditioning devices: the transition from fans as the primary source of cooling to air conditioners.

Saturation data were used to calculate the total number of devices in the U.S. by multiplying household saturation by the number of households (U.S. Census Bureau, 2008). However, the majority of the data used in this study were annual device shipments. Two retirement functions, derived from the CIMS model, were used to simulate device retirement and estimate the device population from 1976 to 2006. A linear function (Equation 1) was used to retire the existing stock of unknown age already in use in households.

$$BS_t = BS_0 - BS_0\left(\frac{T_t - T_0}{L}\right)$$

Equation 1

Where BS_t is the base stock at time t, BS_0 is the initial base stock, T_t and T_0 are simulated and initial year, and L is the lifespan of the device. Each year a constant amount of the base stock was retired until there is no more base stock remaining. This function was used for two scenarios in this study: when there was a stock of an existing technology in 1975, or when saturation data were collected for years preceding shipment data.

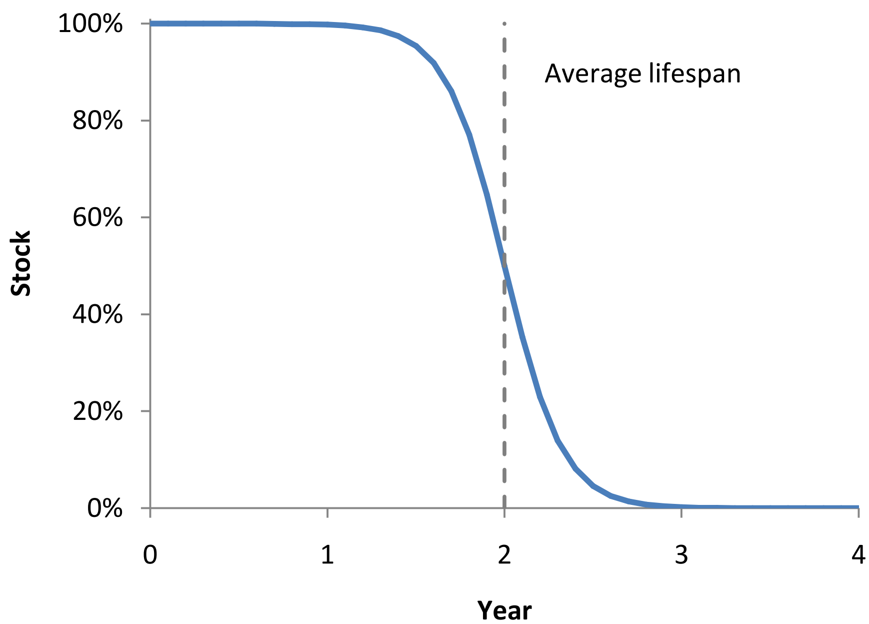
A second retirement function, shown in Equations 2 and 3, was used to retire devices that were added to household over the course of the study from 1976 to 2006.

$$NS_t = NS_p \left(\frac{1}{1 + e^{-11.513 - bet}} \right)$$ **Equation 2**

$$bet = \frac{-11.513 \times (T_t - T_p)}{L}$$ **Equation 3**

Where NS_t is the new stock not yet retired at time t, NS_p is the new stock acquired at time p, T_t is the year at time t, T_p is the year the new stock was acquired, and L is the lifespan of the device. The parameter value of 11.513 was published in an operation manual for the CIMS model (Bataille, 2005). This function uses an s-shaped, exponential curve to simulate the retirement of devices. Figure 5 shows an example of the retirement function of a device with a two year lifespan. Half of the stock is retired before the average lifespan of the device due to early replacement and failure and half is retired afterward to simulate households who keep the device longer than the average.

Figure 5: New stock retirement function



Source: Based on equations contained in Bataille (2005, p.14)

Average device life spans were derived from Sanchez et al. (1998) and Appliance Magazine (2007a).

The total stock of a device in any given year t is the sum of the unretired base stock and the unretired new stock from each previous year, as illustrated in Equation 4.

$$Stock_t = BS_t + \sum_{p=0}^{t} NS_t \qquad \textbf{Equation 4}$$

Where the *Stock* at time t is the remaining base stock (*BS*) added to the sum of unretired devices from all previous years.

2.2 Energy service modelling

Forecasting the adoption of new technologies and individual devices for any period is highly uncertain. Consumer product manufacturers typically use a forecasting period of 18 months to 3 years (Bayus, Hong, and Labe, 1989). Even with such a short forecasting period, sales forecasts of new products are only accurate 40% of the time (Kahn, 2006). Therefore, I aggregated devices together into categories based on the type of energy service they provide. The objective of this aggregation was to attempt to detect a relationship between demand for energy-using devices and some explanatory variable. In turn, these relationships could be used to generate forecasts for the demand of energy-using devices for longer periods, even up to 30 years.

The first step was to define a unit to quantify demand for energy services. Nordhaus (1997) presented an analysis of the demand for lighting as a function of the lumens of light emitted per unit cost of the energy input. Unfortunately, it is difficult to identify a common unit to quantify the service provided by the 134 household goods covered by this study. Thus, this study defines the demand for energy services as the number of energy-using devices per household.

The categories used in this study were compiled from a number of sources. One study identified the relatively rapid growth of entertainment devices, such as radios and televisions, compared to the slow, linear growth of labour saving devices, such as vacuum cleaners and dishwashers (Burwell and Swezey, 1990). Another study noted the rapid growth of electronics compared to non-electronic devices (Sanchez et al., 1998). I made my final distinctions based on a study that created a taxonomy of energy-using household devices (Nordman and Sanchez, 2006). The categories were finalized after examining these studies and determining what data was available to use in a regression analysis on the demand for these devices. Table 1 shows the compiled categories, the number of devices per category, and several examples of the included devices.

Table 1: Categories of devices

Category	*Number of devices*	*Examples*
Electronics	**47**	
Audio	11	home-theatre-in-a-box, MP3 player
Computer	8	desktop computer, modem
Imaging	9	camera, video camera
Television	15	LCD TV, DVD player, cable box
Telephone	4	cordless phone, corded phone
Miscellaneous	**70**	
Air conditioning and refrigeration	12	air conditioner, wine cooler
Labour saving	22	coffee grinder, blender
Personal care	10	electric toothbrush, hair dryer
Thermal	26	electric blanket, coffee maker
Outdoor	**17**	
Labour saving	13	lawn mower, leaf blower
Thermal	4	barbeque, hot tub
Total	**134**	

The first distinction of devices is whether the device is used indoors or outdoors. The second distinction is whether the device provides a service that is primarily derived from electronics or not. Devices not considered part of the electronics category are labelled ‘miscellaneous’ (Nordman and Sanchez, 2006). The final distinction is based primarily on the common service provided by each device. However, there are several other factors that influence the final device categorization. The first constraint is cost data that is available from the U.S. Bureau of Labor Statistics. There is also some observed substitution of devices within this study, such as the replacement of older cathode ray tube (CRT) televisions with newer liquid crystal display (LCD) and plasma flat panel models. Devices that are experiencing substitution are kept within the same category. Finally, the propensity of entertainment devices to diffuse rapidly versus the slower diffusion of labour saving devices is used to classify devices (Burwell and Swezey, 1990). A brief description of each category is given below and a complete list of all the devices and their assigned category is provided in Appendix A.

- *Audio* devices include non-portable home stereo systems and portable audio devices.
- *Computer* devices include desktop, laptop, and palm and pocket computers and internet access devices.
- *Imaging* devices include devices used to either capture or print images.
- *Television* devices include CRT, LCD, plasma, or projection televisions and their peripheral equipment such as DVD players and cable boxes.
- *Telephone* devices include corded, cordless, and wireless telephones as well as answering machines.
- *Air conditioning and refrigeration* include air conditioning devices, such as air conditioners, fans, and (de)humidifiers. Small refrigeration devices, such as under-counter refrigerators and wine coolers, are also included in this category.
- *Thermal* devices included any device where all (or most) of the energy it uses is to provide heat such as microwaves, coffee makers, kettles, irons, or electric blankets.
- *Labour saving* devices are made up of devices that use a small motor such as blenders, coffee grinders, sewing machines, or vacuum cleaners.
- *Personal care* devices include small handheld devices such as hair clippers, hair dryers, massagers, and electric toothbrushes.
- Finally, *outdoor* devices are categorized into *labour saving* devices such as lawn mowers and leaf blowers, and *thermal* devices such as barbeques and hot tubs.

One issue with aggregating devices into service categories is that the service that new technologies provide is constantly changing. Portable devices are the most notable example where cell phones are becoming cameras, mp3 players, and portable televisions. It is difficult to predict with confidence the evolution of these devices beyond the next 10 to 15 years. The aggregated categories presented in this study are an attempt to identify trends that may be useful for forecasting the demand for these devices.

2.3 Energy consumption and greenhouse gas emissions

The unit energy consumption (UEC) of each device is a function of how much the device is used and how much energy is drawn in each mode of use. Each device has three operational modes: active, idle, and off for non-portable devices; and charging, charge maintenance, and no-load for rechargeable devices. Active, or charging mode, represents the energy consumption of the device when it is in use such as when a TV is turned on or when a battery is being charged. Idle, or charge maintenance, energy consumption occurs when devices enter a stand-by mode such as an audio system that has been left on but is not in use or when a rechargeable device has been fully charged but remains plugged in. Finally, off, or no-load, represents when the device is turned off or there is no battery plugged into the charger. However, many devices continue to consume some energy in this mode. For example, when remote controlled televisions are turned off they use some energy waiting for a signal from the remote control.

A UEC for each device is calculated using energy consumption and usage data collected from a number of sources (Sanchez et al., 1998; U.S. Department of Energy, 2006; TIAX, 2007a & 2007b). Appendix B lists the number of hours each device is used per day, the power consumption of each device, the calculated UEC, and the data source for each device. The UEC of each device is calculated by summing the product of the annual usage of each device in each mode and the power consumption in each mode, as seen in equation 5.

$$UEC = T_{active}P_{active} + T_{idle}P_{idle} + T_{off}P_{off} \qquad \textbf{Equation 5}$$

Where *UEC* is the unit energy consumption of each device in kilowatt hours (kWh) *T* is the time the device spends in each mode in hours per year and *P* is the power consumption in kWh. All of the fuels covered by this study were converted to an equivalent kWh using energy conversion factors (Environment Canada, 2008). The amount of time the device is used each year and the amount of power consumed in each mode is assumed to remain constant over time; therefore, the UEC of each device remained fixed. Some technologies, such as breadmakers, use energy for different purposes, such as mixing the dough (labour) and baking the bread (thermal). These devices are assigned to the category in which they use more energy. The household energy consumption of each device is calculated by multiplying the UEC by the average number of devices per household. The energy consumption for each device category is simply the sum of the energy consumption of each device in that category.

The GHG emissions emitted by these devices are calculated using emission factors for the different fuels and expressed as a carbon dioxide equivalent (CO_2e). This measure takes into account the atmospheric warming potential of different GHG gasses, such as methane, and expresses it as an equivalent amount of carbon dioxide (CO_2). There are three types of fuel used by the devices in this study: electricity, natural gas, and gasoline. The emission factor used for natural gas is 0.22 kg CO_2e per kWh and 0.24 kg CO_2e per kWh for gasoline (Environment Canada, 2008). The GHG emissions factor for U.S. electricity is forecast to decline from 0.64 kg CO_2e per kWh in 2006 to 0.59 kg CO_2e per kWh by 2030 (EIA,2009).

2.4 Econometric analysis

Once the growth in demand for energy-using devices had been estimated for the past 30 years, I used econometric analysis to look for relationships between the observed growth of energy-using devices and some explanatory variable.

The two most important, non-economic variables that affect the sales of devices are the replacement of old devices with new ones and the number of new households created each year (U.S. Department of Energy, 2008). This study addresses the number of devices retired and replaced each year using the retirement functions described in section

2.1 of this report. The influence of growth in the number of U.S. households is factored out by dividing the estimated device population by the total number of households in the U.S. each year (U.S. Census Bureau, 2008). Removing these influencing variables revealed the number of devices in use by the average household for the past 30 years.

After removing the influence of non-economic variables, the next step was to assess the impact of economic ones. This study considered the influence that three economic variables could have on demand for household devices: the price of energy (EIA, 2008); mean household income (U.S. Census Bureau, 2009); and the capital cost of these devices. A cost index, calculated by the U.S. Bureau of Labor Statistics (2008), is used in this study as a proxy for capital cost. Unfortunately, only nine years of cost index data are available for all indoor devices except for television and audio devices, which have 31 and 29 years of available data, respectively. Outdoor devices on the other hand have even less data and are treated separately from indoor devices. There are only seven years of data for outdoor devices. Shipment and saturation data are only available for years after 1994. Therefore, the penetration of outdoor devices per household did not stabilize until around the year 2000 in my model. All of the economic and non-economic variable data are included in appendix C at the end of this report. Equation 6 shows the static model that I estimated using an ordinary least squares (OLS) regression. OLS is a common and relatively simple method of performing a linear regression that I used for all of the regressions performed in this study. These regressions, and related statistics, estimated in this study were conducted using R which is a free software environment for statistical analysis.

$$d_t = \beta_0 + \beta_1 lnP_t + \beta_2 lnY_t + \beta_3 C_{it} + e_t \qquad \textbf{Equation 6}$$

Where d is the number of devices per household, P is the price of energy, Y is mean U.S. household income, C is the cost index, $\beta_{1,2,3}$ are the parameters for each of the explanatory variables, β_0 is the intercept of the linear regression model, and e_t is error term. Both the R^2 value and standard error of the multiple regressions were improved by taking the natural logarithm of energy price and income and made the parameters generated for these variables elasticities. The results of the regressions were virtually the same without taking the log of price and income. Taking the log of cost or devices tended to increase the standard error, lower the R^2, and substantially change the results of the these regressions. Other combinations of logging the independent variables led to substantially different outcomes and higher standard error.

The average UEC of each category of devices is assumed to be a function of three independent, or explanatory, variables (equation 7): the price of energy, the ratio of new technologies to the total number, and the total number of devices in the category.

$$ln\ E_t = \beta_1 lnP_t + \beta_2 R_t + \beta_3 d_t + \beta_0 + e_t \qquad \textbf{Equation 7}$$

Where E is the average UEC of a device in the category, P is the price of energy, R is the ratio of new devices in each category, d is the number of devices in each category, $\beta_{1,2,3}$ are the parameters for each of the explanatory variables, β_0 is the intercept of the linear regression model, and e_t is error term. The ratio of new technologies (R) is included to show the impact that the adoption of new technologies has energy consumption. This ratio is simply the penetration of new devices divided by the total number of devices in each category. The total number of devices (d) in each category is included in the regression to account for large variations in the UECs generated by the device model I developed. For many of the device categories, there are very few devices at the beginning of the study period but many by the end. This increase in the number of devices can have a large impact on the average UEC of the category. Therefore, I included this variable to account for these rapid changes in UEC so that this trend is not ascribed to the other variables. After specifying these models, I turned my attention to the many potential pitfalls of applying OLS linear regression to time series data.

Many time series grow over time. Time series that are trending in the same, or opposite, directions can lead to the false conclusion that they are related (correlated) when in fact they are trending due to other, unobserved factors (Wooldridge, 2003). Thus, it was necessary to remove the time trend in a process known as detrending. I detrended the data by running a linear regression of each variable against time and then used the residuals from these regressions as the explanatory variables. With the time trend removed, the actual influence that each independent variable had on the number of devices became more evident.

There are two other common problems that can cause regression statistics to be misleading: heteroskedasticity and serial correlation. Heteroskedasticity is when the variance in an independent variable changes with the value of that estimator. For example, if as the variable gets bigger the variance increases, your variable will become a worse estimator. Serial correlation occurs when there is correlation between the error terms of a regression. Correlation in the error terms violates the assumption that there is no correlation in the error terms, and results in a biased model. A biased model suggests that the data set used in the regression was not a random sample drawn from a population. These two issues will cause OLS regression to underestimate the uncertainty in the parameters of the model.

