RESPONSIVENESS OF RESIDENTIAL ELECTRICITY DEMAND

TO CHANGES IN PRICE, INFORMATION, AND POLICY

A Dissertation
Presented to
The Academic Faculty

by

Youngsun Baek

In Partial Fulfillment
of the Requirements for the Degree
Doctor in Philosophy in the
School of Public Policy

Georgia Institute of Technology
May 2011

RESPONSIVENESS OF RESIDENTIAL ELECTRICITY DEMAND TO CHANGES IN PRICE, INFORMATION, AND POLICY

Approved by:

Dr. Marilyn Brown, Advisor
School of Public Policy
Georgia Institute of Technology

Dr. Paul Baer
School of Public Policy
Georgia Institute of Technology

Dr. Laura Wheeler
School of Public Policy; Fiscal Research Center
Georgia State University

Dr. Douglas Noonan
School of Public Policy
Georgia Institute of Technology

Dr. Valerie Thomas
Joint appointment with the School of Industrial and Systems Engineering
Georgia Institute of Technology

Date Approved: March, 10, 2011

ACKNOWLEDGEMENTS

I wish to thank Professor Marilyn Brown for her guidance and support throughout the whole dissertation process. I am deeply thankful for her comments and insightful feedbacks on many drafts preceding this final work. Dr. Brown provided valuable guidance and helped me build the necessary confidence to challenge myself during the process. Her commitment as my advisor and chair of the dissertation committee was critical for the successful completion of the dissertation project.

Valuable comments on econometric analysis and policy discussions were received from Professors Noonan, Baer, Thomas, and Wheeler. During the course of the NEMS experiments, Steve Wade and John Cymbalsky at EIA, and Stan Hadley at ORNL provided comments on energy simulation techniques. I also thank my friends for their love, support, and understanding throughout this challenging and fascinating journey of graduate education – team mates (Joy Wang, Yu Wang, Rodrigo Cortes, Diran Soumonni, Matt Cox, Ben Deitchman, Etan Gumerman, Xiaojing Sun, and Lizzie Noll) and my buddies Li Tang, Soyoung Park, Yeonji No, Sungsoo Oh, and Taehyun Jung.

Finally, I thank my loving parents and brothers who have been my great source of support and inspiration. They have my unconditional love and gratitude.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BAU	Business as Usual
EIA	Energy Information Administration
GT-NEMS	Georgia Tech version of National Energy Modeling System
MLE	Maximum likelihood estimation
NEMS	National Energy Modeling System
OLS	Ordinary Least Square
RDM	Residential Demand Module
RECS	Residential Energy Consumption Survey
RES	Renewable Electricity Standards

SUMMARY

This study analyzes consumers' behavioral responsiveness to changes in price and policy regarding residential electricity consumption, using a hybrid method of econometric analyses and energy market simulations with the National Energy Modeling System (NEMS). First, this study estimates price elasticities of residential electricity demand with the most recent Residential Energy Consumption Survey (RECS) data, collected in 2005, employing a conventional econometric model and a discrete/continuous choice model. Prior to the NEMS experiments with price shocks and consumers' behavioral features, this study uses NEMS to examine how energy policies would affect changes in retail electricity price in the future.

When climate policies are implemented nationally, electricity prices are estimated to increase by 17% in 2030 with a carbon cap and trade initiatives and by 4% with Renewable Electricity Standards (RES). The short-run elasticity of demand estimated from the 2005 RECS is found to be in a range of –0.81 ~ –0.66, which is more elastic than the current NEMS assumption of –0.15. The 2005 RECS dataset details information about American households' energy consumption. This rich source of micro-level data complements the existing econometric analysis based on time series data.

Electricity price (either census-division average price or household average price), annual income and number of rooms are found to be three major determinants of the level of electricity consumption. The difference in short-run price elasticity leads to a difference in social welfare estimates of energy policies and energy market forecasts. This study suggests that the estimate of social welfare loss caused by electricity price increase is overestimated if the elasticity is assumed to be smaller than the actual responsiveness. Supposing that 1) the short-run elasticity of –0.66 reflects the actual consumers' responsiveness to price changes in the present and future and 2) retail

electricity prices permanently increase by 10%, the welfare loss caused by the price increases would be estimated 0.9 billion dollars less than the current estimates with the elasticity of –0.15. This result suggests that if people are assumed to be more elastic to price signals, the time it takes for a policy to accomplish its goal could be shorter.

In addition to assessing potential savings expected from consumers' behavioral changes with the concept of price elasticity of demand in neoclassical economic theory, this study reviews economic and non-economic theories about behavioral features of energy consumers and discusses how existing information programs could be improved.

CHAPTER 1

INTRODUCTION

Traditional energy policies have focused on price changes such as tax credits and subsidies for energy-efficient goods and on information disclosure such as energy-use labels on appliances (Allcott and Mullainathan, 2010). How the demand for a fuel is affected by its price changes determines the effectiveness of the price, subsidy, and tax policies. For that reason, energy policy makers have sought to understand behavioral patterns of consumers so as to design effective energy pricing policies. Previous studies have argued that a better comprehension of how consumers respond to price increases is important to build a safeguard against sudden supply shock that might occur in the future (Rajeev, 1994). Even though it is well known that the typical household adjusts its energy consumption in response to price changes even over short durations, policy makers do not seriously recognize this fact because clear and unambiguous evidence of such behavior has been lacking (Reiss and White, 2005). One of the reasons that these debates are persistent is that few prior studies document how quickly households respond to energy price shocks (IEA, 2005a, 2005b; Reiss and White, 2005).

On the other hand, many countries have devoted substantial public resources to research and development (R&D) for energy-efficient technologies and to information disclosure programs for the public since energy efficiency depends on these technological developments and the choices of users. In general, the level of energy efficiency in a society is lower than the socially optimal level because there exists a gap between the socially optimal level of energy efficiency and the actual observed energy efficiency. This "efficiency gap" can be explained with some market failure and behavioral failures in the energy market (Hirst and Brown, 1990). Implicit discount rates to consumers may be higher than the market discount rate. Consumers may weigh present and visible cash flows against uncertain future flows. The gap could occur with some hidden costs, such as search costs (Jaffe et al., 2004), or with the irreversibility of energy efficiency investment (Hassett and Metcalf, 1995 &1993; van Soest and Bulte, 2000). Some informational barriers may occur when consumers do not have enough usable information to make investments that are in their own best interests. Even when a bounty of information is available to consumers, the information is often presented in terms that are not specific enough to be useful or to drive change. For these reasons, a comprehensive understanding about consumers' behavioral characteristics is a prerequisite for effective policy design.

