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DISSERTATION

Managing Residential Energy Demand Through Provision of Better Feedback

Myles T. Collins

This document was submitted as a dissertation in December 2010 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Rob Lempert (Chair), Martin Wachs, and Tom Light.

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Abstract

New and affordable technology for providing detailed feedback on household electricity usage presents a host of opportunities for utilities and policy-makers to manage demand. This dissertation examines ways to use these devices to reduce – and shift the timing of - energy use in the residential sector by influencing consumers' behavior. The first portion of the study analyzes the impact of programmable thermostats (PTs) on energy use, focusing on residents' knowledge of climate control settings in the dwelling. I found that of households with natural gas heating systems, young households with PTs used 17 percent less heating energy on average. In addition, residents who did not know their thermostat settings tended to use 10 percent more energy for heating.

The main portion of the dissertation focuses specifically on the potential for better feedback on electricity usage to reduce household energy consumption. The existing literature suggests that feedback can reduce electricity consumption in homes by 5 to 20 percent, but that significant uncertainties remain in our knowledge of the effectiveness of feedback. These uncertainties include the variation in feedback effectiveness between demographic groups and consumers in different climate regions. This analysis uses these uncertainties to perform an exploratory analysis to determine the conditions under which the benefits of feedback outweigh the costs and to compare the cost-effectiveness of providing feedback against that of other DSM programs. I found that benefits would likely outweigh costs for enhanced monthly billing and real-time feedback and that cost-effectiveness was superior to that of other DSM programs for these types of feedback. For feedback that is disaggregated by appliance type, cost effectiveness was competitive with other DSM programs under a limited set of cases.

This study also examines how energy consumption devices should display feedback on GHG emissions from electricity use under a real-time pricing program. I found that load-shifting can cause GHG emissions to increase

or decrease depending on region and season and in no discernable pattern. Therefore, feedback may be more useful and comprehensible to households in the form of total GHG emissions attributable to electricity usage instead of the emission rate of the marginal power plant. Finally, this dissertation explores ways to maximize the effect of feedback by evaluating which appliances may be best suited for appliance-specific feedback. Due to the energy use and behavioral factors associated with each appliance, the most promising appliances were those that heat water for taps, showers, hot tubs, and waterbeds.

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I would like to thank Mark Bernstein for bringing me aboard to co-author a paper on electricity usage feedback as I was working on my literature review, and for providing many helpful comments on my dissertation draft. Also, I appreciate the assistance of Stanton Hadley of Oak Ridge National Laboratory with the ORCED model.

Thanks to my parents, who encouraged me to pursue a Ph.D. and supported me in many ways throughout the process. Thanks also to my brother and sister and the rest of my family, who kept me moving forward despite the obstacles.

Finally, a special thank-you to my wife, Has, and 7-month-old son, Tristan. Has was a tremendous source of support, encouragement, and patience, for which I am eternally grateful. Her willingness to tolerate a husband working into the wee hours of the night made this dissertation a collective accomplishment. And Tristan, while his editorial suggestions were generally unhelpful, did provide plenty of motivation to finish and occasional, much-needed 3am companionship.

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List of Acronyms

AC	Air Conditioning
ASI	Appliance Specific Information
BTU	British Thermal Units
CARs	Computer Assisted Reasoning Software
CDD	Cooling Degree Days
CPP	Critical Peak Pricing
DOE	Department of Energy
DSM	Demand Side Management
ECD	Energy Consumption Display
EIA	Energy Information Administration
EPRI	Electric Power Research Institute
ESB	Energy-Saving Behavior
FERC	Federal Energy Regulatory Commission
GHG	Greenhouse Gas
HDD	Heating Degree Days
IOU	Investor Owned Utility
kWh	Kilowatt Hours
LDC	Load Duration Curve
LPG	Liquid Petroleum Gas
MB	Micro-Behavior
MEF	Marginal Emission Factor
NEMS	National Energy Modeling System
NERC	North American Electric Reliability Corporation
NPV	Net Present Value
ORCED	Oak Ridge Competitive Electricity Dispatch
ORNL	Oak Ridge National Laboratory
P:OP	Peak:Off-Peak
PRIM	Patient Rule Induction Method
PT	Programmable Thermostat
RASS	Residential Appliance Saturation Survey
RECS	Residential Energy Consumption Survey
RQ	Research Question
RTP	Real-Time Pricing
TED	The Energy Detective
TOU	Time-of-Use

Chapter 1:
Introduction

Electricity has brought countless benefits to households throughout the world. However, the ways we generate and use it create problems. Most power plants generate electricity by combusting fossil fuel and subsequently releasing CO_2 and a number of hazardous air pollutants into the atmosphere. Scientists around the world now generally agree that the increased concentration of CO_2 and other greenhouse gases (GHGs) in the atmosphere is altering the climate at an unprecedented rate and will have detrimental effects on the environment and global economy (Meehl, Stocker et al. 2007).

Our system for using electricity in households does not promote the efficient use of electricity, in part because consumers often have only a vague idea of how much energy they use. Utility bills generally come in the mail just once per month and give a numerical total of electricity use and amount owed for the entire house. With this type of infrequent and aggregated feedback, it is difficult for consumers to see the consequences of using particular appliances or keeping them in "standby" mode. Households have neither the information nor the incentives to consume electricity efficiently. In addition, if consumers want to save money or reduce their carbon footprint, they do not know which appliances to use less, which to unplug, and which to replace.

Many government agencies and utilities have existing demand-side management (DSM) programs whose goals are to reduce energy use through policies such as incentives and customer education. A number of studies have shown that providing different types of electricity usage feedback can reduce usage by around 20 percent and can help shift up to 40 percent of peak demand to off-peak hours (Hayes and Cone 1977; IEA-DSM 2005; Mountain 2006). Despite the potential benefits, no benefit-cost or cost-effectiveness analyses have yet been performed to assess policies for providing feedback to residential consumers and compare

them to existing DSM programs. This dissertation examines how and where policymakers should target feedback to maximize its benefit by analyzing the benefits and costs of different forms of feedback.

1.1 Motivation and Background

The ways we generate and use electricity are problematic from both a societal and consumer standpoint. From a societal standpoint, we are concerned about the harm to the environment from power plant emissions and mining operations to obtain fossil fuels. The U.S. accounts for 25 percent of global GHG emissions and the residential sector accounts for 18 percent of emissions in the U.S. (EIA 2009). Reducing energy use in the residential sector could therefore have a significant impact on total worldwide GHG emissions.

From a consumer standpoint, households are concerned with the rise in electricity prices coupled with their increasing demand. The price of electricity has been rising steadily over the past decade and consumers could face even higher prices as new conventional power plants face more obstacles to coming online from the permitting process. Within the household, apart from a monthly bill from the utility, consumers cannot see how much electricity they are using and do not know what portion of their use goes to each appliance. Households also generally do not know about the GHG emissions associated with their consumption as it is not reflected in the price they pay. Consequently, if households want to save money or reduce their carbon footprint, they do not know which appliances to use less, which to unplug, and which to replace. Stern and Aronson (1984) compare receiving this sole, monthly bill to going to a supermarket where individual items are not labeled with a price and the shopper can only see the total, non-itemized bill when they check out.

In-home electricity monitors that display current and historical use may offer a way to make electricity use more visible to consumers and to give them greater control over energy consumption. Advanced metering technologies are now available that were not a decade or two ago and technological advancements have made information easier and to collect,

display, and store. Households can see how much electricity they are using on a real-time basis and observe the immediate effect on total usage of turning certain appliances on and off. Instead of only having the option to adjust behavior in response to costs once per month when the bill arrives, more frequent information would allow consumers to learn how they use energy, adjust behavior more often, and possibly reduce GHG emissions by demanding less electricity.

U.S. Energy Use: Less Per-Household But More Overall

In the late 1970s and early 1980s, total U.S. energy consumption in the residential sector decreased from 10.6 quadrillion BTU (quad BTU) per year to 9.0 quad BTU (Figure 1.1). "Residential energy consumption" includes electricity, natural gas, fuel oil, and liquid petroleum gases (LPG), but does not include petroleum for transportation. From 1982 to 2005, total consumption gradually increased again to 10.5 quad BTU. Of the separate components of "energy," total electricity consumption has increased dramatically since the early 1980's, while natural gas and fuel oil / LPG consumption have slightly decreased (Figure 1.2). Although total residential electricity consumption is expected to decline slightly by 2015, DOE projects that it will increase thereafter to yield an average annual growth rate of 0.7% (between 2009 and 2035) (EIA 2010). Apart from long-term projected growth, state energy policies – such as AB32 in California – will apply external pressures on utilities to reduce demand in order to lower GHG emissions.

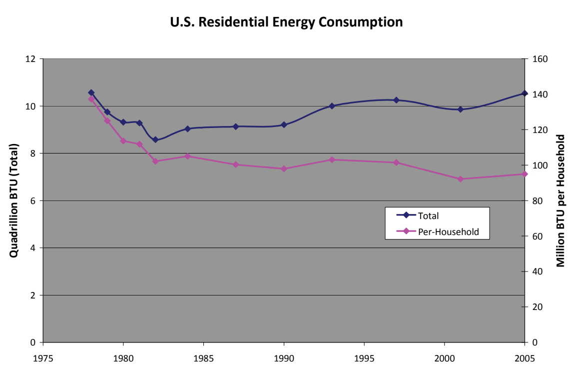

Figure 1.1: Residential energy consumption in the U.S., 1978-2005.

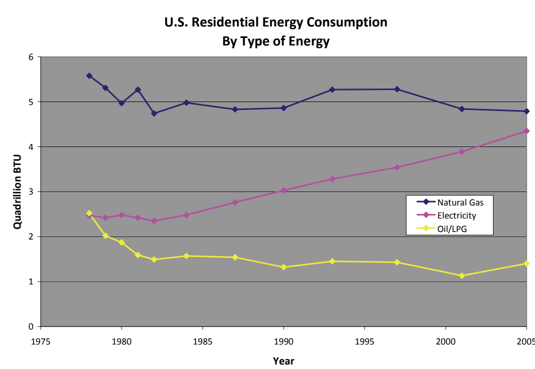

Figure 1.2: Residential energy consumption by type of energy, 1978-2005.

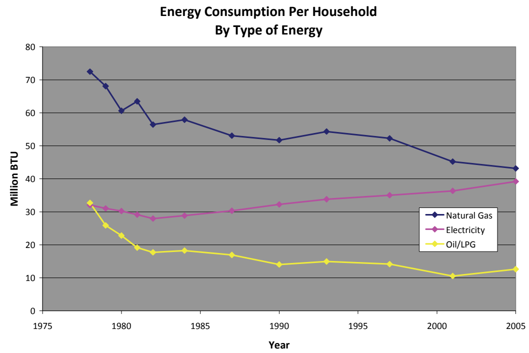

Figure 1.3: Household energy consumption by type of energy, 1978-2005.

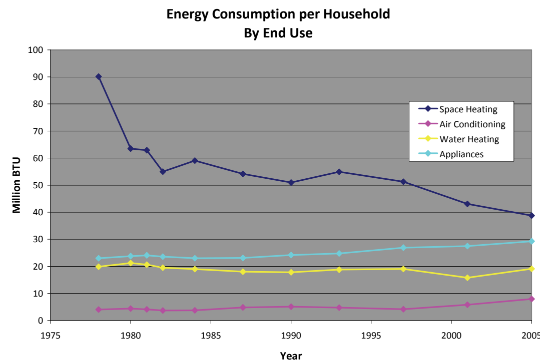

Figure 1.4: Household energy consumption by end use, 1978-2005.

On a per-household basis, we see declines in natural gas and fuel oil/LPG consumption and a more modest percentage-wise increase in electricity consumption (Figure 1.3). A steady increase in the number of people and number of households in the U.S. explains the difference in appearance between the total and per-household figures. Several other factors are driving the trends in the two graphs. The primary fuels for space heaters are natural gas, fuel oil, and LPG. The efficiency of space heaters has improved and the per-household consumption of these fuels has, in turn, declined. Part of the reduction is also due to recent warmer weather, which has reduced the need for people to heat their homes. Increases in energy efficiency and a decrease in number of people per household have also been significant contributors, though trends to larger homes and new energy-using technologies have kept per-household energy use from declining even further (EIA 2009).

Figure 1.4 breaks down household energy consumption into four end uses: space heating, air conditioning, water heating, and appliances. The figure shows an overall decrease in energy for space heating — the largest portion of household energy demand. The amount of energy used for air-conditioning and appliances, however, has been growing. "Appliances" include energy uses from lights and kitchen appliances to audio and computing devices. Generally, appliances and air conditioners receive their power from electricity and Figure 1.5 shows per-household energy use for electricity only. As expected, increases in electricity

use are due to people using more electricity for appliances and air conditioning; we see a 25 percent rise in electricity use for appliances and an even bigger rise (proportionally) for air conditioning.

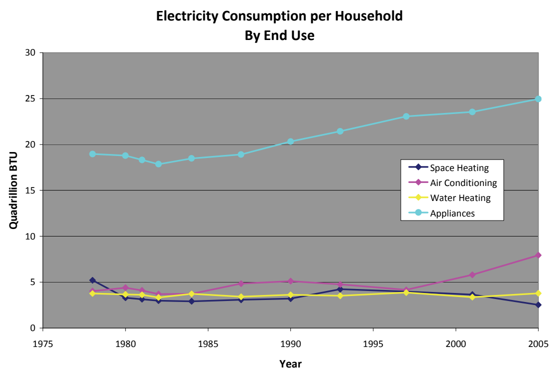

Figure 1.5: Electricity consumption per household by end use, 1978-2005.

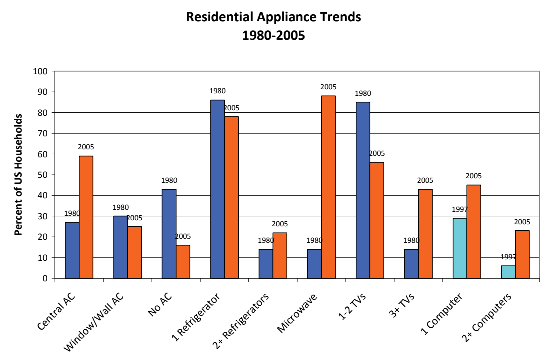

Figure 1.6: Residential appliance trends in the U.S., 1978-2005

We can see at least part of what the increases in electricity use for appliances can be attributed to by looking at Figure 1.6, which shows appliance trends in the U.S. between 1980 and 2005. More houses have central AC while fewer have window/wall units or no AC. More households have switched from just one refrigerator to 2 or more. Almost all households now have microwave ovens, up from just 14 percent in 1980. Looking at television ownership, fewer households have just 1 or 2 TVs and have switched to 3 or more. In fact, the average number of televisions per household has increased from 1.7 in 1980 to 2.7 in 2005 (U.S. Census). Computers, which were not common enough in 1980 to include in the survey are now present in over 65 percent of households, with 23 percent of households owning 2 or more.

Looking ahead to 2030, EIA projects electricity demand to increase by 20 percent from 2007 levels. In part, it attributes this growth in demand to a rise in home cooling as more and more people move to the South and West and also as they convert older homes from window/wall AC to central AC (EIA 2009). In addition to these regional and equipment changes, EIA projects that a 24 percent increase in the number of households will further exacerbate the growth in demand.

Household Electricity Expenditures on the Rise

Since leveling off at the end of the 1990s, the average real price of electricity nationwide has been on the rise. The higher prices, combined with increased electricity use, have led to more household spending on electricity. For consumers in the U.S., real expenditures on electricity have increased from $848 per household in 1978 to $995 in 2005[1] (Figure 1.7). Breaking down the total amount by end use (Figure 1.8), real expenditures for space and water heating are relatively low and have either stayed relatively constant (water heating) or declined (space heating) since 1978, hovering just below $100 (real 2000 dollars). On the other hand, expenditures on electrical appliances and AC have been on the rise. In 2005, the average household spent $201 (real 2000 dollars) on electricity for AC, compared with just $106 ten years earlier. Real spending on electricity for appliances has increased by nearly 20 percent since 1978.

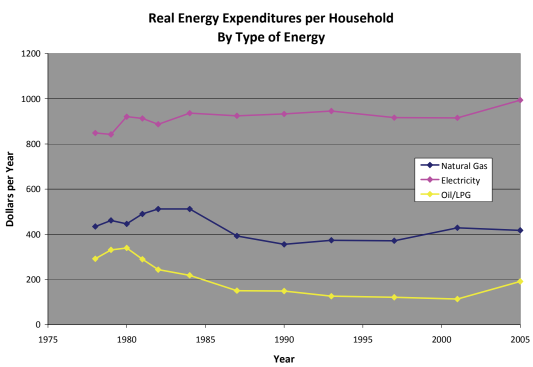

Figure 1.7: Real energy expenditures per household by type of energy, 1978-2005.

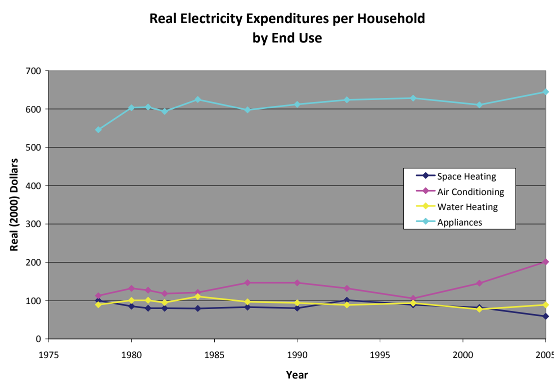

Figure 1.8: Real electricity expenditures per household by end use, 1978-2005.

Prices, residential demand, and household expenditures for electricity have all been rising at the same time. In many other sectors of the economy, when prices go up, we may see a demand response — with demand either declining or growth slowing. We do not seem to be seeing that with electricity. In some cases, it may be hard for consumers to react to electricity price changes when they use electricity for necessities and thus do not have flexibility with how much they use over the near-

[1] Real amounts are adjusted for inflation and are in 2000 dollars.

term. On the other hand, a portion of the increase in expenditures is due to new devices that are not necessities, as well as an increase in the size and energy use of the devices (such as plasma televisions).

The increased price and demand for electricity indicates an outward shift in the demand curve - or, in other words, a new-found tolerance that consumers now have to purchase more electricity even though prices are higher. It is possible that consumers are satisfied with this shift in demand and feel that the ability to use more and bigger devices is well-worth the extra charge on the monthly bill. However, given the lack of information about how much each appliance actually costs to use, it is also quite possible that consumers would act much differently if they had this information. Would people leave their flat-screen TVs on overnight if they knew the minute-by-minute cost? Would they keep the AC running when they left to go to work in the summer? Better information about electricity use could empower consumers to make better decisions and possibly slow growth in or even reduce their demand.

Controlling demand is especially imperative in the current climate of tight supplies. Increasing demand puts a strain on the electrical grid and requires the building of new power plants. According to the North American Electric Reliability Corporation (NERC), long-term capacity is already inadequate and the U.S. will need new transmission to maintain reliability (NRECA 2008). However, building new power plants and transmission lines now takes longer and costs more than it did in the past because of local opposition to additional power plants and transmission lines, rising costs of materials needed for construction, pollution restrictions in regions with already-poor air quality, and expectations for future limits on greenhouse gas emissions. If demand continues to rise, the cost of new power plants could further increase the price of electricity.

Two Roads to Reducing Energy Consumption

Residential electricity use is a large contributor to the strain on the nation's electrical grid. The residential sector consumes about 36% of electricity in the U.S. – more than the commercial or industrial sectors

— and its share has been increasing (EIA 2008). If policy-makers are going to significantly impact electricity demand in the U.S., residential use is a fertile area to look for reductions.

Households may reduce electricity use through two different avenues: 1) using more efficient appliances, and 2) using appliances less. How much electricity can we save through each mechanism above? Brown et al. (2008) examined the potential of using more efficient appliances. The study found that we could reduce electricity use in the business-as-usual case (no major policy changes) in 2030 by one-third and that the investment needed to achieve these savings was modest enough to yield a benefit-cost ratio of 3.5 (not including the cost of policy implementation). The latter option — using appliances less — is more complicated to evaluate. Households could reduce electricity use to zero, but their quality of life would be significantly lower. The key is to find ways to reduce use that do not have a huge impact on comfort or standard of living.

Consumers may also create benefits – in the form of lower-cost power - by using electricity at different times of the day, deferring the need to construct new power plants to handle peak demand. Some utilities have variable rate pricing programs in place to shift demand – with higher prices during peak hours - and such programs are becoming more common. They often can benefit not only the utility, but also consumers, who see lower monthly bills.

Existing government policies aim to work through each of these avenues to try to lower demand in the residential sector. To influence consumer behavior, policy-makers generally design DSM programs to reduce the load on the grid during times of peak use. Consumers may either reduce their use (turning off lights during peak times) or shift their demand to an off-peak hour (waiting to run the dishwasher). To encourage more efficient appliance purchases, policy-makers implement appliance standards, building codes, and rebates or subsidies for buying energy efficient equipment. For example, ENERGY STAR is a program administered by the federal government that allows appliance manufacturers to label

equipment with the Energy Star logo if it meets specified efficiency levels.

While existing DSM programs have made a difference, they have not been enough to curb the overall growth of residential demand. Efficient lighting is still a small percentage of total lighting in our homes and many people still do not choose the most efficient appliances even with the rebates. If people had a better idea of how much electricity each appliance used over time, it is possible they would make different choices both in the near-term with which appliances to use and in the long-term with which appliances to buy. Evidence exists of the former (see Chapter 3), but the latter has not yet been studied (see Section 4.4.5).

1.2 Objective and Research Questions

The current body of research on improving energy use feedback is composed almost entirely of small-scale experiments and utility pilot studies. This research uncovered no policy analyses that examined feedback from a cost-benefit or cost-effectiveness perspective. One reason for the lack of policy studies is the number and magnitude of uncertainties about how different households will react differently to better feedback. Current research, which is often funded by utilities, therefore continues to try to refine estimates for these uncertainties. However, methods exist for treating uncertainties systematically in order to explore the conditions under which benefits of better feedback may be high or low (Bankes 1993). As policy-makers search for ways to improve energy efficiency and moderate increases in demand, it is useful to explore when and where providing better feedback may pass a cost-benefit test or compare favorably with other policies in terms of cost-effectiveness. This dissertation contributes to the current body of literature by undertaking this analysis.

The goal of this research is to identify cost-effective policies for reducing residential electricity consumption. This dissertation will address the following specific research questions:

1. How do households currently interact with their home energy systems and what is the subsequent effect on energy use?
    a. Are programmable thermostats associated with lower energy use?
    b. How do these effects vary with demographics?
    c. Is knowledge of home thermostat temperature settings associated with lower energy use?
2. What are the mechanisms for providing feedback and how effective have they proven to be in reducing consumer energy use?
3. Do the benefits of feedback outweigh the costs?
    a. What is the range of potential benefits?
    b. What are the costs of different forms of feedback?
    c. When, where, and under what demographic circumstances are the benefits of reducing electricity usage the highest?
    d. How does the cost-effectiveness of feedback compare with current efficiency programs?
4. How can utilities use feedback in combination with a real-time pricing program?
    a. What impact does feedback -- in combination with pricing programs -- have on load-shifting?
    b. Without a price on carbon, when would separate feedback on emissions and cost give conflicting incentives for when to use electricity?
5. How can policy-makers maximize the effectiveness of feedback?
    a. Which appliances should policy-makers target for
        i. a) appliance-specific feedback?
        ii. b) load-shifting?
    b. Which regions should policy-makers target to realize the above benefits most effectively?

The next five chapters address the five research questions above – with each chapter dedicated to one research question (RQ). Each chapter is intended as a stand-alone analysis under the central themes of providing feedback and enabling more interactions with home energy systems. The dissertation follows the general progression of examining current interactions with home energy systems, past research and future

implications of providing better usage feedback, and maximizing the effectiveness of feedback.

Chapter 2 addresses the first research question, using data from the 2005 Residential Energy Consumption Survey (RECS). It examines how households currently interact with their climate control systems – focusing specifically on the impact of programmable thermostats (PTs) and knowledge of thermostat settings on overall usage. PTs may eventually be incorporated into Energy Consumption Displays (ECDs), which are the devices that provide feedback on energy use. This research question (and its three sub-questions) have never been addressed using RECS data or in the context of examining differing demographic effects.

The Chapter 2 research questions are important, because the types of households that use PTs to reduce their energy use for heating and cooling may be the same types that respond best to feedback. In addition, as feedback improves knowledge of energy use, an association between knowledge of thermostat settings and lower energy use may indicate a similar association between improved feedback and lower energy use. The analysis finds that of households with natural gas heating systems, young households with PTs used 17 percent less heating energy on average. In addition, residents who did not know their thermostat settings tended to use 10 percent more energy for heating.

The remaining chapters are more directly related to feedback for residential consumers on electricity usage. Chapter 3 (RQ #2) is a literature review of existing feedback studies and a summary of their findings. In general, the literature demonstrates that feedback can reduce electricity consumption in homes by 5 to 20 percent, but that significant gaps remain in our knowledge of the effectiveness of feedback. These gaps include how consumers with different demographics and in different climates will respond differently to feedback.

Chapter 4 takes the key uncertainties from the literature and performs an exploratory analysis to address Research Question 3. It contributes

to the literature by determining the conditions under which the benefits of feedback outweigh the costs and weighing the cost-effectiveness of providing feedback against that of other DSM programs. The analysis finds that moderate levels of conservation – comparable to those found in experiments in the literature - would be necessary for benefits to outweigh costs for two forms of feedback: enhanced monthly billing and real-time feedback given on an ECD. Also, for these two forms of feedback, cost-effectiveness is competitive with other DSM programs. For feedback that is disaggregated by appliance usage, the wide range of cost estimates necessitates moderate to very high levels of conservation to break even on purchasing the high-end feedback meters (and service plans where applicable). Cost effectiveness for this type of feedback is competitive with other DSM programs under some scenarios in some regions.

Chapters 5 and 6 address research questions 4 and 5, respectively. These chapters are shorter, independent analyses related to feedback. Chapter 5 examines the topic of using real-time feedback to shift load from peak to off-peak times. First, it reviews the existing (but small) literature on how feedback on usage and price – under a variable-rate pricing structure - can enhance load-shifting among residential consumers. Next, it examines the form that environmental feedback should take under a real-time pricing program. This question has not been explored in the literature, as the consequences of load-shifting for greenhouse gas (GHG) emissions are often ignored. The analysis finds that load-shifting can cause GHG emissions to increase or decrease depending on region and season and in no discernable pattern. Feedback may thus be more useful and comprehensible to households in the form of total GHG emissions attributable to electricity usage instead of the emission rate of the marginal power plant.

Chapter 6 explores ways to maximize the effect of feedback by evaluating which appliances may be best suited for appliance-specific feedback. It expands on a previous study in the United Kingdom by Wood and Newborough (2003) by using their framework to examine common appliances in U.S. households and rank them by suitability from most suitable to least

suitable. The analysis in Chapter 6 adds appliances that Wood and Newborough did not include and rescores some appliances from a U.S. perspective. It finds that due to the energy use and behavioral factors associated with each appliance, the most promising appliances are those that heat water for taps, showers, hot tubs, and waterbeds. Other appliances on the next tier down are range burners, personal computers, lighting, and central heating systems.

Chapter 2:
Interacting with Home Energy Systems: The Case of Programmable Thermostats and Consumer Awareness

2.1 Summary

This chapter examines how households currently interact with their climate control systems – focusing specifically on the impact of programmable thermostats (PTs) and knowledge of thermostat settings on overall usage. While not addressing feedback specifically, Chapter 2 lies within the broader focus of this dissertation, which is improved consumer information on energy use.

Residential consumers who interact with their PT and use it to save money on utility bills may show similar willingness and ability to use better feedback to reduce electricity use. As both PTs and energy consumption displays are devices which residents may use to interface with their home energy systems, it is useful to explore the associations between PTs and energy use for different demographics, as these demographic variables are also some of the key uncertainties in how households will respond to feedback.

Sachs (2004) calls for "[defining] the class(es) of consumers for whom programmable thermostats are worth promoting…" This analysis uses data from the 2005 RECS to address this issue, examining whether demographic characteristics of households and the climate in which they live impacts the effect of PTs on energy use and behavior. This chapter also uses the RECS data to examine whether knowledge of home temperature levels is associated with energy savings.

This chapter addresses the following specific research questions:

- How do households currently interact with their home energy systems and what is the subsequent effect on energy use?
    - Are programmable thermostats associated with lower energy use?

- How do these effects vary with demographics?
- Is knowledge of home thermostat temperature settings associated with lower energy use?

The analysis finds that of households with natural gas heating systems, young households with PTs use 17 percent less heating energy on average. In addition, residents who do not know their thermostat settings tend to use 10 percent more energy for heating. No significant associations were discovered for cooling energy.

2.2 Background and Data

People may employ one of three temperature control methods for heating and cooling their homes: no thermostat, a standard thermostat, or a programmable thermostat. With no thermostat, a household would control heating and cooling manually with an on/off switch. A standard thermostat automatically turns on the heating or cooling equipment once the space reaches a certain temperature. Programmable thermostats have an automatic setback feature, providing the extra ability to change the temperature setting based on the time of day. For instance, households may decide to lower the temperature by a few degrees during the winter when they sleep if they do not notice the temperature difference while asleep and would prefer to save money on their utility bill. PTs may be connected to the heating system, cooling system, or both.

PTs were originally hailed as harbingers of energy savings. Manufacturers claimed energy use reductions of 15 percent — based on engineering analyses of potential savings — and the ENERGY STAR program offered rebates for their purchase and installation. In California, PTs have been required in new residential construction since 1983 to comply with state building energy efficiency standards.

A number of field studies in the late 1990s and early 2000s found that households with PTs were not realizing the expected savings. In a study of 100 Connecticut households with programmable thermostats, Cross and Judd (1997) found that savings were less than the projected 15 percent

because households stopped using the programmable feature and households with manual thermostats practiced manual setback (i.e. manual adjustments to save energy). In a study of 299 owner-occupied, single-family residential housing units in Wisconsin, Nevius and Pigg (2000) found that self-reported winter thermostats did not vary based on whether the household had a programmable versus a manual thermostat. Conner (2001) found savings of less than 1 percent (not significant) in a study in the Pacific Northwest, and another study (personal communication cited in Sachs, (2004)) in Florida found programmable thermostats were associated with a 2.5 percent (significant) increase in cooling energy. Haiad et al. (2004) used the California Residential Appliance Saturation Survey (RASS) to examine how households used programmable and manual thermostats. The authors then used the results in a simulation to determine differences in energy use and found that households with programmable thermostats actually used more heating energy, but no consistent pattern for cooling energy.

Reasons abound for why PTs are not living up to their potential. Households with manual thermostats sometimes perform the same temperature setbacks that programmable thermostats perform automatically. Occupants could also be using their PTs manually and not taking advantage of the automatic setback function. They may not be using their PTs consistently, or at all. This could be the case particularly when the dwelling already had a PT installed and it was not purchased by the occupant. For those who use the PTs, the automatic program may save less energy than what people are doing manually.

Due to the research showing a lack of savings for PTs, EPA suspended the ENERGY STAR PT specification effective December 31, 2009 (ENERGY STAR website). EPA acknowledges that home energy management systems, which include a communicating climate control component, will likely be part of many homes in the future (ENERGY STAR website). Thus, EPA has begun work on a new ENERGY STAR climate control specification, which will cover home climate controls more generally and not focus only on the automatic setback feature.

Data on the saturation and self-reported use of PTs is available in RECS, which is administered by the Department of Energy (DOE) every four years. It contains information on the physical characteristics of housing units, appliances utilized — including space heating and cooling equipment - demographic characteristics of households, types of heating fuels used, and other information that relates to energy use.

RECS was conducted in two major parts: the Household Survey and the Energy Suppliers Survey (EIA 2010). The Housing Survey collected information about housing units in the U.S. using a sample that was representative of the population. For the Energy Supplier Survey, data was collected on actual household energy usage from questionnaires mailed to the energy suppliers. The sample size for 2005 was 4,382 households, which was the number of completed interviews from an unspecified number of chosen households.

Figure 2.1 shows the saturation of programmable thermostats for heating and cooling systems, based on the RECS 2005 data, which is the most recent year available. Approximately 23 percent of 101.6 million households nationwide with heating equipment have a PT for cooling, while 30 percent have one for heating. Standard thermostats are also more common for heating systems, with 56 percent of households having one, as opposed to 42 percent for cooling systems. Fourteen percent of households have a heating system with no main thermostat, while 42 percent of households have air conditioning without a thermostat. For households that have thermostats, if they have one type for the heating system, they are likely to have the same type for the cooling system. For both heating and cooling systems, approximately two-thirds of the households with PTs report using them to automatically lower the temperature either at night or when they leave the dwelling.

	Cooling			
Heating	No Main	Standard	PT	**Total**
No Main	12%	1%	0%	**14%**
Standard	23%	32%	1%	**56%**
PT	7%	1%	21%	**30%**
Total	**42%**	**35%**	**23%**	**100%**

Table 2.1: Saturation of standard and programmable thermostats for heating and cooling.

For the occupants that have a PT, they may have either purchased and installed it, or moved into a dwelling that already had it. The RECS data does not make this distinction.

Figure 2.1 characterizes heating systems in U.S. households by type of heating equipment and type of fuel. As the figure reveals, most U.S. households have central heating systems and most of those use natural gas as the heating fuel. Several regions do not follow this generalization. Steam/hot water systems are more common than central heating in the New England and also fairly common in Pennsylvania and New Jersey. Most of the fuel oil consumed for heating is in this region. Heat pumps are found in the greatest proportions in the Southern states, and these states also use electricity as the heating fuel more than other regions.