Therefore, I calculate a standard error for each regression parameter that is robust to both serial correlation and heteroskedasticity according to a method outlined in Wooldridge (2003). The first step is to perform a regression (outlined in equation 6) of energy price, income, and cost on the number of devices in each category. Next, I regress each explanatory variable against one another: for example, the residual $\hat{r}_t$ for energy price was obtained by running a regression where income and device cost were the explanatory variables. Equation 8 uses the residual from equation 6 ($\hat{e}_t$) and the residuals obtained by regressing the explanatory variables against each other ($\hat{r}_t$) to calculate a standard error transformation factor ($\hat{v}$).

$$\hat{v} = \sum_{t=1}^{n} \hat{a}_t^2 + 2\sum_{h=1}^{g} \left(1 - \frac{h}{g+1}\right) \left(\sum_{t=h+1}^{n} \hat{a}_t \, \hat{a}_{t-h}\right) \qquad \textbf{Equation 8}$$

where $\hat{a}_t = \hat{r}_t \hat{e}_t, t = 1,2, \ldots, n.$

The parameter *g* is set to one because of the small sample size (Wooldridge, 2003). Finally, the robust standard errors are estimated using equation 9.

$$se(\hat{\beta}_k) = \left[\frac{"se(\hat{\beta}_k)"}{\hat{\sigma}}\right]^2 \sqrt{\hat{\upsilon}}$$ **Equation 9**

Where $se(\hat{\beta}_k)$ is the robust standard error for each independent variable, and $"se(\hat{\beta}_k)"$ and $\hat{\sigma}$ are the non-robust standard error and standard deviation for each variable from the regression of equation 6.

The regression analysis of each category did not yield definitive conclusions about the effect of energy price, income, and capital cost on demand for these devices. In an attempt to find more conclusive results about the effect of these parameters on demand, I performed a panel analysis on the data.

The different categories of devices identified in this study represent several cross-sections of data. A panel analysis involves looking at these cross-sections in unison, over time, to determine if energy price, income, and cost may have a common effect on all of these categories. A fixed effects model is used to estimate this relationship. This type of model assumes that each category has a constant slope (response) but allows an intercept that is different between the cross-sectional (Yaffee, 2005). Allowing a different intercept between each category acknowledges that each of these categories may be influenced by variables that are omitted from the regression equations (Hsiao, 2003). However, the response all of the variables is assumed to remain constant over time. I also use a fixed effects model on two other groupings of devices that I thought may yield some information on how they grow with time. These groupings are discussed in the results section of this report. Equation 10 shows the fixed effects model that was used to estimate demand for household devices.

$$d_{it} = a_1 + a_i group_i + \beta_1 lnP_t + \beta_2 lnY_t + \beta_3 C_{it} + e_t$$ **Equation 10**

Where d_{it} is the demand for devices in each cross-section i, $a_1$is the intercept, $a_i group_i$ represents the intercept for each device category. Similarly, equation 11 shows the regression equation for the panel analysis of trends in UEC.

$$lnE_{it} = a_1 + a_i group_i + \beta_1 lnP_t + \beta_2 R_{it} + \beta_3 d_{it} + e_t \quad \textbf{Equation 11}$$

Where E_{it} is the UEC for each cross-section i, a_1 is the intercept, $a_i group_i$ represents the intercept for each device category. All of the data used in the panel analysis were the same logged and detrended data used in the regression for each individual category.

Similar to the individual categories, the parameters for the panel data are estimated using an OLS regression which is also subject to misleading results caused by serial correlation and heteroskedasticity. These problems may occur in panel data when the variance of the error is different between cross-sections or correlated in time (Beck and Katz, 1995). The panel data on indoor devices I compiled for this study is particularly suited for an analysis referred to as panel-corrected standard errors (PCSEs). Because the number of cross-sections (9) and years covered (9, except for audio and television devices) by this study are the same, the feasible generalized least squares (FGLS) method typically used to address serial correlation can overestimate the significance of the variables (Beck and Katz, 1995). The first step was to run a test for serial correlation in each of the device categories using equation 12.

$$u_t = \rho_1 u_{t-1} + \cdots + \rho_q u_{t-q} + e_t \quad \textbf{Equation 12}$$

Where $\hat{u}_t$ is the error term of a linear regression, $u_{t-q}$is the error of a previous time period, ρ_q is the serial correlation coefficient up to q lags, and $e_t$is the residual error from the regression of the errors. If the serial correlation coefficient indicated that there was more than a 5% chance that the error terms were serially correlated, the data were transformed to remove the serial correlation (Wooldridge, 2003). This transformation used the serial correlation coefficient to weight the values used in the regression to remove the serial correlation and maintain the mean and variance of the sample (Wooldridge, 2003). The equation used to transform the data, known as a Prais-Winston estimation, is shown in equation 13.

$$\widetilde{y_{it}} = y_{it} - \rho_1 y_{it-1} - \cdots - \rho_k y_{it-k}\,,\ \widetilde{x_{it}} = x_{it} - \rho_1 x_{it-1} - \cdots - \rho_k x_{it-k}$$

$$t > 2, k = 1,2, \dots, n. \qquad \textbf{Equation 13}$$

Where *y* is the dependent variable, *x* is the independent variable, ρ is the serial correlation coefficient, and *k* is the order of the serial correlation. Where first order serial correlation was found, equation 14 was used to transform the first variable.

$$\widetilde{y_{i1}} = y_{i1}(1-\rho)^{1/2},\ \ \widetilde{x_{i1}} = x_{i1}(1-\rho)^{1/2} \qquad \textbf{Equation 14}$$

Once the serial correlation of each category was removed they were compiled for panel analysis. I tested the fixed effects model for serial correlation using a statistical package written for R and based upon a method developed in Wooldridge (2002). After ensuring there was no serial correlation in the panel data for both the device and UEC regressions, I used another R package based on the method outlined in Beck and Katz (1995) to calculate the panel-corrected standard-errors. These errors were robust to both serial correlation and heteroskedasticity. The results of these transformations and their corrected standard errors are presented in Chapter 3 of this report.

2.5 Forecasting and incorporating uncertainty

Because forecasts for new products are uncertain, it is important to assess a range of possibilities when it comes to forecasting (Kahn, 2006). There were many assumptions made in this study to generate a historical data set and forecasts. While each of these assumptions is based upon the best available expert advice and literature, there is still a degree of uncertainty in each. Thus, a range of values are used for each assumption.

The three variables used to generate the historical penetration of devices and energy consumption are device lifespan, the number of hours per day that each device is used, and the power consumption in each mode of use. Adjusting the lifespan of each device affects how long people are expected to keep using that device. The longer that people keep the device, the more there are per household. Appliance Magazine (2007b) provided a range of lifespan for most of the appliances. Where a range was not available, a 33% difference in the average lifespan is assumed because that was the average deviation that I observed in the data (Appliance Magazine, 2007b). The next variable is the number of hours people used each device per day. I assume a range of ± 25% for the number of hours each device is used in both active and idle mode. Finally, the power consumption range is derived from a report that contained data on the average power consumption and a best-in-class consumption of a number of devices (TIAX, 2007b). The best-in-class technologies use an average of 34% less energy than the average. In the absence of a best-in-class power consumption, I assume a range of ± 34%.

Forecasting the penetration of household devices requires forecasts of energy price, income, device cost, and the ratio of new devices to existing ones. Forecasts for the price of energy were taken from the EIA (2009). The forecast for income is a linear regression against time based on data collected from the U.S. Census Bureau (2009). The new device ratio is also a linear forecast of the linear trend found in this study. The forecasts of energy price, income, and the new device ratio were assumed to deviate ± 25%. This deviation is incorporated into error bounds around the forecast of device penetration and energy consumption. I generated a forecast for the cost of these devices based on the average decline in the cost indices of 5.4% a year. I assume that the continued decline in the cost of these devices will continue within a range from 0.1% to 10% annually for the next 30 years.

A Monte Carlo simulation is used to estimate the range in uncertainty for the parameters I generated from my regression analysis of device penetration and UEC. I assume that the error of each of these parameters is normally distributed and ran the Monte Carlo simulation 20,000 times to generate a 95% confidence interval for the forecasts generated from my regression equations.

CHAPTER 3: RESULTS AND DISCUSSION

This chapter presents a discussion of the results generated by the examination of the relationships between demand for energy-using devices and several explanatory variables. Section 3.1 presents the trend in household penetration of energy-using devices, not including major appliances, over the past 30 years. Section 3.2 shows how much energy was used by these devices in U.S. households. Section 3.3 explores the trends in energy intensity of the different categories of devices. Section 3.4 presents the results of an econometric analysis on the demand for energy-using devices. The demand and energy consumption of outdoor devices is presented in Section 3.5. Section 3.6 then compares the results of this study to other energy consumption forecasts and the associated GHG emissions.

3.1 Demand for energy-using devices

Over the past 30 years, there has been a substantial increase in the number of energy-using household devices. In 1976, there were 15 energy-using devices in the average American household. Since 1976, nearly one new device has been added each year to reach an average of 41 devices per household in 2006. Table 2 shows the ten most common devices found in the average U.S. household, and Table 3 shows the ten most shipped devices in 2006.

Table 2: Ten most common U.S. household devices in 2006

Device	*Number per household*
Telephones, Wireless	2.0
Telephones, Cordless	1.8
Computer, desktop	1.5
Fans, Ceiling	1.5
Televisions, Color, Direct-View	1.3
Telephones, Corded	1.2
Telephone Answering Devices	1.2
Microwave Ovens	1.1
Air Conditioners	1.1
Hair Dryers	1.0

Source: Generated using retirement functions from data cited in the methods section of this report.

Table 3: Top ten devices shipped in the U.S. in 2006

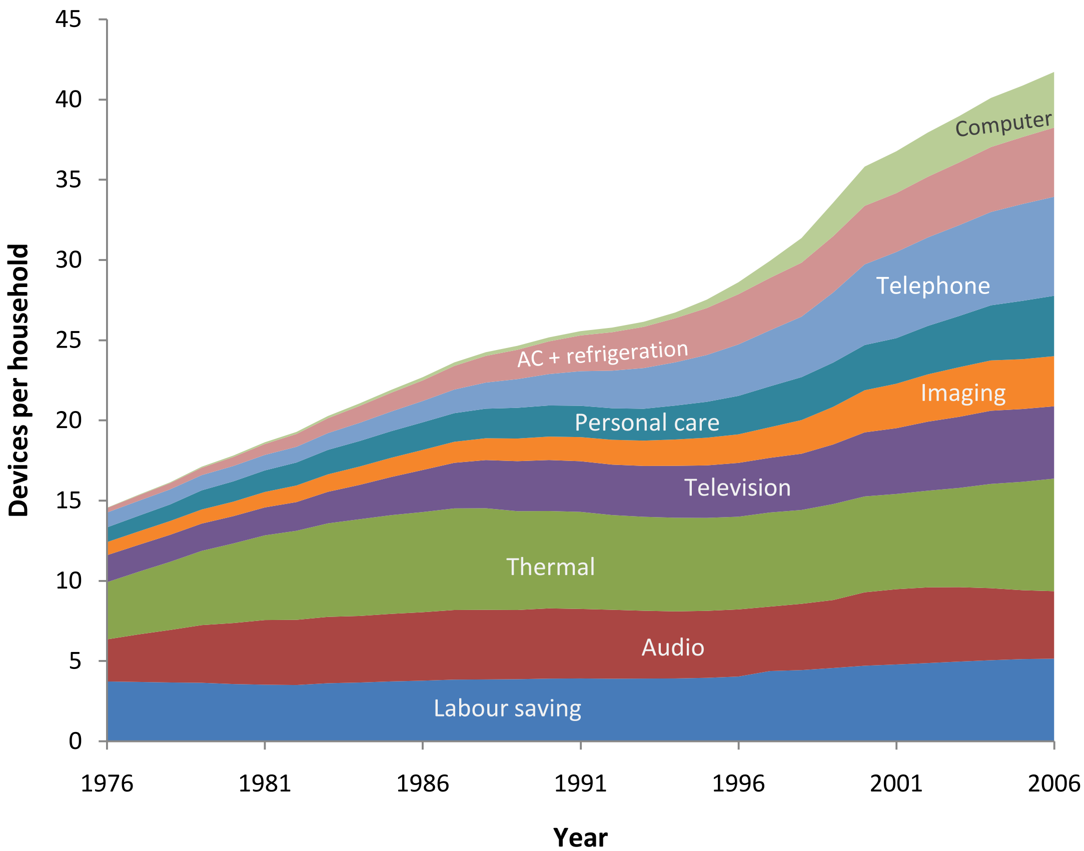
Device	*Number shipped*
Telephones, Wireless	127,454,000
Computer, Desktop	39,697,901
Curling Iron and Styling Combs	32,000,000
Telephones, Cordless	30,883,000
Cameras, Digital	28,838,200
Coffee Makers, Automatic Drip	27,500,000
Telephone Answering Devices	25,609,000
Hair Dryers	24,150,000
MP3 players, Portable	23,475,500
CD Players, Non-Portable	21,714,000

Source: Appliance Magazine (2007a)

Both of these tables indicate that wireless (cellular) telephones have become the most ubiquitous energy-using device in the U.S. By 2006, telephones, with an average of five per household, had become the most common energy-using device included in this study. Desktop computers were the second most common household device in 2006, followed by ceiling fans and televisions. However, these tables do not represent the change that has occurred over the past 30 years in demand for household devices.

Figure 6 shows the penetration of indoor devices from 1976 to 2006 in order of their percentage growth. Labour saving devices grew the least as a percentage of their penetration in 1976 whereas computer devices grew the most. Outdoor devices are covered in a later section of this report.

Figure 6: Household penetration of indoor devices



Source: Generated using retirement functions from data cited in the methods section of this report.

Table 4 shows that from 1976 to 2006, the average number of miscellaneous devices per household doubled from 8.5 to 20.2, whereas the number of electronic devices per household more than tripled from 6.1 to 21.5. Over the past 30 years, there has been a dramatic shift in the devices used in each of these categories.

While audio devices and televisions were the most common electronic devices in 1976, telephones and computer devices were the most common in 2006. Even the slowest growing electronic category, audio devices, increased in household penetration by 60%.

Table 4: Growth in demand for energy services per household

Category	*Devices per household*			
	1976	*2006*	*growth*	*% diff.*
Electronics	**6.1**	**21.5**	**15.4**	**254%**
Telephone	0.9	6.2	5.2	568%
Computer	0.0	3.5	3.4	>1000%
Television	1.7	4.5	2.8	168%
Imaging	0.8	3.1	2.3	283%
Audio	2.6	4.2	1.6	60%
Miscellaneous	**8.5**	**20.2**	**11.7**	**138%**
Air conditioning and refrigeration	0.3	4.3	4.0	>1000%
Personal care	0.9	3.8	2.8	310%
Labour saving	3.7	5.1	1.4	38%
Thermal	3.6	7.0	3.5	97%
Total	**14.6**	**41.7**	**27.2**	**392%**

Source: Generated using retirement functions from data cited in the methods section of this report.