Along the guidelines of the literature, this study probes how energy consumers in the residential buildings sector respond to changes in electricity price in the short run, and analyzes how energy policies and short-run behavioral attributes affect changes in demand and social welfare in the long run. This study discusses these issues around residential electricity demand, price, and policy, answering the four questions listed below:

Q1. How do households respond to changes in electricity price in the residential buildings sector in the short-run?

Q2. Do existing and future energy policies affect residential electricity prices?

Q3. How does the short-run responsiveness (elasticity) influence the long-run demand forecast?

Q4. How do assumptions of consumer behavior affect the ex ante evaluation of policy options?

Q1 is answered in Chapters 2, 3, and 4 by a literature review and estimations of short-run price elasticities. Q2 is discussed in Chapter 5. A set of simple and preliminary NEMS simulations is run to answer this question in Chapter 6. NEMS experiments with various scenarios about price changes and short-run price elasticities are conducted. The first section of policy implications in Chapter 7 discusses how the assumptions about consumer behavior influence the ex ante evaluation of policy options with an example of carbon tax. The concept of consumer surplus is borrowed from economics to explain this relationship.

To answer the questions listed above, this study employs a sequential hybrid approach in addressing this topic. First, this study discusses various econometric analyses using cross-sectional data, and empirically estimates a short-run price elasticity of electricity demand based on the Residential Energy Consumption Survey (RECS) data collected in 2005. Second, this research reviews economic and non-economic theories to understand behavioral features of energy consumers. Third, it probes energy policies that could have a potentially large impact on electricity price and consumption in the future. For this analysis, national climate policies, residential energy efficiency policies, and electricity pricing policies are reviewed. This study then uses the National Energy Modeling System (NEMS) to forecast how national electricity consumption of the residential sector would change in the long run as consumer behavioral patterns and energy policies change. Based on the consumption and price projections, long-run elasticities are calculated and changes in social welfare are estimated in the last chapter. A better comprehension of the relationships among the short-run and long-run elasticities and the involvement of technology shifts could contribute to improving demand-control programs in the residential sector.

As shown in Figure 1.1, variables and concepts discussed in separate chapters are interconnected with causality. Chapter 2 reviews economic models that analyze residential energy demand with cross-sectional data, and Chapter 3 estimates price elasticity of residential electricity demand with a traditional econometric model and a dicrete/continuous choice model. Chapter 4 discusses consumer behavior through various economic and non-economic theoretical lenses. In Chapter 5, this study turns to discussions about energy policies that could have potentially large impacts on residential energy consumption and price. Chapter 6 presents research designs and findings from the NEMS experiments and shows how long-run electricity demand changes in response to price shocks and consumers' short-run behavioral features. The dissertation ends with policy implications and conclusions.

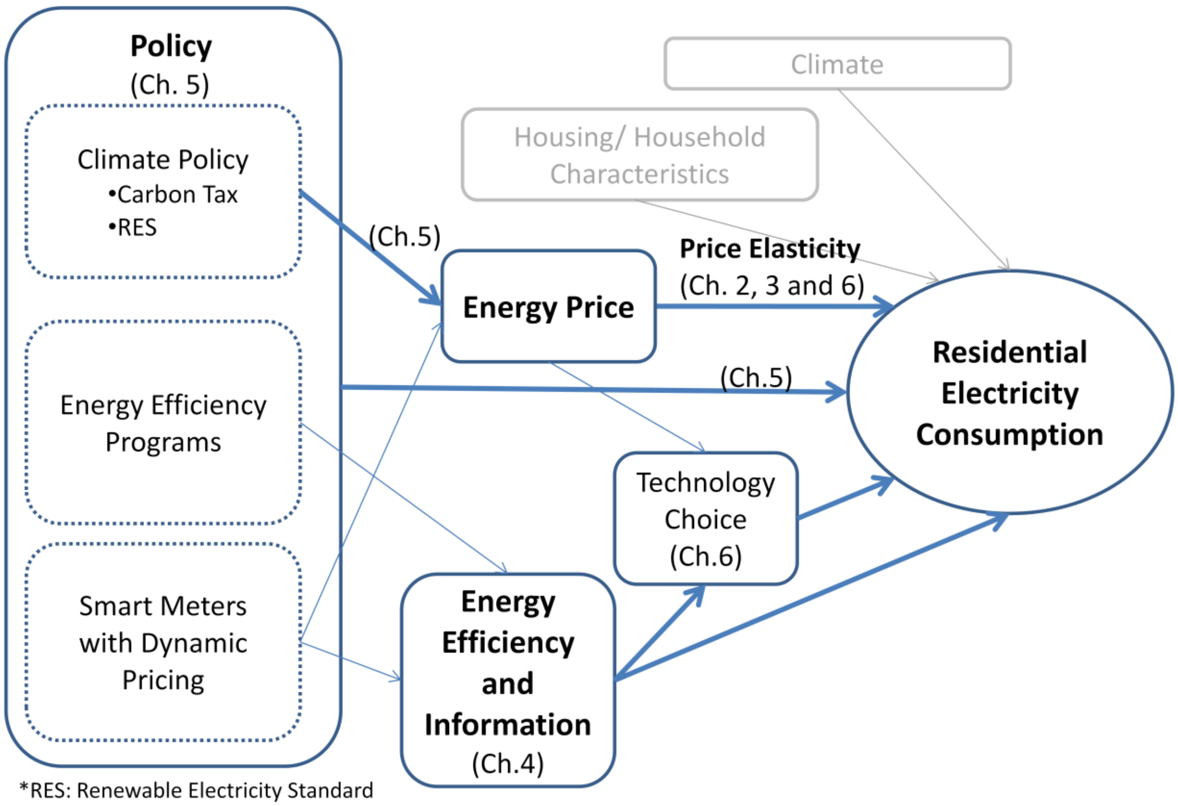

Figure 1.1 Conceptual Framework

CHAPTER 2

A REVIEW OF PRICE ELASTICITY ESTIMATION

2.1 Responses to Price Changes

This study reviews existing literature on price elasticity of energy demand. This review focuses on electricity demand, the residential sector, and cross-sectional data analysis, which are my research interests.

Price Elasticity of Demand

The price elasticity of demand for energy commodities has important policy implications for environmental, energy, and taxation policies since it is a comprehensive indicator of consumer behavior (Rajeev and Morey, 1993; Rajeev, 1994; Hughes et al., 2008). Price elasticity of demand is defined as the percentage change in quantity consumed divided by the percentage change in price. It is generally measured using the logarithmic percentage change formula given by Equation 2.1:

$$Elasticity = \frac{\ln \frac{Q_1}{Q_2}}{\ln \frac{X_1}{X_2}} = \frac{(\ln Q_1 - \ln Q_2)}{(\ln X_1 - \ln X_2)} \qquad \text{[Equation 2.1]}$$

where Q_1 and X_1 are base quantity and price, respectively, and Q_2 and X_2 are an alternative combination of quantity and price. Price elasticity is seriously considered when policy makers determine tax and subsidy rates and estimate the marginal social cost of a price change in each energy commodity (Rajeev, 1994).