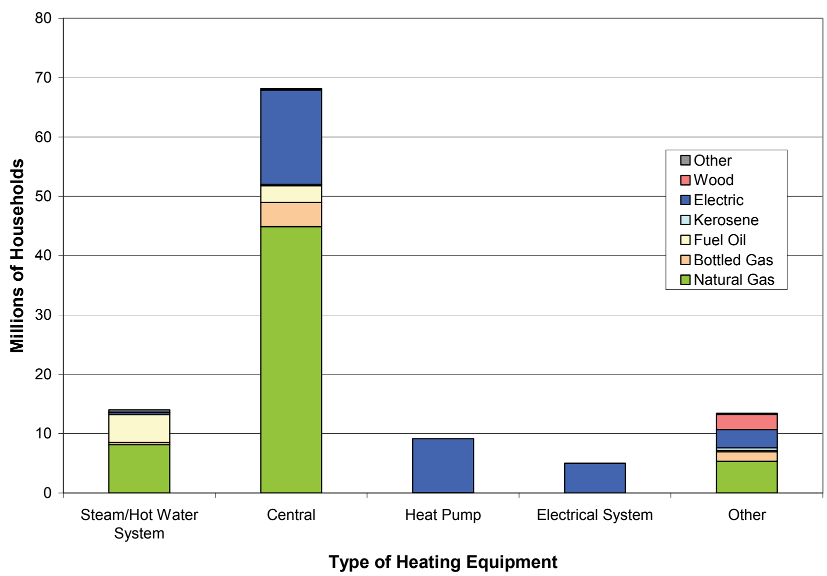

Figure 2.1: Heating equipment by type of fuel for U.S. households.

Looking at the three PT-related charts (Figures 2.2-2.4), we see that most PTs control central heating systems. By type of heating fuel, PTs control over one-third of natural gas systems, and close to one-quarter of electrical systems. Regionally, the largest proportion of PTs are in the East North Central region (Midwestern states), and California.

Households in the East and West South Central regions have the lowest proportion of PTs controlling their heating equipment.

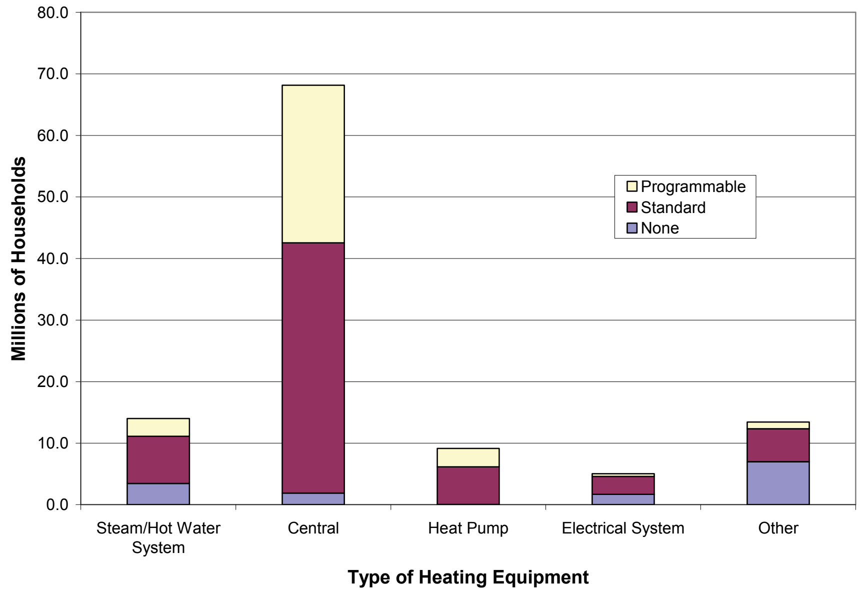

Figure 2.2: Type of thermostat by type of heating equipment.

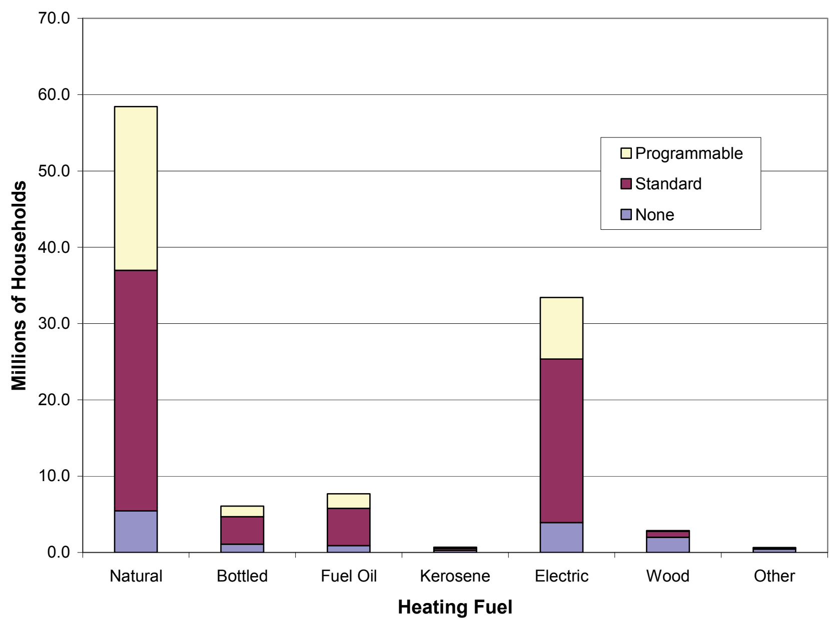

Figure 2.3: Type of thermostat by type of heating fuel.

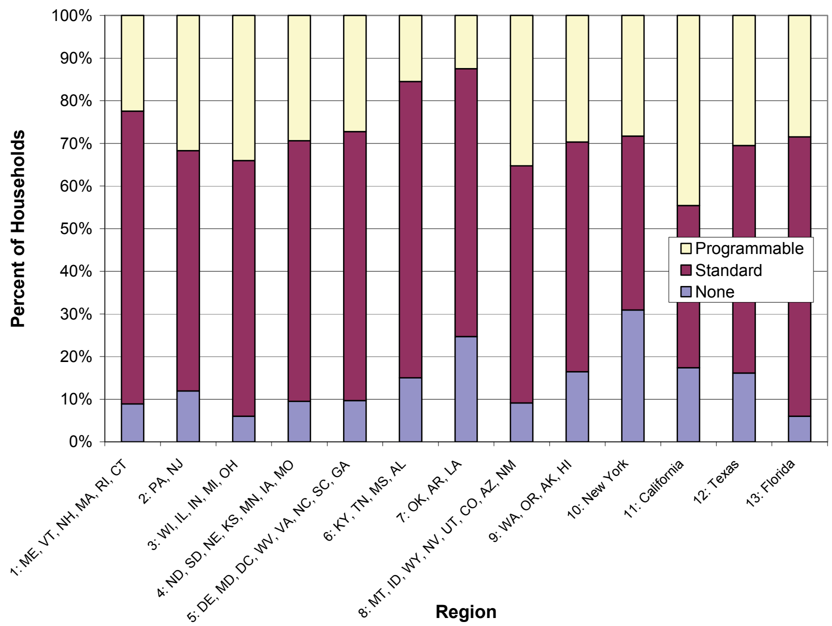

Figure 2.4: Type of heating thermostat by region.

Cooling equipment in U.S. households is less varied, as AC is the only type of cooling equipment included in RECS and all AC units get their power from electricity. There is some difference in type of AC unit, as a unit could either be a central unit, one or more individual window or wall-mounted units, or a combination of both. Figure 2.5 shows the type of AC by region. The largest proportions of homes without AC are in the Mountain states and the Pacific Coast, including California. Individual units are most common in New England, New York, and the Middle Atlantic states. The highest proportions of central AC systems are in the South and Great Plains (West North Central region). Figure 2.10 shows the proportion of central AC systems with PTs by region. The highest proportions of PTs are in the Midwest (East North Central region), Mountain states, and California.

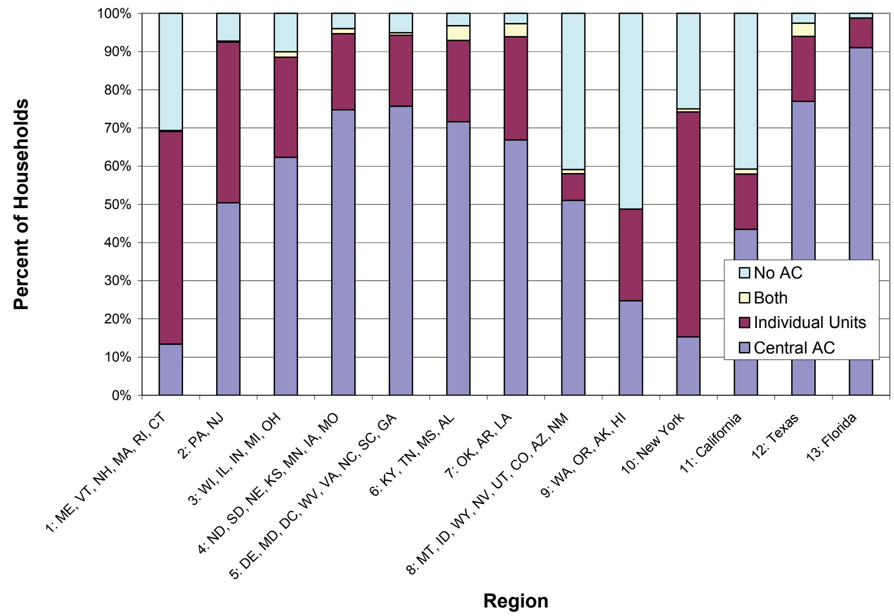

Figure 2.5: Type of AC by region.

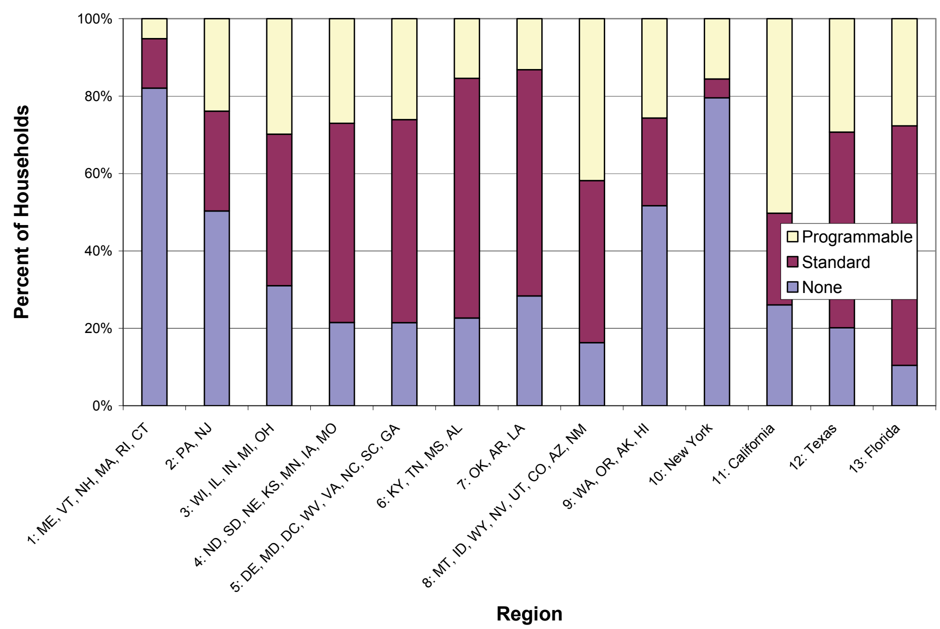

Figure 2.6: Type of thermostat by region (central AC systems only).

2.3 Analysis of RECS Data

The RECS data contains information on PT-related behavior separately for heating and cooling and thus, it is necessary to examine each function individually. It is reasonable to hypothesize that PTs could have a different effect on heating behavior than on cooling behavior for a number of reasons: people may prefer colder temperatures when they sleep; nighttime is naturally colder, which means a greater need for heat but a lower need for AC; the unobservable characteristics that lead people to live in warmer climates may affect their behavior.

The regression analyses looked at several demographic and climate characteristics with regard to PT use and effect on energy use. I treated each characteristic as a dummy variable in order to interact them with a dummy variable indicating the presence of a PT in the dwelling. These dummy variable definitions are:

- High Income: top quartile, above $67,500 per year
- High Heating Intensity: top quartile, above 44.19 Btu/heated square foot/year.
- High Cooling Intensity: top quartile, above 10.26 Btu/cooled square foot/year.
- Young: maximum age of household members is less than 35.
- Cold Climate: top quartile of heating degree-days, above 5927 (relative to 65°F).
- Hot Climate: top quartile of cooling degree-days, above 1858.

2.3.1 Programmable Thermostats for Heating

This part of the analysis includes only households with heating equipment that 1) they use, and 2) *could* use a programmable thermostat. Thus, it excludes households without heating equipment, with heating equipment but who do not use it, and with heating equipment for which a PT is not an option (or for which there were 0 or 1 PTs in the group). Specifically, the analysis excluded households with heating stoves burning wood, coal, or coke, fireplaces, portable electric heaters, portable kerosene heaters, and cooking stoves also used to heat the

home. It also excluded households for which the heating fuel is kerosene, wood, solar, "district steam," or "some other fuel."

The first set of regressions examines the entire U.S. population who heat their homes and looks to find the relationship between PTs and energy use for heating. They control for income, demographics, housing characteristics, heating prices, heating degree days, and regions. The dataset is weighted by population and this analysis uses those weights throughout. Table 2.2 shows the results of these regressions. Each column is a separate regression and incorporates one of the applicable demographic and climate factors as an interaction term (apart from the first column).

For each of the regressions, the PT variable (first row) was not significant, while not having a thermostat at all — whether standard or programmable — was associated with an 8-10 percent increase in heating energy use.[2] These results were similar to others in the literature, which did not find an association between PTs and energy use. Having an income in the top quartile was significantly associated with an 8 percent increase in heating energy usage. The high income-PT interaction term was significant and positive, meaning that having a high income and a PT was associated with 9 percent higher energy use. Young households and households in cold climates who have PTs were associated with 7 percent lower energy use, but the results were not significant.

[2] The exception is the last regression, which included the cold climate interaction variable. This regression did not control for heating degree-days apart from the *cold climate* dummy variable.

Independent Variable	Effect on Heating Energy Use (log BTU)				
Model	1	2	3	4	5
Programmable Thermostat	0.003 [0.021]	-0.03 [0.027]	0.016 [0.022]	0.014 [0.023]	0.007 [0.029]
Standard Thermostat	-	-	-	-	-
No Thermostat	0.095 [0.038]**	0.083 [0.037]**	0.084 [0.033]**	0.093 [0.038]**	0.03 [0.041]
High Income		0.083 [0.033]**			
High Income + PT		0.086 [0.042]**			
High Heating Intensity			0.716 [0.025]*		
High Heating Intensity + PT			-0.014 [0.041]		
Young				-0.025 [0.029]	
Young + PT				-0.069 [0.051]	
Cold Climate					0.225 [0.032]*
Cold Climate + PT					-0.07 [0.045]
Demographics	(6)	(6)	(6)	(6)	(6)
Housing Characteristics	(4)	(4)	(4)	(4)	(4)
Heating Prices	Included	Included	Included	Included	Included
Heating Degree Days	Included	Included	Included	Included	-
Regions	Included	Included	Included	Included	Included
Number of Observations	3959	3959	3959	3959	3959
R-squared	0.813	0.815	0.850	0.813	0.814

Note—for all tables:

+ Significant at 10%
** Significant at 5%
* Significant at 1%

Demographic variables: income, presence of person age 65+, person at home during day, do not pay all of heating bill, own dwelling, main heating system heats other apartments.
Housing variables: heated square feet, type of dwelling, type of heating equipment, year of construction.

Table 2.2: Regression results for households with any heating fuel. Heating energy use is the dependent variable.

The next set of regressions consider only natural gas heating systems, which are the most common form of heating and for which most PTs are installed. Table 2.3 shows the results. The positive association between the high income-PT interaction term and energy use is much smaller (less than 2 percent) and is not statistically significant. However, in this set of results, we see a strong negative association between young households with a PT and energy use. The other

interaction terms remain insignificant. To investigate the two significant interaction associations more carefully - high income-PT for all fuels and young-PT for natural gas systems – I substituted the dummy for having a PT with one for self-reported usage of the PT. This allowed me to weed out the households that were using the PT the same way they would use a standard thermostat. The association for income-PT shrunk and was no longer statistically significant. The young-PT interaction term for natural gas-heated households maintained its magnitude at approximately 16 percent and remained significant with p=0.007.

Independent Variable	**Effect on Heating Energy Use - Natural Gas Only (log Btu)**				
Model	**6**	**7**	**8**	**9**	**10**
Programmable Thermostat	-0.014 [0.023]	-0.023 [0.029]	-0.003 [0.024]	0.01 [0.025]	-0.02 [0.035]
Standard Thermostat	-	-	-	-	-
No Thermostat	0.043 [0.042]	0.037 [0.042]	0.028 [0.038]	0.037 [0.042]	-0.052 [0.048]
High Income		0.087 [0.040]**			
High Income + PT		0.016 [0.047]			
High Heating Intensity			0.582 [0.028]*		
High Heating Intensity + PT			0.018 [0.043]		
Young				0.018 [0.036]	
Young + PT				-0.159 [0.056]*	
Cold Climate					0.169 [0.034]*
Cold Climate + PT					-0.023 [0.047]
Demographics	(6)	(6)	(6)	(6)	(6)
Housing Characteristics	(4)	(4)	(4)	(4)	(4)
Heating Prices	Included	Included	Included	Included	Included
Heating Degree Days	Included	Included	Included	Included	-
Regions	Included	Included	Included	Included	Included
Number of Observations	2230	2230	2230	2230	2230
R-squared	0.696	0.697	0.761	0.697	0.601

Table 2.3: Regression results for natural gas heating systems only. Heating energy use is the dependent variable.

To get an idea of what types of temperature-setting behavior may be accounting for the lack of a PT effect overall and also the significant young-PT effect for natural gas heating, I analyzed the self-reported behavior data contained in RECS. As part of the survey, interviewers asked household members the temperature in their dwelling during the day in winter when someone was home, during the day in winter when no one was home, and during sleeping hours in the winter. Respondents could answer in degrees Fahrenheit for each question, "don't know," or "heat turned off." This analysis approached the household behavior question from two angles. First, for those households who do not turn off the heat at night or when they leave, it examined if PT and non-PT households — and young households with PTs — adjusted the heat differently during those times. Second, it tested whether PT households were more or less likely to turn off the heat completely at night or when no one was home.

The results may give us an idea about micro-behaviors for heating control in the household, but may be problematic for a few reasons. First, the temperature settings are self-reported. This could bias the results if households that are more careful about their energy usage for budgetary reasons give more accurate responses. Second, the data may actually be reporting different measurements, as the survey instructs the interviewer that "if the respondent doesn't know the temperature, but knows the thermostat setting, record the thermostat setting. Otherwise, probe for the best estimate."

We may place households with heating equipment into one of three categories: those who report a temperature for winter during the day, those who report that the heat is turned off, and those who do not know the daytime temperature. This analysis looks only at the households who report a temperature. Of this group, during the night or when they leave the dwelling, occupants may increase the temperature, decrease it, keep it the same, or turn off the heat. Here, I exclude the "don't knows" and the households who simply report turning off the heat at night or when they leave — without reporting an actual temperature.

Table 2.4 shows the results for the regressions testing differences in temperature adjustments. The dependent variable for the two regressions on the left-hand side is the difference between the temperature during the day when someone is home and the temperature either when no one is home during the day or at night when occupants are asleep. Positive values for coefficients indicate that the temperature difference is greater, i.e. occupants turn the heat down more when they leave and/or at night. The dependent variable for the two regressions on the right-hand side is a dummy variable for each action. Positive values for these coefficients indicate a greater likelihood that households with the characteristic turn off the heat at the specified times.

All Fuels				
	Degrees Fahrenheit that Households Turn Down Temperature		Probability that Households Turn off Heat	
Independent Variable	**At Night**	**When Occupants Leave the Dwelling**	**At Night**	**When Occupants Leave the Dwelling**
Programmable Thermostat	1.065 [0.158]*	0.321 [0.193]+	-0.003 [0.007]	-0.025 [0.008]*
Standard Thermostat	-	-	-	-
No Thermostat	-0.373 [0.355]	-0.75 [0.416]+	0.019 [0.015]	0.028 [0.021]
Demographics	(6)	(6)	(6)	(6)
Housing Characteristics	(4)	(4)	(4)	(4)
Heating Prices	Included	Included	Included	Included
Heating Degree Days	Included	Included	Included	Included
Regions	Included	Included	Included	Included
Number of Observations	3581	3479	3709	3709
R-squared	0.073	0.059	0.123	0.197

Table 2.4: Self-reported heating behavior – all heating fuels.

Considering all heating fuels, households that report having a PT show a significant effect (p=0.01) of 1°F at night but only 0.3°F when away (and only significant at p=0.1). Households with no main thermostat tend to be warmer by about ¾°F when residents are away, compared to households with standard thermostats. Similarly, young households tend to be about ½°F warmer at night. For the regressions investigating turning off the heating equipment, we see no significant effects for any

of the independent variables at night. For behavior when the occupants are away, however, we see that households without thermostats are 2-3 percent less likely than those with standard thermostats to turn off the heat.

To investigate the significant young-PT interactions from the Table 2.3 regressions, I performed the same analysis for households with natural gas systems only. The results were similar, but the significant coefficients tended to have larger magnitudes, with the exception of the "Use PT" variable for the "Temp. Differences When Gone" regressions. Although young households that have PTs were associated with less energy use, these regressions do not reveal differences in temperature-setting or on/off behavior as reasons for this observation. It is also possible that this group of households tended to keep their homes at a lower temperature in the winter. However, a check of mean daytime temperatures revealed no significant differences between these households and others, so the reasons for the differences in energy use remain unclear. It is possible that young people with PTs live in dwellings that have some characteristic for which the regressions do not control through construction year or region, such as ability to insulate heat.

Natural Gas Only				
	Degrees Fahrenheit that Households Turn Down Temperature		Probability that Households Turn off Heat	
Independent Variable	At Night	When Occupants Leave the Dwelling	At Night	When Occupants Leave the Dwelling
Programmable Thermostat	1.355 [0.230]*	-0.056 [0.274]	-0.009 [0.009]	-0.038 [0.012]*
Standard Thermostat	-	-	-	-
No Thermostat	0.224 [0.473]	-1.361 [0.523]*	0.02 [0.020]	0.008 [0.025]
Demographics	(6)	(6)	(6)	(6)
Housing Characteristics	(4)	(4)	(4)	(4)
Heating Prices	Included	Included	Included	Included
Heating Degree Days	Included	Included	Included	Included
Regions	Included	Included	Included	Included
Number of Observations	2013	1956	2090	2090
R-squared	0.09	0.061	0.137	0.237

Table 2.5: Self-reported heating behavior – natural gas systems only.

If we are to believe the self-reported temperature setting and on/off actions, given that we saw no significant effects overall for having a PT, we could surmise that households with PTs use the automatic setback feature, but that the relative energy savings compared to standard thermostats are at least partially negated by the latter group being more likely to turn off the heat completely. Certain factors, however, compromise the value of the self-reported behaviors. The data could simply be incorrect, containing too many erroneous estimates of home temperature settings. Figure 2.7 shows a histogram of reported home temperatures between 60 and 85°F. As we might expect from estimates, there are peaks at the temperatures that end in 0 and 5. It is possible that the estimates may contain some bias. Second, the reported temperatures could be the actual temperature for some households and the thermostat setting for others. The differences between the two values would be most pronounced when occupants turn down the thermostat below a point where it could be triggered; for instance, they could have set the thermostat to 65° and reported this value in the survey, even though the ambient temperature never dropped below 70°F. This would only be a problem for homes with thermostats. Third, one survey question might not adequately capture the heating behavior of households. They may set

the thermostat for different temperatures throughout the winter and these settings could depend on the outdoor temperature (Dewees and Wilson 1990). Fourth, unobserved differences in households may account for the energy reductions.

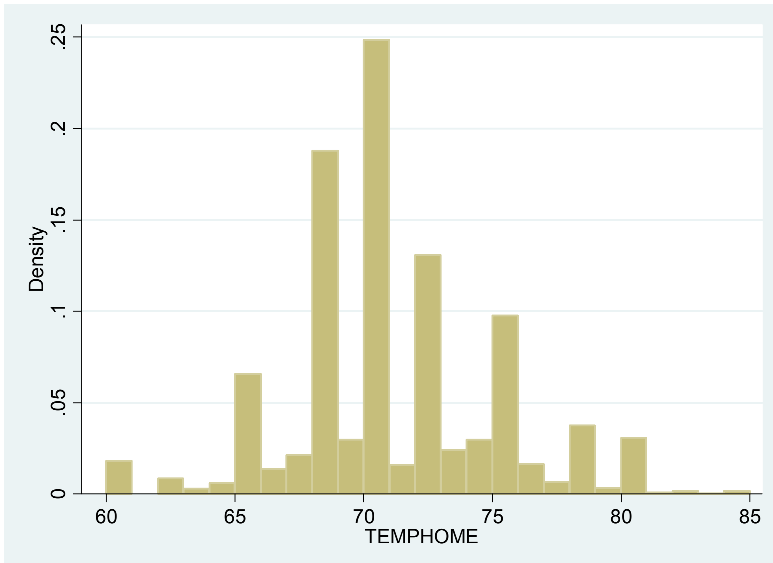

Figure 2.7: Home daytime winter temperature estimates.

2.3.2 Programmable Thermostats for Cooling

The regression analyses for cooling included only households with central AC that during summer months was "turned on quite a bit" or "turned on just about all summer." Individual window and wall units were excluded because none of them were controlled by PTs. I excluded households that reported home temperatures less than 60°F (0.2 percent of households) in the summer, as these estimates seemed to be in error and would skew results when I examined temperature setting behavior.

We do not see any major energy use effects from PTs, which is consistent with the literature. After controlling for income, demographics, household characteristics, electricity prices, cooling degree days, and regions, the association between having a PT and cooling energy use is negligible and insignificant. For the income-PT and hot climate-PT interactions, the initial regressions showed a positive and significant association with energy use, but these became insignificant when the

interaction term was changed from "have PT" to "use PT" (same as for income-PT for heating). We also do not see any large associations between having a PT and temperature setting or on/off behavior.

2.3.3 Awareness of Home Heating and Cooling Temperatures

As this dissertation explores behavior related to awareness of energy use and proactive use of home energy technology, any information in RECS about knowledge of energy use and its connection to actual energy use is germane. There is no variable in RECS that indicates whether households know their energy consumption. However, as described earlier, one of the responses when the interviewer asked household occupants the home temperature during the day in winter was "I don't know." Using this as a proxy, I created a dummy variable for these "*don't knows*" and regressed space heating energy use against the dummy and a number of covariates. One-hundred ninety-two out of 4,004 respondents, equivalent to 4.7 million households out of 101 million households, report *don't know*.

Table 2.6 shows the regression results for all heating fuels and natural gas, respectively. Not knowing home temperature setting is associated with a 9 percent increase in heating energy use. The increase is even more pronounced – 14 percent – when limiting the analysis to only natural gas systems. These increases hold up even in the presence of the young-with PT and young-use PT interaction terms (not shown in the table).

Independent Variable	All Fuels	Natural Gas Only
	Dependent Variable: Heating Energy Use	
Don't Know	0.093 [0.036]*	0.14 [0.041]*
Have PT	0.002 [0.021]	-0.016 [0.023]
Standard Thermostat	-	-
No Thermostat	0.077 [0.038]**	0.018 [0.042]
Demographics	(6)	(6)
Housing Characteristics	(4)	(4)
Heating Prices	Included	Included
Heating Degree Days	Included	Included
Regions	Included	Included
Number of Observations	3959	2230
R-squared	0.814	0.697

Table 2.6: Results from regressing heating energy use against a dummy variable indicating that household does not know home heating temperature. Other covariates are included.

For cooling, only 38 out of 1743 respondents using central AC (representing 2.1 percent of households) report *don't know*. This was not enough to use with all of the covariate controls. Therefore, it was not possible to conduct a thorough analysis for awareness of cooling temperatures.

From a policy perspective, if awareness of temperature settings (and perhaps energy use) is one mechanism for lowering energy consumption, we would naturally ask the question: who are the *don't knows*? Regressing the *don't know* dummy variable against a set of covariates (and including the same households from the heating analysis) gave some indication of the answer to this question. Not knowing daytime winter home temperatures is associated with lower income, not owning the home, and heating equipment that is categorized as either an electrical system or "other," which includes built-in floor/wall heaters, built-in room heaters, and "other equipment."

Figures 2.8 and 2.9 are bar charts showing the distribution of *don't knows* by region and by heating equipment. The Midwestern states (East North Central region) have fewer than 2 percent of households that are *don't knows*, while the warmer states—and New York—are above 5 percent.

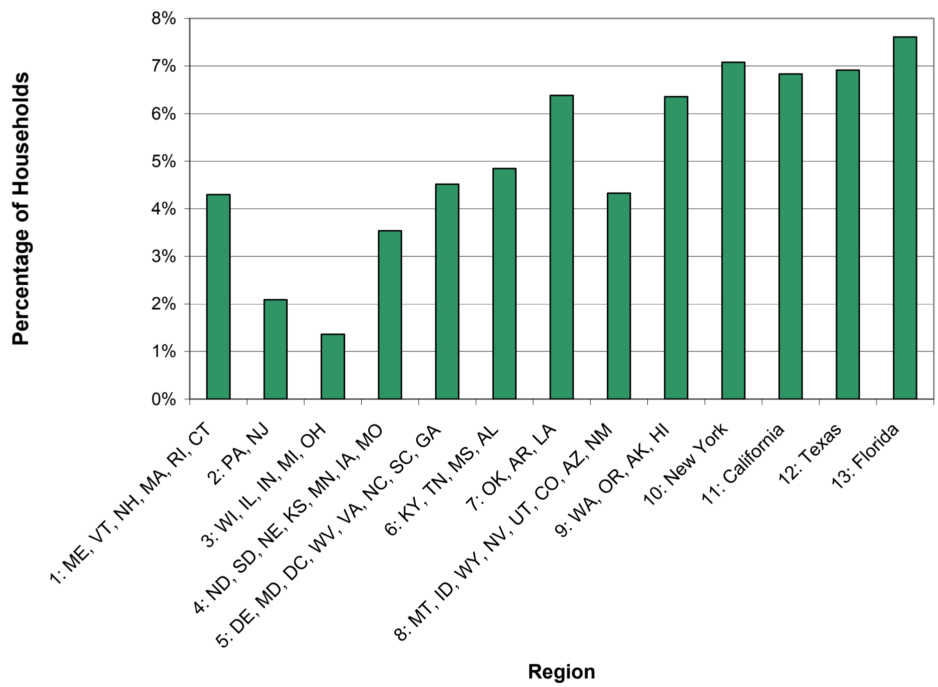

Figure 2.8: Percentage of households that do not know daytime winter heating temperatures, classified by region.

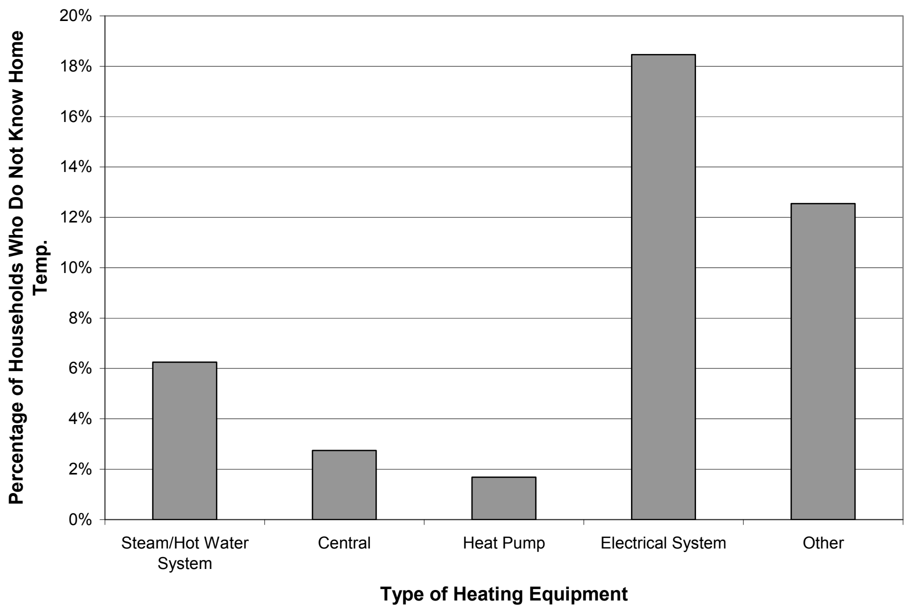

Figure 2.9: Percentage of households that do not know daytime winter heating temperatures, classified by type of heating equipment.

2.4 Conclusion

When examining the potential effects of having a programmable thermostat on energy use for heating and cooling, this analysis did not find any significant associations for the population as a whole, which is what is seen already in much of the literature. However, the association between young households with natural gas systems who use and/or have a PT and the 17 percent reduction in heating energy consumption is one that has not been previously reported. Looking more closely at self-reported temperature setting behavior, this study found that households with PTs reported lowering the heating temperatures at night and when they left the home during the day. However, they were less likely to turn the heat off completely, which could be part of the reason that energy use was not significantly lower for these households. The analysis of temperature settings did not uncover the reason for why young households with PTs consume less energy.

For cooling, there were no large, significant differences between households with PTs and those without. It is evident that heating and

cooling behavior for households is different—even for those with the same type of thermostat for each function.

The analysis found a significant association between awareness of home temperature settings and heating energy use. Those who did not know their daily heating temperature tended to use close to 10 percent more heating energy. Households that were unaware of temperature settings tended to be lower income renters. Targeting these types of households with policies for improving awareness may reduce energy use, but the effectiveness of targeting this particular demographic could be offset by the fact that this demographic also tends to use less energy than higher income home owners.

Chapter 3:
Reducing Demand through Better Feedback

3.1 Introduction and Summary

One potential solution to help control the growth of residential energy use is to provide consumers with more frequent and detailed feedback on how much electricity they are using in their homes. "Feedback," in this context, is household-specific information on electricity use. The typical, monthly bill from the utility is one type of feedback. "Better" feedback would consist of mean more detailed and/or more frequent consumption information apart from the total monthly use and dollar amount owed, so that the consumer could act on the basis of the information to lower his or her bill.

Better feedback can range from technologically simple — such as a more frequent billing cycle — to a more complex system of "smart meters"[3] and energy consumption displays showing real-time usage. We may refer to policies that provide feedback after consumption occurs as either "direct" or "indirect" (Darby 2006). Direct feedback is immediate and from a meter or other display monitor. Indirect feedback has been processed in some way before reaching the user. Examples of indirect feedback are more frequent energy bills and "enhanced" energy bills, which may include household-specific advice for reducing electricity use.