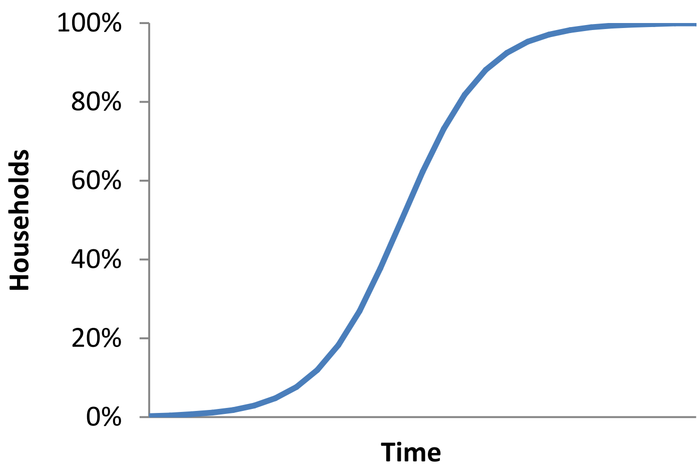
Meanwhile, in the miscellaneous category, the two device categories that use the most energy per unit, air conditioning and refrigeration and thermal, grew the fastest. Kitchen devices, such as coffee makers, made up the majority of the thermal category and grew from 2.3 in 1976 to 5.1 devices per household in 2006: 80% of the growth in this category. Most of this growth is due to the introduction of microwave ovens into homes and a large increase in automatic drip coffee makers. Other notable trends include a decline in the once-popular hot-air corn poppers, presumably replaced by microwave popcorn, and a resurgence in the popularity of slow cookers since 2003. Labour saving kitchen devices grew from 2.1 to 3.3 devices per household over the same period and accounted for 86% of the growth in labour saving category. The change in labour saving kitchen devices is attributable to moderate growth in blenders and food waste disposals. Finally, growth in the personal care category was led by an increase in the adoption of curling irons and styling combs/wands/crimpers, hair dryers, and electric toothbrushes.

There were two more general trends in the penetration of household devices that might be useful in predicting their growth. These trends are described in the next two sub-sections of this report.

3.1.1 Trends in the penetration of household devices

The change in penetration of each device could be classified as either linear or s-shaped. I observed that 35 devices showed a linear household penetration trend and 82 devices that followed an s-shaped curve. This s-shaped pattern of adoption, shown in Figure 7, is commonly referred to as a diffusion curve.

Figure 7: Diffusion curve representing device adoption



The s-shaped diffusion of devices is the result of households following a normal distribution in their adoption. Rogers (1983) identified five types of device adopters based on this distribution: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and the laggards (16%). The innovators and early adopters adopt devices despite potential technological problems, high capital costs, and high risk. As the device is improved, the cost falls, awareness of the new device spreads, and its market penetration increases rapidly.

Berwell and Swezey (1990) found that labour saving devices tended to follow a linear trend and grow more slowly than entertainment devices which experienced s-curve diffusion. This observation led to an assumption that a difference in the type of diffusion of a device may be a good indicator of how fast its market share will grow. Their observation that labour saving devices tend to grow more slowly was consistent with this hypothesis. However, audio devices, which are an entertainment device, did not grow substantially more over the same period. I also found, contrary to Burwell and Swezey

(1990), that half of labour saving devices followed an s-curve. Table 5 classifies each device category based on whether 80% of the devices have exhibited s-curve growth. The predominance of s-curve growth occurred mainly within the electronics category, with the exception of personal care devices. Most of the categories that showed linear growth were part of the miscellaneous grouping with the exception of audio devices.

Table 5: Device diffusion patterns by trend

Category	*Number of devices*			*Percentage*	
	linear	*s-curve*	*total*	*linear*	*s-curve*
S-curve	**6**	**40**	**46**	**13%**	**87%**
Computer	1	7	8	13%	88%
Imaging	1	8	9	11%	89%
Personal care	2	8	10	20%	80%
Telephone	0	4	4	0%	100%
Television	2	13	15	13%	87%
Linear	**29**	**42**	**71**	**41%**	**59%**
Air conditioning and refrigeration	6	6	12	50%	50%
Audio	3	8	11	27%	73%
Labour saving	11	11	22	50%	50%
Thermal	9	17	26	35%	65%
Total	**35**	**82**	**117**		

Source: Generated using retirement functions from data cited in the methods section of this report.

This distinction between the average growth within each category led me to hypothesize that the difference in diffusion patterns may be of use when trying to forecast their growth.

3.1.2 Trends in the demand for new technologies

The second relationship that might provide useful information for modelling the growth of these devices was whether a faster rate of invention, innovation, and adoption could explain some of the variation in growth. Table 6 lists the number of devices that existed in each category in 1976 next to the number of new devices that were added to each category over the past 30 years. Note that this table shows the number of new devices that have been adopted over the past 30 years, not their penetration. Roughly the same number of new devices have been added to both electronic and miscellaneous categories.

Table 6: Number of new devices since 1976

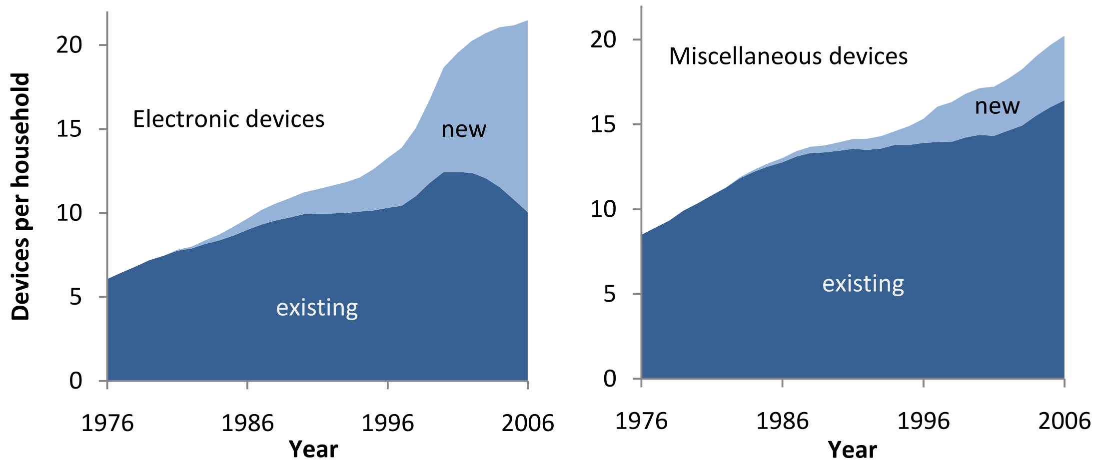
Category	*Number of devices*			*Percentage*	
	existing	*new*	*total*	*existing*	*new*
Electronics	**17**	**30**	**47**	**36%**	**64%**
Audio	5	6	11	45%	55%
Computer	2	6	8	25%	75%
Imaging	2	7	9	22%	78%
Telephone	2	2	4	50%	50%
Television	6	9	15	40%	60%
Miscellaneous	**42**	**28**	**70**	**60%**	**40%**
Air conditioning and refrigeration	7	5	12	58%	42%
Labour saving	10	12	22	45%	55%
Personal care	7	3	10	70%	30%
Thermal	18	8	26	69%	31%
Total	**59**	**58**	**117**		

Source: Data derived from Appliance Magazine (2005a, 2005b, 2007a, 2007b)

The labour saving category showed the largest increase in new devices. Yet, the actual penetration of labour saving devices into households grew slower than any other category: 1.4 devices per household over 30 years as shown in Table 4. Conversely, the telephone category has the smallest number of new devices but showed a higher increase in household penetration than any other device category. It appears therefore that the number of new devices that have been developed over the past 30 years is not a reliable indicator of the growth of household devices.

However, Figure 8 indicates that new electronic devices gain market share more rapidly than new miscellaneous devices. The 30 new electronics devices have reached a total household penetration of 11.4 devices: three times greater than the average penetration of 28 new labour saving devices.

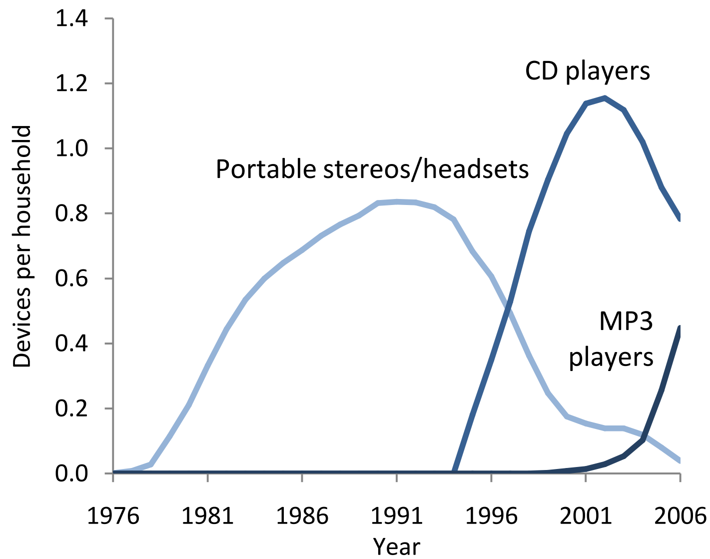
Figure 8: Penetration of new versus existing household devices



Source: Generated using retirement functions from data cited in the methods section of this report.

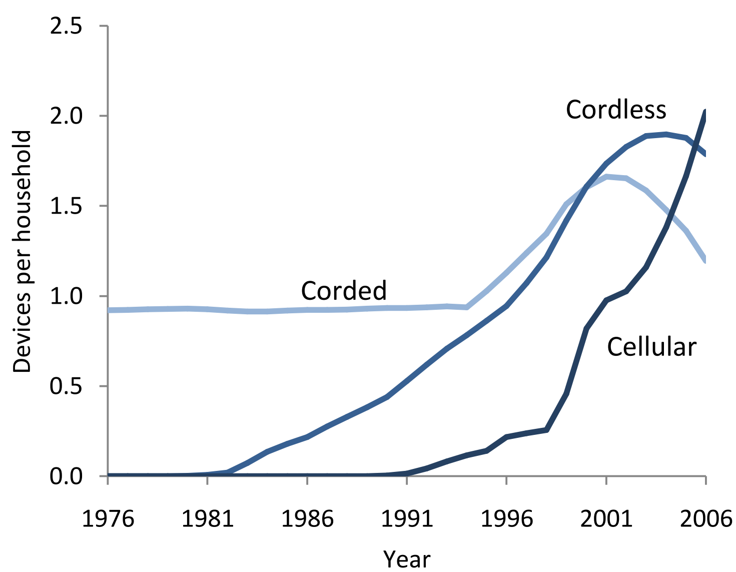
As new technologies are invented and developed, they replace older generations. One study suggests that demand for a device increases when a new generation of technology is adopted (Norton and Bass, 1987). This trend is similar to the dramatic increase in demand for artificial light that has occurred when lighting technology was improved (Nordhaus, 1997; Fouquet and Pearson, 2006). Most of the devices included in this study were improved incrementally and exhibited relatively stable patterns in decline or growth in household penetration. However, several categories of products have experienced rapid replacement by new generations. This trend occurs when a revolutionary new technology is developed and quickly taken up by households. Two examples of the complete replacement of one technology with another were observed in this study: portable CD players replaced portable personal stereos/headsets and exceeded their penetration by 38% (Figure 9), and cordless phones superseded the penetration of corded phones by 14% (Figure 10).

Figure 9: Generations of portable audio devices



Source: Generated using retirement functions from data cited in the methods section of this report.

Figure 10: Generations of telephones



Source: Generated using retirement functions from data cited in the methods section of this report.

The next generations of portable audio devices (MP3 players) and telephones (cellular phones) are already experiencing exponential growth and replacing the previous generation. A number of other device categories exhibited similar trends.

Most of the devices classified as miscellaneous show a more predictable evolutionary growth in household penetration. Many new miscellaneous devices have become available but none show the kind of device replacement exhibited in electronic devices.

The growth of a revolutionary new device is much more dramatic and occurs when a new technology that people find highly desirable is rapidly adopted to replace an older generation. This revolutionary growth in demand was observed in all of the electronic device categories: audio, computer, imaging, telephone, and television.

One of the most dramatic revolutions in device adoption has been the replacement of corded phones with cordless models and subsequently the rapid adoption of cellular, or wireless, telephones. Of the top ten annual device shipments used in this study, the top seven are wireless telephones which shipped 52.6 million units in 2000 growing annually to reach 127 million units in 2006. Cordless telephones held the eighth and ninth position at 40 million units shipped in 2001 and 2003. Wireless phones have dramatically increased the demand for telephone devices. The ease of substitution and enhanced mobility of these new devices made cordless and wireless telephones very popular. Telephones, wireless and cordless, are the two most common household devices with an average of 2.0 and 1.8 (respectively) per household in 2006.

Only one non-electronic service category showed this revolutionary growth. During the 1980s, ceiling fans grew rapidly to peak around 1.5 units per home and were followed by the rapid uptake of air conditioners which are still growing exponentially. There was an average of 1.1 room air conditioners per household in 2006. However, despite this increase in air conditioner penetration, the penetration of ceiling fans remained steady. Increased penetration of air conditioners does not appear to be reducing the average number of ceiling fans per household. Table 7 provides a summary of the device categories that have experienced revolutionary growth.

Table 7: Summary of revolutionary devices

Category	*Device replacement* *Type of device*	*Explanation*
Audio	Portable audio	Portable stereos replaced by CD players followed by MP3 players
	Home stereos	Rack stereo systems and non-portable CD players being replaced by home-theatre-in-a-box
Computer	Computers	Desktops partially replaced by laptops
	Internet access devices	Replacement of dial up modems with high-speed modems
Imaging	Cameras and camcorders	Analogue cameras and camcorders being replaced by their digital counterparts
	Printers	Some replacement of inkjet printers with laser printers
Telephone	Telephone	Replacement of cordless phones with cell phones
Television	Televisions	CRT TVs replaced by LCD and plasma flat panel models
	Video playback	VCRs replaced by DVD players
Air conditioning and refrigeration	Air conditioning	Supplementation of fans with air conditioners

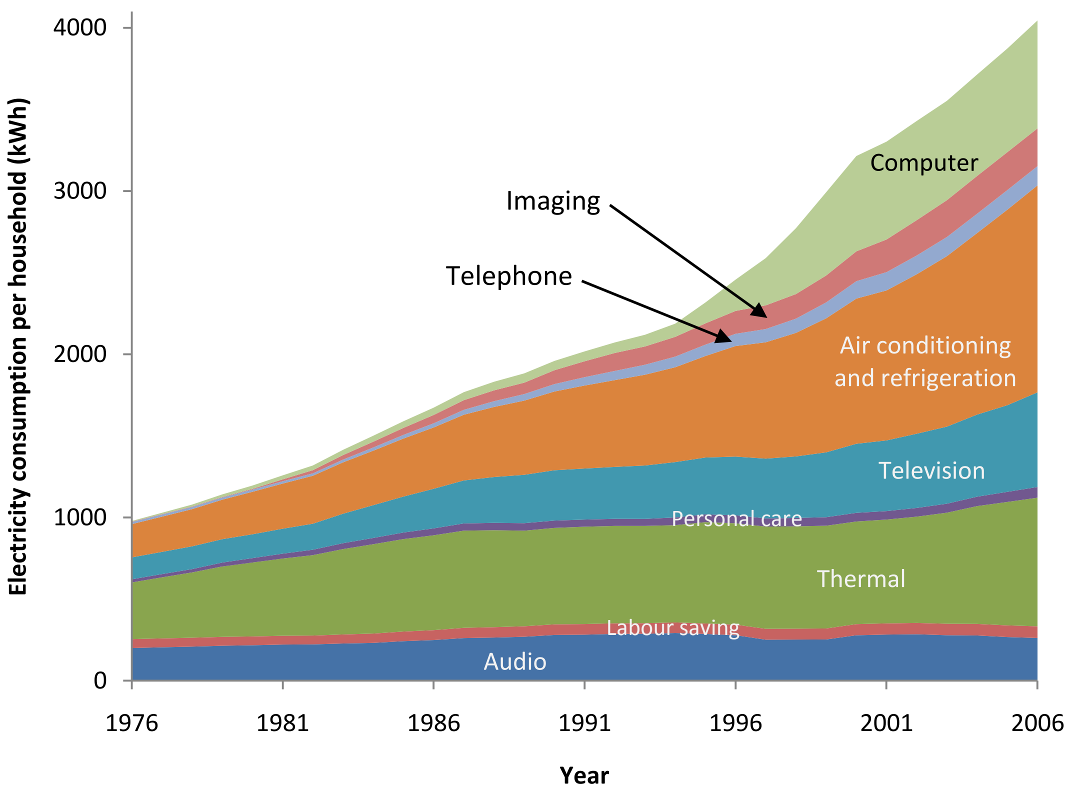
One reason that these electronics categories show this pattern in adoption is the available data. More data on the types of devices being shipped in the miscellaneous category may have showed this type of replacement for other devices, such as automatic coffee makers. However, while the service provided by the device may be improved with a coffee warming plate or a digital clock timer, the method of providing the service has not been as radically changed as observed in the electronics categories. Electronics are much newer in general than the miscellaneous devices that use established technologies, such as motors or heating technologies. New miscellaneous devices are also often a repackaging of an established technology that becomes popular, such as wine coolers. The categories that have experienced this revolutionary replacement of devices were also tested to determine if this type of device replacement had an economically or statistically significant impact on the growth of energy-using devices. However, before presenting the results of my econometric analysis, the next section of this report looks at the electricity consumption of these devices.