Since the Organization of Petroleum Exporting Countries (OPEC) imposed an embargo on petroleum exports in 1973, the U.S. federal government has tried not to depend on foreign energy supplies and finally passed the Energy Independence and

Security Act (EISA) in December 2007. Academia also realized the importance of energy market forecasting and analyzed the responsiveness of energy demand to market changes (Rajeev and Morey, 1993; Rajeev, 1994). Previous studies have argued that a better comprehension of how consumers react to price increases is important for building a safeguard against sudden supply shocks that might occur in the future (Rajeev, 1994).

Responsiveness to Average and Marginal Prices

Standard economic theories on demand forecast posit that a household's electricity demand is responsive to marginal price. Carter and Milon (2005) say, "A key assumption in the price specification debate is that households are well-informed or behave as-if they are." If consumers are given prices regardless of quantity consumed, the marginal price is constant and equal to the average price of the market. However, this situation seldom occurs. Block pricing schemes, which depend on the quantity consumed, are common these days. Regarding block pricing, the previous literature has discussed which of marginal or average price should be entered into the econometric model of demand (Carter and Milon, 2005; Espey and Espey, 2004). Taylor (1975) included marginal price in his model and introduced a variable that accounts for the lump-sum transfers implied by block rates and proposed ways to test the marginal price vs. average price models.

Because of the theoretical background based on neoclassical economics, a majority of studies argue that marginal block price and consumption are simultaneously determined (Halvorsen, 1975; Burtless and Hausman, 1978; Espey and Espey, 2004). McFadden et al. (1978) presented an alternative instrumental variable (IV) approach, whereby observed electricity usage was regressed on dwelling and household characteristics and the typical bills. The predicted quantities and the rate schedule are used to form the predicted price variable, which serves as an IV for marginal prices.

However, the use of marginal price is appropriate only when consumers are fully aware of, and therefore respond to, the marginal price of the nonlinear price schedules that utility companies use (Reiss and White, 2005). For that reason, energy demand is sometimes assumed to depend on average price (Metcalf and Hassett, 1999; Alberini et al., 2010; Fell et al., 2010). Foster and Beattie (1981) argued that households are more likely to respond to the average price, because this requires knowledge of only the total bill and the total consumption. Many studies show that a majority of consumers do not know the marginal energy rates. Brown, Hoffman and Baxter (1975) found that only 4.4% of households knew their marginal prices of electricity. Similarly, Carter and Milon (2005) found that only 6% of households knew their marginal prices of water. In some cases, many individuals showed some cognitive difficulty in understanding nonlinear price structures, and many of them used their average prices rather than actual marginal prices to make their decisions (Brown, Hoffman, and Baxter, 1975; Carter and Milon, 2005). More recently, Borenstein also (2008) found that consumers respond to average price rather than marginal price or expected marginal price. Shin (1985) tested an alternative hypothesis of the average price perception against marginal price. The empirical results support the hypothesis that consumers respond to average price rather than actual block marginal price.

Moreover, almost all of the energy data sources, such as the EIA and the U.S. Bureau of Labor Statistics, provide only the average prices by state, census division, or the nation. Zarnikau (2003) used the average prices of electricity and natural gas of residential energy consumers in each state in 1994 provided by EIA's State Energy Price and Expenditure Report database. The respondents were assumed to face the statewide average prices of electricity and natural gas. Hughes et al. (2008) estimated the short-run price elasticity of gasoline demand and used U.S. city average prices for unleaded regular fuel in 2006 from the U.S. Bureau of Labor Statistics. Puller and Greening (1999) used the same data as Hughes et al. (2008) to analyze how households adjust to gasoline price changes with nine years of U.S. survey data.

Distinction between Short-run and Long-run Elasticities

Based on a broad international survey, Bohi (1981) summarized that short-run energy demand is typically found to be less elastic to own-price changes than long-run demand. The short run is defined as a period of time in which the quantity of at least one input is fixed and the quantities of the other inputs can be varied. The long run is a period of time in which the quantities of all inputs can be varied. By responding to a price movement, the short-run elasticity measures immediate responses, such as changing energy consuming habits, and the long-run elasticity measures total responses, including technology shifts (appliance changes). The short-run and long-run distinctions vary from one appliance to another. In other words, short-run changes may depend principally on changes in consumption of energy services, whereas long-run changes include greater alterations of the energy efficiency of the equipment stock (Gillingham, Newell, and Palmer, 2009). The energy demand of a home is generally determined by equipment efficiency, fuel prices, income, appliance prices, climate, and household and housing characteristics. In the short run, households generally control their energy consumption by changing their energy-use habits. Thus, in the short-run model, fuel switching or technology upgrades are rare and insignificant, in that fuel or technology conversion accompanies a necessary capital stock replacement that is generally observed in the long-run model (EIA, 2003; Wade, 2003). In the long run, however, consumers adjust to price increases by improving equipment efficiency or by changing technology or even fuel type. On balance, in the long-run model, responses to energy price variations in residential building equipment stocks and fuels are considered to occur endogenously. Thus, long-run price elasticities are larger than short-run elasticities because energy efficiency improvements can be considered capital turnover in the long run. Long-run responses are determined by equipment costs, equipment efficiencies, energy prices, discount rates, maintenance costs, and annual equipment-utilization rates (Wade, 2003). In residential energy demand, the input variables of appliance types and building shell types are the most resistant variables.

Price Elasticity of Demand in the Residential Buildings Sector

Whereas many studies analyze price elasticities of transportation fuels such as gasoline, relatively few studies have conducted price elasticity analyses of residential energy use. Most of the econometric studies of residential electricity demand that do exist were conducted primarily during the 1970s and early 1980s, when energy prices were increasing rapidly and concerns about energy conservation were first being raised. The spectrum of price elasticity estimates is broad, and there is no consensus regarding the magnitude of price elasticities of demand for electricity (Espey and Espey, 2004; Athukorala and Wilson, 2010). To quantitatively summarize the studies of residential energy demand, Dahl conducted a meta-analysis in 1993. The EIA supported the research and has utilized the findings to set the assumptions for identifying household demand functions in the NEMS. The meta-analysis conducted by Dahl (1993), "A survey of energy demand elasticities in support of the development of the NEMS," aggregates and summarizes the range of residential elasticities based on four previous studies (listed in Appendix A of this research) and analyzes mainly price elasticities of electricity and natural gas demands. The meta-analysis classifies the previous studies into static, dynamic, and structural models. Based on the meta-analysis, the short-run price elasticity of demand is set at either 0 or –0.15 by end-use service in the Residential Demand Module (RDM) in NEMS: space heating (–0.15), water heating (–0.15), and cooling (–0.15).