This chapter addresses Research Question 2:

- What are the mechanisms for providing feedback and how effective have they proven to be in reducing consumer energy use?

A thorough review of the literature on feedback finds that it can reduce electricity consumption in homes from 5 to 20 percent, but that

[3] The distinguishing feature of smart meters is that they can communicate energy use to the utility without a manual meter-reader. Many smart meters can also display real-time electricity use for the consumer, but it is possible that a meter can give real-time feedback without technically being a smart meter.

significant gaps remain in our knowledge of the effectiveness of feedback on different demographic groups and on households living in different climate regions.

3.2 How Feedback Works

Feedback on electricity use can have two general types of impacts on human behavior. First, it can impact habitual, repetitive behavior such as turning off lights or unplugging appliances. People may accomplish these reductions with no effect on overall lifestyle or, alternatively, they may have to make sacrifices. The second type of impact feedback can have is on appliance purchases, which tend to be infrequent, mid-to-long term decisions as opposed to every-day behavior. As consumers notice from feedback that certain appliances are energy hogs, they can look to replace them with more efficient ones.

3.2.1 Habitual, Repetitive Behavior

We may use either a behavioral or an economic perspective to explain why feedback impacts the habitual behavior of humans. The economic perspective of how feedback works takes the view that people are rational and perform all actions with the objective of maximizing utility using a limited monetary budget (EPRI 2009). However, with an electricity bill that comes only once per month, the amount that households spend on electricity may end up being higher (or lower) than the amount they budgeted. Feedback, in this case, plays the role of reducing uncertainty between what is budgeted and what is spent and thus helps consumers maximize utility (EPRI 2009). The frequent feedback may result in households using more, less, or the same amount of electricity. This situation may also be expanded to the case of an individual appliance if the type of feedback allowed the household to see or deduce the appliance's usage.

According to one behavioral perspective, humans are "imperfectly rational." That is, they may occasionally behave in ways that are not the most beneficial to themselves. Such can be the case with routine, habitual behavior. People perform many everyday activities without

reflection – including using electricity – and according to routines that they have developed over time (Fischer 2008) translating (Matthies 2005). Routines are functional in that people do not have to think hard about each and every decision they make. However, they may not be the best way for an individual to behave because either the person never considered the optimal way to perform the task or the situation changed since the time the behavior was formed.

A household may have at least three motivations for changing their energy use habits:

- Financial: saving money on their monthly utility bill.
- Environmental: reducing their carbon footprint.
- Competitive: outperforming neighbors in saving energy. However, households could also increase their use if they see that their neighbors are using substantially more than they are.

According to one theory, feedback works through a three-step process of 1) learning (change in knowledge), 2) habit formation (change in behavior), and 3) internalization of behavior (change in attitudes) (van Houwelingen and Van Raaij 1989). In the learning phase, consumers use the improved feedback to see how their consumption is specifically tied to particular appliances and activities. They may also learn that their consumption is high or low compared to their neighbors or to historical use, triggering the "competitive" motivation above. Part of the learning process is making small adjustments in behavior to observe through feedback how the changes impact daily, hourly, and minute-by-minute consumption and utility charges. When consumers find the changes favorable, they will form new consumption (or purchasing) habits as part of Step 2 above.

The third phase, internalization of behavior, involves changing beliefs to match the new behavior. For instance, suppose a person was content to leave lights on because she did not think it used much energy. Through better feedback, she learned that the cost to her was substantial and she developed new habits of turning lights off.

Finally, by internalizing the behavior, she adopts a new, disapproving attitude toward leaving lights on to replace her previous attitude of indifference. Of course, the internalization process could work the other way if she learned the cost to her was very small and she wanted to use the lights more.

Another consequence of our imperfect rationality is that *how* information is presented can have as big an impact on behavior as *what* information is presented. This "framing effect" was first described by Tversky and Kahneman (1981), who demonstrated that preferences with respect to monetary outcomes and the loss of human life could change depending on the formulation of the decision problem. It is important, therefore, to keep in mind that the way feedback is presented to consumers may impact their response and that certain types of consumers (depending on education, etc.) may respond better to certain visual formats over others.

3.2.2 Appliance Purchasing Decisions

People often exhibit behavior that goes against their own economic interests when purchasing appliances in the store. For energy-efficient appliance purchases, where consumers may choose between paying more upfront for an efficient appliance or more per month in energy costs, discount rates have been measured as high as 300 percent (Gately 1980). This phenomenon has been dubbed the "energy efficiency gap" and researchers have different explanations for it. Some believe that the cost of obtaining adequate information is too high for consumers to make an accurate determination of what is in their best economic interest. Others, including many behavioral economists, attribute the gap to humans being imperfectly rational and over-valuing the near future relative to the more distant future. Although untested in the literature, it is possible that feedback could influence people to purchase more efficient appliances over time and narrow the energy efficiency gap.

3.3 History of Feedback Studies

In the 1970s, environmental awareness in the U.S was on the rise and the growing environmental movement had just won a major policy victory with the creation of the EPA in 1970. Concurrently, researchers were becoming interested in the applied analysis of environmentally-relevant behavior and academics at U.S. research institutions began conducting small-scale experiments to see how households could be induced to consume less electricity. They were initially looking at three mechanisms in particular: offering people cash rebates for reducing use, providing them with more frequent feedback, and giving them tips on how to conserve energy. Not surprisingly, the cash payments tended to work best, while the conservation tips showed the smallest impact (Hayes and Cone 1977). The feedback results were less clear.

At that time, just like today, households typically received a bill from the utility once per month in the mail. In providing more frequent feedback, the researchers were seizing on the psychological premise presented by Ammons (1956) that the faster a person receives feedback following their control action, the more optimal their performance. Seligman and Darley, as well as Hayes and Cone, published studies in 1977 that tested the efficacy of feedback. Seligman and Darley gave individual feedback – written on lucite displays near the residents' kitchen windows – to 29 physically identical houses 4 times per week for one month. Testing combinations of rebates, feedback, and conservation information, Hayes and Cone gave daily written feedback to 4 households for two separate 7-day stretches. The studies found reductions of 10.5 percent and 18 percent respectively for feedback alone. While promising, the studies could have suffered from the Hawthorne effect (i.e. study subjects reduce energy use because they know they are being studied), as they were small sample sizes and the subjects knew the purpose of the study.

One theme that was (and still is) prevalent in the literature is the role of goal-setting and how it is intertwined with feedback. Becker addressed this question with a 1978 study, citing Locke, Cartledge, and

Koeppel (1968) that the motivational effect attributed to feedback is actually due to the joint effect of feedback and the subject setting a difficult performance goal; feedback is only effective when it leads to the setting of a performance goal and goal-setting is only effective in the presence of feedback that allows subjects to evaluate their performance. Becker found that the combination of feedback with a difficult goal (20 percent reduction of electricity use) led to the biggest reduction in electricity use (15.1 percent), while the same goal with no feedback only led to a 4.5 percent reduction. Feedback with a modest goal (2 percent) led to a 5.7 percent reduction.

The results of the early feedback studies were hampered by low sample sizes and did not always find reductions in energy use. Winett et al. (1978) compared rebates with feedback and conservation information and found that electricity use actually increased by 2 percent over baseline when rebates were not offered. Katsev et al. (1981) found no effect from daily feedback in all-electric apartments in Portland, Oregon. Seaver and Patterson (1976) found feedback alone to be ineffective. Their study, however, looked at fuel oil use and also found that feedback combined with encouragement for reducing use led to future reductions.

Winett et al. (1978) recognized the impracticality of providing daily, written feedback to residential consumers on a large-scale basis. They conducted an experiment comparing this type of feedback with the effect of having people read their own electricity meters, which they felt was more practical as a policy. The feedback was daily and indicated the household's consumption from the day before, the percentage increase or decrease from the previous year’s baseline (with a weather correction), the relationship of the decrease to a reduction goal chosen by the household, and an estimate of the household’s monthly electricity bill in dollars, based on prior day's use. The average conservation for those with daily written feedback was 13 percent, compared to 7 percent for those who read their own meters.

Over the next decade, researchers expanded the scope of studies to test different types of feedback and examined more closely several themes, such as how the household's baseline level of energy use and the climate impact the effectiveness of feedback. Bittle, Valesano, and Thaler (1979) found that higher-energy users showed greater conservation effects from daily feedback than low- and mid-level users. In a 42-day summer study (Bittle, Valesano et al. 1979), the same group of researchers found that effects from daily feedback were greater during mild summer temperatures than during the hotter days. They postulated that it was easier for people to decide not to use AC when the ambient temperature was not very high. When temperatures were too hot, everyone would want to use AC. McClelland and Cook (1979), in a study from around the same time, measured for the first time the effect of real-time feedback from an electrical display.[4] The authors found similar weather results as Bittle, Valesano et al. (1979) – that greater feedback effects were found during periods of moderate temperatures – but hypothesized that the feedback monitors were better for lowering non-heating and cooling loads, while daily feedback was better for heating and cooling uses.

Several U.S. studies in the early 1980's looked at what type of feedback would have the greatest impact. Feedback could compare current use with the households' past use, or with the current use of similar households. It could also give public or private commendations regarding energy use to motivate people to conserve more. Hayes and Cone (1981) used a blind control group and provided treatment households with monthly feedback letters that compared electricity use to the previous year, resulting in a 9.3 percent reduction. Midden et al. (1983) tested different types of feedback: comparison with past use versus comparison with peers and found similar reductions (13.2 and 12.8 percent respectively). Katzev et al. (1981) tested the combination of feedback and social commendation, but did not find any combination of the two to have an effect.

[4] Kohlenberg et al. (1976) used a real-time monitor earlier, but their goal was to reduce peak-time electricity usage. A combination of feedback plus incentives reduced peaking by about 50 percent.

Beginning in the 1990s, a number of European studies emerged, testing the effect of more frequent written feedback or just enhanced billing on energy use. In Europe, the billing system was even less informative than in the U.S. Billing amounts were based on the previous year's average and consumers would generally only see how much they consumed every two months. Therefore, some of the European studies defined "more frequent feedback" as monthly and would look at impacts of billing households for their actual use as opposed to estimated use. Most of the studies were in the UK (Brandon and Lewis 1999; Mansouri and Newborough 1999; Wood and Newborough 2003) and Scandinavia (Nielsen 1993; Wilhite, Ling et al. 1993; Wilhite and Ling 1995; Haakana, Sillanpaeae et al. 1997; Wilhite, Høivik et al. 1999). Brandon and Lewis (1999) gave monthly feedback (among other test conditions) and found the highest reductions (3.7 percent) among high-income households. The other two studies examined real-time feedback for only electric cookers and found reductions of 15-20 percent. The Scandinavian studies used larger sample sizes than most of the previous American studies and though the feedback was more frequent and detailed than the standard bill, it was still relatively infrequent – either every month or every two months. Nielsen (1993) and Haakana (1997) found 3-7 percent reductions, while Wilhite et al. (1993) and Wilhite & Ling (1995) found 5 percent and 10 percent reductions, respectively.

Continuous feedback – using electric monitors that indicate how much electricity the household is using at any given moment – is the current state of the art for feedback devices. They have the advantage over written feedback of being completely automated (not requiring manual meter reads) and likely being much more cost effective on a large-scale basis. Pilot projects testing continuous feedback have been much more common as of late (EPRI 2009), but continuous feedback has been the subject of research since the mid- to late-1970s. The McClelland & Cook (1979) study was first, which found savings of 12 percent. Hutton et al. (1986) did not measure quantitative savings, but did find that over 75 percent of respondents felt that the feedback helped them conserve

energy. Dobson and Griffin (1992) separated feedback by load and found savings of 13 percent.

Ueno et al. (2005) and Ueno et al. (2006) conducted studies in Japan using continuous energy monitors. The meters considered in the 2005 study disaggregated the feedback by appliance and users conserved 17.8 percent. The meters in the 2006 study did not disaggregate by appliance and savings were 9.0 percent. Allen and Janda (2006) found no conservation effect from a continuous feedback device — The Energy Detective (TED) — in a sample of 10 households. However, the device was not user-friendly and it appeared that this may have caused households to ignore it rather than read the manual in order to figure it out. In a more recent study with TED, Parker et al. (2008) found average savings of 7.4 percent among 17 households. The savings impacts among the households varied widely — from - 9.5 percent to 27.9 percent — and the participants were self-selected.

Several recent Canadian projects have tested continuous feedback. The Hydro One pilots (Mountain 2006; Hydro-One 2008), conducted in Ontario, found electricity conservation of 6.5 and 6.7 percent respectively. Mountain (2007) found energy use reductions of 18.1 percent in Newfoundland and 2.1 percent in British Columbia.

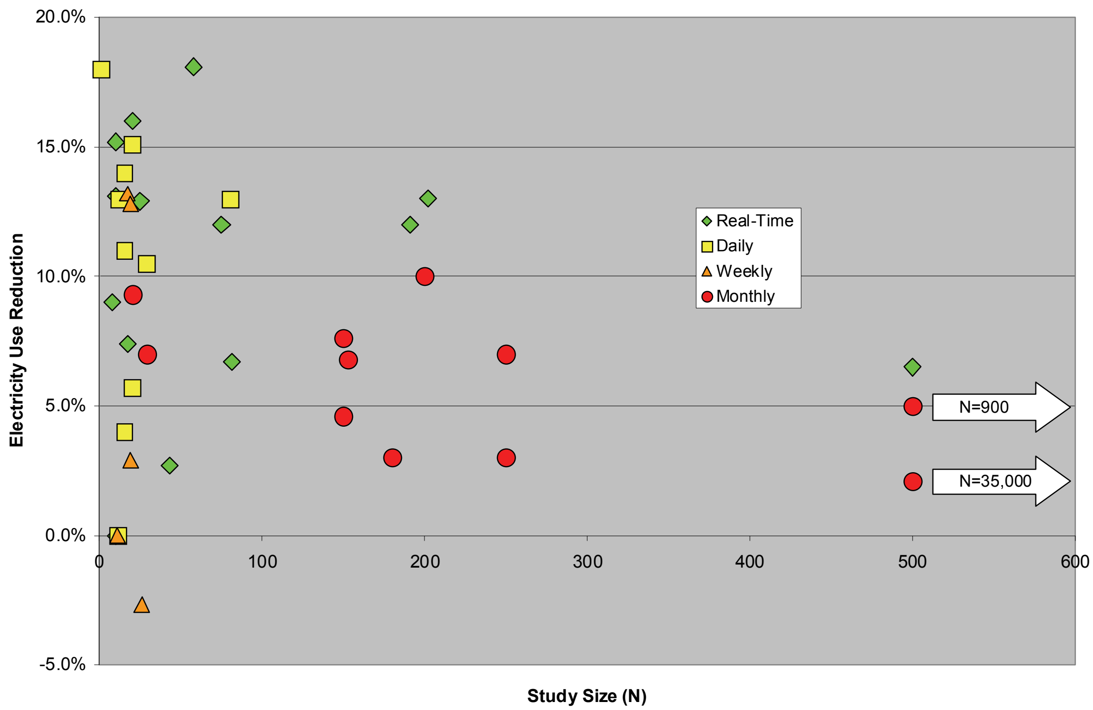

Figure 3.1: Feedback effect sizes found in the literature, graphed over study size (x-axis) and percent reduction (y-axis).

3.4 Most Effective Types of Feedback

Generally, studies in the literature find that direct feedback is associated with residential savings from 5 to 20 percent (Darby 2006). The studies and associated reviews (summarized by EPRI (2009) and Fischer (2008)) find that, in general, feedback works best when it is:

- Provided frequently – Studies where feedback was provided daily or more were usually among the best-performing. When feedback is provided less than daily, conservation is not as high.
- Presented clearly, simply, and appealingly – When surveyed, consumers have responded that they prefer a clear explanation of acronyms and technical terms. For breaking down the components of the total bill, respondents preferred pie charts. They preferred vertical bar charts for comparisons with other periods and horizontal bar charts for comparisons with other households.

- Digital – Computerized feedback (as opposed to paper or verbal) with multiple viewing options (cost, environmental effects, etc.) in general showed the greatest effects.
- Interactive – Some studies showed that feedback was effective when it engaged households above and beyond simply showing energy use. Consumers could interact through the computerized display or by self-meter reading.
- Customized for the specific household – Studies have shown that providing environmental information may be just as effective as cost information. While there may be no reason for separating the two types of information, researchers recommend tailoring the type of feedback information to the norms and motives of the target audience.
- Able to be broken down by appliance – Some of the biggest impacts have been observed when feedback includes a breakdown of electricity use by appliance. This level of detail informs consumers which appliances are efficient and which are not. It also allows them to see how much electricity appliances use in standby mode and can encourage them to unplug unused appliances. From a mid- to long-term perspective, disaggregated feedback could encourage households to purchase appliances that are more efficient (though none of the studies in the literature addressed this effect).

Besides the six characteristics of successful feedback listed above, studies in the literature reveal that the addition of other factors can yield further reductions in energy use. These factors include: goal-setting (e.g. challenging households to reduce energy use by 20%), advice for reducing electricity use, and the ability of the display mechanism to alert residents when usage is high (or unnecessary – like when using air conditioning after the outside temperature has dropped enough to open windows)[5]

[5] See, for instance, Seligman, C., J. Darley, et al. (1978). "Behavioral approaches to residential energy conservation." Saving Energy in the Home: Princeton's Experiments at Twin Rivers: 231, Nielsen, L. (1993). "How to get the birds in the bush into your hand: results from a Danish research project on electricity savings." Energy Policy **21**: 1133-1133,

Figure 3.2 shows the range of energy savings for the major studies in the literature that deal with electricity feedback. The studies can be quite different from one another— some studies may have daily, computerized feedback while others include a high-use alarm — thus, it is not appropriate to compare them too closely to each other. However, the figure can give an idea of the size and prevalence of conservation effects found in the literature. Appendix A lists the details of all feedback studies reviewed for this dissertation and indicates which were not relevant to this study and thus, excluded from the discussion.

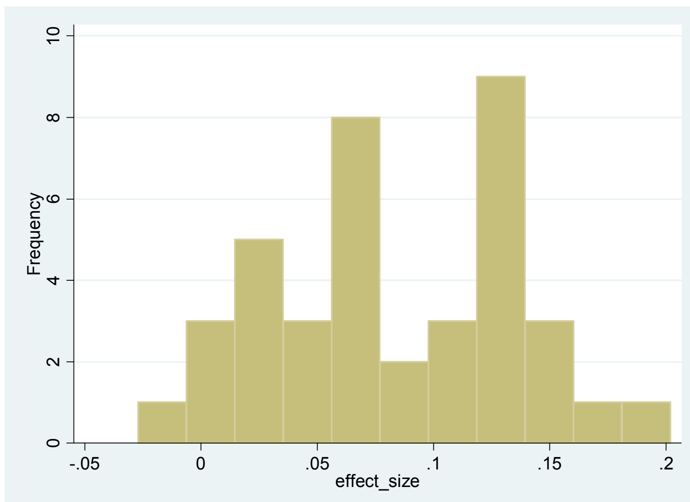

Figure 3.2: Results of studies that measured reductions in electricity use from feedback

3.5 The Next Steps for Feedback Research

Research has shown a potential for feedback to reduce residential electricity consumption. With improved technology and increasing investments in smart grid infrastructure, more opportunities exist to study the effect of feedback using larger sample sizes and more advanced, user-friendly feedback devices than in the past. EPRI (2009)

McCalley, L. and C. Midden (2002). "Energy conservation through product-integrated feedback: The roles of goal-setting and social orientation." Journal of Economic Psychology **23**(5): 589-603, IEA-DSM (2005). "Time of Use Pricing for Demand Management Delivery." International Energy Agency Demand-Side Management Programme..

lists the current array of pilot studies being conducted by utilities, which test feedback in relatively large portions of the customer base.

Moving forward, research should attempt to fill the current gaps in the knowledge about feedback. These gaps include:

1. the impact of various demographics on the effect that feedback has on consumers.
2. the impact of climate on consumers' responses to feedback.
3. the impact of feedback on appliance purchasing habits.
4. the formats of feedback to which consumers respond most strongly.
5. whether households will continue to respond to feedback over time, or whether utilities will need to engage them on a regular basis to maintain conservation effects.

Four of the five gaps listed above were identified in EPRI (2009) and verified during the literature review. Number 2 above – the impact of climate on consumers' responses to feedback – is an additional research gap that was identified in the review.

Chapter 4 performs an exploratory analysis to examine the uncertainties represented by the first two numbered items and their impacts on conservation, feedback benefits, and cost-effectiveness.

Chapter 4:
Exploring the Effectiveness of Feedback Mechanisms

4.1 Summary

The literature review in Chapter 3 revealed the key uncertainties in how feedback will impact households with different demographics and in different climates. This chapter uses the 2005 RECS data to construct a model for simulating energy use reductions for specific geographic and climate regions and for different demographics within the U.S. I use the model to conduct an exploratory analysis over the uncertainties in order to help in answering the following research questions:

- What is the range of potential benefits from feedback?
- What are the costs of different forms of feedback?
- When, where, and under what demographic circumstances are the benefits of reducing electricity usage the highest?
- How does the cost-effectiveness of feedback compare with current efficiency programs?

This chapter reports the findings that for real-time feedback and enhanced monthly billing, conservation levels necessary for comparable cost-effectiveness to other DSM programs are often below the median level reported in the literature. If benchmarked against the conservation levels in studies with the highest sample sizes, the CE estimates for real-time feedback are favorable over the ranges of uncertainty for all regions and for enhanced billing are favorable over some regions. If households with higher energy intensity and income conserved a higher percentage of their total electricity use when they received better feedback, as several studies have found, then enhanced billing will be cost-effective for more regions of the country when benchmarked against highest-N conservation levels. Disaggregated feedback does not appear to be cost-effective at this point in time for feedback systems that individually monitor every outlet in the dwelling.

4.2 Motivation and Background

During the energy crisis of the 1970s, federal and state policy-makers began implementing utility policies to curb increasing energy demand (Gillingham, Newell et al. 2006). These evolved into the current DSM programs, which aim to match a utility's generating capacity with consumer demand through conservation, energy efficiency, and load-shifting. We may classify demand-side energy efficiency policies into one (or more) of four categories (Gillingham, Newell et al. 2006):

- appliance standards
- financial incentives
- information and voluntary programs
- management of government energy use

Feedback on electricity usage could have at least five types of benefits:

1. Behavioral: People in households that receive better and more frequent feedback may consume less electricity by altering their behavior, such as turning lights out more diligently or turning off the television when they leave the room. Benefits from behavioral changes stem from decreased monthly energy bills and reduced GHG emissions.
2. Purchasing Habits: Households that receive better feedback may purchase more efficient appliances because they are more informed about the long-term benefits of the energy savings.
3. Load-Shifting: Better feedback can enable utilities to offer more flexible pricing plans, with electricity prices that change throughout the day (or from day-to-day) to more closely match the wholesale price of the electricity to the utility. These pricing plans can shift usage to off-peak times, averting the need to construct additional peak capacity and saving money for households in the process.
4. Appliance Tradeoffs: As households learn from feedback about the relative energy consumption of different appliances, they may choose to use appliances in different amounts than they were in the past. Although total electricity use may remain the same,

households may gain some utility from their new energy usage patterns.

5. Control: Feedback can benefit consumers by increasing their sense of control over energy use. Regardless of whether a consumer increases or decreases energy use, simply knowing more about how much electricity each appliance uses and knowing why bills are higher or lower than normal may increase her utility.

This cost-benefit and cost-effectiveness analysis focuses mainly on Benefit (1) above – the conservation benefits from behavioral changes - because these benefits are the easiest to estimate. It also addresses Benefit (2), but to a lesser extent. The remaining benefits are much harder to quantify. Chapter 6 examines the benefits from load-shifting. However, these are very utility-specific and the focus of the chapter is less about quantifying the benefits and more about discussing what types of feedback would give conflicting incentives for whether a household should shift usage from peak to off-peak times. Benefits (4) and (5) are even harder to quantify with available data and are not addressed in this study.

Encouraging the provision of feedback – through subsidies, mandates, or other policies – could be part of future utility DSM programs. However, despite numerous studies on the effects of feedback, the potential impacts of a large-scale feedback program remain highly uncertain. Part of the uncertainty stems from the range of responses to feedback between study subjects. Researchers studying the effects of feedback on day-to-day energy use have observed substantial variation in effect size, both within and between studies. The variation is partly due to demographic, housing, and climate characteristics of the households. Some studies have found that certain types of households respond better to feedback than others, but a considerable amount of uncertainty still exists over how different households will respond to the increased level of information. On the demographic side, some studies have found that households with higher income, higher education levels, and higher electricity use show greater reductions when feedback is provided (Bittle, Valesano et al. 1979; Wilhite and Ling 1995; Brandon and Lewis

1999; Parker, Hoak et al. 2008; Ayres, Raseman et al. 2009). Climate will also impact reductions in use, as the same type of house would have a different demand in a hot desert climate than it would in a cool, temperate climate. Households in more extreme climates (hotter in summer and colder in winter) would seem to have more potential for reducing electricity use. However, several studies have found that feedback has more of an impact when temperatures are more moderate (Bittle, Valesano et al. 1979; McClelland and Cook 1979; Mountain 2007).

The variation in effect sizes between studies and the subsequent uncertainty surrounding the impact of feedback presents a good opportunity for exploring the potential regional benefits of feedback using an exploratory analysis. This chapter examines how demographic factors can impact the benefits of feedback in different regions of the U.S. It weighs these potential benefits against cost estimates and compares the cost-effectiveness of feedback to existing DSM programs.

4.3 Model Details

To undertake a cost benefit analysis of providing feedback to residential consumers, I constructed a simple model (hereafter "Feedback Effects Model," or FEM) in Excel to explore the range of potential conservation benefits of the technology. The model uses data from three main sources:

- energy use and demographic data from RECS to estimate energy savings from the various feedback mechanisms.
- power plant emissions data from an Oak Ridge National Laboratory (ORNL) simulation model to estimate GHG avoided per unit of electricity use reduced.
- results of feedback studies to estimate effects from different feedback mechanisms.

Figure 4.1 shows a basic flowchart for FEM, where the sharp (green) rectangles are decision variables, curved (purple) rectangles are deterministic general variables, ovals (blue) are uncertainties, and the hexagon (pink) is the objective variable. For FEM, the objective

variable is the measure of total benefits from providing feedback. The costs of feedback were calculated outside of the model and are addressed in Section 4.4.4.

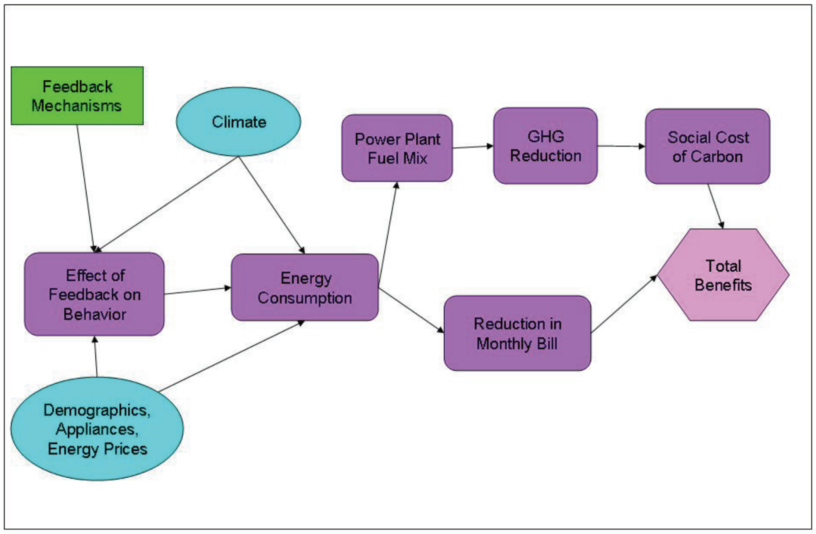

Figure 4.1: Basic flowchart for Feedback Effects Model.

4.3.1 FEM Variables

The total benefits (in dollars per year) depend on the factors represented by the boxes to the left of the *total benefits* box. The decision variable is in green and represents one of four possible frequencies of feedback that households receive: monthly, weekly, daily, and real-time. The model references a database of feedback literature to determine the baseline effect size, which is the magnitude of the reduction in energy use prior to any additional effects from income, energy use, etc.) The *feedback mechanism* (i.e. frequency of feedback) dictates which subset of literature the model will use. Other model parameters also help determine the specific baseline effect. The *quartile* parameter specifies whether the effect size will be the maximum, minimum, median, or a quartile in between those values from the literature for feedback with the specified frequency. The *minimum sample size* parameter further specifies the subset of literature by limiting the database of studies to those with sample sizes at least as

large as this value states. Many feedback studies – especially during the earlier years of research – suffered from low sample sizes and this parameter can instruct the model to disregard the lowest of them. The *earliest year* parameter performs a similar function. It limits the database of studies to only those published after a certain year.

The four variables together determine the baseline per-household reduction from providing feedback. Several other variables add between-household variation to the effect size and complete the process of determining each household's overall effect size from feedback. These "variable effects" differ throughout the population based on three household characteristics and two climate characteristics. The household characteristics are income, energy use, and maximum occupant age; the climate characteristics are heating degree-days (HDD), and cooling degree-days (CDD).

The model classifies the population into deciles for each household characteristic. For example, the 10 percent of households having the highest income would be in the highest decile for household income. Two parameters define the range of effects for each characteristic: upper and lower. Figure 4.2 illustrates how the model treats these variables. The upper value sets the energy reduction level for the highest decile for the characteristic in the data and the lower value sets the energy increase for the lowest decile. For example, if the effectiveness of feedback was 15 percent for high-income households and 5 percent for low-income households, the baseline effect would be 10 percent, and the upper and lower quartile values would each be 5 percent. If the spread was 10 percent but feedback did not impact low-income households at all, the lower value would be 0 and the upper value would be set at 10 percent. The effect on households in the middle deciles is linear, based on the upper and lower values.

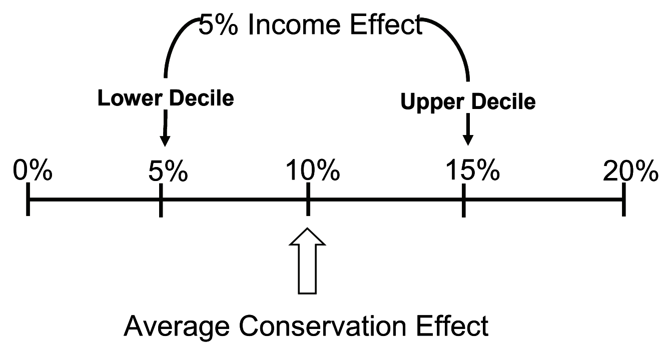

Figure 4.2: Behavior of FEM variables that determine effect size.

The two climate-related characteristics — *heating degree-days* and *cooling degree-days* — represent the effects of feedback on the upper and lower deciles of households in different climates. Heating degree-days are measured by the number of degree-days for a household below 65 degrees F. The higher the number, the more degree days for the household below 65 degrees and, generally, the more the occupants must heat the dwelling. Conversely, cooling-degree days are the number of degree-days for a household above 65°F. The higher the number, the more a household would generally have to cool. Researchers use these two measures to control for climate when examining heating and cooling energy. The measures are, however, imprecise. They reflect only the total number of degree-days above or below 65°F and do not reveal details such as how high temperatures reach during summer days or how long the summer lasts.

The *heating degree-day* and *cooling degree-day* variables function similarly in the model to the three characteristics mentioned above, except that they only impact heating and cooling energy, respectively, and not all electricity. For instance, if we set both the upper and lower *cooling degree-day effect* variables to 5 percent, the difference in electricity use between the upper and lower deciles will be 10 percent only for electricity used for cooling.

Some authors have found — perhaps counter-intuitively — that feedback has a greater conservation effect on households in more moderate climates than on households where summers are hotter and winters are colder (Bittle, Valesano et al. 1979; McClelland and Cook 1979; Mountain

2007). We can account for this effect by adjusting the heating and cooling variables such that the upper decile of heating degree-days is 0 percent or negative — reflecting no energy conservation or an energy increase — and the lower decile is positive — reflecting a decrease in energy use in moderate climates. The model reduces heating and cooling energy in either natural gas or electricity — depending on the type of heating fuel the household uses (all cooling is by electricity-powered AC). It does not allow for decreases in other heating fuels, such as fuel oil or kerosene, as feedback systems for these fuels are uncommon and we are not examining them in this study.

Once FEM calculates the effect of feedback on consumer behavior, it computes household electricity consumption. The model has a worksheet with data from the 2005 RECS, which contains information on the physical characteristics of housing units, appliances each household utilizes—including space heating and cooling equipment, demographic characteristics of the household, local climate, and other information related to energy use. FEM includes the applicable variables from RECS, including amount of electricity each household demands for a number of specific end uses, such as heating and cooling.

4.3.2 RECS Regions

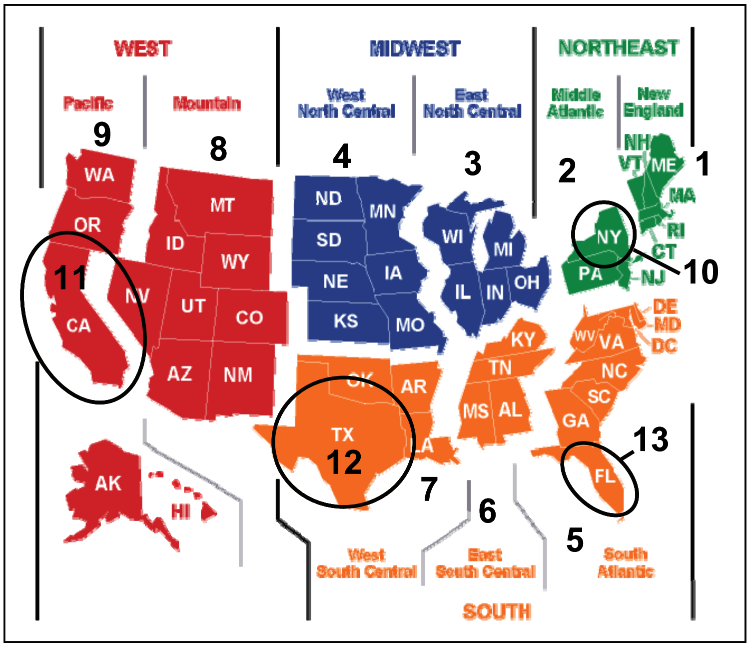

Figure 4.3: Map of the U.S. showing the 13 regions used for this study, which are the 9 RECS regions and the 4 RECS "large state" designations (NY, FL, TX, CA). Source: EIA.