3.2 Household electricity consumption

The electricity consumption of a device category was calculated by multiplying each device's UEC (annual energy consumption) by its household penetration. All of the indoor devices use only electricity as a fuel source. Outdoor appliances that use other fuels are discussed in a later section of this chapter.

While the number of devices nearly tripled from 1976 to 2006, Figure 11 shows that the annual electricity consumption of these devices has quadrupled from around 1000 kWh to 4000 kWh over the same period.

Figure 11: Household electricity consumption



Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

Like device penetration, Table 8 indicates that the electricity consumption of all device categories has increased over the past 30 years. Heating and cooling devices dominated electricity consumption and used 51% of the total electricity consumption in 2006. The next highest energy users were computer and television devices, they made up

16% and 14% of electricity consumption in 2006, respectively. At the other end of the spectrum, the telephone, imaging, personal care, and labour saving categories made up 67% of energy-using devices in the average household but used only 12% of the electricity consumed by these devices.

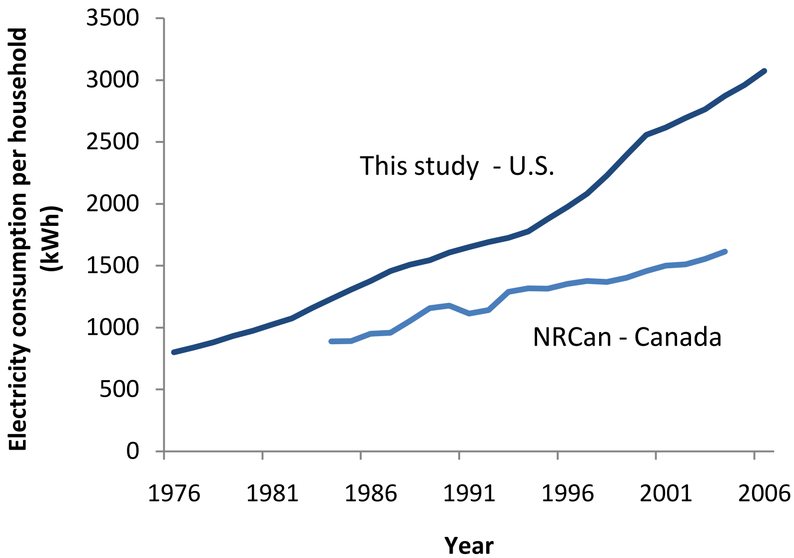
Table 8: Household electricity consumption

Category	*Electricity consumption (kWh)*			
	1976	*2006*	*growth*	*% diff.*
Electronics	**354**	**1,852**	**1,498**	**423%**
Audio	201	262	62	31%
Computer	4	661	657	15720%
Imaging	2	231	229	11370%
Telephone	13	118	105	796%
Television	134	580	445	332%
Miscellaneous	**625**	**2,192**	**1,568**	**251%**
Air conditioning and refrigeration	204	1,268	1,064	523%
Labour saving	55	72	17	31%
Personal care	19	66	46	243%
Thermal	347	788	441	127%
Total	**979**	**4,044**	**3,066**	

Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

There have been other studies of the energy consumption of electronic and miscellaneous devices. Figure 12 compares the estimated electricity consumption of energy-using devices over the past 30 years to an estimate of “other appliances” in Canada (NRCan, 2005). The “other appliances” category includes televisions, VCRs, DVD players, radios, computers, and toasters (NRCan, 2005).

Figure 12: Comparison of estimates of household electricity consumption in Canada and the U.S. from 1976 to 2006



Source: Generated using retirement and UEC functions from data cited in the methods section of this report and Natural Resources Canada (2005).

Recall that the estimated electricity consumption shown in Figure 12 from this study is based on U.S. data. I have also removed the energy consumption of air conditioners from the estimate of this study to make it more comparable to the estimate generated by NRCan. In 1984, the estimate in this study is 39% higher than NRCan's. By 2004, this difference nearly doubles to 78% and may be attributable to higher incomes in the U.S. This study also captures the energy consumption of a lot more devices than the six listed by NRCan as "other appliances".

Another U.S. study examined the penetration and usage of 23 energy-using devices, all of which were included in this study (TIAX, 2007b). They found that in 2006, these devices used 2580 kWh per household on average. Even after removing air conditioners (a difference of 972 kWh), I found that the devices in this study used 20% more electricity than TIAX estimated.

Another relevant comparison for this study is data from the EIA (2009). The EIA breaks down residential electricity consumption into 14 different end-use categories, some of which are similar to those used in this study. They estimated that in 2006, 'color televisions and set-top boxes' used 883 kWh of electricity and 'personal computers and related equipment' used 374 kWh. This study found that televisions used 303 kWh less and computers used 287 kWh more in 2006 than the EIA. Thus, the total for these two categories is virtually the same between studies. Not including space cooling, the EIA's 'other' residential devices used 3,600 kWh while my estimate was 15% lower at 3,100 kWh. In 2006, the EIA estimated that the average household used 2,200 kWh compared to the 1,000 kWh for air conditioners in this study. Therefore, my study substantially underestimates the demand for space cooling in the U.S. This discrepancy was inconsequential because this study was not intended to estimate demand for space cooling (which already exists in the CIMS model). I included air conditioners to show how their addition interacts with air conditioning devices not currently included in CIMS or the EIA estimates. Except for air conditioning, the energy consumption of devices not included in the CIMS model estimated in this study was comparable to other, similar studies.

3.3 Trends in unit electricity consumption

Table 9 shows the ten devices that consume the most electricity as a function of their penetration and UEC.

Table 9: Top ten energy consuming devices in 2006

Device	*Total kWh*	*Devices per household*	*UEC kWh/year*
Air Conditioners	*972*	1.1	907
Computer, desktop	*665*	1.8	365
Aquariums	*239*	0.1	1840
Televisions, Color	*164*	1.3	129
Microwave Ovens	*142*	1.1	131
Portable Heater, Electric	*135*	0.3	475
Security System	*128*	0.2	534
Fans, Ceiling	*123*	1.5	83
CD Players, non-portable	*111*	0.9	122
Set-Top Boxes, Satellite	*79*	0.6	126

Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

Over the past 30 years, the demand for energy-using devices has tripled, and the electricity consumption of these devices has quadrupled. From 1976 to 2006, the average energy consumption of a household device has increased by nearly 50%, from 67 to 97 kWh. However, each service has experienced a unique change in its energy intensity.

Table 10 describes the observed trend in the average UEC for each device category. The UEC for each category is the sum of the energy consumption of all devices in that category divided by the sum of their penetration. I have focused on the most recent trend in the category's UEC because some of the categories' have experienced large fluctuations in their average UEC. Included in this table is how long this trend persisted, the UEC at the beginning of the trend, and a brief explanation.

Table 10: Historical trends in unit electricity consumption

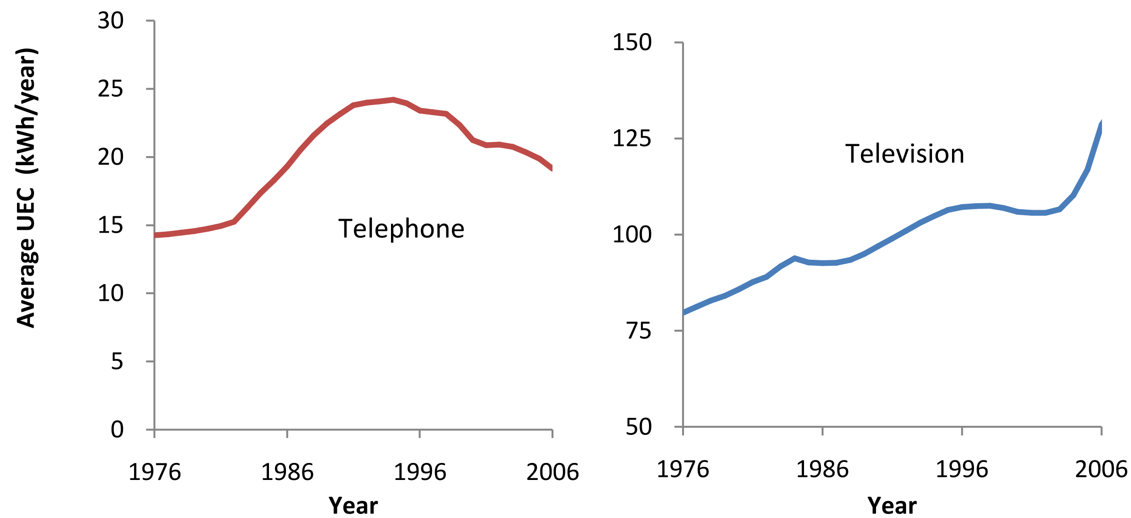
Category	*Trend years*	*UEC, kWh start*	*2006*	*diff.*	*Explanation*
Electronics					
Audio	19	61	62	2%	Adoption of more portable (MP3 players) and energy intensive (home theatre) audio devices caused a stable UEC
Computer	10	272	191	-30%	Increased penetration of laptops
Imaging	8	70	74	5%	Increase in the penetration of laser printers
Telephone	13	24	19	-21%	Decreased with the adoption of wireless telephones
Television	31	80	129	61%	Adoption of more energy intensive TVs
Miscellaneous					
Air conditioning and refrigeration	12	213	294	38%	Increased penetration of air conditioners
Labour saving	14	17	14	-16%	Adoption of many small devices such as blenders and coffee grinders (UEC was initially dominated by vacuum cleaners)
Personal care	20	25	17	-30%	Adoption of shavers, trimmers, and toothbrushes (UEC was initially dominated by hair dryers)
Thermal	25	89	112	26%	Adoption of more energy intensive devices such as aquariums, and portable electric heaters

Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

There do not appear to be any common trends in the change in the average UEC of each device category. The observed trend is unique to each category. Despite a decrease in the UEC, the proliferation of new devices and continued adoption of energy intensive devices has resulted in an overall increase in energy consumption for all of these services.

Televisions and telephones experienced more dramatic revolutionary device replacement than any of the other electronic services. However, these services have experienced very different changes, as shown in Figure 13.

Figure 13: Unit energy consumption of telephones and televisions



Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

Note that the axes used in this figure are different to better illustrate the trends in UEC. Telephones and televisions are two examples of the proliferation and intensification of devices when the service they provide is improved.

The transition between different generations of telephones is apparent from the trend in UEC. Corded phones dominated at the beginning of the study period but more energy intensive cordless phones grew rapidly to drive up the average UEC of a telephone. While the penetration of cordless phones peaked in 2003, the UEC of telephones began to decline after 1994 due to the introduction of wireless, or cellular, telephones.

Over the past 30 years, the amount of energy used per device in the television category increased consistently. Each successive generation of television uses more energy than the last. Televisions evolved from black-and-white to colour and now flat panel LCD and plasma displays. LCD and plasma televisions not only use more energy per square inch of screen than the older generation, cathode-ray tube (CRT) televisions, 15% and 51% respectively, but they are typically two to four times as large (Kaplan, 2007). This trend is mirrored in the adoption of more energy intensive digital projection television systems over their analogue predecessors.

While the energy intensity of some of the device categories have fallen, the average UEC of the devices in this study rose by 50% over the past 30 years. The next section will explore several influencing variables that may be driving these trends.

3.4 Econometric analysis

The econometric analysis of demand for energy-using household devices involved testing the effect of several economic variables. This section includes the results of the regression analysis performed on indoor devices. The regression analysis of outdoor devices is presented in a later section.

The results generated from these regressions yielded mixed results. Table 11 shows the elasticity of demand for the devices in each category in response to a change in the price of electricity. The results are sorted by the response to a change in the price of electricity. It was expected that an increase in the price would reduce demand for energy-using devices, indicated by a negative elasticity. The p-value indicates the probability that the coefficient is significantly different than zero: whether it has a real impact on the penetration of devices. I assumed a confidence level of 90% was suitable for this study. This confidence level assumes that the coefficient is not zero when the p-value is less that 10%, or 0.1.

Table 11: Elasticity of demand for energy–using devices to the price of electricity

Category	*Coefficient*	*P-value*
Labour saving	-1.1	0%
Imaging	-0.8	3%
Personal care	-0.6	11%
Computer	-0.4	55%
Telephone	-0.2	86%
Television	0.4	49%
Air conditioning and refrigeration	0.6	1%
Audio	1.4	17%
Thermal	6.3	0%

A review of 10 studies that examined the elasticity of household electricity consumption to energy price found an average elasticity of -0.38, ranging from -0.76 to -0.19 (Nesbakken, 1999). Only five of the nine device categories covered in this study actually exhibit the expected negative response, three of which were similar to the values found in the literature. Unexpectedly, labour saving devices, which use relatively little electricity (an average UEC of 14 kWh per year), show the largest decrease in demand with an increase in energy price. Thermal devices show the exact opposite relationship: a very large increase in penetration with an increase in energy price even though these devices use a lot more energy than labour saving devices, an average UEC of 112 kWh per year. At a 90% confidence level, I can be confident in only two of the negative responses to price, exhibited by labour saving and imaging devices. However, both of these categories show a strong response, greater than the range shown in the literature, to price despite using very little electricity. These results do not fit with the values identified in the literature and were counter intuitive. Thus, I cannot draw any conclusions on the effect of energy price on the demand for the devices in each of these categories.

Income was expected to have the opposite effect of energy price: demand was expected to rise with an increase in income. A survey of nine studies suggests that the average elasticity of household energy consumption to income is 0.18, ranging from 0.02 to 0.42, which is smaller than the elasticity of demand to energy price (Nesbakken, 1999). Table 12 shows the estimated income elasticities. Seven out of the nine categories showed a positive elasticity: five of which were significant at the 90% confidence level.

Table 12: Income elasticity of demand for energy–using devices

Category	*Coefficient*	*P-value*
Telephone	5.1	3%
Computer	4.8	0%
Thermal	3.7	8%
Air conditioning and refrigeration	1.4	4%
Television	1.0	29%
Labour saving	0.8	2%
Audio	0.1	95%
Imaging	-1.3	1%
Personal care	-2.9	0%

These results show a more consistent influence of income than energy price on demand for energy-using devices. However, seven of the categories of devices show an elastic response to a change in income. In all but one case, these elasticities were much greater than identified in the literature.

The final explanatory variable used to estimate the demand for devices was their cost. A decrease in the cost of a new device was expected to cause an increase in demand. Table 13 lists the estimated response of demand to a change in the capital cost.

Table 13: Demand for devices in response to a change in cost

Category	*Coefficient*	*P-value*
Thermal	-0.073	1%
Telephone	-0.032	0%
Air conditioning and refrigeration	-0.010	0%
Television	-0.004	0%
Computer	-0.001	1%
Labour saving	0.004	50%
Audio	0.006	19%
Imaging	0.017	0%
Personal care	0.073	0%

Similar to energy price, just over half of the devices showed the expected response to a decrease in the cost. However, a 99% confidence level was possible for all of the devices that showed a negative response. On the other end of the scale, the two strongest opposite effects to a change in the cost of the devices were also statistically significant at the 99% confidence level. These results also appeared inconclusive.

Despite such a diversity of effects and confidence levels among the different economic variables, the R^2 values of the regressions were relatively high. That is, the estimated parameters were good at fitting a line to the dependent variable data. The average R^2 was 0.741. High R^2 values may be due to the limited set of time series data: in most cases there were only nine years of cost index data available. These limited series may not have enough observations to show significant variation in the dependent or independent variables. This observation is supported by the below average R^2 values of the audio and television data sets of 0.20 and 0.53, respectively. There were 29 years of cost index data available for audio devices and 31 years of data for televisions.