A small number of studies on price elasticity of residential energy demand were conducted after the 1990s. Reiss and White (2005) conducted a study of California household price response between 1993 and 1997 and found that 44% of households exhibited no short-run price response. This means that the households did not respond to electricity price changes by changing their energy consumption habits. The heterogeneity of price elasticities across households is primarily attributed to differences in appliance holdings. While the own-price elasticity for households without an electric space heater or a central or room AC is –0.08, households that have central AC are eight times (–0.64) more elastic, and those that have electric space heaters exhibit even higher elasticities (–1.02) than those that do not have them (Reiss and White, 2005).

The broad spectrum of estimates can create confusion without more detail about the differences in the data and analytical techniques utilized. Responding to the research demand, Espey and Espey (2004) conducted a meta-analysis with short-run price elasticity estimates ranging from –2.01 to –0.004 with a mean of –0.35 and long-run price elasticity estimates ranging from –2.25 to –0.04 with a mean of –0.85. The base model used for comparison in the meta-analysis is generally used for price elasticity estimation and is a double-log, static, reduced-form OLS model using annual cross-sectional time-series data for the aggregate United States and a marginal price for electricity.

One of the most hotly debated issues in the literature of price elasticity is price specification, as discussed in the previous section. Economic theories suggest that the use of marginal price is ideal. However, average price is often the only price data available. These meta-analyses can be used to guide such analysis of energy demand and to provide confidence bounds or adjustment to estimates derived with less than ideal data, for instance, aggregated data or average prices. Table 2.1 presents the ranges of own-price elasticity estimates analyzed in the two representative meta-analyses of residential electricity demand: Dahl’s (1993) and Espey and Espey’s (2004).

Table 2.1 Ranges of Estimates of Electricity Own-price Elasticities

Short Run		Long Run	
Range	Reference	Range	Reference
0.14~0.44	Dahl (1993)**	0.32~1.89	Bernstein and Griffin (2006), Hsing (1994)
0.004~2.01 (mean of 0.35)	Espey and Espey (2004)***	0.04~2.25 (mean of 0.85)	Espey and Espey (2004)

*Absolute values shown; all values are negative
** Dahl's (1993) meta-analysis incorporates research results from previous studies conducted from the late 1970s to early 1990s. The previous works applied a variety of methods to estimate the elasticity values.
*** Espey and Espey's (2004) analysis includes a wider range of studies conducted from 1971 to 2000.

2.2 Estimation and Interpretation of Models of Energy Demand

Conventional Econometric Models with Cross-sectional Data

Standard economic theory posits that the demand for energy at the residential level depends on energy prices, the prices of other goods, income, and other characteristics of a household (Deaton and Muellbauer, 1980). Variables commonly included in electricity demand are appliance stock, the prices of substitute fuels, and some measure of temperature, usually heating and cooling degree-days. In addition to these three variables, housing characteristics (e.g., square footage, number of stories, number of rooms) and household characteristics (income, education level, age of household members) are included in the model (Bohi, 1981).

Electricity demand has been estimated most commonly using a reduced-form, double-log, static model (Espey and Espey, 2004). The simplified demand equation used in conventional econometric models for price elasticity analysis appears in Equation 2.2:

$$\ln Q_{it} = a + b \ln X_{it} + u_{it} \qquad (i=1,\ldots,N, \quad t=1,\ldots,T) \qquad \text{[Equation 2.2]}$$

where Q_{it} is annual consumption of energy consumer of i in time t; X_{it} is the vector of explanatory variables; and u_{it} is the random error term. The variable X_{it} generally includes 1) prices of energy fuels, 2) income, and 3) other exogenous variables. The log linear nature of Equation 2.2 implies that the vector of estimated parameters b represents elasticities (Houthakker, Verleger, et al., 1974; Halvorsen, 1975; Houthakker, 1980; McClung, 1988).

Halvorsen (1975) estimated both a demand equation and a price equation together. Since the price equation was included, he employed a two-stage least-squares procedure used in typical supply and demand analysis. His explanatory variables included in the X_{it} vector in Equation 2.2 are marginal prices of electricity and natural gas, prices of electrical equipment, income, and a variety of weather and housing measures. The estimated own-price elasticity of demand was found to be highly significant at –1.1. He also estimated a significant income elasticity of 0.51 (Halvorsen 1975).

According to Espey and Espey (2004), about one-third of the sample of their meta-analysis used aggregate data encompassing the entire contiguous 48 states. Several studies in the sample analyzed specific census divisions or census regions, whereas others analyzed demand in a particular city, such as Los Angeles, or used data obtained from specific utility companies or service areas, such as the Tennessee Valley Authority. Several of the studies included in their analysis modeled the demand for electricity in other countries, including Mexico, Costa Rica, Canada, and Israel. The global energy market changed dramatically before and after around 1973, when the OPEC asserted its strength, and 2007, when the economic recession started. The authors included publication years to determine whether there were systematic changes in elasticity estimates over time.

While many econometric analyses of residential energy demand are based on aggregated time-series data, the literature of electricity demand estimation for the residential sector that makes use of micro data has been scanty. This is because cross-sectional data do not allow for analyzing the dynamics between prices and demand changes of a consumer (Filippini and Pachauri, 2004). The time-series analyses postulate some lag structure in the estimation to reflect the fact that some adjustments in usage take time, such as the acquisition of new appliances. The most common lag structure is the use of a lagged dependent variable. The lagged dependent variable to capture long-run adjustments imposes a fixed relationship between short-run and long-run elasticities, whereas other lag specifications do not necessarily do so. However, time-series analyses with aggregate data at the macro (national) level prevalent in price elasticity estimation do not consider differences of housing and household characteristics across homes (Vaage, 2000; Metcalf and Hassett, 1999; Westoby and Pearce, 1984). Fell et al. (2010) argued that the estimates of price elasticity could be affected by aggregation bias and recommended using household-level data (cross-sectional micro data). A high degree of heterogeneity within the households in a nation justifies the use of detailed micro data in the modeling of the energy demand. An increasing number of studies have been conducted using micro datasets in the OECD countries, such as Sweden (Leth-Petersen, 2001; Jung 1993).

Price specification and rate structure are important issues in the model specification, as discussed earlier. Most of the previous studies use the marginal price of electricity, but still many use the average price. Other price specifications, such as the price perception model (Shin, 1985), also appear in the literature. Flat rates, decreasing block rates, and increasing block rates are other alternative price specifications. Haas and Schipper (1998) pointed out that elasticities when prices are falling are different from those when prices are rising.