Benefits from Electricity Reductions

Once FEM calculates the amount of electricity that each household consumes, it finds the total benefits of the energy reductions from two sources – bill savings and GHG reductions – illustrated in Figure 4.1. The GHG reductions represent the benefits to society, and Figure 4.1 shows the calculation steps in the upper pathway from Energy Consumption to Total Benefits. The lower pathway shows the private benefits, reflected in the lower monthly electricity bills. Calculating the decrease in electricity bills is relatively straightforward, as RECS reports the estimated amount spent on each type of energy fuel (e.g. electricity, natural gas, fuel oil) and also each end-use (heating, cooling, appliances, etc.).

The savings in cost represent the maximum benefits that consumers realize by reducing energy use, because the figures do not account for any disutility associated with reducing consumption to save money. When

consumers make decisions to conserve energy – such as by using less hot water or turning lights off around the house – it is likely they lose some utility by having to expend the extra effort. With perfect information relating consumption to cost, they will only conserve when the utility of lowering their bill (and reducing their GHG footprint) outweighs the disutility of using less energy. However, researchers can only observe the bill savings and this measure thus represent the maximum benefits.

The benefits from emissions reductions are more complicated to calculate. From a societal standpoint, reducing emissions reduces the negative externalities associated with power generation – namely, respiratory problems from pollution and climate change from GHGs. Markets already exist for many pollutants, such as NOx and SOx, and thus, the cost to society of emitting the gases is already included in the cost of generating electricity. However, as carbon does not yet have a price, the costs to society of emitting GHG are not part of the price of energy. Therefore, FEM computes the reduction in GHG emissions and uses estimates of the social cost of carbon to convert the amounts to monetary benefits.

The process incorporates the results from running the Oak Ridge Competitive Electricity Dispatch (ORCED) model, which simulates the dispatch of electrical generating plants in response to varying demand and/or supply scenarios throughout the country. This model calculates the amount of GHG emitted per kWh consumed in each region of the country. The following subsection explains the model in detail. (Chapter 5 utilizes ORCED more extensively to simulate a wider variety of demand scenarios.)

4.3.3 ORCED Model

ORCED was developed by researchers at Oak Ridge National Laboratory (ORNL) using Visual Basic in Microsoft Excel (see (Hadley 2008)). The model is useful for evaluating the impacts of changes in demand or supply on the electrical grid. Complex proprietary models, used by

various utilities and energy industry consultants, are more accurate, but also more time consuming and expensive. ORCED's transparency, flexibility, simplicity, and open access reduce the time needed to simulate demand scenarios relative to the more complex proprietary models and make it a more appropriate tool for the purposes of this experiment.

ORCED groups the U.S. into thirteen regions and dispatches power plants to meet demand in each region for a given year. Figure 1 shows a flow diagram for ORCED. The demand side of the model is on the left and the supply side is on the right. The grey shaded boxes represent steps already completed by the ORNL researchers and included in the model that I did not modify. The white boxes show the steps completed for this experiment. As the shadings show, the supply and baseline demand data was already included in the model.

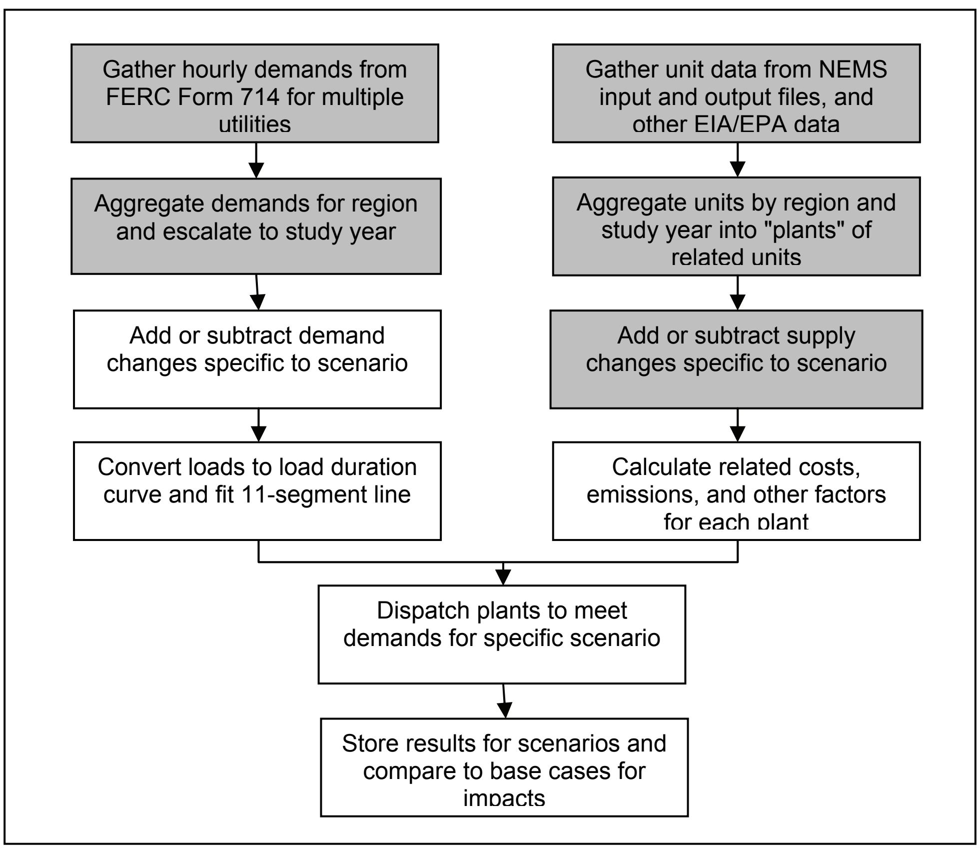

Figure 4.4: Flow diagram for ORCED (from (Hadley 2008)).

The supply side data contains a list of over 21,000 generating plants and their individual parameters, including nameplate capacity, seasonal capacity, heat rate, generating technology, fuel type (up to 3), emission rates, operating costs, and age. The data is from the EIA National Energy Modeling System (NEMS) and other EPA/EIA sources. As ORCED relies on NEMS for much of the supply-side information in the model, the 13 ORCED regions — shown in Figure 4.5 — are the same as those in NEMS. The model uses the power plant parameters to group each plant into one of 200 bins for each region, illustrated in the second shaded box from the top on the right-hand side of Figure 4.4. The exceptions are hydro and pumped storage plants, which the model treats differently than the rest of the plants. Each bin thus contains a group of similar generating plants. Depending on the type of study being performed, model users may adjust the supply of electricity by modifying the plant data, as shown in the next box down in Figure 4.4. This study does not make supply adjustments. The model calculates overall parameters for each of the 200 groups and feeds this information into the Dispatch module.

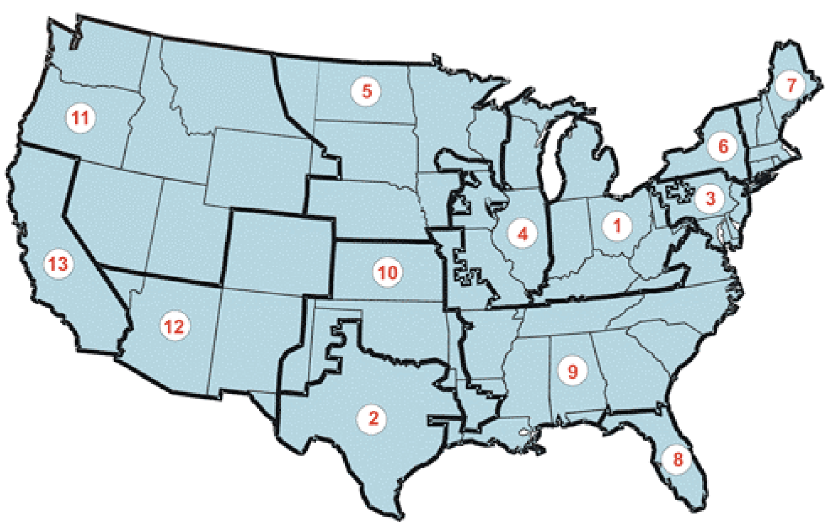

Figure 4.5: ORCED regions (Alaska and Hawaii not included in model) (from (Hadley 2008)).

On the demand side of ORCED, the model creators collected data from FERC filings of utilities to determine the hour-by-hour demand for each region for the year. Utilities or their respective ISOs are required to

submit hourly loads to FERC on their Form 714. The model aggregates to hourly loads for each region, illustrated in the second box from the top on the left-hand side of Figure 4.4. One of the model worksheets lists the demand for each of the 8,760 hours per year (8,784 if it is a leap year). At this point, model users may adjust the hourly demand for particular seasons or times of day. For instance, this study reduces peak demand in each season by 5 percent and increases off-peak demand by 5 percent to test the effects of load-shifting. ORCED takes the final hourly demand figures for each of the three seasons and constructs a load duration curve (LDC), which is a negatively sloped curve with demand in gigawatts on the y-axis and percent of season on the x-axis. The curves show the percentage of time that demand exceeded a particular level for each of the three seasons. The model approximates each 200-point LDC with an eleven-line segment to ease computation time in the Dispatch module. Demand modifications, such as the peak and off-peak adjustments in this study, change the shape of the LDCs.

Once the steps specifying supply and demand parameters are complete, the model dispatches plant groups to meet the demand based on their costs for providing power. Each region will generally have three types of plants: baseload, intermediate, and peaking. Baseload plants provide power virtually all of the time (at some level of capacity) and tend to have high fixed costs and low variable costs. The low variable costs mean low bid prices because of low marginal costs. The providers obtain large numbers of these power contracts in order to spread out the high fixed costs. The intermediate plants are used for a substantial part of the year, but still cycle on and off. Their marginal costs of operation are higher and fixed costs lower than baseload plants. Peaking plants have the highest variable costs and lowest fixed costs and are used only when baseload and intermediate plants cannot meet all of the demand. Each region may have peak hours which differ from other regions, but this modified version of ORCED uses the same general peak/off-peak schedule for all regions and seasons.

The model sorts the 200 plant groups from the Supply module into order of increasing variable cost for each season and dispatches them to meet

the demands specified by the LDCs. It assigns supply to demand based on which type of plant can supply the necessary load for the lowest marginal cost. Different types of plants will thus provide electricity at different times of the day. The model also adjusts power plant capacities for planned and forced outages.

The model gives total emissions of CO_2, NOx, and SO_2 for each region as outputs. While the NOx and SO_2 emission rates are specific to each plant (as reported to FERC), the CO_2 emission rates are specific only to the type of fossil fuel used by the plant.

Procedure for Running ORCED Model

The purpose of using ORCED is to obtain a marginal emission factor (MEF) for each region. The MEFs indicate how much GHG emissions will decrease for every kWh of demand reduced. I modified the model to simulate a reduction in demand of 5 percent year-round during peak hours in order to observe the associated decrease in GHG emissions and calculate the MEF. Peak hours for the model are are Monday-Friday, 3:00-9:00pm and Saturday-Sunday, 1:00-9:00. The model outputs for each scenario that I utilize are Megawatt-years of electricity generated and kilotons of CO_2 emitted. To compute an estimate for the marginal emissions per kilowatt hour for Region A, I take the difference in emissions between the scenario of 5 percent peak reductions and baseline and divide by the difference in generation between the scenario and Baseline:

$$MEF_A = \frac{CO_2^{Baseline\_A} - CO_2^{5\%\_reduction\_A}}{kWh^{Baseline\_A} - kWh^{5\%\_reduction\_A}} \tag{1}$$

Completing the Calculation of Total Benefits

The MEFs for each region have been pre-loaded into FEM, so ORCED is not called every time the user runs the model. Using the MEFs from ORCED, FEM calculates the amount of avoided GHG emissions for each household. The final step is to convert this reduction into a monetary benefit. To do this, FEM utilizes estimates of the social cost of carbon, which reflects the marginal cost to society of a metric ton of CO_2 emissions. In March of 2010, the U.S. Interagency Working Group on the Social Cost

of Carbon released guidelines for including the social cost of carbon in regulatory impact analyses. The federal guidelines rely on three frequently-cited integrated assessment models — FUND (Tol 2002; Tol 2002; Anthoff, Tol et al. 2009; Tol 2009), DICE (Nordhaus and Boyer 2003; Nordhaus 2008), and PAGE (Hope 2006; Hope 2008) - for developing the cost estimates. FEM uses the point estimate of $21.40 per metric ton of CO_2 emitted to quantify the societal benefits of emissions reductions. As outputs, FEM provides the private benefits, societal benefits, and total benefits for each of the 13 regions.

Using FEM to Explore Benefits of Feedback

The analysis follows the outline below. Once the steps are complete, I use the results to address when the benefits of feedback outweigh the costs, and how the cost-effectiveness of providing feedback compares to that of other DSM programs.

1) Calculate average benefits for each type of feedback
2) Explore regional differences in:
   a) Demographics and climate
   b) Power plant emission rates
3) Use exploratory modeling to examine regional benefits
   a) Determine where feedback has greatest impact from a
      i) Regional perspective
      ii) National perspective
   b) Find the scenarios that yield the greatest regional differences
4) Incorporate costs of feedback
5) Estimate changes in appliance purchasing behavior

Steps (1) and (2) use standard runs of the model, while (3) and (4) use exploratory modeling. To perform the exploratory modeling analysis, I use FEM in conjunction with the Computer Assisted Reasoning (CARs™) software package. Exploratory modeling allows me to examine the impact of feedback over a range of potential values for the model parameters. With predictive modeling and standard sensitivity analysis, one could enter best guesses for model parameters and uncertainties to obtain a prediction for the impact of particular types of feedback and the

subsequent change in benefits from incremental changes in input parameters. Exploratory modeling provides an alternative means of using models to examine policy questions. The results of a model run are not treated as a prediction for what will occur, but instead as one plausible outcome (Bankes 1993; Lempert, Popper et al. 2003).

An exploratory analysis is particularly useful when there is uncertainty over how the future will unfold or over the values of model parameters. In this case, the uncertainties are the impact of demographics and climate on the effect of feedback on energy use. Instead of giving a "best guess" of the value of each parameter, we can explore the range of benefits over many different combinations of parameter values. Controlled by CARs, FEM can test the impact of the feedback mechanisms over thousands of scenarios. Each "scenario" is a combination of input values, representing one possibility of the impact of demographics and climate on the effect of feedback. This exploratory analysis will provide an understanding of the behavior of this system and will illuminate the conditions under which certain feedback mechanisms perform well and under which they perform poorly in different regions of the country.

Table 4.1 summarizes the relevant information for the analysis in an XLRM table. CARs systematically varies the values of the Uncertainties (X) to create thousands of scenarios. For each scenario, it tests the impact of the Policy Levers (L). In this case, the policy levers are mutually exclusive, as only one type of feedback (monthly, weekly, daily, or real-time) may be provided. The Relationships (R) are defined by FEM and are covered earlier in this section. The table lists three Measures (M), or outputs. As explained above, the Total Benefits measure is a sum of the first two measures (in $2010), which represent the private and societal benefits of feedback, respectively.

X - Uncertainties	L - Policy Levers
Income Effect Energy Intensity Effect Age Effect Heating Degree Day Effect Cooling Degree Day Effect	Monthly Feedback Weekly Feedback Daily Feedback Real-Time Feedback
R - Relationships	**M - Measures**
See Model Description	Electricity Bill Reductions GHG Reductions Total Benefits

Table 4.1: XLRM table for analysis of feedback effects.

4.4 Results

This section follows the five steps listed above.

4.4.1 Calculate average benefit for each type of feedback

It is useful to get a general idea of the model space before completing the exploratory analysis in Steps (3) and (4) (Sections 4.4.3 and 4.4.4 respectively). To do so, we may examine the average effects of the different types of feedback and see what the corresponding private and societal benefits would be. FEM uses a collection of 38 experimental feedback groups to estimate effects from different types of feedback. (On occasion, two or more experimental groups may come from the same feedback study.) Figure 4.6 presents the range of observed energy reductions from the different types of feedback, starting with enhanced billing on the left and increasing the frequency toward the right. The green bars represent the experimental group with the highest energy reduction observed in the literature for that type of feedback. The yellow bars represent the median effect size and the red bars represent the minimum. The daily and real-time feedback types do not show a red bar because the minimum effect sizes were zero. The maximum effect size steadily increases as the feedback is more and more frequent, from 10.0 percent for enhanced billing to 18.1 percent for real-time. The pattern

is similar for the median values, except that weekly feedback is lower than enhanced billing; the range is 2.9 to 12.0 percent. Three experimental groups showed zero energy reduction (one each for weekly, daily, and real-time), but only one group — in the weekly category — showed an overall increase in energy use (2.7 percent).

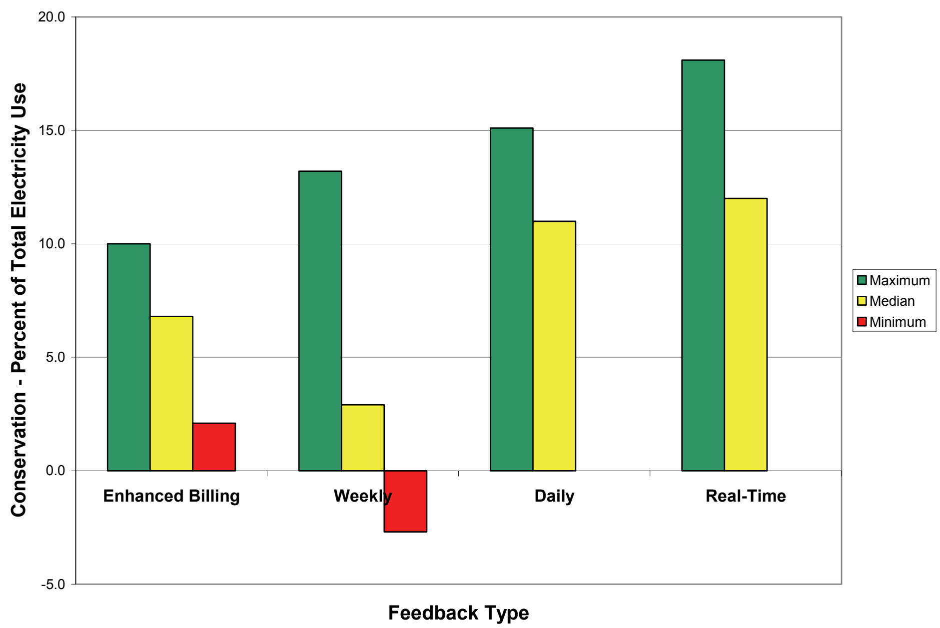

Figure 4.6: Percent reductions in energy use observed in the literature from four types of feedback.

Figures 4.7 to 4.9 show the private, societal, and total benefits, respectively, from feedback. Figure 4.7 illustrates that the maximum observed electricity reductions yield benefits ranging from $112 (all amounts in real 2010 dollars) for enhanced billing to $203 for real-time feedback. The shape of the bar chart mirrors that of the percentage reductions in Figure 4.6, as FEM is essentially calculating the factor by which to multiply the energy reductions to obtain the benefits in a monetary figure. The exception is the private benefit of weekly feedback, which is zero — not negative — in Figure 4.7. The reason for this is if a household chooses to consume more energy when they are getting more frequent feedback, we can only assume that they are making a more precise utility tradeoff between money and electricity than they were when feedback was less frequent. We cannot assume that better

information is giving them a negative benefit; the minimum private benefit would be zero, which is the value in Figure 4.7. The median savings range from $38 for weekly to $156 for real-time feedback.

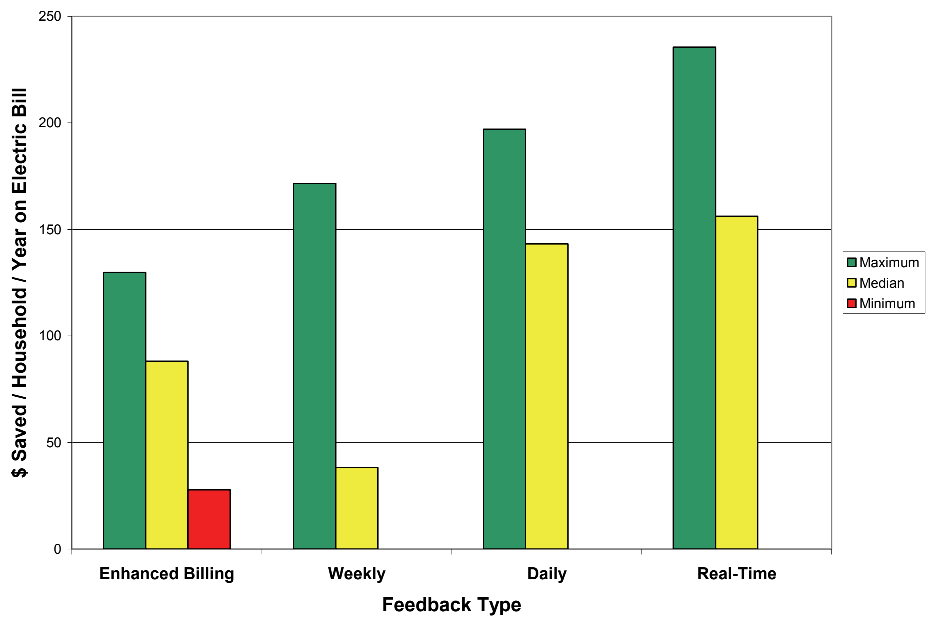

Figure 4.7: Private benefits attributed to feedback, measured in dollars per year of decreased electricity bills.

Figure 4.8 illustrates the societal benefits beyond the household benefits from reducing GHG emissions. The magnitude of yearly benefits is roughly one-fifth that of private benefits. The range is $26 to $47 for maximum effects and $7 to $31 for median effects. This bar chart mirrors Figure 4.6 with no exceptions. In this case, the minimum value for weekly feedback is negative, because there is a social cost of the household consuming more electricity. Figure 4.9 shows the total benefits, summing the amounts from Figures 4.7 and 4.8. The maximum benefits for real-time feedback are just over $280 per year.

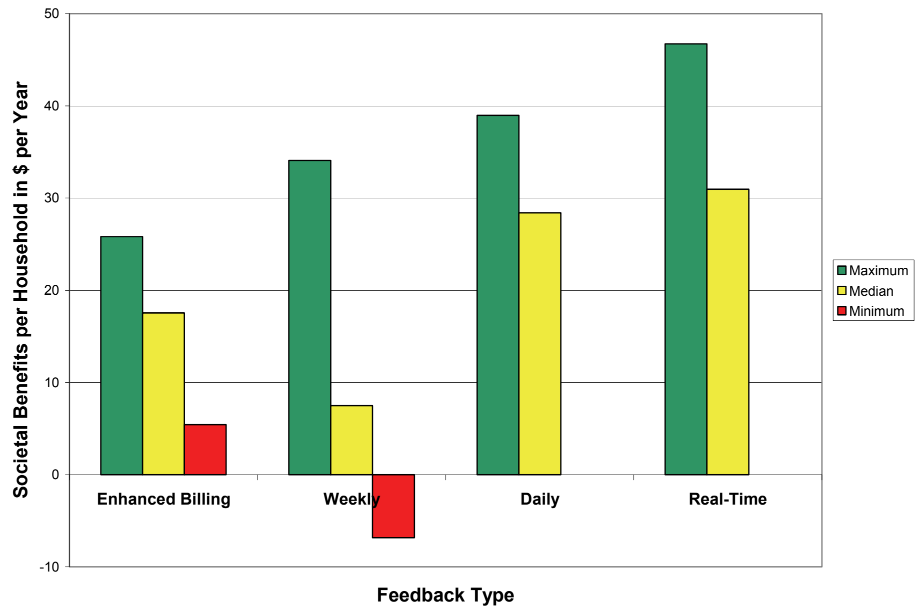

Figure 4.8: Societal benefits from reduced GHG emissions attributed to feedback, measured in dollars per year.

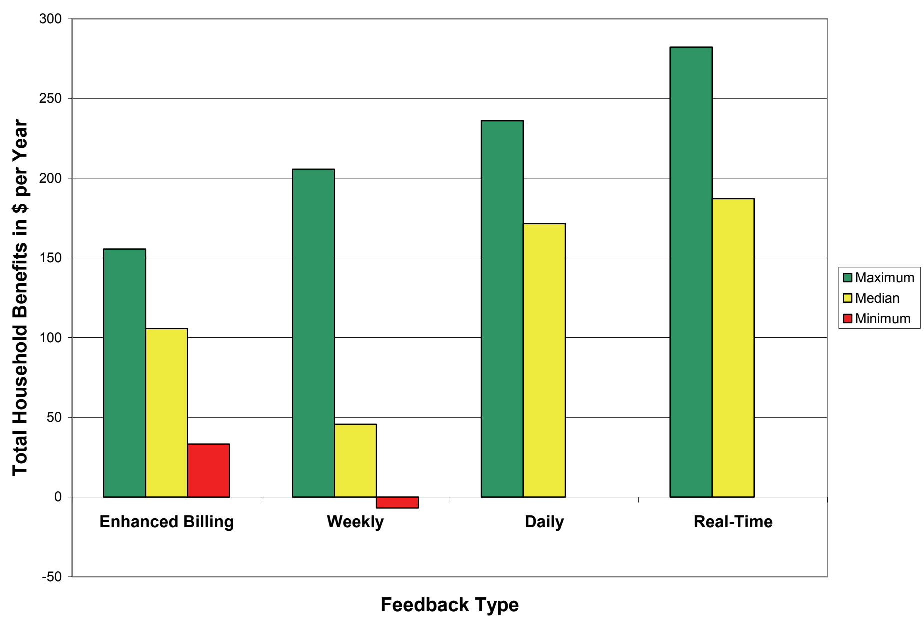

Figure 4.9: Sum of private and societal benefits (Figures 4.7 and 4.8) attributed to four types of feedback.

4.4.2 Explore regional differences

This section examines the regional differences in demographics, climate, and energy use. The potential for the effects of feedback to differ across these factors is the source of variation for the exploratory analysis in sections (3) and (4) below. As the source of the data is RECS, all of the figures show the variation in 2005. Figure 4.10 shows the average price of electricity by region (in real $2010), calculated by taking total electricity expenditures per region and dividing by total kWh consumed. The average price of electricity was highest in the state of New York at just over to 18 cents per kWh, followed by New England (15.4 cents/kWh) and California (14.9 cents/kWh). Electricity was cheapest in Region 6 (Kentucky, Tennessee, Mississippi, Alabama) at 8.7 cents/kWh.

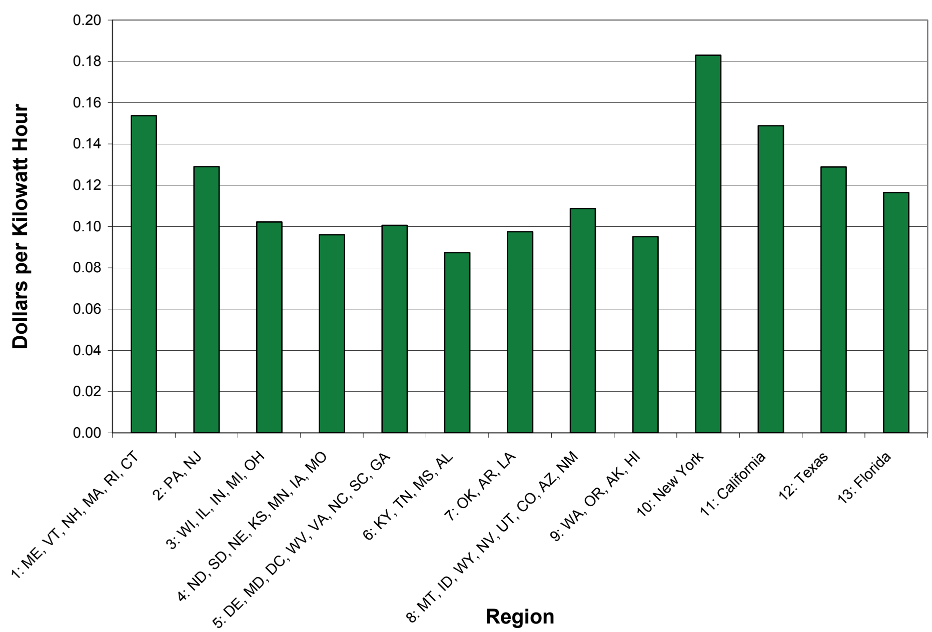

Figure 4.10: Average price of electricity (in $2010) by region for 2005.

Figure 4.11 illustrates average household electricity use by region for 2005. The lowest average use was in the three regions with the highest price per kWh: New York (6,885 kWh), California (6,991 kWh), and New England (7,432 kWh). The highest use occurred in the East South Central region (15,938 kWh), Florida (15,848 kWh), and Texas (15,151 kWh). Figure 4.12 shows average household electricity expenditures. Residents

of Texas and Florida pay the most for electricity, averaging $1,850-1,950 per household per year.

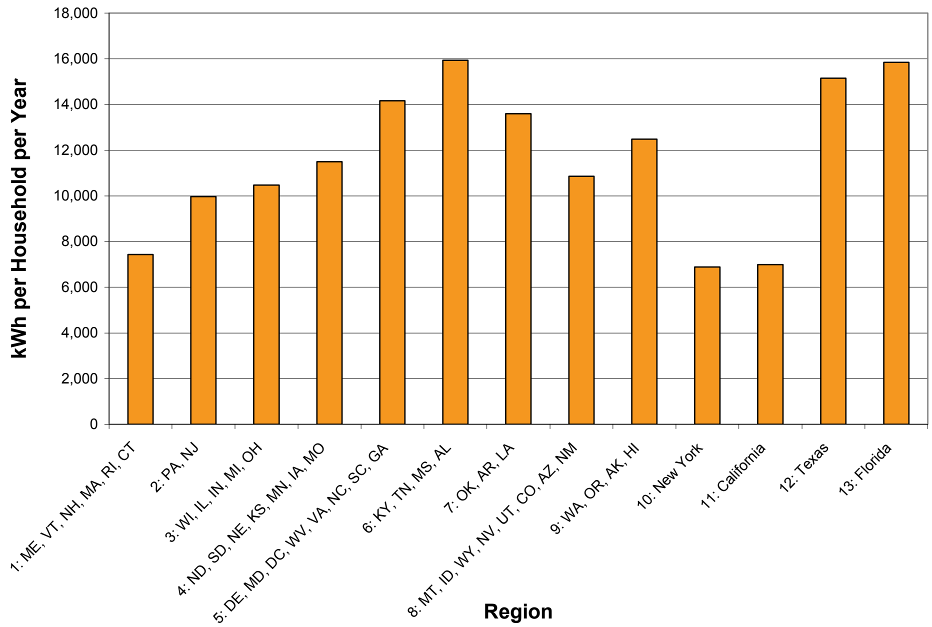

Figure 4.11: Average electricity use per household for 2005.

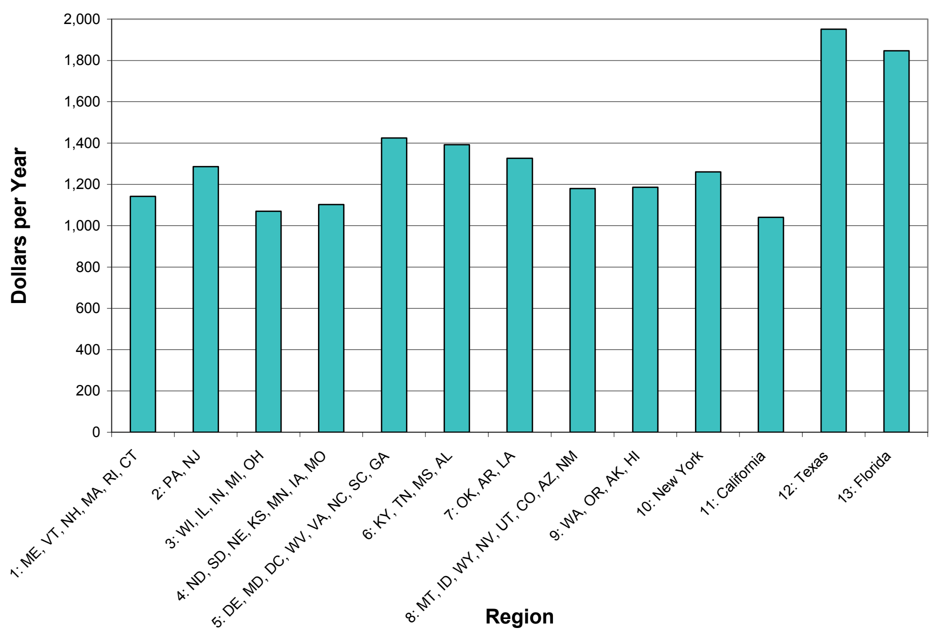

Figure 4.12: Average yearly household electricity bill for 2005.

Figure 4.13 shows the marginal CO_2 emissions factors, obtained by simulating a 5 percent year-round peak demand reduction with ORCED in

Section 4.3.3. The higher the value of the MEF, the more CO_2 is emitted per kWh of electricity generated. The Regions 5 and 6 have the highest MEFs, at just over 2.0 lbs. CO_2/kWh. Figure 4.14 shows the reductions in fuel use that account for the variation in MEFs. In general, regions that would reduce generation from coal-fired plants at a higher rate have higher MEFs.