In summary, this regression analysis did not offer a clear picture of how these three economic variables influenced demand for energy-using devices. However, demand showed the most consistent response to income. A major limitation of this analysis was the limited amount of cost data. For all but two of the devices categories - audio and television - there are only nine years of price index data available from the Bureau of Labor Statistics. Thirty observations is the recommended minimum for time series analysis (Beck and Katz, 1995). However, I discovered that one way to overcome this lack of data in each category was to look for statistical relationships across all of the data using a fixed effect panel model.

The results of the fixed effects panel model that I used to analyse the demand for energy-using devices, including panel-corrected standard error terms, are contained in Table 14. The estimated parameters for each of the economic variables had the expected response: demand decreased with an increase in electricity price or cost and increased with growth in income.

Table 14: Results of the fixed effects panel analysis

Variable	*Coefficient*	*Standard error*	*t-value*	*p-value*
Electricity price	-0.521	0.313	-1.66	9%
Income	0.518	0.570	0.91	36%
Device cost	-0.0012	0.0003	-4.80	0%

The elasticity of demand to energy price of -0.52 fell within the range of elasticities, from -0.76 to -0.19, found in 10 other studies on household energy consumption (Nesbakken, 1999). While this showed an inelastic response to price, there was only a 9% chance that there was actually no response to a change in energy price which met the 90% significance level. The elasticity of demand to income of 0.52 was also inelastic but was somewhat higher than the range, from 0.02 to 0.42, found in 9 other studies (Nesbakken, 1999). However, this elasticity does fit with an average elasticity of 0.55 to income generated from an analysis of 10 household devices that use electricity (Golder and Tellis, 1998). These results indicate that income does somewhat drive demand for energy-using devices. The p-value for income indicates there was a 36% chance that income did not have this effect.

Finally, I found that the cost of these devices was the most significant of the three economic variables. However, the parameter estimated for the influence of time on the demand for energy-using devices was 0.068 with a confidence level greater than 99%. I estimated this parameter for time by running a panel analysis of time against the demand for these devices without detrending the data. This analysis showed that the impact of cost on demand for devices was small compared to that of time.

Another feature of this regression was a low R^2 value of 0.15: only 15% of the variation in the penetration of energy-using household devices was explained by these variables. People's demand for energy-using devices appears to be only slight affected by changes in energy price, income, and cost. A portion of the observed variation could be explained by consumer sentiment (Golder and Tellis, 1998). While household income has steadily increased over the past 30 years, people's confidence in their financial security may fluctuate and affect their demand for devices (Golder and Tellis, 1998). Another explanation for increasing demand could be the availability of new devices. In general, electronic devices were not as established in households in 1976. Over the course of the past 30 years, electronic devices appear to have been invented and innovated at a faster rate than miscellaneous devices, causing them to diffuse rapidly into households.

I tested the data for two other relationships in an attempt to better explain the growth in demand for energy-using devices. The first was whether there was a significant difference between the growth rate of devices that experienced a predominantly linear or s-curve diffusion pattern. I assigned only two groups, or cross-sections, to the fixed effects model: device categories in which the devices showed either predominantly linear or s-curve growth.

Table 15 shows the results of this regression. As expected, the panel data shows the effect of each variable is the same. While the intercepts of the evolutionary/revolutionary categories did show a difference, the p-value indicated that I could not be certain of this effect. Therefore, I could not conclude that the diffusion pattern that a device follows necessarily indicates whether it will penetrate people's households faster or slower.

Table 15: Fixed effects model of electronic and miscellaneous device categories

	Coefficient	*Standard error*	*t-value*	*p-value*
Variable				
Electricity price	-0.524	0.310	-1.69	9%
Income	0.520	0.569	0.91	36%
Device cost	-0.001	0.000	-4.80	0%
Intercept				
S-curve	-0.0042	0.019	-0.22	83%
Linear	-0.0002	0.032	0.12	90%

Table 16 shows the results of the next distinction that I tested for: evolutionary versus revolutionary growth in demand for new devices. This regression showed small difference in the effect of revolutionary growth in demand versus evolutionary, but again the correlation was insignificant. One issue with these distinctions was the imbalance of data. For the evolutionary versus revolutionary regression I had 94 points of data for the revolutionary category compared to only 28 for the evolutionary category.

Table 16: Fixed effects model of evolutionary and revolutionary device categories

	Coefficient	*Standard error*	*t-value*	*p-value*
Variable				
Electricity price	-0.525	0.310	-1.69	9%
Income	0.520	0.569	0.91	36%
Device cost	-0.001	0.000	-4.80	0%
Intercept				
Revolutionary	-0.0030	0.017	-0.18	85%
Evolutionary	0.0000	0.039	0.08	94%

The relationship of both s-curve diffusion and revolutionary changes in demand for energy-using devices were statistically insignificant. That is, neither of these relationships was able to offer any further explanation for the growth in energy-using household devices over the past 30 years.

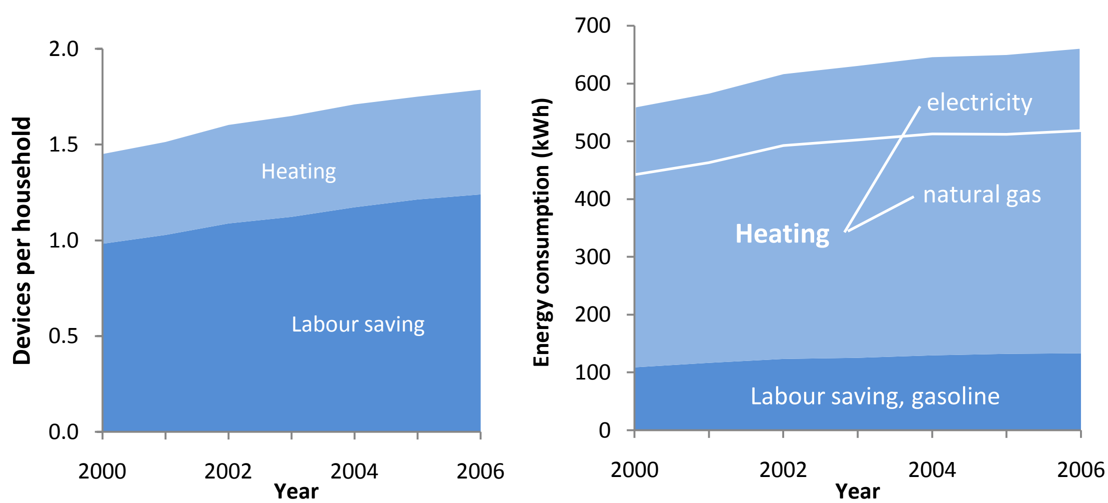
The results presented in this chapter so far have all been related to demand for indoor devices. The next section will explore trends in outdoor devices.

3.5 Outdoor appliances

This study examined the energy consumption and resulting GHG emissions of 17 devices used outside. These devices are presented in a separate section because there are no saturation or shipment data available from before 1995. Therefore, the device populations did not stabilize in the model until the year 2000. These devices also use three different fuels: electricity, natural gas, and gasoline. Figure 14 shows the trend in outdoor appliance penetration and energy consumption from 2000 to 2006.

While labour saving devices are the most numerous, thermal devices, such as hot tubs and gas grills (barbeques) are much more energy intensive. Labour saving devices have an average UEC of 112 kWh per year compared to an average of 969 kWh for thermal devices.

Figure 14: Outdoor device penetration and energy consumption



Source: Generated using retirement and UEC functions from data cited in the methods section of this report.

Only one outdoor device uses natural gas: outdoor gas grills. Natural gas is assumed to be a proxy for propane since no data was available on the type of gas used in these grills. These grills use more energy than any other outdoor device. The remaining energy consumption was attributed to thermal devices that used electricity, such as electric grills and hot tubs, and the gasoline consumption of labour saving devices, such as lawn mowers and leaf blowers. There is a small amount of electricity used by electric lawn mowers. However, this electricity amounted to only 5 kWh per year in 2006, less than 1% of all outdoor device energy consumption. By 2006, outdoor thermal and labour saving devices used 668 kWh of electricity and equivalent natural gas and gasoline. Unfortunately, I could not find any other studies on the energy consumption of outdoor household devices to verify these figures. Finally, I estimated that in 2006 outdoor device use emitted 208 kg of CO_2 equivalent, approximately 2% of all residential GHG emissions.

I also used the penetration data on outdoor devices to create a fixed effects model. Four cross-sections were included in this regression: electric labour saving devices, gasoline powered labour saving devices, electric thermal devices, and natural gas thermal devices. The results of this model are contained in Table 17. The results of this regression are not very reliable due to the very small amount of data, only six years and four cross-sections. In all cases, the estimated parameters indicate that the variables have the opposite effect on the number of devices than expected. Energy price has a very small and insignificant positive effect on demand, similar to device cost. The regression also indicates that a one percent increase in income was found to actually decrease the demand for outdoor devices by 0.34%. This is the opposite effect that was expected. One explanation could be that people hire workers to do their lawn care for them when their income increases.

Table 17: Fixed effects model of outdoor devices

Variable	*Coefficient*	*Standard error*	*t-value*	*p-value*
Electricity price	0.002	0.022	0.09	93%
Income	-0.341	0.046	-7.42	0%
Device cost	0.001	0.001	0.91	38%

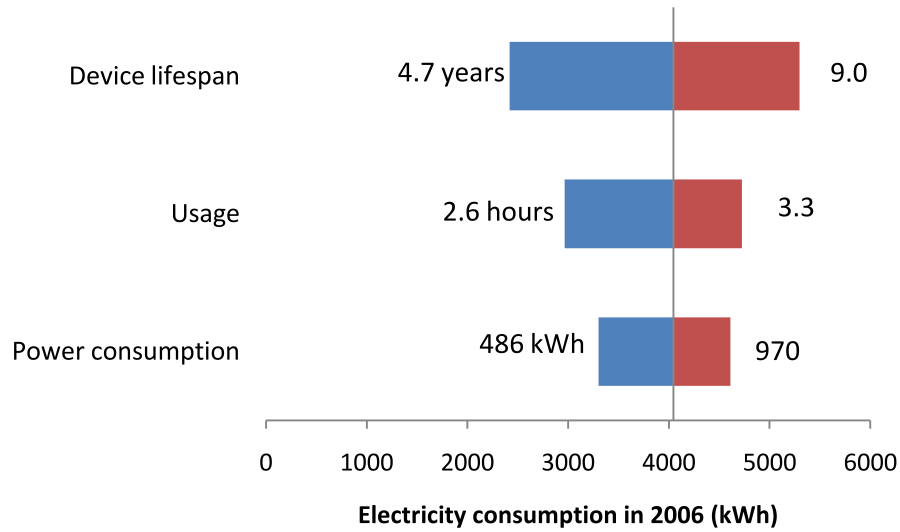
The R^2 value of this regression indicates that these variables explained 44% of the change in demand for outdoor energy-using devices. I did not use the results of this analysis to generate a forecast for outdoor devices because the results were based on a very small sample size.

3.6 Forecasting device penetration and energy consumption

Energy modellers are always trying to forecast how energy-use will evolve. I used the parameters estimated in the fixed effects model for indoor devices to generate a forecast of the increasing penetration of and energy consumption of household devices up to 2030.

There is a lot of uncertainty in the forecasts that I generated and it is important to report this uncertainty to make these forecasts useful and credible (Morgan and Henrion, 1990). The first source of uncertainty comes from the assumptions used to estimate the historical trends in the penetration and energy consumption of these devices. Figure 15 shows a single parameter sensitivity analysis of the variables I used to generate these historical trends and the bounds of uncertainty for each variable. The y-axis is centered on the estimated electricity demand of indoor devices in 2006: 4,044 kWh. The bars indicate how much this electricity consumption deviated given the uncertainly interval I established for each parameter. This analysis indicates that these trends are most susceptible to uncertainty in the device lifespan followed by the amount each device is used and finally by the power consumption in each mode of use.

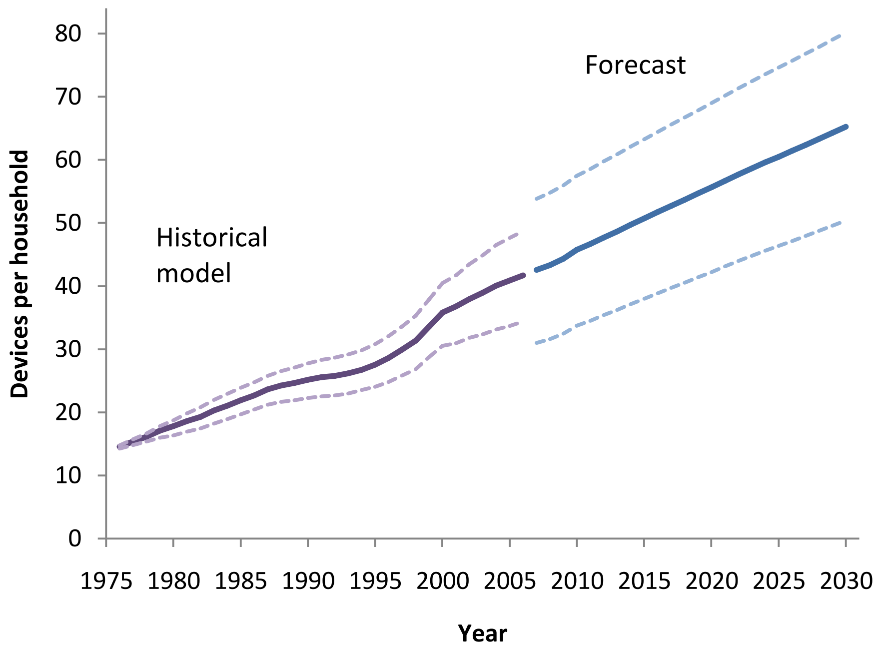
Figure 15: Tornado diagram of a single parameter sensitivity analysis



These ranges of values were incorporated into the estimated historical trends. Figure 16 displays this forecast along with the uncertainty bounds generated using the range in variables outlined in the methods chapter and a 95% confidence interval for the Monte Carlo analysis of the regression parameters.

This forecast indicates that the average U.S. household will adopt another 24 energy-using devices by 2030 despite a forecast increase in the price of electricity (EIA, 2009). Uncertainty in these forecasts suggests that the estimate for the total number of devices ranges from a low of 50 to a high of 85 devices per household in 2030.

Figure 16: Forecast of devices per household



This increase will be partially due to an increase in income and a decrease in the cost of devices. However, the low R^2 of the fixed effects model and the strong influence of the time variable indicate that the demand for these devices may be largely driven by other factors.

Generating a forecast for electricity consumption of these devices required a forecast of their average UEC. Table 18 contains the results of the fixed effects regression model of the effect of electricity price, the ratio of new devices, and the number of devices on the average UEC of indoor devices. I found that an increase in the number of devices per household reduced the average UEC of an indoor device. This response contradicts the earlier finding that the average UEC of an indoor device increased by 50% over the past 30 years. This regression also showed that as the ratio of new devices increased, the average UEC increased. Finally, I expected an increase in energy price would reduce the average energy consumption of devices because people would forego purchasing more energy intensive devices or adopt more efficient ones. However, this regression found that an increase in electricity price led to an increase in demand, even if the response was inelastic.