Based on the literature review, a conventional model of residential energy demand with cross-sectional data is summarized and ultimately selected for estimating short-run price elasticities of residential electricity demand similar to Equation 2.3 (Variables are defined in Table 2.2). This model is employed for Model I and Model II (short-run models), analyzed in Section 4.2 in the following chapter. The detailed model specifications of the two models are discussed in Chapter 4.

$$lnQD = \alpha + \beta_1\, lnFPRICE + \beta_2\, lnINCOME + \beta_3\, lnCHARACTER + \beta_4\, lnCLIMATE + \beta_5\, EQUIPMENT + u \quad \text{[Equation 2.3]}$$

Table 2.2 List of Variables of Typical Models

Variable Name	Description
QD	*Electricity consumption in each household (Btu)*
FPRICE	*Fuel prices*
INCOME	*Annual income*
CHARACTER	*Housing and household characteristics*
CLIMATE	*Climate*
EQUIPMENT	*Equipment Portfolio*

Discrete/Continuous Choice Model

Previous micro-level studies in the 1970s and 1980s limited their analyses to short-run models to avoid more complex settings utilizing a discrete choice model of appliance number and type (Puller and Greening, 1999). The conventional models for estimating energy (electricity) demand have been estimated most commonly using a reduced-form, double-log, static model (Espey and Espey, 2004). Although reduced models are less cumbersome and easier to estimate, structural models are more likely to be considered more accurate, as they separate the dynamic features of demand and allow for the identification of the sources of consumption behavior (Bohi, 1981).[1] Therefore, several studies published after the 1980s considering the choice of appliance number and

[1] Many studies estimated a structural model of electricity demand using simultaneous equations to jointly estimate appliance stock demand and electricity use. In such cases, the estimated price elasticity is the long-run price elasticity.

type as a continuous variable or a function rather than a dummy variable have been published (Vaage, 2000; Greene and Hu, 1986; Puller and Greening, 1999). McClung (1988), for instance, employed the discrete choice model for appliance portfolio selection. He categorized the alternatives into 1) gas space-and-water heating with no central air conditioning, 2) gas space-and-water heating with central air, 3) electric space-and-water heating with central air, and 4) oil space-and-water heating without central air, and the estimated expected probability for each option is selected. The estimated probability replaces the appliance holding dummy variable.

The conventional models with the dummy variables may have some endogeneity issues. In an econometric model, a parameter or variable is said to be endogenous when there is a correlation between the parameter and the error term. However, the endogeneity may arise because of a measurement error. Conventional econometric models for estimating energy demand with cross-sectional data employ a set of dummy variables indicating appliance choice of each observation. Within this model specification, it is important to test the statistical exogeneity of appliance dummy variables, because demand for electricity is derived through the use of energy-consuming durables (Dubin and McFadden, 1984). Dubin and McFadden (1984) attempted to test this bias using a subsample of the 1975 survey of 3249 households carried out by the Washington Center for Metropolitan Studies (WCMS) for the Federal Energy Administration.

Employing a structural model of electricity demand using simultaneous equations to jointly estimate appliance stock demand and electricity use, McFadden first introduced a Random Utility Maximization Model (RUM) in 1981. He merged a discrete choice model for appliance choice and a continuous decision model for electricity demand. Many electricity demand problems involve a discrete choice of appliance as well as a continuous consumption of electricity. For instance, if a consumer selects electricity as the fuel for all of his appliances, he will surely have a greater demand for electricity than another consumer who selects all natural gas appliances. McFadden (1981) argued that because electricity consumption of a household is highly correlated with the consumer's appliance choices, the electricity consumption and the choice of appliance should be considered together. He stated that the discrete/continuous choice model is able to capture these sorts of effects parametrically and hence should more accurately describe consumer behavior. The discrete decision impacts the consumer's consumption of continuously defined goods. The choice of appliances portfolio requires a discrete orientation, while the amount of electricity consumed forms a continuous question. Likewise, the decision to select natural gas appliances suggests a lower than average demand for electricity. Later, in 1984, Dubin and McFadden published a complete articulation of the discrete/continuous choice model. The model jointly determines the demand for appliance and the demand for electricity by appliance. Dubin and McFadden (1984) also argued that some other model specifications that ignore the fact that appliance choice and energy use are interconnected will lead to biased and inconsistent estimates of price elasticities, since the demand for durables and their uses are related to decisions made by the consumers. They assumed consumers face a finite, mutually exclusive set of alternatives that comprise their space heating choice, and the alternatives vary with respect to cost, efficacy, and the preference of the consumer. The mathematical model of Dubin and McFadden (1984) is presented in Appendix G.

The discrete/continuous model introduced by Dubin and Mcfadden (1984) has been used by many studies that use cross-sectional survey data and assume the optimizations of appliance purchase and appliance use jointly and simultaneously occur. Thus, their model implies that price elasticity is interpreted as the long-run response (Dubin and McFadden, 1984; McClung, 1988; Vaage, 2000). Vaage (2000) used this discrete/continuous model in research conducted in Norway since an overwhelming share of Norwegian households installed mixed heating systems and a relatively strong price response is to be anticipated. The majority of U.S. households, however, have single-fuel-based heating systems. Thus, it is almost impossible for them to switch fuel types in a short period of time. Even though he used the discrete/continuous model for his study, Vaage (2000) pointed out that an obvious limitation of the model is a lack of data on capital costs. For empirical implementation of the discrete choice part of the Dubin-McFadden model with RECS data, McClung (1988) involved three very strong assumptions. The first and the most important assumption is that real capital costs evolve slowly enough that contemporary real prices reflect costs at the date of acquisition. Proponents of time-series analysis may argue that the assumption is too strong to accept in that it is clear that the choice of appliances and the uses of them happen with a significant time lag. Second, he assumes that the supply of houses containing various equipment portfolios is perfectly elastic to its price differentials, which reflect the different capital costs of the various portfolios. Third, he assumes that consumers have correctly anticipated future energy prices from the date of acquisition. These three assumptions allow the author to treat portfolio selection (discrete choice) as a contemporaneous decision with the quantity of fuel (continuous choice) to be purchased.

This chapter discusses the previous literature's estimates on price elasticity of demand with cross-sectional data. Based on knowledge from this chapter, the empirical estimation of price elasticity of residential electricity demand in this study is conducted with the 2005 Residential Energy Consumption Survey data. The estimation details are presented in Chapter 4.