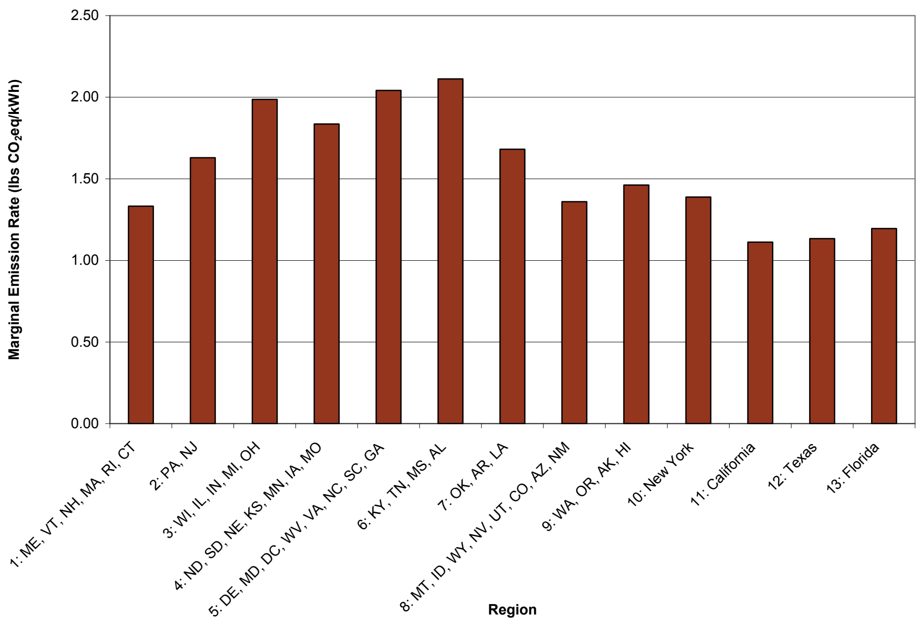

Figure 4.13: Regional marginal emission factors calculated by running the ORCED model.

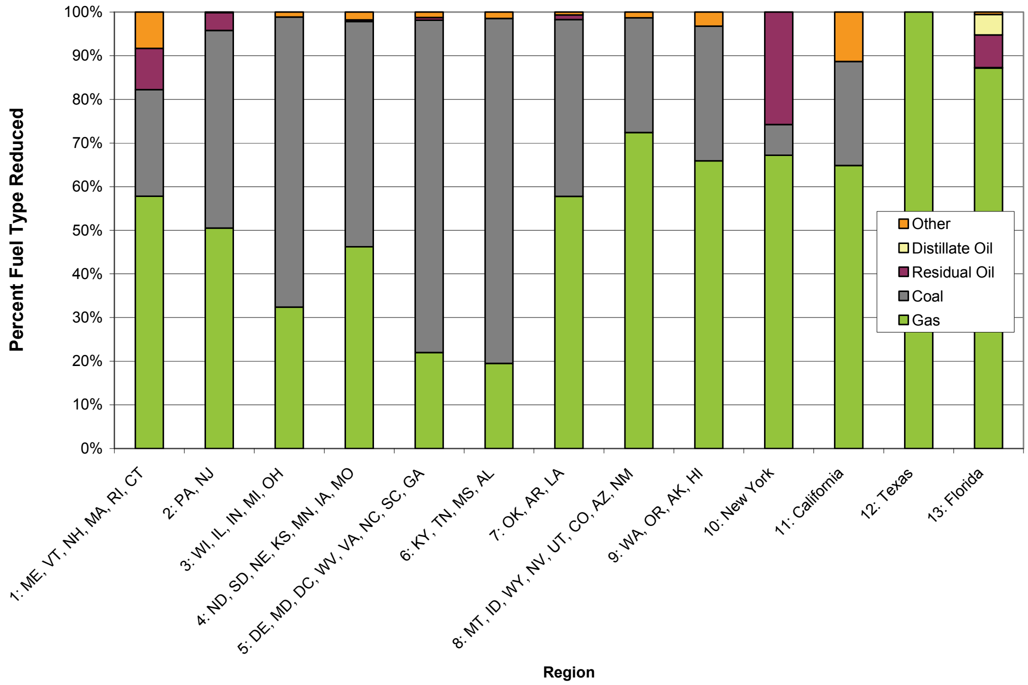

Figure 4.14: Types of fuels saved from reducing total year-round peak generation by 5 percent in each region.

Figures 4.15 and 4.16 show the variation in several demographic and climate factors between regions. Figure 4.15 illustrates the difference between regions in average household income (thick blue bars) and energy intensity (thin gold bars). Energy intensity is defined as household energy use divided by square footage of the dwelling and is expressed in the figure as kWh/sqft. We see the highest incomes – above $65,000 per year (real $2010) – in California. Other regions with high incomes – between $60,000 and $65,000 – are Region 8 (Montana, Idaho, Wyoming, Utah, Colorado, Arizona, New Mexico) and Region 9 (Washington, Oregon, Alaska, Hawaii). Regions 6 and 7 have the lowest yearly incomes (between $44,600 and $47,300) by over $5,000, and include Kentucky, Tennessee, Mississippi, Alabama, Oklahoma, Arkansas, and Louisiana. While California has the highest mean income, it also has the second-lowest energy intensity at 4.8 kWh/sqft, tied with Region 2 (Pennsylvania, New Jersey). Region 1 (New England) has the lowest energy intensity, at 4.5 kWh/sqft.

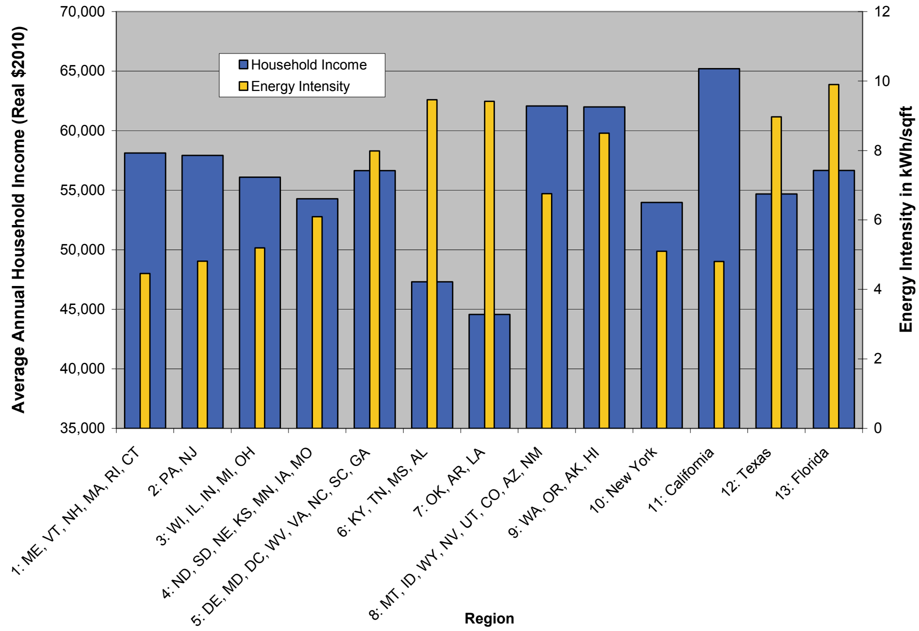

Figure 4.15: Regional demographic differences: average annual household income and energy intensity.

Figure 4.16 shows the average number of HDD and CDD per region for 2005, according to RECS.[6] The thick blue bars represent HDD and one may consider these values an estimate for how cold the regions are, with more HDD meaning a generally colder climate. Similarly, the thin orange bars show the number of CDD and reflect, generally, how hot the climate is. Texas and Florida lead this category, while New England and the Midwest are the coldest regions. Figure 4.17 illustrates what the per-household benefits would be in each region from a uniform (and hypothetical) 10 percent reduction in electricity use from feedback. Green bars represent bill savings and purple bars represent per-household societal benefits.

[6] Data handlers added a random error to HDD and CDD in RECS to avoid giving too much information about location.

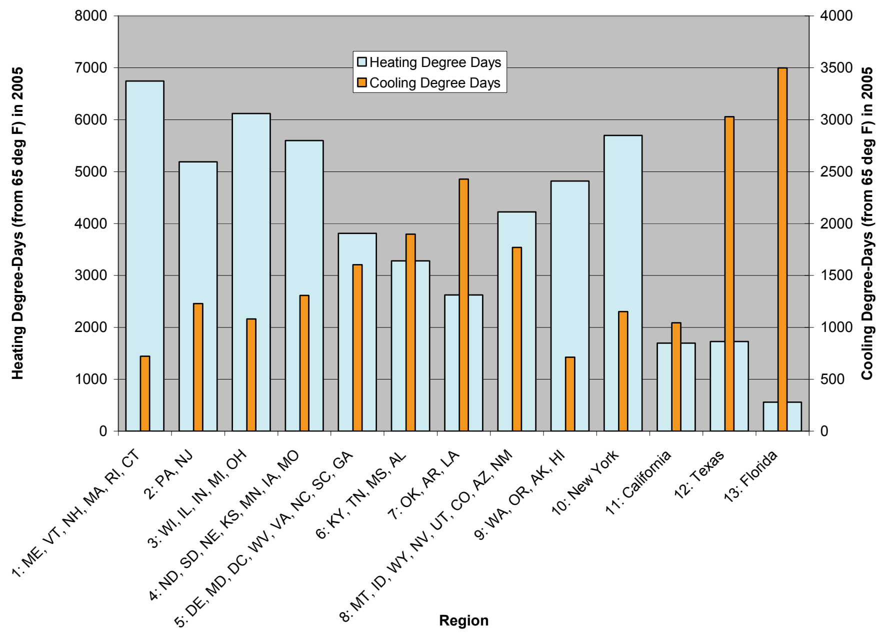

Figure 4.16: Regional climate differences, expressed in heating degree-days and cooling degree-days

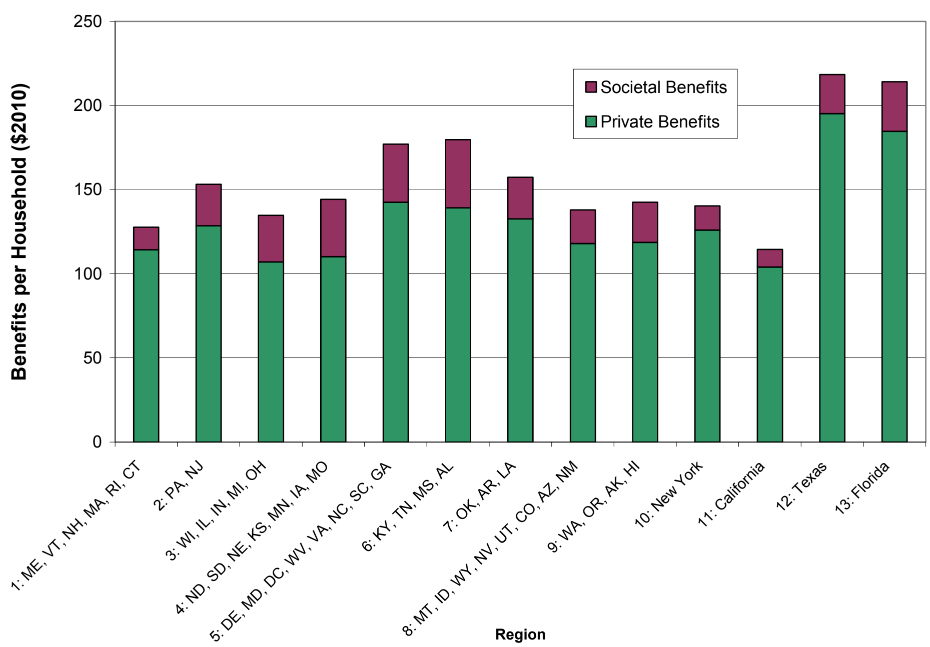

Figure 4.17: Total benefits per household from feedback (in real $2010), assuming a 10 percent uniform reduction and 2005 demographics, climate, and energy use.

4.4.3 Use exploratory analysis to examine regional benefits

To explore the model space, we must first define the boundaries for the space that the analysis will explore. I will explore the range of values for the uncertainties, which are the effects that particular demographics, climate, and energy use have on the response of the consumer to feedback. CARs creates thousands of scenarios over the ranges of uncertainties. I have approximated the uncertainty ranges from studies in the literature. Table 4.2 lists the ranges and references.

Uncertainty	Experimental Range	Reference
Income Effect	0 - 7.5%	Ayres, 2009; Wilhite & Ling, 1995
Energy Intensity Effect	0 - 5%	Ayres, 2009; Bittle et al., 1979-80; Brandon & Lewis, 1999; Parker et al., 2008
Age (Younger Conserve More)	0 - 5%	Wilhite & Ling, 1995
Moderate Summer	0 - 5%	McClelland & Cook, 1979-80; Bittle et al., 1979-80; Mountain, 2007 (two cited in EPRI)
Extreme Summer	0 - 5%	
Moderate Winter	0 - 5%	
Extreme Winter	0 - 5%	

Table 4.2: Ranges of uncertainties for exploratory analysis and the list of studies that define them.

As explained in Section 4.3.1, FEM varies the uncertainties symmetrically around the average uniform effect. This means that the average effect size would remain the same as the uniform effect if each household had the same weighting. However, as we are dealing with percentages, each household is automatically weighted by electricity use. Thus, the overall average effect per household for the country will increase or decrease slightly depending on which uncertainty is varied. If we set the energy intensity effect to 5 percent, the households with higher energy intensity will respond more strongly to feedback than households with lower energy intensity. Households with high intensity (and probably higher use overall) will therefore be reducing their electricity use by close to 15 percent, while households that tend to use less energy will be reducing by less. The overall, nationwide reduction would be close to 11 percent. Figure 4.18

illustrates this phenomenon, showing the overall, average effect for the country when each of the uncertainties is set to 5 percent. Two of the uncertainties — extreme winter and moderate summer — yield an overall decrease in reductions when set to 5 percent. This reveals that high electricity use is positively correlated with energy intensity, income, youth, and warmer climates (moderate winters and hot summers).

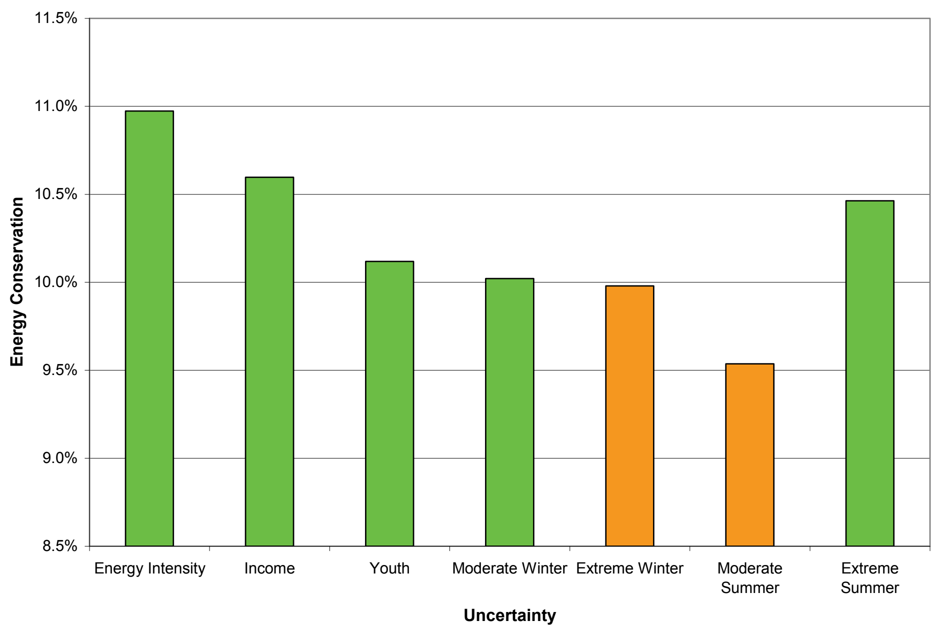

Figure 4.18: Impact of varying uncertainties on overall energy use.

Regional Perspective

This section uses an exploratory analysis to examine the conservation potential for feedback region by region, to determine when the potential is highest and lowest for each part of the country. Although this analysis takes the results from studies completed at the utility level or smaller and applies them to a national model, it is not assuming perfect external validity for the studies. In fact, a number of them suffer from small sample sizes and likely selection bias. The model exploration simply explores what the differences in regional benefits would be if the trends reported in small-scale studies were to be present at the national level.

With an exploratory analysis, it is necessary to generate a large number of cases – or "scenarios" - each with a different set of uncertainty values to represent one possibility of what the real effects of feedback could be. This can reveal combinations of uncertainties which yield the highest and the lowest benefits. For this analysis, the uncertainty space was the range of demographic and climate effects. Using CARs, I created a database of 10,000 cases, systematically varying the effect sizes. Once completed, I used scenario discovery (Bryant and Lempert 2010) to determine which conditions yielded the top 20 percent of benefit values for each region. Scenario discovery utilizes a modified version of the Patient Rule Induction Method (PRIM) algorithm on the database of cases to find ranges of the weight space with larger numbers and denser clusters of high-value cases (Friedman and Fisher 1999). More precisely, PRIM seeks to describe the set of scenarios, S_i, for each region where average household benefits are in the top quintile using one or more sets of limiting constraints $B_k = \{a_j \le x_j \le b_j, j \in L_k\}$ on the ranges of a subset of the input parameters $L_k \subseteq \{1,...,M\}$. In this case, the input parameters are the uncertainties listed in Table 4.1. Each set of simultaneous constraints B_k is a box. PRIM computes the boundaries of each box by optimizing over three criteria: density, coverage, and interpretability. Density is the fraction of high-regret points in the box, coverage is the portion of total high-regret points in the box, and interpretability is high when the number of constraints is low (see (Bryant and Lempert 2010)).

Figure 4.19 illustrates a key component of the scenario discovery process. The plot shows a trajectory of points, each representing a different possible box definition for characterizing the top quintile of benefits for Region 1. It also illustrates the tradeoff between density and coverage for choosing a box. Moving from left to right, the density of points in each box decreases from 100 to 20 percent and the coverage increases from 30 to 100 percent. This is a result of gradually relaxing the constraints to include more high-benefit points but also, as a consequence, more points that are not in the top quintile. The color changes for the points along the trajectory indicate that a

constraint has been dropped. For example, the maroon points all include the constraints defined by energy effect, income effect, and CDD, while the purple points only include energy effect and income effect.

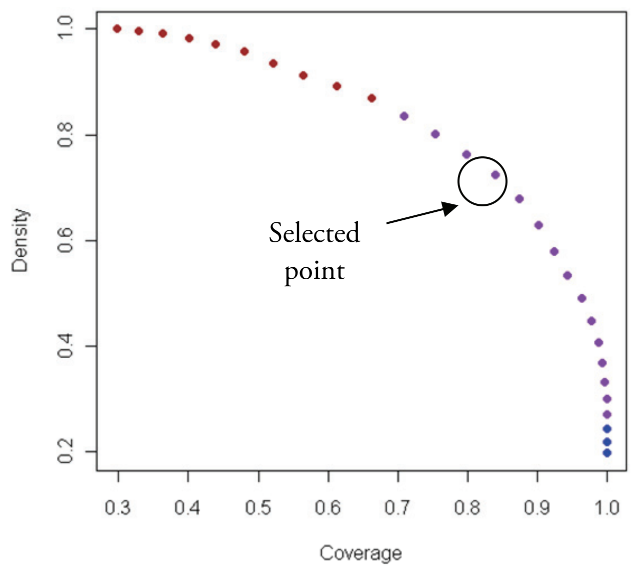

Figure 4.19: Selected point on the density-coverage tradeoff curve during the scenario discovery process. Red points represent boxes with 3 binding constraints, purple points represent 2, and blue points 1.

To define a box for each region, I found a point on the trajectory near the elbow of the curve that sacrificed some density for coverage, but was not quite at the point on the trajectory where the slope was less than -1. Once I had selected a box for each region, I placed the regions with similar box definitions into one of seven groups. Figure 4.20 shows the boundary definitions for each group of regions. The green areas show the ranges of uncertainties that roughly define the conditions when benefits are highest for each region in the group. If an uncertainty is not highlighted in green, it is not a binding constraint for the region. When multiple uncertainties contain green highlighting, the values must be within the highlighted range for all of the uncertainties.

Figure 4.20: Highest and lowest per-household benefits for each region. Green areas show ranges of uncertainties for which feedback benefits would be in top 20 percent of cases for each region.

A green area for a region could indicate an association with high energy use for the variable and/or a relatively higher decile value for the variable for the region. An interpretation of the figure follows for each group:

- Northeast (Regions 1, 2, 10: ME, VT, NH, MA, RI, CT, NY, PA, NJ): The highest per-household benefits occur when households with higher income respond to feedback more than those with lower income. More specifically, the highest benefits occur when the difference in feedback effect between the 10 percent of households earning the most and those earning the least is 9 to 15 percent. In addition, the differing effect of feedback across the energy intensity variable must be low. This makes sense considering Figure 4.15, which indicates low energy intensity for households in this group relative to the rest of the country.
- Appalachia, Texas, and The South (Regions 6, 7, 12, 13: KY, TN, MS, AL, OK, AR, LA, TX, FL): This group sees the highest benefits when households with high energy intensity respond 6 to 10 percent more to feedback than those with low energy intensity. Also, households in hotter climates must conserve more from feedback than those in lower climates. The four regions in this group had the highest energy intensity and CDD in the country, as shown in Figures 4.15 and 4.16.
- Great Plains, Pacific Coast (excluding California) (Regions 4, 9: ND, SD, NE, KS, MN, IA, MO, WA, OR, AK, HI): The boxes in these states are defined by a high energy intensity effect and high income effect. Higher income is generally associated with higher energy use in the literature (Schipper, Bartlett et al. 1989). We see from the figure that almost every region has an income effect as one of the binding constraints. This seems to confirm the income-energy use association and suggest that enough high-income households are present in each region for the effect to be an almost-universal binding constraint.
- California (Region 11): High benefits are defined in California strictly by a high income effect. The fact that it is the only

binding constraint reflects California's position as the region with the highest average annual income, shown in Figure 4.15.

- Midwest (Region 3: WI, IL, IN, MI, OH): With 4 binding constraints, Region 3 has the most of any group. Here too, the income effect is present. The second constraint is the age effect; this region sees high benefits when young people respond more favorably to feedback than older households. The other two constraints — moderate summer and cold winter (i.e. low CDD and high HDD) — show that the region has high benefits when people in cooler climates, such as the Midwest, respond more favorably to feedback.
- South Atlantic (Region 5: DE, MD, DC, WV, VA, NC, SC, GA): Three constraints define the high-benefit cases for states along the southern Atlantic coast: a high energy intensity effect, a mid-high income effect, and warmer summers. The box is similar to that of Appalachia, Texas, and The South, except for the addition of the income constraint. This indicates that the climate and energy use are similar for the groups, but that both energy intensity and summer temperatures are slightly lower (on average) for the South Atlantic.
- Mountain States (Region 8: MT, ID, WY, NV, UT, CO, AZ, NM): High income and hot summers define the box for the western mountain states.

National Perspective

The previous section examined household benefits in each region. However, as we saw from Figure 4.20, the level of benefits differs between regions. This section looks at the top and bottom 20 percent of benefits from the country as a whole. Figure 4.20 suggests where we might find the highest and lowest benefits, but now we look to define the scenarios and regions that define the best and worst cases.

To find the region-scenario combinations, I first compiled the 13 regional benefits from each of the 10,000 cases to make a list of 130,000 region-specific benefits. From this list, I found the top and bottom 20 percent thresholds to use with scenario discovery. The

scenario discovery process was similar to that for the regional perspective, but instead of finding the threshold for each region that corresponded to the upper quintile of benefits, I used the pre-determined upper and lower thresholds. Figure 4.21 shows the results of the analysis.

The two columns on the right-hand side of the figure show the percentage of total high-benefit and low-benefit cases that occur in each region. As it states, the majority of low-benefit cases occur in New England (Region 1), California (Region 11), and New York (Region 10). In New England, the low cases occur for all but the lowest values of the energy intensity effect. In New York, we see the high energy intensity and low income effects, and in California, low-mid income effect values. The box boundary definitions for New York and California are virtually the reverse of the constraints for the high-benefit cases for these regions.

Most high-benefit cases are in Texas (Region 12), Florida (Region 13), and Region 6 (Kentucky, Tennessee, Mississippi, and Alabama). The scenario discovery boxes are very similar to those from the regional analysis.

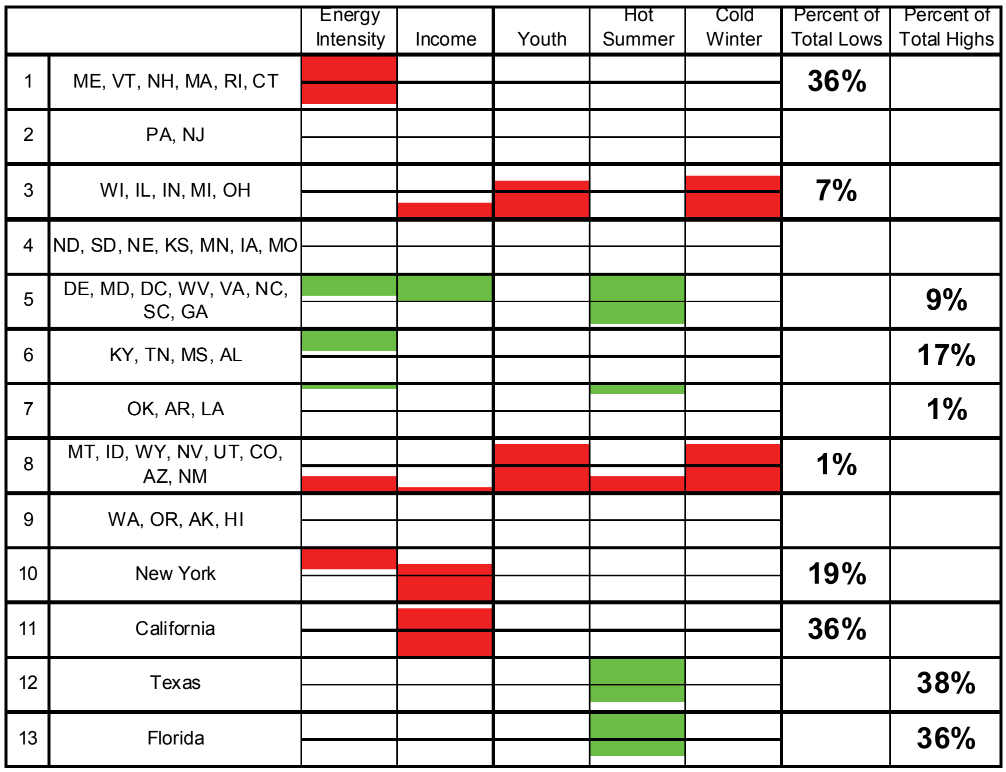

Figure 4.21: Highest and lowest per-household benefits from a national perspective.

Regional Differences

We are also interested to see when the difference between average household benefits is greatest and when it is smallest. One of the variables in the database of 10,000 cases included the benefits ratio between the region with the highest benefits and that with the lowest. The range of household benefit ratios for the 10,000 cases is 1.5 to 2.8. When the ratio is 1.5, the range of average household benefits for the 13 regions is relatively small and at 2.8 is fairly large. I repeated the scenario discovery process with the 10,000 ratios to find which uncertainties defined the highest and lowest 20 percent of cases. Figures 4.22 and 4.23 show the dot plots for each box. The same two uncertainties define the boxes: energy intensity effect and CDD. The highest — and thus, more unequal — 20 percent of cases occur when households with high energy intensity respond more favorably to feedback and when hot summer temperatures lead to a greater feedback response. The opposite is true for the lowest 20 percent of cases (i.e. smallest

relative range of benefits): low energy intensity effect and households with moderate summers responding more strongly.

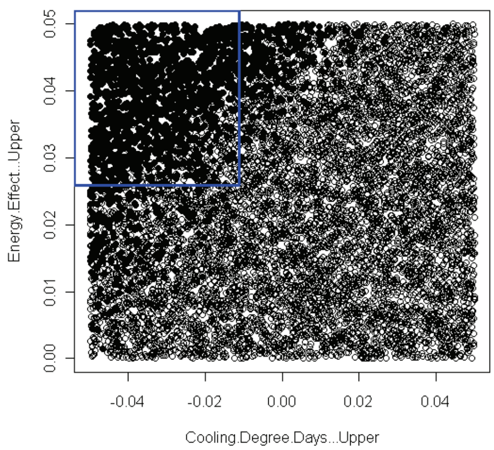

Figure 4.22 – Highest 20 percent

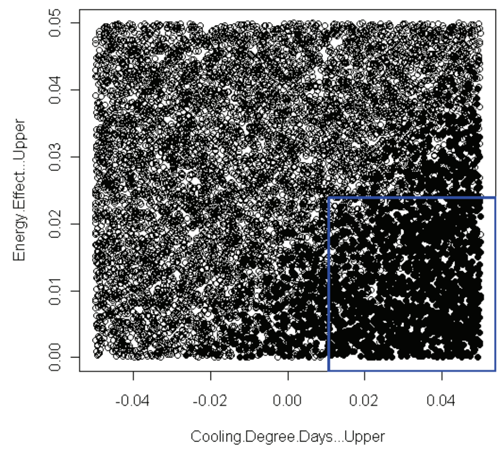

Figure 4.23 – Lowest 20 percent

4.4.4 Incorporate Costs of Feedback

We have been considering a range of benefits centered around an average reduction of 10 percent. To determine whether investments in feedback are worth the expense and how long it would take to pay back the cost of equipment and service (if applicable), this section examines the costs of feedback systems to compare them to the benefits. I searched for cost estimates both in the literature and from companies currently offering feedback products and services. The following subsections review the results of the search by type of feedback.

Enhanced Billing

EPRI (2010) gives a number of cost estimates for different types of feedback in their report "Guidelines for Designing Effective Energy Information Feedback Pilots: Research Protocols." For enhanced monthly billing, they estimate the increase in per-household bill processing to be \$12 to \$20 per year. This cost estimate is for a feedback pilot that would include 30,000 treatment customers for 2 years and 10,000 treatment customers for 1 year. The additional cost of enhanced billing for an entire utility's customer base may decrease over the long term.

Once the initial data processing protocols were established, the cost of automatically computing more information for each additional customer every month would be negligible.

Daily/Weekly Feedback

Google PowerMeter provides a feedback system that displays on a home computer. The system is available for free if Google has an agreement with the household's electrical utility[7] and the standard meter has been replaced with a smart meter. With this arrangement, the household could view their consumption in one-hour increments. If the household is not within the necessary service area, it may purchase a device that connects to the electrical meter and the Google PowerMeter software reads the signal from this device. Devices from three manufacturers are currently compatible with Google PowerMeter. Microsoft Hohm™ provides a similar service and is compatible with the PowerCost meter from Blue Line Innovations.

Daily feedback is currently available on the market, but only for customers whose utilities have replaced their standard meters with smart meters and who have made arrangements with a computer-based feedback provider, such as Google or Microsoft. The distinction between weekly, daily, and real-time feedback is somewhat difficult to make in practice. If a household wanted daily feedback, they could obtain a reading for how much power they used during the day, but the device they used would also have the ability to provide feedback more frequently. When searching for a unique device or service that provided *only* daily or weekly feedback, I was unable to find one.

Real-time Feedback

Two real-time feedback options are currently commercially available for households. The first, discussed here, is to have one overall consumption device for the household — preferably (from a conservation standpoint) in a centralized location in the dwelling. Some devices

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[7] As of August 8, 2010, the utilities were First Utility in the United Kingdom, JEA in Florida, San Diego Gas & Electric in California, and Yello Strom in Germany. Source: http://www.google.com/powermeter/about/get-powermeter.html

work only with smart meters, while others connect to standard meters. The range of one-time purchasing costs observed on the market was $110 to $268. Table 4.3 lists the sources for the figures. While this table reflects the prices available directly to residential consumers, it is likely that utilities could purchase large numbers of meters at a discount if they chose to provide their customers with the meters themselves. Note that the table does not include a comprehensive list of feedback devices, only a sample of the most widely-available and marketed devices.

Real-time Meter Source	Cost ($)	Component	Comments
Black & Decker	99	Power Monitor	Basic digital.
Blue Line Innovations	109	PowerCost BLI 28000	Device connects to standard, non-smart meters. Display is basic digital.
	268	PowerCost BLI 31100	Includes WiFi gateway, which connects the PowerCost monitor wirelessly to Microsoft Hohm.
The Energy Detective (TED)	120	1001	Includes basic digital monitor. Not compatible with Google PowerMeter.
	165	1001 with Footprints	1001 plus data-logging software.
	200	5000-G	Includes one set of CTs, one MTU, and one Gateway and works with Google PowerMeter
	240	5000-C	Same as 5000-G but includes display monitor.
Aztech	249	Aztech In-Home Display	Connects wirelessly to a smart meter.
Current Cost	129	Standard System	No Web Bridge. Only displays usage on Current Cost monitor.
	169	Google PowerMeter Package	Includes "Web Bridge," which allows connection to PowerMeter (and viewing usage online).

Table 4.3: Costs of real-time feedback devices obtained from company websites.

Real-time Disaggregated Feedback

The second option for implementing real-time feedback in a household is to have the feedback disaggregated by circuit or appliance. Although the search for providers of disaggregated feedback was not exhaustive, it was thorough and uncovered two companies that provide such a

product/service directly to the household.[8] TED offers an $85 add-on to their real-time monitors, which monitors and communicates usage from a separate circuit in the household. For each additional circuit that a household wanted to monitor, the cost would be $85 on top of the $200 or $240 cost of the display and Google PowerMeter interface. Powerhouse Dynamics has a different pricing arrangement. This company's service covers every outlet in the home (the website says the eMonitor 24 is sufficient for "most American homes") and charges by the month after the initial 2-year or 5-year purchase.

Disaggregated Real-time Meter Source	Cost ($)	Component	Comments
The Energy Detective (TED)	200	5000-G	Includes one set of CTs, one MTU, and one Gateway and works with Google PowerMeter
	240	5000-C	Same as 5000-G but includes display monitor.
	85	MTU/CT Set	CTs attach to an individual breaker to sub-meter a circuit. MTU transmits signal.
Powerhouse Dynamics	689	eMonitor 12 + 2 yrs service	2 main panels + 10 circuits
	829	eMonitor 12 plus 5 yrs service	Extended service with reduced costs
	949	eMonitor 24 + 2 yrs service	2 main panels + 22 circuits
	1197	eMonitor 24 + 5 yrs service	Extended service with reduced costs

Table 4.4: Costs of real-time feedback devices that disaggregate usage.