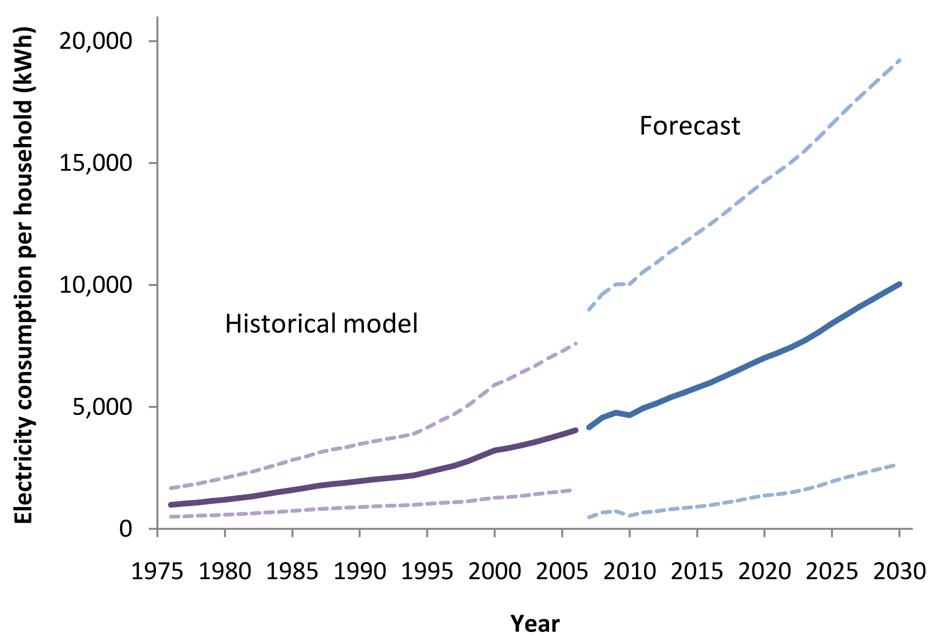
Table 18: Fixed effects model of the average UEC of an indoor device

	Coefficient	*Standard error*	*t-value*	*p-value*
Electricity price	0.313	0.135	2.32	2%
New device ratio	0.233	0.156	1.49	14%
Devices	-0.149	0.016	-9.59	0%

Similar to the demand for devices, the panel analysis of UEC has a low R^2 of 0.106, capturing only 11% of variation in the dependent variable.

Combining the device and UEC forecasts yielded the estimated electricity consumption of indoor energy-using devices up to 2030. This forecast, presented in Figure 17, indicated that the electricity consumption of energy-using devices would continue to grow at an exponential rate up to 2030. Total electricity consumption would more than double to 10,000 kWh of electricity per year in 2030. While this is a substantial increase, the rate of increase was slightly slower. From 1976 to 2006 electricity consumption grew by 10.5% annually compared to the expected 10.3% annual growth from 2007 to 2030.

Figure 17: Forecast of household electricity consumption of energy-using devices

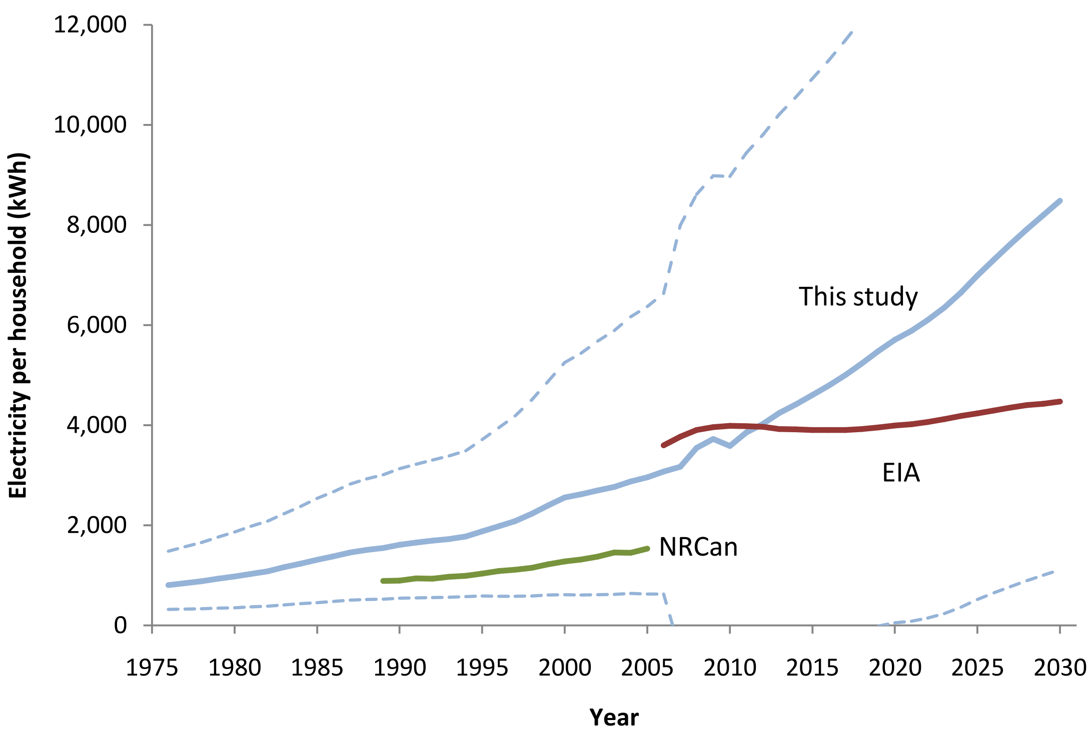


This forecast also has large uncertainty bounds. In 2006, the estimate of 4000 kWh has a lower limit of 1,600 kWh (-61%) and an upper limit of 7,600 kWh (+88%).

This interval increases to -74% to +91% in 2030. Figure 18 compares this trend to two other estimates of energy-using devices (NRCan, 2005; EIA, 2009). I removed the electricity consumption of air conditioners from my forecast in Figure 17 because both the EIA and NRCan address space cooling separately. However, the electricity consumption of other air conditioning and refrigeration devices, including humidifiers, air cleaners, small refrigerators and wine coolers, were included in my forecast.

The EIA (2009) forecast is based on a simulation model calibrated using the energy consumption measured in a sample of households. While the EIA forecast is 15% higher in 2007, by 2030 my forecast exceeded it by 89% to consume an average of 8,500 kWh of electricity per household.

Figure 18: Household electricity consumption model comparison, not including air conditioners



The NRCan trend included in Figure 18 was presented and discussed in section 3.2. The EIA generates forecasts for the average CO_2e emitted by a unit of electricity and the total CO_2e emissions caused by fuel consumption in the U.S. residential, commercial, and industrial sectors up to 2030. Similar to this study, the EIA (2009) estimates that the energy consumption of "other" energy-using devices is higher in the U.S. than in Canada.

The estimates I produced in this report suggest that, not including air conditioning, the devices included in this study used 27% of household electricity in 2006. By 2030, the EIA forecasts that the average U.S. household will use 7,200 kWh of electricity, not including the forecast of "other" devices in Figure 18. The forecast generated from this study indicates that the electricity of energy-using household devices not including space heating, space cooling, water heating, lighting, and major appliances could grow to use 8,500 kWh by 2030: an average of 54% of household electricity consumption. Note that the EIA estimated that the electricity consumption of space heating, space cooling, lighting, water heating, and major appliances will fall from 8,400 kWh in 2006 to 7,200 kWh in 2030.

In 2006, these findings indicate that the devices included in this study were responsible for 2.0 tonnes of CO_2e emissions, 19% of all emissions from the U.S. residential sector. The EIA (2009) estimates that in 2030 the average U.S. household will emit 9.4 tonnes of CO_2e. By 2030, these energy-using devices are forecast to climb to 5.0 tonnes of CO2e emissions, over 50% of the total residential CO_2e emissions.

CHAPTER 4: SUMMARY AND CONCLUSIONS

4.1 Summary and conclusions

A large body of literature describes how energy efficiency could reduce energy consumption and GHG emissions. However, even while politicians and efficiency advocates talk about energy efficiency, the demand for energy-using devices has continued to climb.

In this study, I constructed 30 years of data on the penetration and energy consumption of 134 energy-using household devices. I found that over the past 30 years, the number of indoor energy-using devices in the average U.S. household tripled from 15 in 1976 to 42 in 2006. At the same time, the average electricity consumption of these devices quadrupled from 1000 kWh per year to over 4000 kWh. These trends indicate that the average amount of electricity used by the devices included in this study have increased by nearly 50%.

One of the objectives of this study was to attempt to detect a relationship between the growth of energy-using devices and key explanatory variables. The 134 individual devices were grouped together based upon the service they provided, such as LCD televisions, DVD players, and cable boxes grouped into the ‘television’ category. My hypothesis was that these categories might provide evidence of relationships between energy consumption and people’s demand for the services that energy-using devices provide. These relationships could then be used to inform technologically explicit models that sometimes fail to anticipate the impact that new technologies can have on demand for energy services.

The relationships between the energy consumption of these device categories and the variables that may explain their evolution were tested using econometric analysis. I regressed the demand for devices in each of these service categories on energy price, household income, and the cost of these devices. The results of these regressions suggested that income and device cost had a significant effect on demand. However, the results of these regressions were very uncertain. Therefore, I used a panel analysis on this data. Assuming that each service category was a cross-section, I used a fixed effects model to test the effect of these variables on demand for energy-using devices. Demand showed an inelastic response of -0.52 to the price of energy and with only a 9% chance that there was in fact no response. Income showed a similar inelastic elasticity of 0.52 but there was a much higher chance (36%) that the elasticity is zero. Finally, the influence of cost was not reported as an elasticity and was the most statistically significant of these three variables. However, my regression shows that this effect is small compared to the influence of time. With such a low R^2 of 0.15 and a high correlation with time, there are obviously other drivers of these patterns. I tested two other effects using this fixed effects model: whether there was a difference in the demand for devices that grew according to an s-shaped diffusion curve or devices that showed the replacement of one generation of technology with another. However, neither of these effects was found to have a significant effect on demand for energy-using devices.

The results of this analysis indicate that there is a relationship between demand for energy-using devices and energy price, income, and the cost of a device. However, these variables explain only 15% of the variation of demand for energy-using devices over the past 30 years. A panel analysis on the effect of time indicated that it had 50 times more influence than a change in the cost of a device. This finding suggests that rising incomes coupled with the invention and innovation of energy-using devices over the past 30 years have allowed people to fulfill their desire for increased comfort, convenience, connectivity, and entertainment. Un-restricted fulfillment of these desires has caused demand for indoor energy-using household devices to increase exponentially over the past 30 years.

I also looked at the penetration and energy consumption trends of outdoor devices. In 2006, there was an average of 1.7 outdoor energy-using devices per household that used a total of 650 kWh of energy per year. This consumption of electricity, gasoline, and natural gas for hot tubs, grilling, and lawn maintenance were responsible for 2% of total residential GHG emissions in 2006. A fixed effects model was developed for outdoor devices but I had very little confidence in the results due to a very small data set.

Finally, I generated forecasts of the demand for energy-using devices up to 2030 based upon the results of the fixed effects models of the demand for energy-using devices and UEC. These forecasts indicated that the electricity consumption of the devices included in this study will grow from 4000 kWh in 2006 to 10,000 kWh by 2030. Incorporating uncertainty into this forecasts resulted in a lower limit of 2,700 kWh (-74%) and an upper limit of 19,200 kWh (+91%).

This study found that people's demand for energy services is somewhat insensitive to changes in the price of energy. Given these results, it may be advisable to model the demand for energy-using devices as a function of income and time. This model would assume that the historical trend of cheap energy, rising incomes and the increasing availability of new and desirable devices would continue. Therefore, the only way to reduce the GHG emissions caused by these devices would be to remove GHG emissions from the source of their energy, namely electricity. There are many climate change policies that could reduce the GHG emissions from the electricity sector.

The explanatory variables used in this study have remained relatively stable: the price of electricity has not changed substantially, incomes have continued to rise linearly, and the cost of these devices has consistently fallen. A climate change policy that does induce a change in energy price that could have an effect on people's disposable income may be effective at changing demand for energy-using devices. However, the signal sent by that policy would likely have to be a strong one.

4.2 Recommendations and future research

This section contains a summary of recommendations for future research related to how this study could be expanded and improved.

4.2.1 Data collection and analysis

The first avenue of future research is on the data that I used to estimate the trends in device penetration and energy consumption. This study is based on a historical trend in the number of energy-using devices that I generated using retirement functions. It would be useful to compare the population of devices simulated in this study to actual household penetration data. Very little data are available on the amount of time people use these devices in each mode of operation and the power consumption in each of these modes. Unfortunately, there is little data on how many of these devices exist, how much they are used, and how much energy they use when they are plugged in. The sheer number of energy-using devices and the rate at which they are invented, innovated, adopted, and thrown away makes collecting this sort of information very difficult.

There are also several technologies that are currently evolving very rapidly but for which no data could be found. One is the evolution of more powerful video game consoles that provide more features and may use an increasing amount of energy. Another area is the incorporation of wireless internet devices into desktop and laptop computers and wireless internet routers that are always switched on.

The data on outdoor appliances was also very limited. Only 11 years of shipment and saturation data were available compared to 30 for many of the other devices included in this study. Further, there are several outdoor devices that are becoming more popular, such as patio heaters and outdoor audio equipment for which no data could be found.

Another area of uncertainty was the data used in the fixed effects model. The results that I did derive from this model of indoor devices were useful. However, the cost data for most of the device categories was limited to 9 years, much shorter than the recommended 30. It may be beneficial to collect more data on the cost of these devices to better inform a panel analysis.

4.2.2 Energy modelling

While this study attempted to use aggregated service categories to overcome some of the weaknesses of bottom-up modelling, it was prone to its own faults. While the economic variables included in this study were found to have some effect on the demand for energy-using devices, the low R^2 value and strong effect of the time variable indicated that there were other influences on the demand for energy–using devices. By foregoing the technological explicitness of the CIMS model some of the details of these technologies were removed including the declining capital cost of an individual device or its operating cost. The regression results in this study indicated the difficulty in soliciting an effect from more aggregated data. A middle ground between these two approaches may be useful to explore in order to retain more of the technological richness of the CIMS model.

There are also many other effects on the demand for new devices. On the supply side, there is a never ending supply of new energy-using devices being invented and re-invented to attempt to satisfy people's desires. On the demand side, there are also many factors that influence the diffusion of a new technology such as consumer sentiment about the risk of purchasing a costly new technology or device, how well the new technology is marketed, or how good a substitute that device is for a previous generation. Several of these factors may be worth further exploration.

The demand for electronic devices appeared to grow more quickly than miscellaneous devices. While some testing was done on this hypothesis, a more detailed comparison of the service provided by electronic devices versus miscellaneous devices may provide some explanation of their rapid growth. It is possible that the rapid increase in demand for electronic devices, and perhaps miscellaneous devices, is linked to the improvement of electronic circuitry and computer chips. If this is the case, the next generation of revolutionary devices could be anticipated by looking at their underlying technology. For example, Huber and Mills (2005) suggest that dramatic improvements currently being made in laser technology may cause a revolution in electronic devices and nanotechnology.

Finally, it was found that demand for energy-using devices was insensitive to variation in the price of energy. However, during the historical period of this study, income rose consistently and the price of household energy did not change very much. It is possible that a large change in the price of energy would cause a substantial change in demand for energy-using devices. Research into instances where people have experienced a substantial change in the price of energy may provide more information on the influence of energy price on people's demand for energy-using devices.

4.2.3 Scoping issues

There are two final issues that I have identified that make scoping a project in forecasting the energy consumption of new devices difficult. First, some household devices are only useful when they are connected to an external network. For example, the increasing amount of infrastructure being deployed to support wireless electronic devices. Even though cell phones use less energy in the home than a cordless phone, the question remains as to how much energy is used by the infrastructure of towers and computer systems to support these devices.

Finally, devices are becoming more complex and incorporating more features and technologies. Cell phones now include cameras, MP3 players, and video players. These trends are proceeding very rapidly and are difficult to capture. I would suggest that adding features to devices, such as cell phones, will not necessarily replace stand-alone digital camera’s or video devices, they will just increase usefulness and the energy consumption of the devices that they are added to. This would be an interesting avenue for future research: how technologies are invented, evolve, and are repackaged into devices that people want.