A review of post-2000 studies

Recently, deregulation, record cold winter temperatures, unstable oil prices, and continuing global warming concerns have rekindled interest in understanding the demand for electricity, particularly in predicting the impact of price changes on consumption (Espey and Espey, 2004). Espey and Espey conducted a meta analysis with 36 previous studies on price elasticity estimation of residential electricity demand. Except for Garcia-Cerrutti (2000), all of the articles in their sample are studies conducted from the 1970s to the 1990s. To figure out the recent research trend in price elasticity estimation, this chapter reviews studies conducted after 2000. Appendix H summaries 12 studies published after 2000 in peer review journals. The majority of the studies used longitudinal data to estimate price elasticity of residential electricity demand. Both real energy prices and average energy prices are employed for these analyses. Double-log function with natural logarithm is still widely used both in time-series and cross-sectional data analyses. Almost all of the studies used lagged dependent and independent variables to analyzed dynamic relationships between electricity consumption, its price, and other variables. Among the 12 studies that this chapter reviewed, only Vaage (2000), Filippini and Pachauri (2004), and Yoo et al. (2007) used cross-sectional data, but none of them analyzed the U.S. context. The median value of the price elasticities estimated with U.S. data is –0.17; that with non-U.S. longitudinal data is –0.33; that with non-U.S. cross-sectional data is –0.51. Table 2.3 summarizes the empirical results and methods of the 12 studies reviewed in this chapter.

Table 2.3 Empirical results of the residential demand for electricity

Sources	Location	Study Period	Price Elasticity	Approach/ model	Data characteristics	Functional form	Price Measure	Estimation technique
Dergiades and Tsoulfidis (2008)	U.S.	1965-2006	–1.07	ARDL approach (cointegration)	Time series	Dynamic/ Natural log	Average price	OLS
Neeland (2009)	U.S.	1970-2007	–1.6 to 0.6	ADF unit root test, Johansen cointegration test	Time series	Dynamic/ Natural log	Real Price	Rolling regression
Horowitz (2007)	U.S.	1977-1991/ 1992-2003	–0.28 to –0.16	DID estimator	Cross-section time-series	Reduced form	Average price	
Nakajima and Hamori (2010)	U.S.	1993-2008	–0.33 to –0.14	Panel cointegration test	Panel	Dynamic/ Natural log	Real overall unit price	OLS
U.S. with longitudinal data			**–0.17 (Median)**					
Atakhanova and Howie (2007)	Kazakhstan	1994-1997	–0.24 to –0.13	Arellano-Bond (system) GMM Anderson-Hsiao instrumental variable fixed effects	Panel	Dynamic/ Natural log	Real retail price	Regression
aHoltedahl and Joutz (2004)	Taiwan	1957-1995	–0.15	ADF unit root test VAR system Conditional ECM model	Time series	Dynamic	Real price	
Hondroyiannis (2004)	Greece	1986-1999	–0.41	ADF unit root test Johansen cointegration test Vector error-correction model (VECM)	Time series	Linear double-logarithmic form	Real price	Johansen-Juselius estimation method with Gaussian errors/ MLE
Narayan and Smyth (2005)	Australia	1969-2000	–0.54 to –4.47	Bounds testing procedure Conditional error-correction model	Time series	Dynamic/ Natural log	Real price	
Athukorala and Wilson (2010)	Sri Lanka	1960-2007	–0.62 (long run) to –0.16 (short run)	ADF test Phillips-Perron unit root test VAR system V ECM	Time series	Dynamic	Average real price	Regression
Non-U.S. countries with longitudinal data			**–0.33 (Median)**					
Vaage (2000)	Norway	1980	–1.29 and –1.24	Discrete/continuous choice model	Cross section	Natural log		MLE(Probit)/ OLS
Filippini and Pachauri (2004)	India	1993-1994	–0.51 to –0.29	Single equation approach	Cross section	Natural log	Average price	
Yoo et al. (2007)	South Korea	2005	–0.25	Bivariate specification of Heckman (1979)'s sample selection model	Cross section	Natural log	Average price	
Non-U.S. countries with cross-sectional data			**–0.51 (Median)**					

Among the 12 studies, Neeland (2009), Horowitz (2007), Nakajima and Hamori (2010), and Dergiades and Tsoulfidis (2008) are more thoroughly reviewed in that they have the same geographical and sectoral scope as that of this dissertation. Neeland (2009) analyzed historical data of residential electricity demand in the United States for the period 1970-2007 through the Augmented Dickey-Fuller (ADF) unit root test which is the most common unit root test in time series analysis. Their results indicated that the primary driver of adjustments in electricity consumption is the own price elasticity of demand and growth in real income per capita. Methodological feature of his study is the use transcendental logarithm functions. The chief advantage of the translog functions is their ability to estimate substitution elasticities between energy and non-energy inputs or between different energy commodities. The method, however, has several limitations including concavity violations and a latent lack of degrees of freedom. Horowitz (2007) analyzed how electricity demand had changed over the past three decades particularly in light of government involvement in electricity demand. His study found that moderate to strong commitment to energy efficiency programs reduced electricity intensity by 4.4 percent in the residential sector. He also indicated that the U.S. economy had transformed electricity demand with respect to three key economic variables of electricity price, income as measured by per capita income or gross state product, and technological change. Nakajima and Hamori (2010) estimated changes in the residential electricity market to examine the household sensitivity as a result of retail electricity market deregulation policies to residential electricity rates. A panel data analysis was used to determine if the variables were stationary and to estimate price elasticity. They found that deregulation of the retail electricity market had not changed consumers more sensitive to electricity rates and that retail deregulation policies were not the cause of the difference in price elasticity between deregulated and non-deregulated states. By adopting these explanatory variables concerning temperature, their study was able to capture the seasonality of electric power consumption. Dergiades and Tsoulfidis (2008) also examined the residential demand for electricity in the U.S. economy. They defined the demand as a function of per capita income, price of electricity, price of oil for heating purposes, weather conditions, and stock of occupied housing over the period 1965-2006. They employed the occupied stock of houses as a proxy for the stock of electrical appliances and identified and ascertained a possible equilibrium relationship among the variables through the recently advanced Autoregressive Distributed Lag (ARDL) approach to cointegration. Their empirical findings supported to a stable long-run relationship among the variables and implied that the sign and magnitude of short-run and long-run elasticities were comparable to other similar studies. On balance, the review of theses 4 U.S. studies and other 8 non-U.S. studies indicate that the U.S. residential electricity demand is relatively stable and inelastic, and the responsiveness is symmetric before and after various changes in market regulations and environments.

Comparison of cross-sectional and time-series analyses

In order to discuss methodological differences between longitudinal and cross-sectional data analyses, a understanding of the two research methods is required. Because conventional and advanced research methods for the cross-sectional data analysis are discussed in the earlier sections, this section discusses the major concepts in the time-series data analysis such as stationarity, unit root test, error correction model, and cointegration. Time-series data typically contains a trend and the trend must be removed prior to commencing any estimation. Detrending procedures separate the trend from the cyclical component of the series. Considerable number of early studies had investigated price elasticity of electric power demand, and more recent works have been quite active in empirically analyzing nonstationarity of variables (Narayan and Smyth, 2005; Neeland, 2009).