With the centralized feedback devices from the previous section, it was easy to compare prices because they could be characterized as one upfront capital purchase. To compare the different pricing structures of disaggregated feedback, we can examine the pricing structure using net present value (NPV) over a certain period of time. Table 4.5 illustrates the results. The NPV for the seven options is between $665 and $2,110. The key tradeoffs — apart from product features such as display format that a customer might prefer — are number of covered household circuits and length of time to maintain the product or

[8] Two other companies—Tendril and Comverge—also provide a disaggregated feedback service but work with utilities. They do not offer their products and services directly to residential consumers.

service. TED products are a one-time cost, whereas eMonitors charge a monthly fee. All else being equal, the longer the service is in place, the more advantageous the technology with a one-time cost (such as TED) becomes. To characterize the cost of this type of feedback, we may say that the NPV of the cost is roughly between $1,000 and $1,700 to fully cover a dwelling for 10 years.

Product/Service	NPV
TED 5000-C + 5 circuits	$ 665
TED 5000-C + 10 circuits	$ 1,090
TED 5000-C + 22 circuits	$ 2,110
eMonitor 12 + 2 yrs service	$ 1,271
eMonitor 12 + 5 yrs service	$ 1,064
eMonitor 24 + 2 yrs service	$ 1,716
eMonitor 24 + 5 yrs service	$ 1,552

Table 4.5: 10-year NPV of 7 options for disaggregated feedback using 5% nominal discount rate.

4.4.5 Estimate Changes in Appliance Purchasing Behavior

It is possible that feedback on electricity use could encourage households to buy more energy efficient appliances as people get a better idea of how much electricity their appliances use compared to more efficient models. The Energy Star program is the largest and most well-known energy-efficiency program in the U.S. It includes a voluntary labeling program and the Energy Star logo is consequently the most recognizable symbol of efficiency in the U.S. appliance market. If feedback increases sales of efficient appliances, it is likely that this increase would manifest itself as an increase in the market share of Energy Star products.

The magnitude of an increase in Energy Star market share is highly uncertain. It will undoubtedly depend on how feedback is presented to consumers. If feedback is disaggregated and messages are presented to the users about the energy consumption of individual appliances, this would probably be more effective in changing appliance purchasing habits than if the feedback is just a numerical reading of household electricity use. It is possible in the future that ECD software could

track the energy use and associated spending for each appliance and give the household recommendations for more efficient appliances, along with the projected saving from lower energy use over upcoming years and rebate programs for which the household could apply. Therefore, the type and quality of feedback will contribute to the effect on appliance purchasing habits.

The question of what impact feedback will have on appliance purchases is complex. No research has yet been conducted to measure this particular effect of feedback. If previous research existed, we could base a rough estimate on established research findings. Without any previous findings, any estimates would be highly speculative. Even if feedback had been provided to a sample of households in the last several years, it is likely that its impact on appliance purchasing would be delayed. While the feedback could have convinced a household to choose the efficient version of a particular appliance, the occupants may have several more years of use left on the current appliance. Many other factors would determine the timing of the appliance replacement, with feedback perhaps speeding the replacement in only the most compelling cases with the highest potential benefits.

Shifts in efficiency standards for Energy Star also make estimating future market shares complex. If Energy Star standards were static from year to year, we could graph the increase in market share for each appliance and extrapolate what would happen in the future. However, standards often change. As the best available technology improves, the efficiency standards become more demanding. An appliance purchased in 2008 may have the same energy intensity as an Energy Star appliance purchased in 2004, but the latter may not be rated Energy Star because the standards changed. Thus market share may slip from one year to the next when the reason for the decrease is that the standard became more stringent and not that the overall efficiency of appliance sales was lower. While a quantitative estimate of the desired effect would be impossible, we can at least examine historic data and give several potential projections.

History of Energy Star

The literature contains yearly evaluations (for most years) and projections of the effectiveness of the Energy Star program. Webber et al. (2000) published the first and Sanchez et al. (2008) published the most recent. The reports attempt to isolate the effect of the Energy Star program on overall efficiency levels of appliances in households, without including the impact of appliances that meet Energy Star standards but do not carry the label. As Sanchez (2008) explains, we can think of all appliance purchases as being for products that meet Energy Star minimum requirements and those that do not. For the appliances that do, we can attribute their sales to the Energy Star program (i.e. the appliances have an Energy Star label) or not.

Figure 4.24 shows Energy Star market share growth since 2000 in labeled products for the commercial and residential markets. The program began in the 1990s. Since reaching 6 percent savings in 2000 for combined commercial and residential electricity demand, it has climbed steadily to an estimated 14 percent savings in 2008. Residential and commercial electricity demand levels in the U.S. have been similar since 2000, with commercial demand fluctuating between 88 and 98 percent of residential demand. Given a few general assumptions about portions of appliances in each sector, I estimate that residential savings from Energy Star are between 50 and 60 percent of the total savings due to the labeling program.

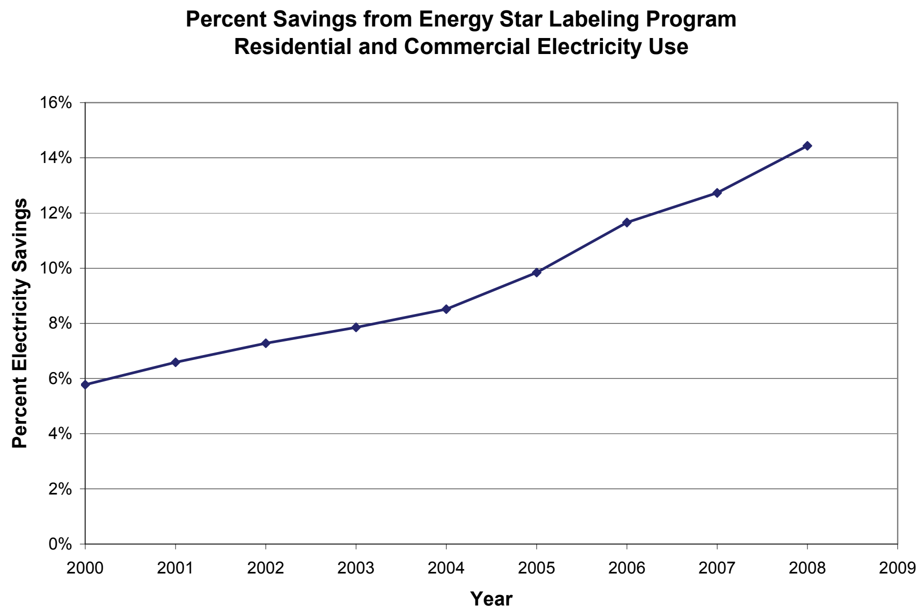


Figure 4.24: Combined savings in the commercial and residential electricity sectors due to the Energy Star appliance labeling program.

Future Residential Demand Scenarios

In the absence of research linking feedback with appliance purchasing habits or overall appliance efficiency levels, I employ five future electricity demand projections from 2008 to 2025 that vary based on the assumed level of appliance efficiency. Four of the scenarios are from EIA 2010 Annual Energy Outlook, while the "No Energy Star" scenario uses data from Sanchez et al. (2007). Figure 4.25 shows the five scenarios for efficiency in U.S. households, with time on the x-axis and total residential electricity consumption on the y-axis. The four scenarios at the bottom of the graph were taken from the AEO. The Reference case (pink) represents business-as-usual, with moderate gains in efficiency. The 2009 Technology case (dark blue) projects energy use with a normal stock turnover but without any technological gains beyond the 2009 levels of efficiency. The No Energy Star (gold) case represents energy consumption without the Energy Star program. This case is purely illustrative of the success of the program and does not imply that the EPA and DOE would terminate the program. Sanchez (2007) estimates energy savings for 2008 due to the program and projects savings through 2025; the graph adds these saving to the Reference case. The higher

electricity use in 2008 is due to the impact of the Energy Star program from its current and previous years of operation, as Energy Star appliances purchased during earlier years continue to realize savings into the future.

The High Technology and Best Available Technology cases (red and green, respectively) represent alternative scenarios for increased efficiency between 2008 and 2025. The scenarios include efficiency improvements to both the appliance stock and building shells. Theoretically, if feedback encourages people to purchase more efficient (e.g. Energy Star) appliances, the corresponding electricity use trajectory would be lower than the Reference case and bounded by the Best Available Technology case. Thus, the High Technology case is one possible trajectory for electricity use with feedback. Without feedback, Energy Star will continue to grow in popularity and market share, saving consumers money on their electricity bills. However, with feedback, this rate may increase and bring additional benefits to consumers.

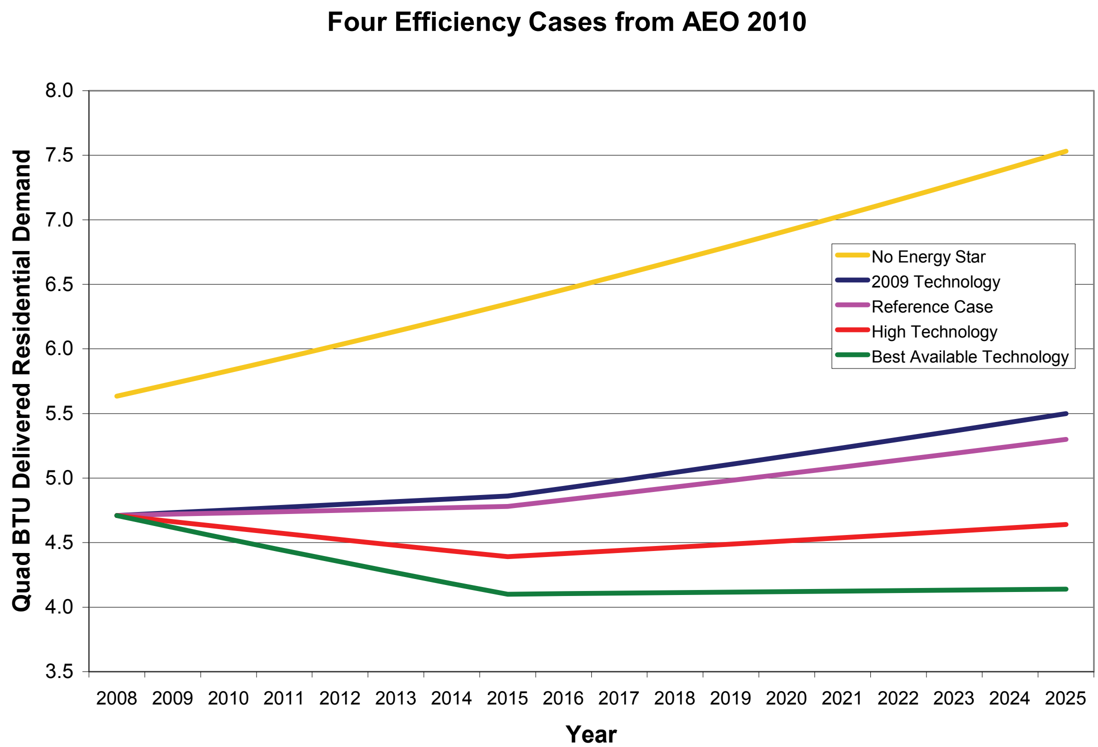


Figure 4.25: Four scenarios for future efficiency levels and one illustrative scenario showing estimated efficiency levels without the Energy Star program.

Figure 4.26 shows the percent savings of the High Technology and Best Available Technology cases over the Reference case from 2008 to 2025. The data is the same as that of Figure 4.25, but shows percent reductions from the Reference Case instead of total demand. Although the Best Available Technology case utilizes what are projected to be the most efficient appliances and building shells on the market, it does not represent the maximum achievable level of efficiency. The case uses normal stock turnover rates, meaning that some building shells and equipment installed prior to 2009 have not been replaced. If households are compelled to make the replacements before the life of the equipment is over – either mandatorily (e.g. regulations) or voluntarily (e.g. feedback) – we could see even higher rates of efficiency possible.

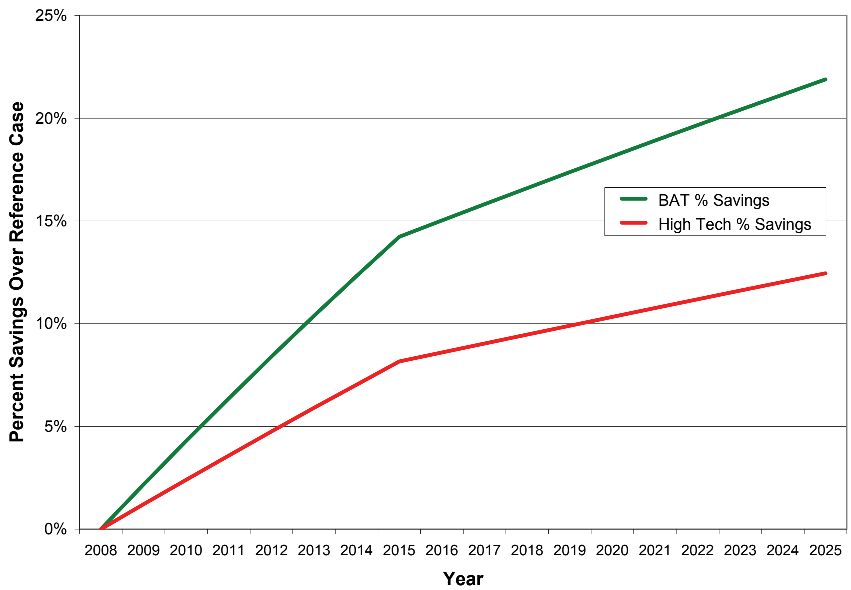


Figure 4.26: Percent savings over Reference case for High Technology and Best Available Technology cases.

We can use the AEO scenarios to estimate how much money households will save on their energy bills from using more Energy Star appliances. However, quantifying the net benefit is difficult because we do not know how much more the efficient appliances will cost than the standard, non-efficient versions. Households that use their Energy Star appliances enough times over the years will eventually save more money on bills than they spent to purchase the appliance – especially with the Energy Star rebates available from utilities. It is reasonable to assume that most households will only purchase the Energy Star version of an appliance when it is in their long-term economic interest. (On the other hand, many households do not buy the more expensive Energy Star units even when it is better economically over the long-term. This is the Energy Efficiency Gap mentioned earlier.) Thus, we may assume that the financial benefit over the life of the appliance is a minimum of zero, but beyond that we cannot estimate what it would be. The only benefit we can estimate with any accuracy is the social benefit from reduced GHG emissions, which is proportional to the amount of energy saved.

A tradeoff exists between the impact of feedback from behavior (i.e. using less electricity day to day) and from purchasing more efficient appliances. As households replace inefficient appliances with more efficient ones, the value of feedback decreases from a behavioral standpoint. With an appliance that consumes more energy, each action to reduce its use would yield a higher benefit. Once a household replaces the appliance, each behavioral action to save energy yields less benefit. Reducing overall energy use by 10 percent yields greater savings for households with less efficient appliances and higher energy bills.

4.5 Comparing Feedback Benefits and Costs

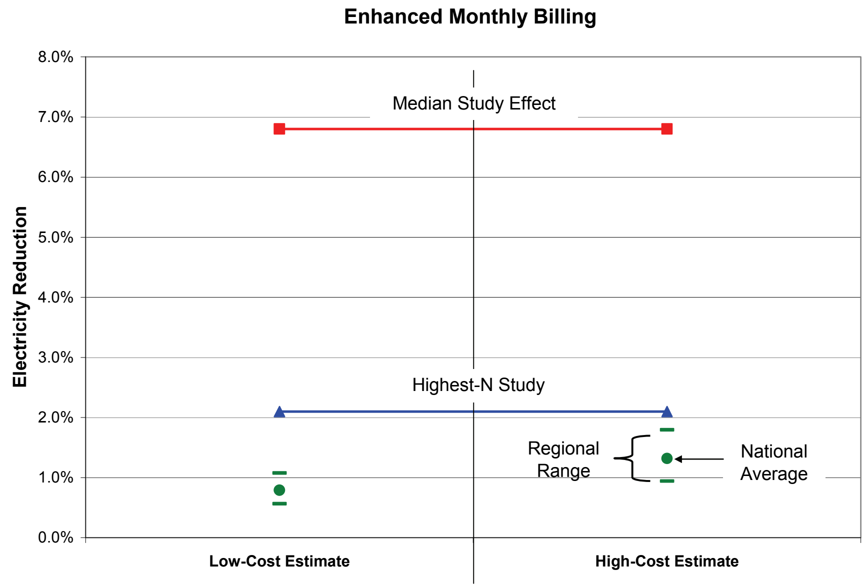
The exploratory analysis revealed that a range of regional benefits are possible depending on the impact of demographic and climate characteristics on the feedback effect. Even without these potential differences in feedback effects, average household electricity consumption between regions can be quite different. To simplify the cost-benefit analysis, this section considers a uniform reduction in electricity with no additional demographic or climate-related effects.

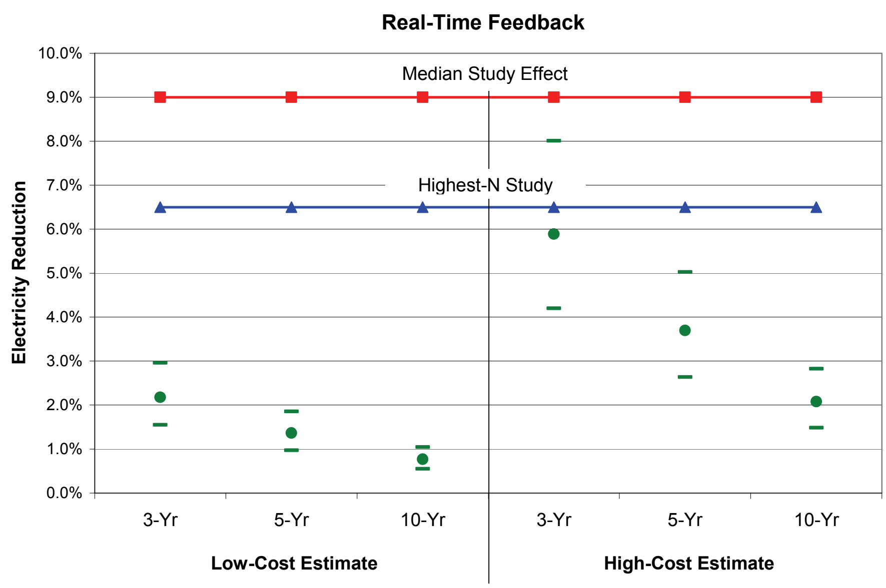
Table 4.6 lists the average percent reduction in electricity use in order for the region as a whole to break even on providing feedback to every household. The table includes three types of feedback: enhanced monthly, real-time (centralized), and real-time disaggregated. It divides real-time feedback into the two sub-categories because of the significant cost differences. The table does not include weekly and daily feedback. Daily feedback uses the same equipment – and therefore, investment – as real-time feedback, but the benefits are smaller. The exception to this characterization occurs when utilities invest in smart meters for their customers, at which point the customers may sign up for free feedback at hourly intervals (e.g. from Google or Microsoft at no cost). However, a smart-meter cost-benefit analysis is outside the scope of this study. The table does not consider installation or any program costs for both types of real-time feedback, as such estimates were not available.

The table gives breakeven conservation amounts for both a low-cost and high-cost estimate, and also over three different time frames – 3, 5, and 10 years starting in 2010. The three figures that follow – Figures 4.27a, b, and c – convey the same information in graphical form. For enhanced monthly billing, each timeframe yields nearly-identical conservation percentage for each region, as the monthly costs and benefits are almost identical.

		Region												
Scenario	**All U.S.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Enhanced Billing														
Low-Cost Estimate														
3-Yr	0.8%	1.0%	0.8%	0.9%	0.9%	0.7%	0.7%	0.8%	0.9%	0.9%	0.9%	1.1%	0.6%	0.6%
5-Yr	0.8%	1.0%	0.9%	1.0%	0.9%	0.7%	0.7%	0.8%	0.9%	0.9%	0.9%	1.1%	0.6%	0.6%
10-Yr	0.9%	1.1%	1.0%	1.1%	1.0%	0.8%	0.8%	0.9%	1.1%	1.0%	1.0%	1.3%	0.7%	0.7%
High-Cost Estimate														
3-Yr	1.3%	1.6%	1.4%	1.5%	1.5%	1.1%	1.1%	1.3%	1.5%	1.4%	1.5%	1.8%	0.9%	1.0%
5-Yr	1.4%	1.7%	1.4%	1.6%	1.5%	1.2%	1.2%	1.3%	1.6%	1.5%	1.5%	1.9%	1.0%	1.0%
10-Yr	1.6%	1.9%	1.6%	1.8%	1.7%	1.3%	1.3%	1.5%	1.8%	1.7%	1.7%	2.1%	1.1%	1.1%
Real-time														
Low-Cost Estimate														
3-Yr	2.2%	2.7%	2.3%	2.5%	2.4%	1.9%	1.8%	2.1%	2.5%	2.4%	2.4%	3.0%	1.6%	1.6%
5-Yr	1.4%	1.7%	1.4%	1.6%	1.5%	1.2%	1.1%	1.3%	1.5%	1.5%	1.5%	1.9%	1.0%	1.0%
10-Yr	0.8%	0.9%	0.8%	0.9%	0.9%	0.7%	0.6%	0.7%	0.9%	0.8%	0.9%	1.0%	0.5%	0.6%
High-Cost Estimate														
3-Yr	5.9%	7.2%	6.1%	6.8%	6.6%	5.0%	5.0%	5.6%	6.6%	6.4%	6.6%	8.0%	4.2%	4.4%
5-Yr	3.7%	4.5%	3.8%	4.3%	4.1%	3.2%	3.1%	3.5%	4.2%	4.0%	4.1%	5.0%	2.6%	2.7%
10-Yr	2.1%	2.5%	2.2%	2.4%	2.3%	1.8%	1.8%	2.0%	2.3%	2.3%	2.3%	2.8%	1.5%	1.5%
Real-time Disaggregated														
Low-Cost Estimate														
3-Yr	14.6%	17.8%	15.1%	16.8%	16.4%	12.5%	12.3%	13.9%	16.5%	15.9%	16.4%	19.9%	10.4%	10.8%
5-Yr	9.2%	11.2%	9.5%	10.6%	10.3%	7.9%	7.7%	8.7%	10.3%	10.0%	10.3%	12.5%	6.5%	6.8%
10-Yr	5.2%	6.3%	5.3%	5.9%	5.8%	4.4%	4.3%	4.9%	5.8%	5.6%	5.8%	7.0%	3.7%	3.8%
High-Cost Estimate														
3-Yr	46.4%	56.6%	48.0%	53.4%	52.0%	39.7%	39.0%	44.1%	52.3%	50.4%	52.0%	63.1%	33.1%	34.4%
5-Yr	29.1%	35.5%	30.1%	33.5%	32.6%	24.9%	24.5%	27.7%	32.8%	31.6%	32.6%	39.6%	20.8%	21.6%
10-Yr	16.4%	20.0%	16.9%	18.8%	18.4%	14.0%	13.8%	15.6%	18.5%	17.8%	18.4%	22.3%	11.7%	12.1%

Table 4.6: Breakeven conservation levels for three types of feedback under high and low cost estimates and 3-, 5-, and 10-year timeframes.


Enhanced Monthly Billing
8.0%
7.0%
6.0%
5.0%
4.0%
3.0%
2.0%
1.0%
0.0%
Electricity Reduction
Median Study Effect
Highest-N Study
Regional Range
National Average
Low-Cost Estimate
High-Cost Estimate


Real-Time Feedback
10.0%
9.0%
8.0%
7.0%
6.0%
5.0%
4.0%
3.0%
2.0%
1.0%
0.0%
Electricity Reduction
Median Study Effect
Highest-N Study
3-Yr
5-Yr
10-Yr
3-Yr
5-Yr
10-Yr
Low-Cost Estimate
High-Cost Estimate

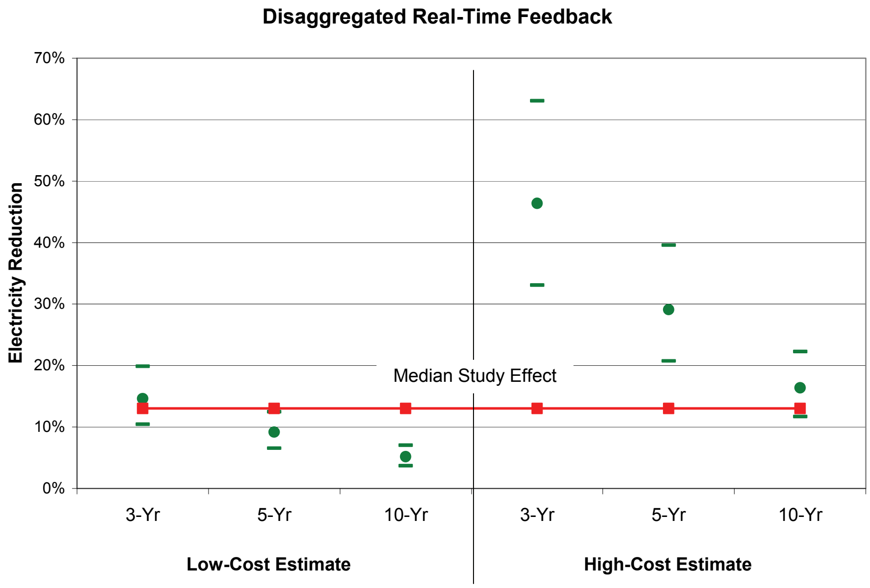


Figure 4.27a, b, c: Breakeven conservation levels for enhanced monthly billing, real-time feedback, and disaggregated real-time feedback. The red line shows the median study effect and blue line shows the highest-N study effect. Green points indicate breakeven conservation levels on a national average, while the dashed green lines show the range of regional breakeven conservation levels.

For the real-time feedback, the necessary reductions to break even decrease as the timeframe increases. The reason for this is that costs are upfront for equipment; the longer the equipment functions effectively, the greater the benefit-cost ratio. This same pattern is true for real-time disaggregated feedback, as the high and low cost estimates both came from the TED product in Table 4.5, which does not include a monthly service fee.

As illustrated earlier, the median effect sizes found in the literature for each type of feedback are 6.8 percent for enhanced billing, 9.0 percent for real-time, and 13.0 percent for real-time disaggregated. Thus, the required conservation levels are well-below the median for both enhanced monthly billing and real-time feedback – even for the high cost estimates. For disaggregated feedback, the low-cost estimates are below the median if the equipment lasts for at least 4-5 years. For the 3-year estimate, the median is near the breakeven conservation level

only for some of the regions. For the high-cost estimates, more substantial conservation levels would be required for the feedback investments to pay off – even over 10 years (except for Texas and Florida, which have breakeven levels of around 12 percent).

As many of the studies had small sample sizes, one may want to compare breakeven levels to not only the median effect size in the literature, but also to the study with the largest sample size. A large-scale feedback provision program would undoubtedly resemble one of the larger studies more than it would a smaller one. The largest enhanced monthly billing study was described in Ayres (2009). The sample size was 35,000 and the effect size 2.1 percent. The largest real-time feedback sample size was 500 and the effect was 6.5 percent. The disaggregated feedback studies numbered only two, and both effect sizes were very similar (12.9 and 13.1 percent).

4.6 Comparing Cost-Effectiveness to Other DSM Programs

We could consider the DSM cost-effectiveness figures estimates of the opportunity cost of providing feedback. However, this viewpoint may be incomplete. It is possible that feedback has synergistic effects with other DSM programs. For example, it may make information campaigns and appliance rebate programs more successful. Nonetheless, we compare the range of cost-effectiveness estimates from the literature with the potential cost-effectiveness of feedback from this study.

Utilities often report the amount spent on DSM programs and the megawatt-hours saved per year. However, a straightforward yearly cost-effectiveness figure using these figures can be misleading. Spending on DSM programs in one year generate savings that recur for many years into the future. For example, rebates for energy efficient appliances will save energy every year for the life of the appliance. The literature reported here accounts for this time lag in the reported cost-effectiveness estimates.

Gillingham et al. (2006) reviews the literature on DSM programs and finds a range of cost-effectiveness figures from 0.8-23 cents per kWh.

This means that utilities spend somewhere between 0.8 and 23 cents to reduce electricity usage by one kilowatt-hour. The low end of the estimate is from Fickett et al. (1990), who found the 0.8 cents per kWh figure. At the high end are Loughran and Kulick (2004), who claim that utilities have overstated energy savings because some of the people that take advantage of DSM program incentives are those who would have made the efficiency improvements regardless of the incentives. They estimated cost-effectiveness from 1989-1999 at 14.6 to 22.9 cents per kWh for the full sample of 324 utilities and 6.3 to 12.5 cents per kWh for a subsample of the larger utilities that likely had more experience administering DSM programs. For the same data, utilities estimated an average of 2 to 3 cents per kWh saved. In a recent study, Arimura et al. (2009) find that DSM expenditures over the last 18 years have a cost-effectiveness of 6.0 cents per kWh.

Looking only at utility rebate programs, Nadel (1992) found that utilities spend 1.9 to 6.7 cents per kWh. Datta and Gulati (2009) obtained a figure of 3.5 cents per kWh for rebates for efficient clothes washers.

If a utility – or government entity – chose to devote resources to encouraging installation of ECDs, it could do so through several different policies. It could proactively install an ECD in every household that did not refuse the device. Alternatively, it could offer a rebate to any household that decided to install its own ECD. One would expect the rebate option to be more cost-effective, as a household with the motivation to install an ECD without a strong external impetus would also likely be more motivated to see greater returns to the effort. With installation by the utilities, more households would receive the ECD, but some may be less interested in using it to achieve savings.

To compare the cost-effectiveness of feedback against that of other DSM programs, I take the median conservation level – and also the conservation level for the study with the largest sample size - for each type of feedback addressed in Section 4.5: enhanced billing, real-time,

and real-time disaggregated. Table 4.7 lists the cost-effectiveness estimates for each region and for the U.S. overall. The "Scenario" column on the left-hand side of the table gives the type of feedback. The next column to the right lists the real ($2010) cost of providing feedback over 10 years. The cost estimates are averages. For enhanced billing, the costs are for 10 years at $16 per year, which is the average of the high and low estimates - $20 and $12 per year, respectively. For the real-time and disaggregated feedback, the costs are the average of all available feedback equipment and/or services listed in Section 4.4.4.

The third column from the left in Table 4.7 lists conservation levels from the applicable studies. The top three rows of data are in relation to the median conservation level found in the literature for each type of feedback. The remaining columns to the right list the CE estimates in cents per kWh for each type of feedback regionally and for the U.S. overall. These CE estimates assume a uniform reduction in electricity and no additional feedback effects (i.e. energy intensity effect, income effect, etc.) Pink shading indicates CE levels higher (less cost-effective) than other DSM programs. For this threshold CE level, I use the 6 cents per kWh estimated by Arimura (2009).

			Cost-Effectiveness in Cents per kWh Reduced														
	Real 10-Year Cost	Median of		Region													
Type of Feedback	Per Household	Studies	All U.S.	1	2	3	4	5	6	7	8	9	10	11	12	13
Enhanced Billing	$160	6.8%	2.0	3.1	2.3	2.2	2.0	1.6	1.5	1.7	2.1	1.9	3.4	3.3	1.5	1.5
Real-time	$175	9.0%	1.7	2.6	1.9	1.8	1.7	1.3	1.2	1.4	1.8	1.5	2.8	2.7	1.3	1.2
Real-time Disaggregated	$1,353	13.0%	8.9	13.8	10.3	9.8	8.9	7.2	6.4	7.5	9.4	8.2	14.9	14.6	6.8	6.5
		Highest-N Studies														
Enhanced Billing	$160	2.1%	6.5	10.1	7.5	7.1	6.5	5.3	4.7	5.5	6.9	6.0	10.9	10.7	4.9	4.7
Real-time	$175	6.5%	2.3	3.6	2.7	2.5	2.3	1.9	1.7	1.9	2.4	2.1	3.8	3.8	1.7	1.7

Table 4.7: Cost-effectiveness estimates for three types of feedback over 10 years. Pink shading indicates cost-effectiveness levels higher than other typical DSM programs (6 cents per kWh).

We see that if we assume effectiveness levels equal to the median of studies, the enhanced billing and real-time feedback will be cost-effective relative to other DSM programs, with CE levels between 1.2 cents and 3.4 cents per kWh over 10 years, depending on the region. For real-time disaggregated feedback, CE ranges from 6.4 to 14.9 cents per

kWh. These levels are all above the 6 cent per kWh threshold. The bottom two rows give CE estimates for the studies with the highest sample sizes – 35,000 for enhanced billing and 500 for real-time (discussed in Section 4.5). Assuming these lower conservation levels, real-time feedback is still cost-effective over 10 years, with CE estimates between 1.7 and 3.6 cents per kWh. For enhanced billing, however, the results are mixed. For the U.S. as a whole, CE is 6.5 cents per kWh. However, 6 regions within the U.S. have CE levels below the threshold. If policy-makers wanted to use a more conservative estimate for energy reductions for enhanced billing, these six regions would be the most cost-effective for implementing feedback policies.

Exploratory Analysis for Cost-Effectiveness

For the two rows in Table 4.7 with pink shading, representing CE above 6 cents per kWh for uniform feedback effects, I used FEM to perform another exploratory analysis. The results indicate what values for the 5 uncertainties would make CE levels either above or below the threshold. Figures 4.28a and 4.28b show the results for real-time disaggregated feedback (median effect size) and enhanced monthly billing (highest N effect size) respectively. In each figure, the pink shading shows regions without any cost-effective cases. The light green shading (Figure 4.28 only) indicates regions with all cost-effective cases. For regions with a mix of cases above and below the threshold, the red shading denotes values of uncertainties for which cases are not cost-effective. The right-most column indicates the percentage of cases in each region that were not cost-effective when varying the uncertainties.

For disaggregated feedback (Figure 4.28a), regions 6, 12, and 13 – representing the states of Kentucky, Tennessee, Mississippi, Alabama, Texas, and Florida - have some cases where feedback is cost-effective. For Region 6, half the cases have CE above the threshold and the red shading reveals that these cases occur when the Energy Intensity effect is less than 2.5 percent. Conversely, the cost-effective cases occur when Energy Intensity is greater than 2.5 percent. For Texas (Region 12), cost-effective cases occur when feedback is most effective during hot summers and non-cost-effective cases occur when feedback is most

effective during moderate summers. This is also true for Florida (Region 13), with the additional requirement that the Energy Intensity effect is less than 3 percent.