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APPENDICES

Appendix A: Device list

Device	*Location*	*Type*	*Service*	*Trend*	*Fuel*
Air Cleaners	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity
Air Conditioners	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Aquariums	Indoor	Miscellaneous	Thermal	linear	Electricity
Audio systems, Compact or Rack	Indoor	Electronics	Audio	linear	Electricity
Auto Engine Heaters	Indoor	Miscellaneous	Thermal	linear	Electricity
Blanket	Indoor	Miscellaneous	Thermal	linear	Electricity
Blenders, hand-held	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Blenders, stand type	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Breadmakers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Bug Killers	Outdoor	Outdoor	Labour saving	s-curve	Electricity
Camcorders, Analogue	Indoor	Electronics	Imaging	s-curve	Electricity
Camcorders, Digital	Indoor	Electronics	Imaging	s-curve	Electricity
Cameras, Analogue	Indoor	Electronics	Imaging	s-curve	Electricity
Cameras, Digital	Indoor	Electronics	Imaging	s-curve	Electricity
Can Openers	Indoor	Miscellaneous	Labour saving	linear	Electricity
CD Players, non-portable	Indoor	Electronics	Audio	s-curve	Electricity
CD Players, Portable	Indoor	Electronics	Audio	s-curve	Electricity
Chain Saws, Gasoline	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
Coffee Grinders	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Coffee Makers, Automatic Drip	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Coffee Makers, Automatic Perk	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Compact Audio Systems	Indoor	Electronics	Audio	s-curve	Electricity
Compactors	Indoor	Miscellaneous	Labour saving	linear	Electricity
Computer, desktop	Indoor	Electronics	Computer	s-curve	Electricity
Computer, notebook	Indoor	Electronics	Computer	s-curve	Electricity
Computer, palm and pocket	Indoor	Electronics	Computer	s-curve	Electricity
Copiers, Plain Paper	Indoor	Electronics	Imaging	s-curve	Electricity
Corn Poppers, Hot-Air	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Corn Poppers, Hot-Oil	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Curling Iron and Styling Combs/Wands/Crimpers	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Deep Fryers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Dehumidifiers	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity
Disposers, food waste	Indoor	Miscellaneous	Labour saving	linear	Electricity
DVD player, portable	Indoor	Electronics	Television	linear	Electricity
DVD players and recorders	Indoor	Electronics	Television	s-curve	Electricity
Espresso Makers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Facsimile Equipment	Indoor	Electronics	Imaging	s-curve	Electricity

Device	*Location*	*Type*	*Service*	*Trend*	*Fuel*
Fan, desk	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity
Fan, stand	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Fan, window	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Fans, Ceiling	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Food Choppers/Mincers	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Food Processors	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Food Slicer	Indoor	Miscellaneous	Labour saving	linear	Electricity
Front-Engine Lawn Tractors	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
Frypans/Skillets	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Griddles, Automatic	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Hair Clippers	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Hair Dryers	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Hair Setters	Indoor	Miscellaneous	Personal care	linear	Electricity
Heating Pads	Indoor	Miscellaneous	Thermal	linear	Electricity
Hedge Trimmers, Gasoline	Outdoor	Outdoor	Labour saving	linear	Gasoline
Home Theatre in a Box	Indoor	Electronics	Audio	s-curve	Electricity
Hot Plates	Indoor	Miscellaneous	Thermal	linear	Electricity
Humidifiers	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Ice Cream Makers	Indoor	Miscellaneous	Labour saving	linear	Electricity
Irons, Steam and Spray	Indoor	Miscellaneous	Thermal	linear	Electricity
Juice Extractors	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Juicers	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Kettle	Indoor	Miscellaneous	Thermal	linear	Electricity
Knife	Indoor	Miscellaneous	Labour saving	linear	Electricity
Lawn Mower, electric	Outdoor	Outdoor	Labour saving	linear	Electricity
Leaf Blowers, Back-Pack, Gasoline	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
Leaf Blowers, Hand-Held, Gasoline	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
Massagers, Foot Bath	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Massagers, Hand-Held	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Microwave Ovens	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Minidisc players, portable	Indoor	Electronics	Audio	s-curve	Electricity
Mixers, hand-held	Indoor	Miscellaneous	Labour saving	linear	Electricity
Mixers, stand type	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Modem, Cable	Indoor	Electronics	Computer	s-curve	Electricity
Modem, dial-up	Indoor	Electronics	Computer	s-curve	Electricity
Modem, DSL	Indoor	Electronics	Computer	s-curve	Electricity
Mounted Air Cleaner	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity
MP3 players, non-portable	Indoor	Electronics	Audio	linear	Electricity
MP3 players, portable	Indoor	Electronics	Audio	s-curve	Electricity
Multimedia players, portable	Indoor	Electronics	Computer	s-curve	Electricity
Outdoor Grills, Electric	Outdoor	Outdoor	Thermal	linear	Electricity
Outdoor Grills, Gas	Outdoor	Outdoor	Thermal	linear	Natural gas

Device	*Location*	*Type*	*Service*	*Trend*	*Fuel*
Polishers/Waxers	Indoor	Miscellaneous	Labour saving	linear	Electricity
Pool Pump/Heaters	Outdoor	Outdoor	Thermal	linear	Electricity
Portable Heater, Electric, Fan-Forced	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Portable Personal Stereos/Headsets	Indoor	Electronics	Audio	s-curve	Electricity
Power Mowers, Walk-Behind	Outdoor	Outdoor	Labour saving	linear	Gasoline
Printer	Indoor	Electronics	Imaging	s-curve	Electricity
Printer, Laser	Indoor	Electronics	Imaging	s-curve	Electricity
Radios, Home	Indoor	Electronics	Audio	linear	Electricity
Rear-Engine Riding Mowers	Outdoor	Outdoor	Labour saving	linear	Gasoline
Refrigerators, Built-In, Undercounter	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity
Refrigerators, Compact (<6.4 cu.ft)	Indoor	Miscellaneous	Air conditioning and refrigeration	s-curve	Electricity
Rice Cookers/Steamers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Riding Garden Tractors	Outdoor	Outdoor	Labour saving	linear	Gasoline
Rotary Tillers	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
Router	Indoor	Electronics	Computer	linear	Electricity
Sandwich Makers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Security System	Indoor	Electronics	Imaging	linear	Electricity
Set-Top Boxes, Cable	Indoor	Electronics	Television	s-curve	Electricity
Set-Top Boxes, Satellite	Indoor	Electronics	Television	s-curve	Electricity
Set-Top Internet Access Devices	Indoor	Electronics	Television	s-curve	Electricity
Sewing machine	Indoor	Miscellaneous	Labour saving	linear	Electricity
Shampooers/Steam Cleaners	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Shavers, Men's	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Shavers, Women's	Indoor	Miscellaneous	Personal care	linear	Electricity
Slow Cookers	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Snowthrowers, Gasoline	Outdoor	Outdoor	Labour saving	linear	Gasoline
Spa/Hot Tub	Outdoor	Outdoor	Thermal	linear	Electricity
Tape & Radio/Tape Recorders	Indoor	Electronics	Audio	s-curve	Electricity
Telephone Answering Devices	Indoor	Electronics	Telephone	s-curve	Electricity
Telephones, Corded	Indoor	Electronics	Telephone	s-curve	Electricity
Telephones, Cordless	Indoor	Electronics	Telephone	s-curve	Electricity
Telephones, Wireless	Indoor	Electronics	Telephone	s-curve	Electricity
Television Projection Systems	Indoor	Electronics	Television	s-curve	Electricity
Televisions, Black & White (Monochrome)	Indoor	Electronics	Television	linear	Electricity
Televisions, Color, Direct-View	Indoor	Electronics	Television	s-curve	Electricity
Televisions, Digital Projection	Indoor	Electronics	Television	s-curve	Electricity
Televisions, Hand-held	Indoor	Electronics	Television	s-curve	Electricity
Televisions, LCD	Indoor	Electronics	Television	s-curve	Electricity
Televisions, Plasma	Indoor	Electronics	Television	s-curve	Electricity

Device	*Location*	*Type*	*Service*	*Trend*	*Fuel*
Toaster Ovens	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Toasters	Indoor	Miscellaneous	Thermal	linear	Electricity
Toothbrushes/Plaque Removers	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Trimmers, Beards & Moustache	Indoor	Miscellaneous	Personal care	s-curve	Electricity
Trimmers/Brushcutters, Gasoline	Outdoor	Outdoor	Labour saving	s-curve	Gasoline
TV/DVD/VCR Combinations	Indoor	Electronics	Television	s-curve	Electricity
Vacuums	Indoor	Miscellaneous	Labour saving	linear	Electricity
Vacuums, Central	Indoor	Miscellaneous	Labour saving	linear	Electricity
Vacuums, Hand-Held, Electric	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
Vacuums, Hand-Held, Rechargeable	Indoor	Miscellaneous	Labour saving	s-curve	Electricity
VCR Decks	Indoor	Electronics	Television	s-curve	Electricity
Video game consoles	Indoor	Electronics	Television	s-curve	Electricity
Waffle Irons/Sandwich Grills	Indoor	Miscellaneous	Thermal	linear	Electricity
Waterbed heater	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Whirlpool Baths/Bath Mats, Portable	Indoor	Miscellaneous	Thermal	s-curve	Electricity
Wine coolers/chillers	Indoor	Miscellaneous	Air conditioning and refrigeration	linear	Electricity

Appendix B: Device energy consumption

Device	Usage (hours per day)			Power consumption (W)			UEC	Source
	Act-ive	Idle	Off	Active	Idle	Off	kWh/ year	
Air Cleaners	3.0	0.0	21.0	60	0.0	0.0	66	U.S. DOE (2006)
Air Conditioners	2.0	0.0	22.0	1,243	0.0	0.0	907	Energy Star (2009b)
Aquariums	24.0	0.0	0.0	210	0.0	0.0	1,840	TIAX (2007b)
Audio systems, Compact or Rack	4.3	2.0	17.7	45	43.0	3.0	122	TIAX (2007b)
Auto Engine Heaters	0.1	0.0	23.9	1,000	0.0	0.0	37	U.S. DOE (2006)
Blanket	2.0	0.0	22.0	164	0.0	0.0	120	U.S. DOE (2006)
Blenders, hand-held	0.1	0.0	23.9	225	0.0	0.0	5	Usage from Sanchez et al. (1998), wattage from home model.
Blenders, stand type	0.1	0.0	23.9	300	0.0	0.0	7	Usage from Sanchez et al. (1998), wattage from home model.
Breadmakers	0.5	0.0	23.5	600	0.0	2.0	127	Public Utility District of Clallum County (2007)
Bug Killers	2.0	0.0	22.0	30	0.0	0.0	22	Estimated from online manufacturer websites
Camcorders, Analogue	0.3	15.8	8.0	10	0.4	0.4	4	McAllister and Farrell (2007)
Camcorders, Digital	0.3	15.8	8.0	10	0.4	0.4	4	McAllister and Farrell (2007)
Cameras, Analogue	0.5	15.5	8.0	3	0.2	0.2	2	McAllister and Farrell (2007)
Cameras, Digital	0.5	15.5	8.0	10	0.9	0.2	8	TIAX (2007a)
Can Openers	0.1	0.0	23.9	82	0.0	0.0	3	U.S. DOE (2006)
CD Players, non-portable	4.3	2.0	17.7	45	43.0	3.0	122	Assume same as audio systems
CD Players, Portable	0.3	1.1	22.6	1	0.3	0.1	1	See 'BatteryOpdDevices' sheet in 'Energy Consumption Data' workbook. Assumptions from Webber et al. (2007) and Calwell and Reader (2002), assume charged every 2 weeks.
Chain Saws, Gasoline	0.2	0.0	23.8	1,435	0.0	0.0	119	CARB, 1998
Coffee Grinders	0.1	0.0	23.9	150	0.0	0.0	5	Usage assumed and power consumption taken from my home model.
Coffee Makers, Automatic Drip	0.1	0.6	23.3	1,100	70.0	0.4	61	TIAX (2007b)
Coffee Makers, Automatic Perk	1.0	3.0	20.0	600	80.0	2.0	321	Sanchez et al. (1998)
Compact Audio Systems	2.3	2.0	19.7	23	16.0	7.0	81	TIAX (2007b)
Compactors	0.3	0.0	23.7	400	0.0	0.0	50	Sanchez et al. (1998)
Computer, desktop	8.1	0.9	15.0	117	5.0	3.0	365	TIAX (2007b), added in monitor usage as well.
Computer, notebook	6.5	2.5	15.0	25	2.0	2.0	72	TIAX (2007b)

Device	Usage (hours per day)			Power consumption (W)			UEC	Source
	Act-ive	Idle	Off	Active	Idle	Off	kWh/ year	
Computer, palm and pocket	1.2	20.5	2.3	5	0.6	0.6	7	Assume usage same as cell phones TIAX (2007b); Power consumption McAllister and Farrell
Copiers, Plain Paper	0.1	3.4	20.5	39	10.0	0.0	14	U.S. DOE (2006)
Corn Poppers, Hot-Air	0.0	0.0	24.0	1,400	0.0	0.0	6	Sanchez et al. (1998)
Corn Poppers, Hot-Oil	0.0	0.0	24.0	575	0.0	0.0	2	Sanchez et al. (1998)
Curling Iron and Styling Combs/Wands/Crimpers	0.1	0.0	23.9	27	0.0	0.0	1	U.S. DOE (2006)
Deep Fryers	0.1	0.0	23.9	548	0.0	0.0	20	U.S. DOE (2006)
Dehumidifiers	3.3	0.0	20.7	475	0.0	0.0	570	from NIA spreadsheet on dehumidifiers. Assume usage same as fans in TIAX (2007b)
Disposers, food waste	0.1	0.0	23.9	400	0.0	0.0	10	U.S. DOE (2006)
DVD player, portable	0.3	1.1	22.6	86	17.1	7.6	78	From online battery distributors, assume charged once per 2 weeks, 6000 mAh battery.
DVD players and recorders	1.2	2.5	20.4	17	12.5	2.2	34	Usage from TIAX (2007a), consumption TIAX (2007b)
Espresso Makers	0.1	0.0	23.9	360	0.0	0.0	19	Sanchez et al. (1998)
Facsimile Equipment	0.5	23.5	0.0	175	20.0	0.0	203	Sanchez et al. (1998)
Fan, desk	0.7	0.0	23.3	30	0.0	0.0	8	Sanchez et al. (1998), Based on operation of a window fan, 3 hrs/day, 3mo/yr
Fan, stand	0.7	0.0	23.3	30	0.0	0.0	8	Sanchez et al. (1998), Based on operation of a window fan, 3 hrs/day, 3mo/yr
Fan, window	0.7	0.0	23.3	30	0.0	0.0	8	Sanchez et al. (1998), Based on operation of a window fan, 3 hrs/day, 3mo/yr
Fans, Ceiling	6.6	0.0	17.4	35	0.0	0.0	84	TIAX (2007b)
Food Choppers/Mincers	0.0	0.0	24.0	250	0.0	0.0	2	Sanchez et al. (1998)
Food Processors	0.0	0.0	24.0	250	0.0	0.0	2	Sanchez et al. (1998)
Food Slicer	0.0	0.0	24.0	250	0.0	0.0	2	Sanchez et al. (1998)
Front-Engine Lawn Tractors	0.1	0.0	23.9	11,004	0.0	0.0	546	CARB, 1998
Frypans/Skillets	0.1	0.0	23.9	164	0.0	0.0	6	U.S. DOE (2006), assume same as automatic griddles.
Griddles, Automatic	0.1	0.0	23.9	164	0.0	0.0	6	U.S. DOE (2006)
Hair Clippers	0.0	0.0	24.0	15	0.0	1.4	12	Sanchez et al. (1998), assume same as men's shavers, but used 1/5 of the time.
Hair Dryers	0.1	0.0	23.9	1,300	0.0	0.0	43	TIAX (2007b)
Hair Setters	0.1	0.0	23.9	350	0.0	0.0	10	Sanchez et al. (1998)