The stationarity means a feature of data that the stochastic properties of a variable are invariant with respect to time. Suppose Y is the variable to be modeled. The mean of

Y_t, its variance, and its covariance with other Y values, say Y_{t-k}, do not depend on t. Economic time-series data often look non-stationary just because of underlying trend, which could be explained by exogenous factors such as population growth. Thus, if the trend were removed, the data would be stationary. For that reason, it is important to test for nonstationarity before proceeding with estimation. Running regressions on nonstationary data can give rise to misleading or spurious values such as R^2 and t statistics, resulting in erroneous conclusions that a meaningful relationship exists among the regression variables. Addressing this issue, Box-Jenkins (1970) developed time-series analysis which begins by transforming the variable to ensure that it is stationary. Although many scientific time series data are stationary, most economic time series data are trending and thus clearly cannot be stationary. Thus, Box and Jenkins claimed that most economic time-series data could be made stationary by differencing before estimating. A variable is said to be integrated of order d, written *I(d),* if it must be differenced *d* times to be made stationary. Thus, stationary variable is integrated of order zero, written *I(0)*. Usually after taking logs to remove heteroskedasticity. This creates a new data series, Y*, which becomes inputs that actually used for the Box-Jenkins analysis (Kennedy, 2008).

A traditional econometric equation for estimating demand is specified with a generous lag structure on the explanatory variables and/ or the dependent variable. This equation has been manipulated to reformulate it in terms that are more easily interpreted, producing a term representing the extent to which the long-run equilibrium is not met. This term is called an error correction term in that it reflects the current error in achieving long-run equilibrium. A distinctive feature of this error correction model is that the long-run equilibrium position appears explicitly rather than being implicit in the structure of the system showing itself in the error correction term. This type of model has been known as an error correction model (ECM). Since the 1970s, the Box-Jenkins time-series analysis has been actively used. The success of their model and some modified models is because traditional econometric structural models were too static. Their model was flexible enough to analyze an economy in which the observed is more frequently out of equilibrium (Kennedy, 2008).

A linear stochastic process has a unit root if there is a root of the characteristic equation of the process which is non-stationary. If the other roots of the characteristic equation lie inside the unit circle, in other words, have a modulus less than one, then the first difference of the process will be stationary. The most common unit root test is the Augmented Dickey-Fuller (ADF) test. If one can reject the null hypothesis that a series possesses a unit root, then the series is trend stationary, or integrated of order zero *(I(0))*. If one cannot reject the null of a unit root, then the series is difference stationary. A unit root is a feature of processes that evolve through time that can cause problems in statistical inference if it is not adequately treated.

After the stationarity of each variable has been determined an analysis of their interaction can be performed with the assistance of cointegration tests. This involves normalizing coefficients and testing for co-movement among variables (Kennedy, 2008). A long-run equilibrium relationship could be extracted through the application of cointegration technique in that it reveals the dynamic interactions among the variables under consideration. Suppose that C is electricity consumption, Y is income, and P is its price. If the hypotheses of no cointegration relationships among lnC, lnY, and lnP are rejected, then the effects of lnY and lnP on lnC must be estimated. Cointegration test offers a possible solution to the familiar problem that data non-stationarity may lead to spurious regression results (Neeland, 2009). Cointegration can be thought of in a transitory or long-run sense. Neeland (2009) points out that increasing number of observations through the use of monthly data does not add to the robustness of the cointegration results because it is the length of the period that matters, not the number of observations. The identification of a possible equilibrium relationship among the variables is ascertained through the recently advanced ARDL (Autoregressive Distributed Lag) approach to cointegration (Dergiades and Tsoulfidis, 2008).

The post-2000 studies reviewed in this chapter use a time-series or a panel data analysis with a dynamic model. However, time series studies lack information concerning appliance stock, building characteristics, differences in climates, and demographic characteristics and are usually aggregates over the entire nation's or region's data. The use of this cross-sectional data, on the other hand, allows researchers to consider the interventions across the households; thus, the cross-sectional data was used for this dissertation, especially Chapter 3 is intended to estimate how differences in housing and household characteristics affect consumers' short-run responsiveness to price changes. In addition, since the underlying theory of consumer demand is based on the behavior of individual agents, the use of micro data, which reflects individual and household behavior, more closely, is able to reflect the nature of consumer responses (Yoo et al., 2007). According to the literature review of price elasticity estimation studies, as most studies made use of aggregated time series data, they failed to offer the information about influence of household's characteristics on the residential electricity demand. Therefore, this dissertation estimates the residential electricity demand using the cross-sectional data for analyzing the influence of household and housing characteristics. Based on the discussions about the cross-sectional data analysis in the earlier section and the time-series data analysis in this section, the strengths and weaknesses of the two methods are summarized in Table 2.4.

Table 2.4 Pros and Cons of Longitudinal and Cross-sectional Data analyses

	Longitudinal/Macro Data Analysis	Cross-sectional/Micro Data Analysis
Pros	• Trace actual changes for a unit of analysis to respond to price changes (Show a dynamic model for a market to reach a new equilibrium). • Be able to consider market integrations and stability.	• Consider individual households' responses. • Be able to consider differences in housing and household characteristics. • Reflect individual and household behavior more closely, hence enable to have a better understanding of the nature of consumer responses. • Degree of freedom is high (The number of observations compared to that of variables is relatively high).
Cons	• Latent lack of degree of freedom (The number of observations compared to that of variables is relatively low.) • Potential non-stationarity could hinder the analysis. • Not be able to reflect variations in individual consumers' characteristics	• Non-response rates of certain groups could result in sample selection biases. • Not be able to capture the actual responsiveness of a consumer to changes in price over time.