		Energy Intensity	Income	Youth	Hot Summer	Cold Winter	Percent of Non-Cost-Effective Cases within Region
1	ME, VT, NH, MA, RI, CT						**100%**
2	PA, NJ						**100%**
3	WI, IL, IN, MI, OH						**100%**
4	ND, SD, NE, KS, MN, IA, MO						**100%**
5	DE, MD, DC, WV, VA, NC, SC, GA						**100%**
6	KY, TN, MS, AL						**50%**
7	OK, AR, LA						**100%**
8	MT, ID, WY, NV, UT, CO, AZ, NM						**100%**
9	WA, OR, AK, HI						**100%**
10	New York						**100%**
11	California						**100%**
12	Texas						**55%**
13	Florida						**34%**

Figure 4.28a: Results of exploratory analysis for real-time disaggregated feedback with median conservation level of 13.0 percent.

For the 2.1 percent conservation estimate for enhanced monthly billing, Figure 4.28b indicates that Regions 2-4, 7-8, and 11-13 all have cases above and below the CE threshold. Regions 4, 8, 12, and 13 have very few cases that are not cost-effective. California (Region 11) is almost all non-cost-effective, with the exception of the portion of cases when the Income Effect is very high. Regions 2, 3, and 7 have between 10 and 71 percent of cases above the threshold. For Regions 2 and 3, the Income Effect determines the cases above the threshold. For Region 2, non-cost-effective cases result when the Income Effect is medium to low and for Region 3 only when it is low.

		Energy Intensity	Income	Youth	Hot Summer	Cold Winter	Percent of Non-Cost-Effective Cases within Region
1	ME, VT, NH, MA, RI, CT						**100%**
2	PA, NJ						**71%**
3	WI, IL, IN, MI, OH						**35%**
4	ND, SD, NE, KS, MN, IA, MO						**3%**
5	DE, MD, DC, WV, VA, NC, SC, GA						**0%**
6	KY, TN, MS, AL						**0%**
7	OK, AR, LA						**10%**
8	MT, ID, WY, NV, UT, CO, AZ, NM						**6%**
9	WA, OR, AK, HI						**0%**
10	New York						**100%**
11	California						**93%**
12	Texas						**2%**
13	Florida						**4%**

Figure 4.28b: Results of exploratory analysis for enhanced monthly billing with largest-N conservation level of 2.1 percent.

Chapter 5:
Using Feedback to Encourage Load-Shifting

5.1 Objectives

- How can utilities use feedback in combination with a real-time pricing program?
    - o What impact does feedback -- in combination with pricing programs -- have on load-shifting?
    - o Without a price on carbon, when would separate feedback on emissions and cost give conflicting incentives for when to use electricity?

5.2 Summary

The marginal cost of wholesale electricity is more expensive during times of peak demand during the day. Utilities often give customers incentives for reducing demand during these peak periods to avoid the higher marginal costs and to defer capital expenditures on greater capacity. One way utilities lower peak load is to offer variable rate pricing structures, which charge more for electricity when it is more expensive – generally during peak hours. This offering is more common for commercial and industrial customers, but is increasingly common for residential customers. As the sophistication of metering infrastructure and ECDs grow, the technology may have the capability to display both real-time cost and emissions information, which depend on what types of plants are generating power at the margin. For emissions, the ECDs could either use a per-kWh average value or use the marginal emissions rate.

This study utilizes the ORCED model in a simulation and finds that load-shifting does not always lead to lower GHG emissions. Therefore, as utilities try to shift demand from peak to off-peak times, they should display emissions data based on a total per-hour rate for the household and not on the per-kWh marginal emissions rate. Using the marginal emissions rate could give consumers an incentive to consume electricity at certain times that conflicts with marginal cost information.

5.3 Motivation and Background

Each day, utilities must generate enough power to meet consumers' demand. As electricity must be consumed when it is generated, utilities generate only what is needed, while keeping some extra capacity ready to dispatch quickly. A load curve represents electricity demand over time throughout the day. During the summer, a typical utility may face a load curve with demand that peaks in the afternoon and early evening, when homes and businesses use power-hungry air conditioners. Different types of power plants tend to satisfy different portions of the load curve and three general categories of plants exist: base load, intermediate load, and peak load plants.

Base load plants satisfy the demand at the bottom of the load curve — the minimum level of power demanded throughout the day. In general, the base load is between 35 and 40 percent of the maximum load for the day (Cordaro 2008). These plants take a relatively long time to start up (apart from hydro) and have limited ability to vary their output level, so they tend to be dispatched at full or close to full capacity (WIPSC 2009). Once running, base load plants provide continuous and reliable power at the lowest cost. They are often large steam generating plants fueled by lignite coal or nuclear energy (Cordaro 2008). Some hydro power is also often in the base load.

Intermediate load plants generally operate between 30 and 60 percent of the time and fill the gap between base load and peak times. These plants increase their output throughout the day as demand increases, then decrease it again at night. They tend to be older coal and natural gas plants that were once used for base load but replaced by more efficient units. Thus, power from intermediate load plants is more expensive than base load power. These plants are larger, more efficient, and less expensive to operate than peak load plants.

Peak load plants, or "peaker" plants, operate around 10 to 15 percent of the time and are the smallest type of plant. They are the most

expensive type of plant to operate, but the easiest and least expensive to build and may be turned on and off relatively quickly to respond to changes in demand. Peaker plants are usually natural gas combustion turbines.

Residential electricity consumers may be motivated to conserve electricity by the amount they save on their bill and/or the amount of GHG they prevent from reaching the atmosphere. To accomplish these goals, consumers can conserve electricity, as covered in Chapter 4. However, they may also — under certain circumstances — save money and GHG emissions by changing the time of day when they use power. Depending on the fuel mix of the utility and whether a variable rate pricing scheme is in place (with higher prices for peak demand), shifting demand from peak to off-peak times may benefit certain consumers.

Flexible Pricing Options

A number of flexible pricing options for electricity exist to differentiate the price by season or time of day. Several of the most common options are as follows:

- *Time-of-Use (TOU)* is the most common residential price option. Utilities that offer this option give customers a daily rate schedule that may change based on season. For instance, the Salt River Project utility offers the following rate schedule to its customers:
  - Higher cost hours: May-October 1-8pm, November-April 5-9am and 5-9pm
  - Lower cost hours: All other times[9]
- *Critical Peak Pricing (CPP)* is another flexible pricing option. Utilities offer it almost exclusively to commercial and industrial customers with relatively high demand. Customers may opt into a CPP plan, which generally raises electricity prices significantly during summer "CPP Events," which are days when overall demand is

[9] Source: http://www.srpnet.com/prices/home/tou.aspx

high. In return, they receive lower electricity rates for the remainder of the year.

- Hourly real-time pricing (RTP) is an option offered by some utilities where the price varies by the hour. The advance notice may be one day or one hour. If it is the latter, the utility generally sends the customer an estimated price 24 hours in advance and updates the estimate one hour before the price is to take effect. Georgia Power Company offers a RTP option to eligible customers, which include only commercial/industrial entities that maintain a peak 30-minute demand of 5,000 kilowatts or more (in comparison, an average residence consumes about 11,040 kilowatt-hours annually (EIA 2010)). Some utilities are beginning to offer RTP options to residential consumers as well, such as ComEd in Illinois. ComEd gives residences a day-ahead price prediction and updates the real-time prices on an hourly basis. Customers may see the prices and view their hourly load profiles online. ComEd also notifies their customers by email, text, or telephone if the average price per kilowatt hour is expected to surpass 14 cents.

Besides inducing customers to shift load from peak to off-peak times, variable rate pricing structures can shift some of the burden of price volatility hedging from the suppliers to the consumers. Wholesale electricity prices move up and down on the market depending on the time of day and types of plants supplying the load. When consumers pay a flat rate for electricity, the suppliers hedge all of the price volatility by purchasing power at the wholesale market price. As pricing structures shift from a single flat rate to varying by time of day, the hedging burden shifts from suppliers to end-users. Figure 5.1 illustrates this shift.

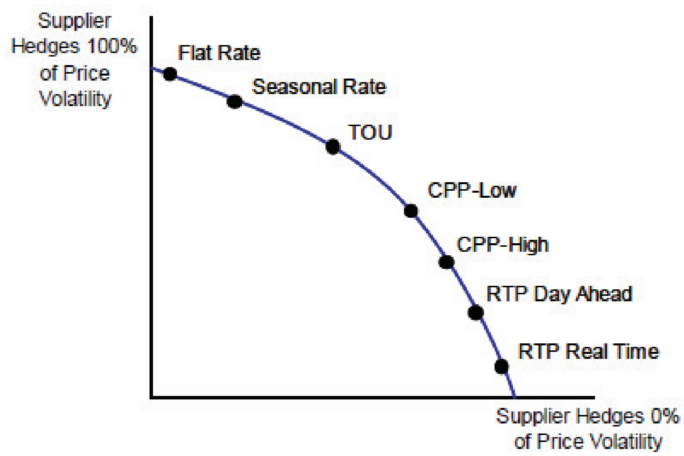


Figure 5.1: The hedging tradeoff for suppliers and end-users for various variable rate pricing structures. From: (Faruqui and Wood 2008).

Real-time pricing charges customers the (nearly) precise marginal cost of the electricity, while other pricing alternatives may only charge more during times of year and/or days when demand is highest. Using feedback in conjunction with a variable rate pricing structure may help influence households to shift more energy consumption from peak to off-peak times than just the pricing structure alone. With the exception of real-time pricing, utilities could implement any of the variable rate structures with either smart meters or standard meters (with the necessary meter reading devices) and with supplemental energy displays. RTP only works with smart meters because the customers would need to receive signals from their utilities as the price changed throughout the day. Section 5.4 explores the literature on this load-shifting effect of feedback and examines how to quantify the benefits of the additional load shift attributable to feedback.

Effect of Load-Shifting on GHG Emissions

With the flexible rate pricing options, electricity would be more expensive for consumers during peak times. However, these peak times may not necessarily be the times when GHG emissions are highest. In the absence of regulations that put a price on GHG emissions — either through a cap and trade program or carbon tax — the price of electricity does not reflect the negative impact of electricity use on society through the mechanism of climate change. Different regions of the

country rely on different fuels to power their base load, intermediate load, and peak load generating plants. Depending on the region, consumers may have conflicting motivations for how to manage their energy use – based on whether they are motivated by the desire to spend less on their bill or to reduce GHG emissions. For instance, one particular region may rely heavily on GHG-intensive coal for its intermediate load power and more expensive, but lower GHG-emitting, natural gas plants for peak power. Consumers in the region that received real-time price and emissions information would thus have to determine when to consume electricity based in part on the relative importance to them of GHG emissions versus monetary savings. Section 5.5 describes an experiment that used the ORCED simulation model to explore the circumstances under which consumers might face a tradeoff between price and emissions when deciding when to use electricity.

5.4 Benefits of Feedback from Shifting Load

While the conservation effect of feedback has been explored by several dozen studies in the literature, almost no studies have been undertaken on the load-shifting effect of feedback. By "load-shifting effect," I mean the impact that feedback can have on consumers in shifting their electricity consumption from peak times to off-peak times. It would thus be the difference in shifted load between consumers with and without feedback who were on the same pricing structure.

By improving a utility's efficiency and asset utilization, peak load reductions reduce generation and delivery costs in addition to deferring transmission and distribution capacity investments (EPRI 2010). Consumers may subsequently see these cost savings reflected in lower prices for electricity. The California Standard Practice Manual (2002) outlines four types of benefits load-shifting brings from a utility perspective: savings due to avoided additional capacity, avoided generation, avoided transmission, and avoided distribution. These savings include the deferred costs of adding additional generation, transmission, and distribution resources.

A review of the literature found only three studies that address the load-shifting effect of feedback. Kasulis et al. (1981) gave some consumers on different rate structures information with their bill about the effect of altering consumption patterns. The results of the feedback were mixed, but they did find that households were willing to schedule activities in response to reminders. Sexton et al. (1987) examined the load-shifting effect of feedback in a TOU setting and also whether the effect varied depending on different peak to off-peak (P:OP) rate differences. The authors found that real-time feedback did not yield conservation effects, but did encourage P:OP shifts and that the size of the shift was larger for higher P:OP rate ratios. The Hydro One (2008) pilot implemented real-time feedback in combination with TOU rates. With TOU pricing and no feedback, households shifted an average of 3.7 percent of their load from peak to off-peak during summer months. With TOU and real-time feedback, average load-shifting was 5.5 percent during summer. On a hot summer day (over 30°C), this figure increased to 8.5 percent. Feedback thus improved load-shifting in summer months by 1.8 percent and on hot days by 4.8 percent.

For each type of variable rate structure, the ratio of peak to off-peak price could take many different levels. Instead of measuring the impact of feedback on each type of scheme, it would probably be more appropriate to think of the impact of feedback on the elasticity of consumption than on percentages of shifted load. With frequent feedback on both usage and price, residential customers could be more or less sensitive to price. Lacking the data to evaluate the precise effects of feedback on load-shifting, this analysis is outside the scope of this study and a quantification of load-shifting benefits was thus not included in the cost-benefit analysis.

5.5 Conflicting Incentives from Real-Time Pricing and Environmental Feedback

With household energy displays, households may be able to see their real-time consumption, spending, and GHG emissions. The display could either show the GHG emissions of the marginal kWh being generated or use

an average value per kWh to show a total level of GHG emissions that increases proportionally with each kWh of demand. The former depends on the fuel source and efficiency of the power plant generating the marginal kWh of electricity, while the latter depends on the overall carbon footprint of the utility's generating resources and the household's current demand. This section describes an experiment using the ORCED model to test when and where price and emissions feedback may lead to conflicting incentives for residential consumers. It examines whether it would be more appropriate for an ECD to show an average or a marginal GHG emissions rate.

Households may be motivated to conserve energy by reducing the monthly bill and/or reducing GHG emissions. If a household is enrolled in a variable rate pricing plan, in the absence of a price on carbon incorporated into the price of electricity, it must make a tradeoff between cost and emissions when deciding when to use electricity. For this simulation, I assume that households want to minimize the hourly price they pay for electricity when they are on a variable rate pricing structure by using non-essential appliances during off-peak rather than peak times. I also assume that household members want to minimize their GHG footprints such that, when given two otherwise equivalent options about when to use electricity, they would use it when GHG emission rates were lowest. This assumption is consistent with recent polling results that show a desire among Americans to regulate emissions of GHGs.[10]

5.5.1 Experimental Procedure

1. Modify the ORCED model to simulate:
    - 5 percent decrease in electricity demand during peak hours in summer, winter, and spring/fall.
    - 5 percent increase in electricity demand during off-peak hours in summer, winter, and spring/fall.

[10] ABC News/Washington Post Poll. June 3-6, 2010. N=1,004 adults nationwide. See http://www.pollingreport.com/enviro.htm.

For the purposes of the simulation, peak hours are Monday-Friday, 3:00-9:00pm and Saturday-Sunday, 1:00-9:00pm. The 5 percent reductions are for the entire U.S. electricity demand, of which the residential sector makes up 38 percent. If the entire 5 percent was due to demand reductions in the residential sector, the decreased residential demand would be equivalent to a residential reduction of around 13 percent.

The model defines the seasons as:

Summer:	June 1 – September 30
Winter:	December 1 – February 28
Spring/Fall:	October 1 – November 30 and March 1 – April 30

The total number of simulated scenarios is:

13 Regions
x 3 Times (Baseline, 5% Pk Red., 5% Off-Pk Inc.)
x 3 Seasons
117 Total Scenarios

The difference in geographical regions between ORCED and RECS necessitates some adjustments and approximations. I found MEFs for each ORCED region, then assigned each regional MEF to each state within the region. Each region in RECS is a weighted average of the state MEFs, weighted by the region's share of electricity generation, as given by the EPA eGRID totals for 2005. I used a similar procedure for the fuel mix calculations.

2. Calculate the peak and off-peak marginal emission rates for summer, winter, and spring/fall in terms of pounds CO_2/kWh. When we compare the peak MEF to the off-peak MEF, the result will give an approximate per-kWh GHG reduction benefit from shifting load from peak to off-peak hours (assuming a ~5 percent load shift).

   The model outputs for each scenario that I utilize are megawatt-years of electricity generated and kilotons of CO_2 emitted. To

compute an estimate for the marginal emissions per kilowatt hour, I take the difference in emissions between each individual scenario and the Baseline scenario and divide by the difference in generation between the two scenarios:

$$MEF_A = \frac{CO_2^{Baseline} - CO_2^{Scenario\_A}}{kWh^{Baseline} - kWh^{Scenario\_A}} \quad (1)$$

This calculation results in a MEF for both peak reductions and off-peak increases for each of the 13 regions for each of the 3 times of year. To find the marginal environmental benefit (in terms of CO_2), I subtract each off-peak MEF from the corresponding peak MEF. The result yields the marginal CO_2 reduction per kWh of shifted load:

$$M(CO_2\_benefit)_A = MEF_A^{Peak} - MEF_A^{Off-Peak} \quad (2)$$

If the marginal CO_2 benefit is greater than zero, shifting load from peak to off-peak times will lower CO_2 emissions; the opposite is true if the marginal benefit is negative.

3. Examine the fuel mix for each region and determine what types of plants account for the reductions/increases.

4. Determine when and where feedback on electricity usage would give conflicting incentives with feedback on GHG emissions under a pricing structure that charged more for peak use.

5.5.2 Results

Table 5.1 shows the results of the simulations. The peak and off-peak MEFs for each season are shown in the six columns to the right of the "Region" column. When a region's peak MEF is greater than the off-peak MEF for a particular season, it would be beneficial, from the perspective of reducing GHG emissions, to shift load to off-peak times. If the off-peak value is greater than the peak value, shifting load

would result in greater CO_2 emissions. The three columns on the right-hand side of the table contain the differences between peak and off-peak MEFs for each region. The cells with green shading show a benefit to load-shifting. Orange shading indicates negative values, where the off-peak MEF is greater than that of the peak. White boxes indicate that the difference between peak and off-peak was less than 0.05 lbs CO_2/kWh, either positive or negative.

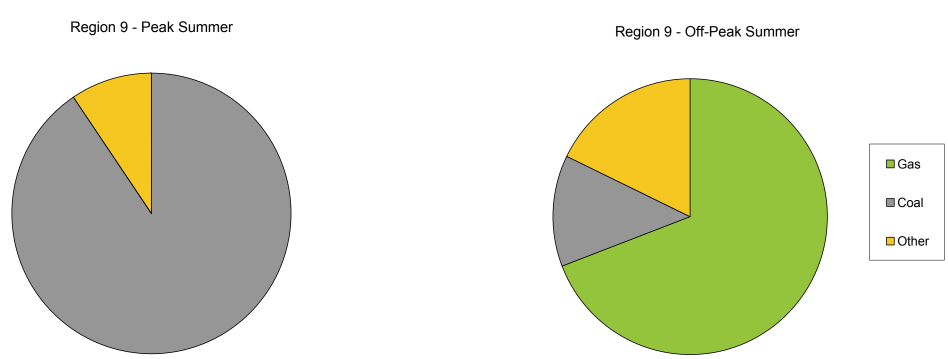
Region	Summer		Winter		Spring/Fall		Marginal Averted Emissions (lbs CO_2/kWh)		
	Peak	Off-Peak	Peak	Off-Peak	Peak	Off-Peak	Summer	Winter	Spring/Fall
1	1.40	1.25	1.07	1.04	1.44	1.14	0.15	0.03	0.30
2	1.51	1.33	1.86	1.95	1.60	1.60	0.18	-0.09	0.00
3	2.02	1.93	1.76	1.83	2.10	1.93	0.09	-0.08	0.17
4	1.89	2.03	2.18	2.18	1.56	1.63	-0.13	0.00	-0.08
5	1.82	1.89	2.18	2.20	2.20	2.08	-0.07	-0.02	0.12
6	1.91	2.00	2.16	2.18	2.30	2.15	-0.08	-0.02	0.16
7	1.53	1.64	2.01	1.91	1.65	1.61	-0.11	0.10	0.04
8	1.57	1.20	1.80	1.69	1.01	1.21	0.37	0.11	-0.21
9	2.40	0.90	0.94	0.94	0.93	0.94	1.50	0.00	-0.01
10	1.64	1.59	1.08	1.03	1.34	1.41	0.05	0.04	-0.07
11	1.28	1.26	1.16	1.24	0.92	0.92	0.02	-0.08	0.00
12	1.28	1.06	0.93	0.95	1.07	0.99	0.22	-0.01	0.08
13	1.30	1.05	0.92	0.97	1.22	1.04	0.25	-0.04	0.17

Table 5.1: Differences in marginal emission factors between peak and off-peak generation. All values are in pounds CO_2 per kWh of electricity.

As we can see from the table, according to the model results, there is not always a CO_2 emissions benefit from shifting load from peak to off-peak hours. During summer months, a clear benefit exists in only 7 of the 13 regions. In four regions, the benefit is negative and in two regions, it is within the 0.05 lbs CO_2/kWh from 0. In the winter, 2 regions show a positive benefit, 3 show a negative benefit, and the remaining 8 are close to 0. In spring/fall, 6 regions have a positive benefit, 3 show a negative benefit, and 4 are close to 0. There are no regions that have a benefit during all seasons of the year. Regions 1, 12, and 13 have 2 seasons with a positive benefit and one season where the benefit is ambiguous. Conversely, only Region 4 has more than one season when load-shifting is detrimental (summer and spring/fall); the benefit is 0.00 for load-shifting during winter.

When examining the magnitude of benefits, Region 9 – the Pacific Northwest and Alaska/Hawaii - stands out with a difference between summer peak and off-peak emission rates of 1.50 lbs CO_2/kWh. This is by far the greatest load-shifting benefit in the table; the next-highest benefit is in Region 8 during the summer, where the difference between peak and off-peak is 0.37 lbs CO_2/kWh. The only other load-shifting benefit greater than or equal to 0.30 is in the spring/fall in Region 1. The negative benefits — where load-shifting yields an increase in CO_2 emissions — are generally lower, as the highest magnitude (lowest value) is -0.21 lbs CO_2/kWh for spring/fall in Region 8.

Among the outputs of the ORCED model are the fuel mixes for each demand scenario. We may thus examine which type of power plants account for the 5 percent peak reductions and 5 percent off-peak increases in demand for each of the load-shifting simulations. The pie charts in Figures 5.2 and 5.3 show the proportion of each type of fuel that accounts for these reductions/increases. Figure 5.2 shows the difference in marginal peak and off-peak generation. For Region 9 during summer, we see that reducing peak demand (left-hand pie chart) leads to less coal-generated electricity at the margin, while each kWh of added off-peak demand is generated mostly from natural gas (right-hand pie chart). In Region 8 during summer, marginal off-peak power contains a greater proportion of "other" fuels than marginal peak power, accounting for the environmental benefit to load-shifting. In Region 1 during the spring and fall, off-peak marginal power has less coal and more "other" fuels than marginal peak power.



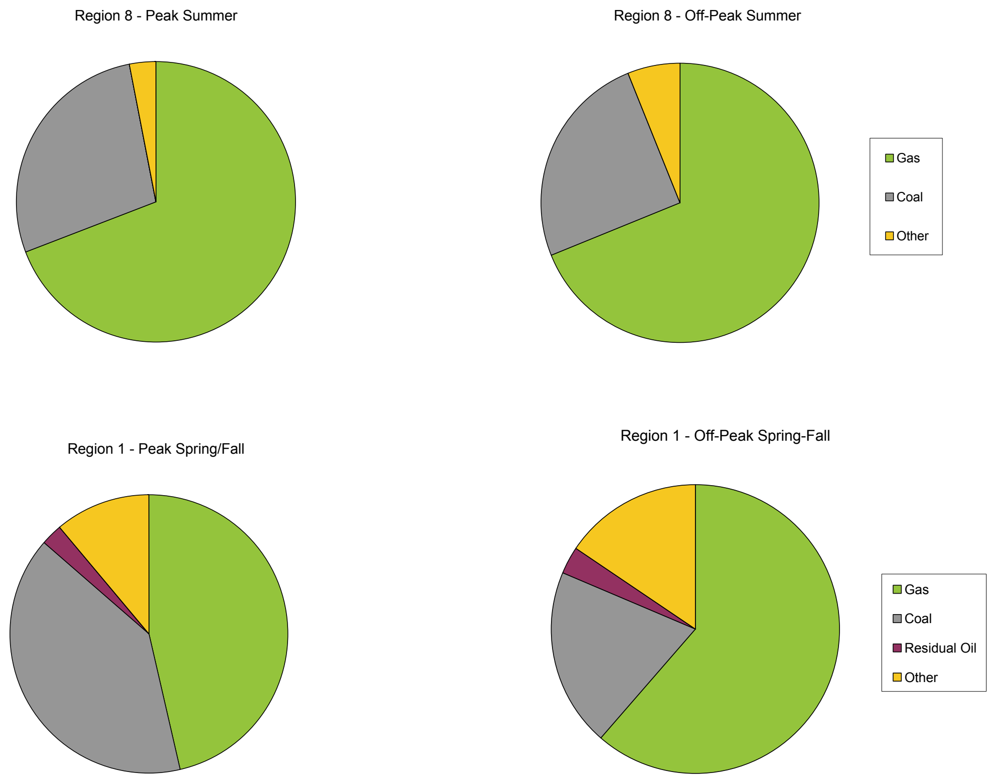
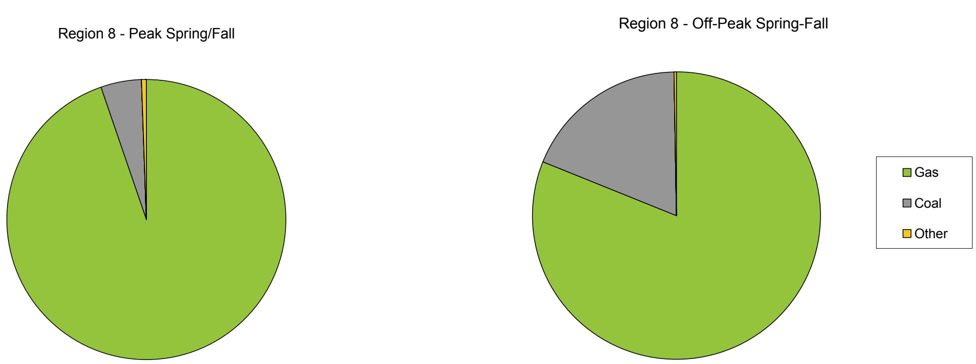


Figure 5.2: Fuel-use shifts for 3 regions/seasons with highest GHG emission decreases from load-shifting.

As Figure 5.3 shows, the three regions and seasons where load-shifting causes the greatest GHG emissions increases are Region 8 during spring and fall, and Regions 4 and 7 during summer. It appears that in each case, the increases are due to more generation from coal and less from natural gas.



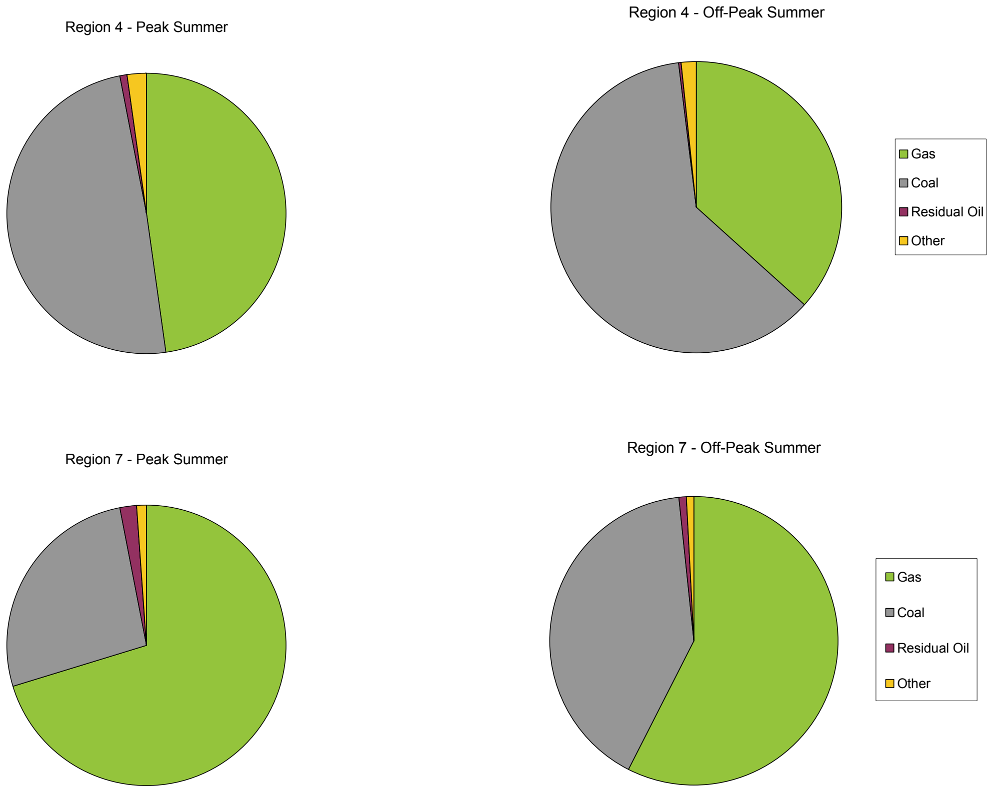


Figure 5.3: Fuel-use shifts for 3 regions/seasons with highest GHG emission increases from load-shifting.

5.6 Conclusions

A number of options exist for conveying GHG emissions information to residential consumers through ECDs. A "pounds of CO_2" figure, without putting the number into any context, is unlikely to mean much to the average consumer. The devices could give the number some meaning by comparing it to other uses – such as driving a car or mowing the lawn. Suppliers could provide either average or marginal emissions information. The emission rate per hour (or other rate of time) does not change based on time of day, as it is the household's portion of the total GHG footprint of the utility's generating assets. Marginal emissions would depend on the time of day. If ECDs showed marginal emissions instead of average, consumers could derive context by comparing certain times of day with others and trying to consume when the emission rate was low.

The experiment in this chapter showed that shifting load from peak to off-peak times may be beneficial from a financial standpoint, but it does not always result in lower GHG emissions. Sometimes, increases in off-peak demand will yield higher GHG emissions than peak demand. As the price of electricity does not currently incorporate the social cost of emitting GHGs, real-time pricing programs will always make peak demand more expensive than off-peak demand. (They would likely make peak demand more expensive even with a social cost of GHGs incorporated into the price, but the difference would be less when load-shifting increased emissions.) When off-peak power had higher GHG emissions than peak power, real-time cost and real-time GHG feedback would be in conflict. Consumers trying to reduce both their energy bill and GHG emissions would have to make a tradeoff between the two.

In addition to this conflict, the load profiles of some utilities may make real-time GHG emissions feedback information difficult to use. For example, take a utility with a large proportion of coal in its base load, coal and natural gas in its intermediate load, and natural gas in its peak load. The GHG emissions profile for this utility would be highest for intermediate load, then base load, and lowest for peak load. During off-peak times, the emission rate would be moderate, giving consumers an incentive to consume more electricity. The extra consumption could activate the intermediate load plants, which would increase the real-time GHG emissions. To lower the GHG rate once again, households would naturally decrease demand. However, if they were concerned only with GHG in deciding when to use power, they would actually lower the marginal GHG emissions rate more by increasing demand enough to need the peaker plants. Given the possibility for uneven load profiles and the conflicting types of feedback, it would be simpler for ECDs to use the total household per-hour GHG emission rate instead of the marginal rate. Marginal emission rates may be too much information to be useful to households.

Chapter 6:
Maximizing the Effectiveness of Feedback

6.1 Summary

The objective of this chapter is to determine how policy-makers can use the provision of feedback to target consumer behaviors that will yield the greatest benefits. This chapter expands upon a framework for characterizing appliances developed by Wood and Newborough (2003) to determine where, when, and how appliance-specific feedback could be most effective. It addresses behavioral changes that feedback may induce and identifies specific appliances and regions where the benefits are highest. Previous chapters discussed various reductions in electricity use, but not how consumers actually achieved those reductions (i.e. through increasing the AC temperature setting in the summer or turning off lights more diligently). Due to the way different appliances are used, the jobs they do, and the power they draw from the grid, certain appliances will facilitate energy reductions better than others.

This chapter aims to answer the following research questions:

- How can policy-makers maximize the effectiveness of feedback?
    - Which appliances should policy-makers target for
        1. appliance-specific feedback?
        2. load-shifting?
    - Which regions should policy-makers target to realize the above benefits most effectively?

This analysis finds that the most promising electric appliances for appliance-specific feedback are those that heat water for taps, showers, hot tubs, and waterbeds. The South and Northwest have the highest market penetration of these appliances. The best appliances to target for load-shifting are dishwashers, clothes washers, and clothes dryers. The South and Northwest again are among the regions with highest market penetration for these appliances.

6.2 Motivation and Background

A number of options exist for giving consumers real-time feedback. Earlier discussions focused on centralized feedback as opposed to appliance- or room-specific feedback. However, installing multiple meters in a home is a possibility for achieving greater energy savings. Consumers could sub-meter specific rooms or appliances, such as by putting a separate meter in the kitchen to cover all appliances in the room, or on an electric stove to continually inform the users of their energy use for the appliance. Consumers could also sub-meter at the point of end-use for the appliance. For instance, the AC control may be in the main room of the house near the central feedback display, but one or more displays could also be placed in the rooms that are being cooled.

This chapter will follow three steps:

1. Determine the appliances for which people may alter their behavior to get the largest potential a) conservation and b) load-shifting effects from real-time feedback.
2. Determine which regions have the highest proportion of households with the top appliances from (1).
3. Account for seasonal and peak/off-peak marginal emission rates to determine the best appliances for each region to target, using the results from (1) and (2).

6.3 The Wood/Newborough Framework

Wood and Newborough (2003) examined ECDs from a theoretical perspective and developed a framework for characterizing appliances to explore what the best ways for displaying feedback might be. The authors considered appliance-specific information (ASI) as one option, where a particular appliance has a feedback device attached to it (or perhaps eventually built into the appliance). The authors characterized a number of appliances common in UK homes to determine which would be most suitable for ASI. This analysis expands their framework to cover typical appliances in U.S. homes and also to explore which regions and times

would be best to target for energy reductions from particular appliances.