Device	Usage (hours per day)			Power consumption (W)			UEC	Source
	Act-ive	Idle	Off	Active	Idle	Off	kWh/ year	
Heating Pads	0.2	0.0	23.8	60	0.0	0.0	3	Sanchez et al. (1998)
Hedge Trimmers, Gasoline	0.1	0.0	23.9	671	0.0	0.0	31	CARB, 1998
Home Theatre in a Box	4.3	2.0	17.7	38	34.0	0.6	89	TIAX (2007a)
Hot Plates	0.1	0.0	23.9	822	0.0	0.0	30	U.S. DOE (2006)
Humidifiers	1.0	0.0	23.0	274	0.0	0.0	100	U.S. DOE (2006)
Ice Cream Makers	0.1	0.0	23.9	200	0.0	0.0	7	Online manufacturer reports.
Irons, Steam and Spray	0.1	0.0	23.9	1,350	0.0	0.0	53	TIAX (2007b)
Juice Extractors	0.0	0.0	24.0	125	0.0	0.0	0	Sanchez et al. (1998)
Juicers	0.0	0.0	24.0	125	0.0	0.0	0	Sanchez et al. (1998)
Kettle	0.1	0.0	23.9	1,500	0.0	0.0	75	Sanchez et al. (1998)
Knife	0.1	0.0	23.9	27	0.0	0.0	1	U.S. DOE (2006)
Lawn Mower, electric	0.1	9.7	14.2	1,500	3.6	0.0	67	U.S. DOE (2006)
Leaf Blowers, Back-Pack, Gasoline	0.2	0.0	23.8	746	0.0	0.0	43	CARB, 1998
Leaf Blowers, Hand-Held, Gasoline	0.2	0.0	23.8	2,983	0.0	0.0	255	CARB, 1998
Massagers, Foot Bath	0.0	0.0	24.0	1,200	0.0	0.0	20	Usage Sanchez et al. (1998), Wattage from Brookstone online.
Massagers, Hand-Held	0.0	0.0	24.0	15	0.0	0.0	0	Sanchez et al. (1998)
Microwave Ovens	0.2	0.0	23.8	1,500	0.0	3.0	131	TIAX (2007b)
Minidisc players, portable	0.3	1.1	22.6	1	0.1	0.1	1	See 'BatteryOpdDevices' sheet in 'Energy Consumption Data' workbook. Assumptions from Webber et al. (2007) and Calwell and Reader (2002), assume charged every 2 weeks.
Mixers, hand-held	0.1	0.0	23.9	55	0.0	0.0	2	U.S. DOE (2006)
Mixers, stand type	0.0	0.0	24.0	300	0.0	0.0	4	Sanchez et al. (1998)
Modem, Cable	24.0	0.0	0.0	6	0.0	0.0	53	TIAX (2006)
Modem, dial-up	24.0	0.0	0.0	6	0.0	0.0	53	TIAX (2007b), assume same as broadband modems. Assume standbye mode uses same amount as on.
Modem, DSL	24.0	0.0	0.0	6	0.0	0.0	53	TIAX (2006)
Mounted Air Cleaner	3.0	21.0	0.0	60	0.0	0.0	66	U.S. DOE (2006)
MP3 players, non-portable	4.3	2.0	17.7	45	43.0	3.0	122	Assume same as audio systems
MP3 players, portable	0.3	1.1	22.6	4	0.6	0.3	3	Usage copied from portable CD players, consumption from McAllister and Farrell (2007)
Multimedia players, portable	0.3	1.1	22.6	86	17.1	7.6	78	Assume same as portable DVD players.
Outdoor Grills, Electric	0.5	0.0	23.5	4,932	0.0	0.0	900	U.S. DOE (2006)

Device	Usage (hours per day)			Power consumption (W)			UEC	Source
	Act-ive	*Idle*	*Off*	*Active*	*Idle*	*Off*	*kWh/ year*	
Outdoor Grills, Gas	0.5	0.0	23.5	4,816	0.0	0.0	879	U.S. DOE (2006)
Polishers/Waxers	0.0	0.0	24.0	700	0.0	0.0	8	Online manufacturer.
Pool Pump/Heaters	2.2	0.0	21.8	1,360	0.0	0.0	1,102	TIAX (2007b)
Portable Heater, Electric, Fan-Forced	1.0	0.0	23.0	1,300	0.0	0.0	475	U.S. DOE (2006)
Portable Personal Stereos/Headsets	1.4	3.1	19.4	6	4.9	1.8	22	TIAX (2007b)
Power Mowers, Walk-Behind	0.1	0.0	23.9	2,983	0.0	0.0	107	CARB, 1998
Printer	0.1	4.4	19.5	20	5.0	2.0	23	TIAX (2006)
Printer, Laser	0.1	4.4	19.5	250	80.0	4.5	173	U.S. DOE (2006)
Radios, Home	1.0	0.0	23.0	2	0.0	1.0	9	U.S. DOE (2006)
Rear-Engine Riding Mowers	0.1	0.0	23.9	6,738	0.0	0.0	313	CARB, 1998
Refrigerators, Built-In, Undercounter	24.0	0.0	0.0	45	0.0	0.0	390	Energy Star (2009a)
Refrigerators, Compact (<6.4 cu.ft)	24.0	0.0	0.0	45	0.0	0.0	390	Energy Star (2009a)
Rice Cookers/Steamers	0.1	0.0	23.9	490	0.0	0.0	24	Public Utility District of Clallum County (2007)
Riding Garden Tractors	0.2	0.0	23.8	10,727	0.0	0.0	640	CARB, 1998
Rotary Tillers	0.1	0.0	23.9	2,983	0.0	0.0	111	CARB, 1998
Router	24.0	0.0	0.0	6	0.0	0.0	53	TIAX (2006)
Sandwich Makers	0.1	0.0	23.9	1,200	0.0	0.0	37	Sanchez et al. (1998), assumed same as Waffle Irons/Sandwich Grills.
Set-Top Boxes, Satellite	8.9	15.1	0.0	15	14.0	0.0	126	TIAX (2007b)
Security System	24.0	0.0	0.0	61	0.0	0.0	534	TIAX (2007b)
Set-Top Boxes, Cable	7.5	16.5	0.0	16	15.0	0.0	134	TIAX (2007b)
Set-Top Boxes, Satellite	8.9	15.1	0.0	15	14.0	0.0	126	TIAX (2007b)
Set-Top Internet Access Devices	24.0	0.0	0.0	6	0.0	0.0	53	TIAX (2007b), assume same as broadband modems. They are always on.
Sewing machine	0.1	0.0	23.9	100	0.0	0.0	4	http://www.absak.com/library/power-consumption-table
Shampooers/Steam Cleaners	0.0	0.0	24.0	1,300	0.0	0.0	16	Energy consumption from online manufacturer.
Shavers, Men's	0.1	0.0	23.9	15	0.0	1.4	13	Sanchez et al. (1998)
Shavers, Women's	0.0	0.0	24.0	15	0.0	1.4	12	Sanchez et al. (1998)
Slow Cookers	0.2	0.0	23.8	200	0.0	0.0	16	Sanchez et al. (1998)
Snowthrowers, Gasoline	0.0	0.0	24.0	4,541	0.0	0.0	75	CARB, 1998
Spa/Hot Tub	0.1	23.9	0.0	3,039	225	0.0	2,041	TIAX (2007b)
Tape & Radio/Tape Recorders	4.3	2.0	17.7	45	43.0	3.0	122	Assume same as audio systems
Telephone Answering Devices	0.5	0.0	23.5	4	0.0	3.8	33	U.S. DOE (2006)

Device	*Usage (hours per day)*			*Power consumption (W)*			*UEC*	*Source*
	Act-ive	*Idle*	*Off*	*Active*	*Idle*	*Off*	*kWh/ year*	
Telephones, Corded	1.9	15.6	6.5	4	2.0	0.0	14	Assume usage same as cordless phones.
Telephones, Cordless	1.9	15.6	6.5	4	3.5	2.5	29	TIAX (2007b), average between phones with and without answering devices
Telephones, Wireless	1.2	20.4	2.4	3	0.5	0.3	5	TIAX (2007b)
Television Projection Systems	5.1	0.0	18.9	150	0.0	2.2	295	Usage,TIAX (2007b); Power consumption, Sanchez et al. (1998)
Televisions, Black & White (Monochrome)	4.0	0.0	20.0	23	0.0	0.0	33	Sanchez et al. (1998)
Televisions, Color, Direct-View	5.1	0.0	18.9	65	0.0	1.0	129	Usage,TIAX (2007b); Power consumption, Kaplan (2007)
Televisions, Digital Projection	5.1	0.0	18.9	197	0.0	11.5	446	Usage,TIAX (2007b); Power consumption, Kaplan (2007)
Televisions, Hand-held	0.3	1.1	22.6	86	17.1	7.6	78	Assume same as portable DVD players.
Televisions, LCD	5.1	0.0	18.9	176	0.0	1.6	338	Usage,TIAX (2007b); Power consumption, Kaplan (2007)
Televisions, Plasma	5.1	0.0	18.9	383	0.0	6.6	759	Usage,TIAX (2007b); Power consumption, Kaplan (2007)
Toaster Ovens	0.1	0.0	23.9	1,300	0.0	0.0	33	TIAX (2007b)
Toasters	0.1	0.0	23.9	1,050	0.0	0.0	39	TIAX (2007b)
Toothbrushes/Plaque Removers	0.1	24.0	0.0	2	1.6	0.0	14	McAllister and Farrell (2007)
Trimmers, Beards & Moustache	0.1	0.0	23.9	15	0.0	1.4	13	Sanchez et al. (1998), assume same as men's shavers.
Trimmers/Brushcutters, Gasoline	0.1	0.0	23.9	671	0.0	0.0	31	CARB, 1998
TV/DVD/VCR Combinations	5.1	0.0	18.9	80	0.0	5.0	184	TIAX (2007a), DVD/VCR combination plus direct view color TV data.
Vacuums	0.1	0.0	23.9	1,080	0.0	0.0	42	TIAX (2007b)
Vacuums, Central	0.1	0.0	23.9	1,080	0.0	0.0	42	TIAX (2007b)
Vacuums, Hand-Held, Electric	0.4	20.2	3.4	5	3.7	0.8	29	TIAX (2007b)
Vacuums, Hand-Held, Rechargeable	0.4	20.2	3.4	5	3.7	0.8	29	TIAX (2007b)
VCR Decks	0.4	2.2	21.4	16	12.0	4.5	47	TIAX (2007b)
Video game consoles	1.1	1.5	21.4	36	36.0	0.8	41	TIAX (2007b)
Waffle Irons/Sandwich Grills	0.1	0.0	23.9	1,200	0.0	0.0	37	Sanchez et al. (1998)
Waterbed heater	8.5	15.5	0.0	350	2.0	0.0	1,096	TIAX (2007b)
Whirlpool Baths/Bath Mats, Portable	0.0	0.0	24.0	1,200	0.0	0.0	20	Assume same as Massagers, foot bath.
Wine coolers/chillers	24.0	0.0	0.0	45	0.0	0.0	390	Assume same as compact refrigerators.

Appendix C: Economic and non-economic variables: Historical and forecast

Year	*U.S. households* *U.S. Census Bureau (2008)*	*Price of electricity* *EIA (2009)* *US$2007 per kWh*	*Mean income* *U.S. Census Bureau (2009)* *US$2007*
1976	72,867,000	0.1359	49,442
1977	74,142,000	0.1386	50,179
1978	76,030,000	0.1370	51,713
1979	77,330,000	0.1326	52,047
1980	80,776,000	0.1349	50,462
1981	82,368,000	0.1414	49,847
1982	83,527,000	0.1474	50,150
1983	83,918,000	0.1494	50,257
1984	85,407,000	0.1428	52,202
1985	86,789,000	0.1425	53,413
1986	88,458,000	0.1404	55,519
1987	89,479,000	0.1358	56,587
1988	91,066,000	0.1311	57,291
1989	92,830,000	0.1279	58,963
1990	93,347,000	0.1243	57,521
1991	94,312,000	0.1224	56,301
1992	95,669,000	0.1213	56,238
1993	96,391,000	0.1195	58,537
1994	97,107,000	0.1173	59,673
1995	98,990,000	0.1143	60,708
1996	99,627,000	0.1105	62,009
1997	101,018,000	0.1089	64,007
1998	102,528,000	0.1051	65,873
1999	103,874,000	0.1016	68,114
2000	104,705,000	0.0992	68,792
2001	108,209,000	0.1005	68,171
2002	109,297,000	0.0974	66,677
2003	111,278,000	0.0983	66,590
2004	112,000,000	0.0982	66,373
2005	113,343,000	0.1003	67,277
2006	114,384,000	0.1065	68,459

Cost indices					
Category	Audio	Computer	Imaging	Telephone	Television
Index	Audio equipment	Personal computers and peripheral equipment	Photographic equipment	Telephone hardware, calculators, and other consumer information items	Televisions
1976					608.7
1977					601.6
1978	170.7				601
1979	176.4				609.3
1980	180.5				617.5
1981	186.2				622.9
1982	188.4				614.6
1983	185.3				593.3
1984	180.5				563.8
1985	174.4				523.7
1986	169.6				491.2
1987	171.8				470.5
1988	171.3				458.1
1989	171.4				449.3
1990	172.2				440.4
1991	174.8				430.4
1992	174.4				427.4
1993	173.5				417.4
1994	173.3				412.7
1995	170.1				402.1
1996	167.6				380.8
1997	164.2				364.3
1998	157.4	807.2	234.9	246.3	349.5
1999	150.9	552.3	228.1	218.6	324.1
2000	148.2	424.2	221.9	197.1	294.6
2001	142.6	304.5	209.4	176.9	264.5
2002	135.6	229.1	195.7	161.1	236.7
2003	128.4	181.6	180.7	143.7	206
2004	121.9	157.9	159.8	129	177.1
2005	112	132.1	141	118.6	157
2006	105.9	111.5	123.2	108	131.7

Cost indices						
Source	U.S. Bureau of Labor Statistics					
Category	Thermal	Labour saving	Personal care	Outdoor Heating	Outdoor Labour saving	Air conditioning and refrigeration
Index	Microwaves, Small cooking appliances, Irons	Food preparation appliances, Small kitchen appliances (non-cooking), Vacuum cleaners	Personal care appliances	Outdoor equipment and supplies	Outdoor equipment and supplies	Refrigeration appliances, Air treatment products
1998	131.8	111.8	30.6	110.1	110.1	111.6
1999	126.9	109.2	30	108.8	108.8	108.8
2000	123.6	109.1	28.8	105.2	105.2	107.3
2001	119.2	109	27.2	104.9	104.9	105.5
2002	113.7	108.6	25	104	104	103.3
2003	108.8	106.2	25.2	102.4	102.4	99.7
2004	103.6	106.8	26.4	100.7	100.7	95.7
2005	101.5	104.9	27.3	100.4	100.4	96.8
2006	100.7	104	27.6	100.1	100.1	98.1

Year	*Price of electricity EIA (2009) US$2007 per kWh*	*Mean income forecast US$2007*	*Cost index forecast*	*New device ratio forecast*
2007	0.106	67,609	96.2	0.387
2008	0.110	68,310	91.0	0.408
2009	0.111	69,012	86.0	0.429
2010	0.105	69,713	81.3	0.451
2011	0.107	70,415	76.9	0.472
2012	0.107	71,116	72.7	0.493
2013	0.108	71,817	68.8	0.515
2014	0.108	72,519	65.0	0.536
2015	0.108	73,220	61.5	0.557
2016	0.109	73,922	58.1	0.579
2017	0.109	74,623	55.0	0.600
2018	0.110	75,324	52.0	0.622
2019	0.111	76,026	49.1	0.643
2020	0.112	76,727	46.5	0.664
2021	0.111	77,429	43.9	0.686
2022	0.112	78,130	41.5	0.707
2023	0.113	78,831	39.3	0.728
2024	0.114	79,533	37.1	0.750
2025	0.116	80,234	35.1	0.771
2026	0.118	80,936	33.2	0.793
2027	0.119	81,637	31.4	0.814
2028	0.120	82,338	29.7	0.835
2029	0.121	83,040	28.1	0.857
2030	0.122	83,741	26.5	0.878