For this exercise, a high ranking for appliances does not mean that we would reduce the most electricity from them. It means that we have the greatest potential to do so through behavioral changes induced by ASI. For instance, a refrigerator may be able to deliver large savings from feedback. However, these changes will likely be due to reading usage information from a central ECD, because most households do not constantly adjust their refrigerator temperature. For a refrigerator, it is more likely that a person raises the temperature by a couple degrees and maintains the temperature for a long period of time. A continuous energy use meter at the appliances is more helpful for appliances that people use more interactively and can adjust more frequently.

Wood and Newborough group appliances into four categories, based on the level of automation and number of settings for the appliances. Table 6.1 shows the four categories and gives examples of appliances that would be in each category. In general, a low level of automation requires the user to be in close proximity to the appliance when using it. When the number of settings is high and level of automation is low, users interact more with the appliances and have the most options for the level of energy the appliances will consume. Thus, at least theoretically, we can attribute a high potential for saving energy through behavioral changes to appliances in Group 1 and a low potential to the appliances in Group 4. Changing behavior is easier for high-complexity appliances for two reasons (Sauer, Wiese et al. 2003). First, behavioral patterns for using appliances progress from knowledge-based to skill-based more rapidly when operation is less complex. Once a person is operating an appliance using skill-based behavior, the behavior is harder to change. Second, people use instruction manuals less when the appliance is less complex. Therefore, appliances with low numbers of settings — those in Groups 2 and 4 — have associated behaviors that are harder to change using an ECD, while the appliances in Groups 1 and 3 would be better candidates for more feedback.

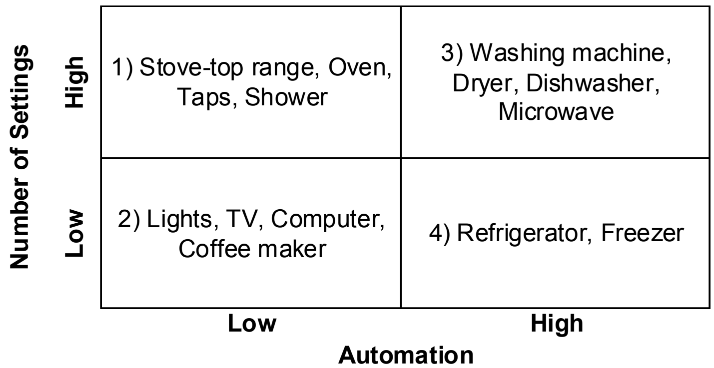


Figure 6.1: Four general categories of appliances based on complexity.

Using an even finer resolution than the four groups, Wood and Newborough rank typical appliances in UK households by how effective ASI would be in reducing energy use from that appliance through behavioral changes. They use three criteria in their ranking:

1) Feasible micro-behaviors, consisting of five micro-behavior factors:
    a. Interactions with controls
    b. Proximity to controls
    c. Interactions with end-use
    d. Proximity to end-use
    e. Applicable energy saving behaviors
2) Appliance control to end-use relationship
3) Annual energy consumption of the appliance

I address each criterion below.

The first criterion (1a-c) is a measure of the complexity of the appliance and the number of behaviors associated with it. Each appliance contains a set of controls, which users manipulate to achieve a desired end use. For example, for a stove, the end use would be cooked food. A shower's end use is hot water and for central AC the end use is a cool room. When a person uses an appliance, to some degree, she interacts with the appliance controls and with the end use. For instance, with an oven range, users "interact" with the burner controls to a relatively high degree while cooking, but with a dishwasher the settings are rarely if ever adjusted during a cycle. Similarly, someone

cooking will "interact" with the food (i.e. check it, stir its contents) to a high degree compared to the dishes getting cleaned, which users will generally only check once the machine stops. Criteria 1a and 1c reflect the degree that the user interacts with the controls and the end-use, respectively, during the energy-consuming behavior.

The proximity of the user to the appliance controls and the end uses will also positively influence the potential feedback effect. Appliances for which both the controls and end uses are continuously seen are televisions, showers, and stoves. These appliances receive the highest score for criteria 1b and 1d. The controls and end uses for appliances like refrigerators, washing machines, and dishwashers can be seen throughout the day but not continuously during the energy consuming event. These appliances receive a lesser score for these criteria. Wood and Newborough hypothesize that the greater the interactions with, and proximity to, both the controls and the end uses, the greater the ability of feedback to alter behavior.

For criterion 1e, Wood and Newborough introduce the concept of a micro-behavior (MB), which they define as a "distinctive behavior within an energy-consuming event (e.g. during a 'water event' the consumer might alter the flow of water or test the temperature of the water with their hand)." MBs could either be related to consuming energy, saving energy, or unrelated to energy use. To understand how feedback may change behavior, Wood and Newborough propose six categories of energy-saving behaviors (ESBs):

1) On/off behavior: users can save energy by manually turning the appliance off. This includes turning appliances off at the appropriate time (e.g. not leaving the television on when not in the room) and turning appliances off from "standby mode," such as a stereo.
2) Energy frugality: users can reduce energy consumption by avoiding excessive power/flow levels. Example: turning the hot water tap down when washing one's face or doing dishes.
3) Time frugality: users can turn appliances off before typical end of use without sacrificing level of service. Example:

ending a timed dryer cycle early if the load is dry or not leaving the refrigerator door open.

4) Fitting behavior: users can match a heat source to the amount of liquid/solid needed to complete a job. Example: Only boiling the necessary amount of water on the stove, or indicating the appropriate-sized wash load on a clothes washer.
5) Inter-appliance behavior: users can choose to complete the same task with an appliance that uses less energy.
6) Reasonable alternative behavior: users can complete the task with a device or method that does not consume energy. Example: hanging clothes on a clothes-line to dry.

Criterion 2, the appliance control to end use relationship, uses the following classification: "High: whilst using controls, user can also detect end use. Medium: end use is enclosed, thus, user must do work to access end use, e.g. open a door etc. Low: user must wait for half an hour or more to gain feedback." (Wood and Newborough 2003). For Criterion 3, yearly energy use figures are for a family of four from the Public Service of New Hampshire (2009).

6.4 Results

Table 6.1 contains appliance rankings for those appliances included in RECS. For appliances in the table that were included in the Wood and Newborough study, I used many of their rankings, but changed some whose scores did not seem consistent with most American households. For appliances not included in the Wood and Newborough study, I generated the rankings for this analysis. Each of the three criteria for the final score is ranked on a scale from 1-5 and the final score is the sum of the three component parts. Score 1 is an average of the 5 sub-scores included in 1a), b), and c) (with the 1-6 scale for part c converted to a 1-5 scale). Score 2 is for the appliance to end-use relationship, scoring 1 for low, 3 for medium, and 5 for high. Score 3 normalizes the yearly energy use in kWh to a 1-5 scale.

Unlike this analysis, Wood and Newborough do not convert rankings into numbers to perform combinatorial functions on the components. They keep

the rankings as "low," "low-medium," "medium," "medium-high," and "high." However, the final rankings for appliances do imply some additive function for the final score, even though it is not described.

	Feasible Micro-Behaviors - Criterion 1						Criterion 2	Criterion 3	
Appliance	Control Interactions	Control in Visual Field	End-Use Interactions	End-Use in Visual Field	Number of Applicable ESBs	Normalized Application of ESBs	Appliance Control to End-Use Relationship	Typical Usage (kWh per Year)	Source
Electric water heater	5	4	5	5	3	2.5	5	3888	W&N
Waterbed heater	3	2	5	5	3	2.5	4	2820	MC
Hot tub, spa, or jacuzzi (indoor)	3	2	5	5	4	3.3	4	1944	MC
Range burners	5	4	4	5	6	5.0	5	288	W&N
Desktop PC	2	5	5	5	2	1.7	5	384	MC
Central electric heating	5	3	4	5	4	3.3	4	864	W&N / MC
Lighting - 5 rooms (10x60W)	1	4	4	5	2	1.7	5	720	MC
Lighting - 3 rooms (8x60W)	1	4	4	5	2	1.7	5	576	MC
Plasma TV	1	5	4	5	1	0.8	5	540	W&N
Central air conditioning	5	3	4	5	4	3.3	4	600	MC
Electric dehumidifier	3	3	4	5	2	1.7	4	1136	MC
Laptop	2	5	4	5	2	1.7	5	84	MC
Big-Screen TV	1	5	4	5	1	0.8	5	348	W&N
Cable box	1	5	4	5	1	0.8	5	300	MC
Stereo equipment	3	3	4	5	2	1.7	5	120	MC
DVD player	2	5	4	5	1	0.8	5	84	W&N
Video game system	1	5	4	5	1	0.8	5	240	MC
Color TV	1	5	4	5	1	0.8	5	192	W&N
Ceiling fan	2	2	4	5	3	2.5	5	108	MC
Coffee maker	4	4	1	3	2	1.7	5	144	MC
Electric humidifier	3	3	4	5	2	1.7	4	308	MC
20+ gallon heated aquarium	2	2	2	4	2	1.7	4	996	MC
Oven	4	4	2	4	6	5.0	3	300	W&N
Electric well pump	2	2	1	2	1	0.8	5	468	MC
Freezer	2	3	1	3	3	2.5	1	2592	W&N
Refrigerator	2	3	1	3	3	2.5	1	2400	W&N
Electric toaster oven	3	4	1	3	4	3.3	3	120	MC
Clothes dryer	3	3	1	3	5	4.2	1	1440	W&N
Microwave	3	3	1	3	2	1.7	3	180	W&N
Clothes washer	3	3	1	3	4	3.3	1	228	W&N
Automatic dishwasher	3	3	1	3	4	3.3	1	120	W&N

Table 6.1: Component scores for appliances for ASI rankings. The "Source" column indicates if the appliance was added and score determined by Wood & Newborough ("W&N"), this analysis ("MC"), or the appliance was added by Wood & Newborough but the score altered in this analysis ("W&N/MC").

Figure 6.2 gives the final results from the table and highlights several important trends. Electrical water heaters use a relatively large amount of energy. When using hot water from taps or the shower, people are close to both the appliance controls and the end use (hot water) and they can employ all six ESBs. The combination of high energy use with the potential for changing behavior makes water heating the top candidate for reducing energy use through real-time feedback; the

appliances with the top three scores on the chart all involve heating water.

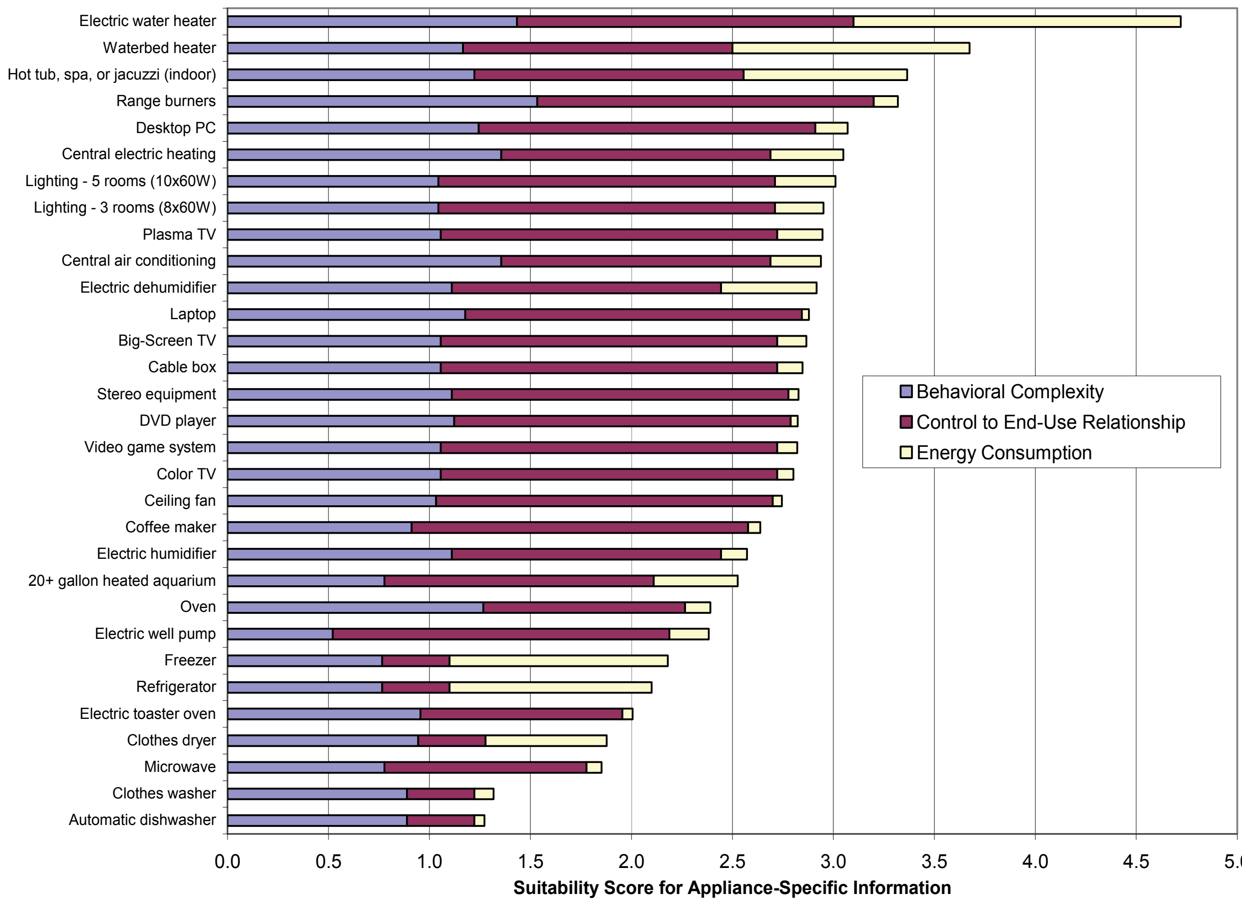


Figure 6.2: Final scores and rankings of appliances for ASI.

After the hot-water related appliances, the stove-top range is next on the list — ranked 4th. Like water heaters, it is characterized by a combination of high energy use and high potential for feedback to change behavior. After range-burners, the next tier of appliances is a mix of devices that use less energy — but which are more suited to having real-time feedback impact their usage — and higher-energy appliances with a more modest potential for behavioral changes. On the lower-energy side are televisions (with the exception of plasma televisions), computers, stereo equipment, and video game systems. Their scores are boosted by the user being close to both the controls and end uses of the appliances while they are using them. The higher energy-using appliances are central heating, AC systems, lighting (8-10 60-Watt bulbs for 3-5

rooms), and dehumidifiers. For lighting and television, the level of behavioral complexity is low as users have a limited number of settings. However, the control to end-use scores are high, because people tend to watch television with the remote in hand and light switches are generally in the same room as the lights. Heating and cooling systems have more behavioral complexity, as users can adjust temperature settings and add or remove clothes to maintain comfort. However, for these systems, one thermostat often dictates the temperature for large portions of the dwelling. Therefore, the thermostat may be in a different area of the house from where occupants spend much of their time. According to the Wood/Newborough framework, this lowers the potential of feedback to change heating and cooling behavior.

6.4.1 Targeting Specific Regions

Now that we have a prioritized list of appliances, we can evaluate the market penetration rate for the appliances in different areas of the country. This information can guide policy-makers to target regions where we would expect ASI for certain appliances to be most effective.

Table 6.2 illustrates the market penetration rate for each appliance for each region of the country. The appliances are in ASI rank order from Figure 1. The green cells indicate the three regions with highest penetration for each appliance and the pink cells indicate the lowest penetration rates. Refrigerators, televisions, and light bulbs had market penetration rates close to 100 percent across all regions (yellow rows in Figure 1). Therefore, Figure 1 lists the average number of these appliances in each region. The row for light bulbs counts bulbs that households self-reported as being on for between 1 and 12 hours per day.

	Region												
Appliance	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Electric water heater	26%	24%	29%	29%	64%	68%	43%	26%	64%	12%	11%	43%	89%
Waterbed heater	2%	2%	4%	1%	1%	2%	1%	3%	2%	1%	1%	4%	1%
Hot tub, spa, or jacuzzi (indoor)	1%	2%	0%	0%	0%	1%	1%	1%	2%	1%	4%	2%	0%
Range burners	64%	47%	53%	65%	72%	79%	51%	58%	84%	30%	35%	54%	92%
Desktop PC	71%	71%	68%	68%	65%	60%	63%	71%	76%	58%	75%	67%	71%
Central electric heating	5%	10%	11%	17%	48%	49%	34%	24%	42%	8%	23%	47%	90%
Bulbs on 1-12 hours/day	3.68	3.91	3.96	4.18	3.69	4.34	3.90	3.83	3.09	3.17	3.55	3.73	2.95
Plasma TV	3%	3%	4%	1%	2%	1%	5%	3%	1%	3%	5%	4%	6%
Central air conditioning	69%	93%	90%	96%	95%	97%	97%	59%	49%	75%	59%	97%	99%
Electric dehumidifier	26%	19%	28%	15%	12%	7%	3%	1%	3%	16%	1%	2%	3%
Laptops	22%	29%	16%	24%	20%	15%	15%	20%	20%	17%	25%	22%	20%
Big-Screen TV	21%	26%	28%	24%	25%	22%	26%	32%	26%	22%	33%	33%	33%
Stereo equipment	71%	66%	73%	75%	68%	70%	65%	78%	77%	73%	74%	72%	73%
DVD player	78%	81%	81%	79%	79%	80%	84%	82%	86%	72%	84%	81%	79%
Color TV	2.33	2.74	2.56	2.52	2.63	2.49	2.38	2.31	2.35	2.24	2.49	2.51	2.56
Ceiling fan	53%	65%	74%	79%	77%	80%	84%	71%	47%	43%	57%	84%	77%
Coffee makers	63%	64%	61%	68%	60%	66%	62%	61%	63%	48%	52%	62%	62%
Electric humidifier	20%	16%	24%	22%	12%	11%	6%	15%	5%	10%	5%	5%	1%
20+ gallon heated aquarium	2%	3%	4%	5%	6%	2%	4%	5%	5%	5%	2%	3%	3%
Oven	65%	48%	53%	66%	74%	82%	55%	60%	88%	32%	40%	61%	92%
Electric well pump	15%	14%	14%	14%	17%	17%	13%	11%	19%	13%	1%	7%	15%
Freezer	22%	27%	37%	47%	38%	42%	42%	39%	43%	15%	17%	27%	17%
Refrigerator	1.22	1.26	1.30	1.31	1.26	1.20	1.13	1.20	1.31	1.19	1.22	1.20	1.18
Electric toaster oven	45%	48%	26%	24%	35%	30%	29%	32%	28%	38%	36%	28%	44%
Clothes dryer	60%	48%	56%	64%	75%	82%	82%	66%	72%	29%	35%	66%	75%
Microwave	78%	94%	91%	90%	87%	84%	92%	96%	92%	82%	85%	86%	84%
Clothes washer	76%	85%	86%	85%	86%	90%	89%	88%	83%	62%	76%	82%	83%
Automatic dishwasher	57%	58%	55%	63%	62%	59%	52%	66%	68%	37%	55%	62%	66%

Table 6.2: Market penetration of appliances by region. Green indicates the 3 regions with the highest levels of market penetration for the particular appliance. Pink shows the 3 regions with the lowest market penetration. Yellow indicates appliances with high levels of penetration in all regions and therefore the value given in the cell is the number of appliances.

Three regions stand out as having several of the top appliances with the highest penetration rates (these columns have more green cells in the top several rows). The regions are Region 6 (Kentucky, Tennessee, Mississippi, Alabama), Region 9 (Washington, Oregon, Alaska, Hawaii), Region 12 (Texas), and Region 13 (Florida). Targeting ASI to the top appliances in these regions is likely to have the greatest impact on behavior.

The regions with the lowest market penetration rates of the top-ranking appliances are Region 2 (Pennsylvania, New Jersey), Region 4 (North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri), Region 7 (Oklahoma, Arkansas, Louisiana), and Region 10 (New York).

6.4.2 Load-Shifting

Three appliances have flexible functionality, meaning timing does not matter and the functions of the appliances would be the same whether households used them during peak or off-peak times. The appliances are dishwashers, clothes washers, and clothes dryers. For these three appliances, delayed feedback – perhaps in conjunction with dynamic pricing – could work to convince households to use the appliance during off-peak times. Table 6.3 shows the percentage of households in each region that have each appliance. The light green shading indicates the regions with the highest portion of households that own the appliance and pink indicates the lowest portions. Regions 6-8 appear to be best for targeting households to shift the loads of the three appliances, while targeting households in Regions 10 and 11 might be less effective due to lower penetration rates.

Region	Clothes Washer	Clothes Dryer	Dishwasher
1: ME, VT, NH, MA, RI, CT	76%	60%	57%
2: PA, NJ	85%	48%	58%
3: WI, IL, IN, MI, OH	86%	56%	55%
4: ND, SD, NE, KS, MN, IA, MO	85%	64%	63%
5: DE, MD, DC, WV, VA, NC, SC, GA	86%	**75%**	62%
6: KY, TN, MS, AL	**90%**	**82%**	59%
7: OK, AR, LA	**89%**	**82%**	52%
8: MT, ID, WY, NV, UT, CO, AZ, NM	**88%**	66%	**66%**
9: WA, OR, AK, HI	83%	72%	**68%**
10: New York	62%	29%	37%
11: California	76%	35%	55%
12: Texas	82%	66%	62%
13: Florida	83%	75%	66%

Table 6.3: Percentage of households in each region with listed appliance. Green and pink are the highest and lowest 3 regional market saturation levels for each appliance.

From the perspective of reducing GHG emissions, we may use the data from Table 5.1 (GHG emissions increases/decreases from shifting load from peak to off-peak hours) to determine the impact on GHG emissions using the three appliances in Table 6.3 during off-peak instead of peak hours. Table 6.4 shows the pounds of CO_2 averted per day per household from shifting appliance usage from peak to off-peak hours. The calculations utilize appliance load data (kWh per load) and usage data (loads per

day) from EPA. Green shading indicates positive CO_2 benefits from shifting the appliance load of more than 0.05 lbs CO_2 per day per household. Yellow indicates small positive benefits – between 0.00 and 0.05 lbs CO_2 per day. Red shading indicates negative CO_2 benefits of any size.

Region	Pounds CO_2 Averted Per Day Per Average Household								
	Clothes Washer			Clothes Dryer			Dishwasher		
	Summer	Winter	Spring/Fall	Summer	Winter	Spring/Fall	Summer	Winter	Spring/Fall
1	0.08	0.02	0.16	0.07	0.01	0.14	0.05	0.01	0.10
2	0.08	-0.04	0.00	0.04	-0.02	0.00	0.04	-0.02	0.00
3	0.02	-0.02	0.04	0.01	-0.01	0.02	0.01	-0.01	0.02
4	-0.06	0.00	-0.04	-0.05	0.00	-0.03	-0.04	0.00	-0.02
5	-0.02	0.00	0.03	-0.02	-0.01	0.03	-0.01	0.00	0.02
6	-0.05	-0.01	0.09	-0.06	-0.01	0.11	-0.02	-0.01	0.04
7	-0.10	0.09	0.04	-0.13	0.12	0.05	-0.04	0.04	0.01
8	0.19	0.06	-0.11	0.16	0.05	-0.09	0.11	0.03	-0.07
9	1.14	0.00	-0.01	1.25	0.00	-0.01	0.81	0.00	-0.01
10	0.01	0.01	-0.02	0.00	0.00	-0.01	0.01	0.00	-0.01
11	0.00	-0.02	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00
12	0.09	0.00	0.03	0.09	0.00	0.03	0.06	0.00	0.02
13	0.12	-0.02	0.08	0.14	-0.02	0.10	0.08	-0.01	0.06

Table 6.4: Pounds of CO_2 averted per day per average household from shifting appliance usage from peak to off-peak times.

From a policy perspective, in the absence of a variable rate pricing schedule, it would be easier to persuade households to shift their appliance loads for the entire year and not just for certain months of the year. For Regions 1, 2, 8, 9, 12, and 13, it appears that the reductions in GHG emissions from shifting load would more than compensate for the increased emissions during parts of the year. For the other 7 regions, from an environmental perspective, the load-shifting benefits for the three appliances are more ambiguous.

Chapter 7:
Summary and Conclusions

7.1 Summary

This dissertation has addressed a number of questions regarding the potential for feedback to reduce electricity use in the residential sector. Chapter 2 analyzed the impact of programmable thermostats on energy use, focusing on residents' knowledge of climate control settings in the dwelling. In addition, it examined several demographic characteristics (the same characteristics as Chapter 4) to determine whether PTs had different impacts on various sub-populations. The analysis found that of households with natural gas heating systems, young households with PTs used 17 percent less heating energy on average. In addition, residents who did not know their thermostat settings tended to use 10 percent more energy for heating. Neither of these findings had been previously reported in the literature.

Chapter 3 reviewed the literature related to feedback and its impact on energy use. In general, the literature finds that feedback can reduce electricity consumption in homes by 5 to 20 percent, but that significant gaps remain in our knowledge of the effectiveness of feedback. These gaps include how different types of consumers will respond differently to feedback. Chapter 4 used these key uncertainties from the literature and performed an exploratory analysis to determine the conditions under which the benefits of feedback outweighed the costs. It also compared the cost-effectiveness of providing feedback against that of other DSM programs. It found that moderate levels of conservation – comparable to the median level found in experiments in the literature - would be necessary for benefits to outweigh costs for enhanced billing and real-time feedback. Also, assuming these forms of feedback could realize median conservation levels, cost-effectiveness was competitive with other DSM programs. For disaggregated feedback, the wide range of cost estimates necessitates moderate to very high levels of conservation to break even on purchasing the high-end feedback meters (and service plans where applicable). Cost effectiveness for

this type of feedback was competitive with other DSM programs under some scenarios in some regions.

Chapter 5 examines the question of what form environmental feedback should take in the case of a real-time pricing program. It finds that to be as useful as possible to consumers, feedback should utilize total household emission rates instead of marginal emission factors. The reason is that load-shifting helps utilities save money, but emissions from peaker plants are not always less than those from intermediate load plants. Chapter 6 used a method developed by Wood and Newborough (2003) to determine which appliances should be targeted for appliance-specific feedback.

7.2 What Story Do the Results Tell About Feedback?

This dissertation has shown that although the CE of feedback is uncertain and the effectiveness will likely vary substantially from household to household, the conservation levels necessary for comparable cost effectiveness with other DSM programs are realistic and obtainable. The favorable CE estimates hold up over all ranges for the uncertainties for real-time feedback – both for median and highest-N conservation levels. For enhanced billing, the favorable CE estimates hold up only for median conservation levels. For conservation levels from the largest enhanced billing study, the CE estimates are favorable for certain regions and uncertainties, but not all. The CE figures, however, will depend on the cost of enhanced billing programs. The estimates for this study were $12-20 per customer per year and it is possible that the marginal cost for each additional customer may decrease dramatically once a program is established.

The regions with the highest electricity usage naturally show the best average cost-effectiveness. These regions are the South – from the southern Atlantic coast west to Texas – and the Northwest. The South tends to be warmer - leading to more electricity use for AC. Both the South and Northwest use more electricity (relative to other fuels) for heating than other regions and have higher energy intensity than other regions of the country as well. As several studies have found, if

households with higher energy intensity and income conserve a higher percentage of their total electricity use when they have better feedback then enhanced billing will be cost-effective for not only the South and Northwest, but also Western Mountain and Great Plains states.

Disaggregated feedback does not appear to be cost-effective at this point in time for feedback systems that individually monitor every outlet in the dwelling. However, residents may monitor appliances or sockets one by one to reduce costs and only monitor the appliances for which use would be changed most by real-time feedback. One potential feedback disaggregation strategy would be to given appliance-specific feedback at the appliance and not at the central display. Appliances that are most promising for this type of feedback are those that have a combination of high yearly energy use and large number of energy-saving behaviors associated with them. These include hot water taps, showers, hot tubs, and waterbeds. Other appliances on the next tier down are range burners, personal computers, lighting, and central heating systems. Utilities should consider encouraging real-time feedback with several individually-monitored appliances until the costs for complete disaggregation are lower.

Real-time feedback has benefits over enhanced feedback, whether the real-time feedback is disaggregated or not. First, it should enhance other demand-response and DSM programs, including making users more responsive to RTP programs and bringing the consequent benefits of load-shifting. Second, it probably has a greater effect on appliance purchasing decisions, as households can see the contribution to total energy use of each individual appliance on a continuous basis. Third, real-time feedback can be more easily customized for individual households. If a device can provide feedback every few seconds, it can also provide it hourly, daily, weekly, or monthly. With the proper software to manipulate data, ECDs could present usage patterns in formats most helpful to each individual household.

7.3 The Future of Feedback

Installing real-time feedback devices and ECDs in dwellings could have an impact on current levels of electricity use and also lay the foundation for future advancements in home energy management. Hybrid and full-electric vehicles are reaching the market and could soon comprise a substantial portion of automobile sales. The vehicles will add demand to the grid and it will be important to try to control times at which consumers recharge their cars so that peak load does not increase to the point that more peak capacity is needed to meet a very infrequent level of demand.

Energy efficiency and demand response programs give utilities some ability to reduce overall and peak usage. Better feedback could increase the programs' effectiveness by informing consumers of their immediate usage and also by beginning to integrate the two types of programs. Generally, households make decisions on energy efficiency on an appliance-by-appliance basis and make decisions on which optional rate structure (demand response) to enroll in separate from the energy efficiency decisions. These decision-making processes are actually small-scale optimizations, as households attempt to maximize their utility subject to a budget constraint.

The separation of energy efficiency and demand response decision-making is evident in the internal structure of utilities. In the case of California's IOUs, separate divisions handle the two types of programs and they have traditionally marketed the programs separately and not in combination. Over the last two years in California, this approach has begun to change with the promotion of Integrated Demand Side Management. The CPUC is encouraging efforts of the IOUs to market their programs together, thereby combining resources and increasing cost-effectiveness.

Instead of optimizing on the basis of one appliance at a time, consumers could eventually make more holistic energy decisions based on detailed data on usage patterns and existing appliance efficiency levels. Given a household's recorded usage patterns, appliance stock,

and discount rate, automated optimization algorithms could give advice on which appliances to update and which rate plan to use. This optimization could extend to advice on self-generation options, such as rooftop photovoltaics, and physical improvements to the dwelling, such as new insulation.

Eventually, as feedback becomes more commonplace, the same devices that display electricity feedback could also display natural gas and water usage information so that households could keep track of – and reduce – all energy and water inputs. The optimization process could extend beyond just electricity to all energy and water inputs.

Feedback on ECDs within the home could begin to lead to more interaction with utilities. Once feedback devices are installed and utilities determine which types of households respond best to which types of feedback, they could develop programs to challenge customers with conservation goals or competitions. Chapter 3 found that both goals and peer comparisons were factors that influenced the effectiveness of feedback. Many possibilities exist for using feedback to influence the timing and level of electricity usage and more will likely be discovered if and when feedback systems are more widespread.

7.4 Opportunities for Future Study

A number of opportunities exist to further the deployment of advanced metering infrastructure – including ECDs - and its ability to interact with consumers.

- Researchers should study the effectiveness of online feedback for customers with smart meters. Online tools generally present usage data to consumers in 15-minute to 1-hour intervals. Some customer classes may prefer this type of feedback and use it to realize comparable demand reductions to ECDs. Utilities can evaluate ECD deployment plans based on results of these studies.
- Consumers may be willing to allow utilities to curb their peak demand in exchange for lower rates. Utilities could potentially lower demand for individual households by raising AC cooling or refrigerator temperatures by a few degrees. Researchers should

examine which types of consumers would allow their utility to automatically lower their demand and also which types of appliances these households would prefer having the utility partially control. Feedback could be one aspect of this study, as it would help consumers determine which appliances use the most energy and thus would help utilities reduce demand by the largest amount feasible.

- Feedback in commercial and industrial buildings has not been well-studied. Manufacturing facilities are likely to keep good track of power usage, but opportunities could exist for lowering demand in office settings with a combination of incentives and better feedback.

7.5 The Broader Context: Regulating a Smarter Grid

In the U.S., gains are being made on the policy front toward encouraging the provision of feedback. The Energy Independence and Security Act of 2007 established official U.S. policy for supporting the Smart Grid, including the "provision to consumers of timely information and control options."

At the state level, in California, SB 17 became law on January 1, 2010 and ordered the state's three investor owned utilities (IOUs) to submit Smart Grid Deployment Plans by July 1, 2011. The deployment plans must "[promote] a 'Smart Customer' who is informed, empowered and able to use electricity efficiently and in ways that promote environmental goals." The CPUC is now in proceedings (R-08-12-009) to further guide the development of California's smart grid.

As smart grid technology becomes more widespread, state policy-makers should examine whether state policies and regulatory structures are designed appropriately to accommodate the changes to the grid and the impending generation of large quantities of usage data. This analysis showed that bill savings in the range of $200 per year are feasible for some households with better feedback. One upcoming issue will be whether current regulatory policies establish incentives to realize

these savings and which entities - consumers, utilities, or third parties - will be driven to do so.

Decoupling electricity rates at the state level could improve the incentive for utilities to install more advanced technology, such as ECDs. "Decoupled" rates refer to state regulatory structures in which the revenue of a utility is not tied to its sales. For instance, in California, which has decoupled rates, IOUs earn a fixed rate of return on their capital investments and operations and maintenance expenses. Rates are determined in conjunction with the CPUC based on the projected level of sales and the amount of revenue the utility would need to earn the fixed rate of return.

Decoupling rates removes the inherent disincentive for utilities to reduce electricity use. However, in itself, it is not an adequate incentive for utilities to help their customers reduce usage. The existing incentive comes from state laws requiring utilities to implement DSM programs and providing financial bonuses for achieving program targets. One policy innovation being tested in California is the opening up of the demand response market to third party "aggregators," who will be able to sell peak demand response (i.e. reductions from peak users) on the wholesale market.

As more households get better feedback on usage and meters that can communicate with the utility, and the grid becomes smarter, the relationship between utilities and their customers will fundamentally change. Apart from bill savings from better feedback, enhanced automation in the smart grid should enable a number of benefits, including improved system reliability and stability, lower transmission costs, and better integration of renewable energy and energy storage. The proper regulatory structure should allow utilities the flexibility to adapt to a rapidly changing market, while providing the proper incentives for utilities, their customers, and/or third parties to realize the maximum benefits from the new technology.

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