As summarized in Table 2.4, microeconomic approaches with micro/cross-sectional data to the residential electricity demand modeling also enable different heterogeneous household groups to be analyzed. Thus, these approaches allow for a wide variety of household characteristics within the estimated equations to be considered. In order words, the use of cross-sectional data allows the variation in electricity consumption across demographic and geographic subgroups to be examined more extensively (Filippini and Pachauri, 2004; Yoo et al., 2007). However, price elasticity estimates are affected by non-response rates of certain groups. Yoo et al. indicated that 75 households (19.7%) of 380 sampled households gave non-response about the residential electricity demand in the survey. When a sample that does not take into account the non-respondents, the statistical analysis using the sample cannot be seen to represent the entire population, and finally results in loss of information or statistical efficiency (Yoo et al., 2007). In the econometric analysis presented in Chapter 3, Model III indicates that the model lost almost 1,000 observations, because the 1,000 respondents did not (were not able to) provide information about the type of heating equipment or that of cooling equipment. In order to solve this problem caused by missing observations, Baht (1994) employs the bivariate model, which is apt to treat such missing data. This bivariate model is methodologically similar to the sample selection model. Non-response can cause sample selection bias which results in inconsistent parameter estimates. In order to deal with the issue of sample selection bias, a sample selection model proposed by Heckman (1979) has been commonly used to solve the problems caused by the bias. However, empirical applications of the model in the residential electricity demand function estimation remain lacking (Yoo et al., 2007). The main contribution of the study conducted by Yoo et al. (2007) is that they explore the bivariate model that produces consistent parameter estimates and unbiased mean electricity demand estimates when estimating the residential electricity demand function. Moreover, their paper compares the results with those from a model that assumes no sample selection bias and tested for sample selection bias by using two test procedures.

CHAPTER 3
PRICE ELASTICITY ESTIMATION

The price elasticity of demand is an important concept in energy demand forecasting, particularly for the analysis of energy-efficiency programs. However, the spectrum of price elasticity estimates is broad, and there is no consensus regarding the magnitude of price elasticities of demand for electricity (Espey and Espey, 2004; Athukorala and Wilson, 2010). This study uses three different econometric models to estimate the elasticities. The first two models use a conventional log linear function with a set of dummy variables representing equipment choice. One difference between the two models is whether to use census division-level average prices or observation-specific average prices. One uses average electricity and natural gas prices by census division, and the other employs average prices that each household actually faces. The observation-specific prices of electricity are derived by a calculation of annual electricity bill divided by annual electricity consumption. Those of natural gas are derived from the same formula. The third model employs a continuous/discrete choice model, discussed in depth in Chapter 2.

As mentioned in Chapter 1, the main purpose of estimating short-run price elasticity is to see how sensitively the long-run demand projections computed by NEMS respond to the updated short-run price elasticity estimated from the latest survey data. In other words, this study estimates the short-run price elasticity of residential electricity demand using cross-sectional data to extract only the intrinsic energy-consumption habits (characteristics) in the short term. Short-run price elasticities estimated in Section 3.2 of this chapter are planned to be plugged into a NEMS model because it contains a parametercontrolling short-run demand adjustments. For that reason, I run the conventional econometric model with two variations in price (census division level vs. household level) and diagnosed with various test statistics. Section 3.3 presents results from the discrete/continuous choice model. All of the three models use the latest Residential Energy Consumption Survey (RECS) data collected by EIA in 2005.

3.1 Data

The RECS provides information on the use of energy in residential buildings in the United States. This information includes the physical characteristics of the housing units, the appliances, the demographic characteristics of the household, the types of fuels used, and other information that relates to energy use. It also provides energy consumption and expenditures data for natural gas, electricity, fuel oil, liquefied petroleum gas (LPG), and kerosene. The data are organized by twelve different topics: 1) housing unit characteristics; 2) kitchen appliances; 3) other appliances; 4) space heating; 5) water heating, air conditioning (AC), and miscellaneous; 6) fuels used and fuel payment; 7) fuel bills and non-residential uses; 8) household characteristics; 9) energy assistance and housing unit square footage; 10) characteristics of energy supplier data; 11) energy consumption; and 12) energy expenditure.

This study uses these RECS data for the econometric model to estimate the short-run price elasticity of electricity demand. The first RECS was conducted in 1978, and the latest (twelfth) survey was conducted in 2005. The 2005 RECS collected data from 4,382 households in housing units statistically selected to represent the 111.1 million housing units in the United States. The RECS data are classified by multiple geographical classifications: four census regions, nine census divisions, and the four most populous states (California, Florida, New York, and Texas). The RECS consists of two major parts: the household survey and the energy supplier survey. The household survey gathers information about the dwelling and many socioeconomic characteristics of each household. To obtain accurate and detailed measures of energy consumption, expenditures, and price data, EIA takes these data directly from the utilities serving the individual households. The data are collected by questionnaires mailed to all the suppliers of the households in the household survey. Its variables comprise building type, fuel, end-use, and technology categories. The end-use equipment combinations are used as control variables for the econometric analysis. For the long-run model, it is necessary to factor in technology choices for new and retiring equipment depending on capital costs, operating costs, and maintenance costs of competing end-use technologies.

The RECS is a national area-probability sample survey that collects energy-related data for occupied primary housing units. The universe for the sample design of the RECS includes all housing units occupied as primary residences in the 50 states and the District of Columbia. The definition of "household" is the same as that used by the U.S. Census Bureau. By definition, the RECS does not include vacant housing units, seasonal units, or second homes. The basic sample is designed to represent the total population of households for each of the nine census divisions in the United States. The sample design for the RECS is based on multistage area probability design. The universe is broken up into successively smaller and statistically selected areas. The process begins with the selection of Primary Sampling Units (PSUs) and ends with the selection of individual households. The total land area of the 50 states and the D.C. was divided into 1,786 PSUs, based on county and independent city boundaries and on Metropolitan Statistical Areas (MSAs) defined in 1990. The primary mode of stratification of PSUs is by the nine census divisions. The strata are independently defined within census divisions for the four most populous states and for two states with unique weather conditions (Alaska and Hawaii). The stratification is also based on MSA or non-MSA status of PSUs and on dominant residential space-heating fuel and weather conditions. The PSUs are grouped into 116 strata, with one PSU selected from each stratum. The Secondary Sampling Units (SSUs) consist of one or more census blocks, selected directly from census statistics. Blocks were combined as necessary to create SSUs that contained at least 50 housing units. The SSUs that contained very large numbers of housing units were divided into smaller listing segments, and one listing segment is selected for detailed address listing. Specific addresses chosen from each of the field listings comprised the ultimate cluster of the RECS sample. An ultimate cluster of housing units to be contacted for interview was randomly selected from the penultimate cluster. These housing units constitute the assignments given to interviewers.

3.2 Conventional Econometric Models (Models I and II)

To estimate how individual households respond to short-run price changes at the micro level, this study chooses to use log linear demand functions employed by Halvorsen (1975), Houthakker (1980), McClung (1988), and Dahl (1979). The literature revealed that demands on energy are normally influenced by fuel prices, household income and choice of equipment, and housing and demographic characteristics.

This econometric analysis uses the EIA's RECS data and employs the ordinary least squares (OLS) estimation technique. As discussed previously in the methodology section, the log linear nature of the demand equation implies that the vector of estimated parameters represents the elasticities. Finally, the study defines the residential energy demand equation of a consumer as a function of fuel prices (own price and competing good's price), income level, climate (heating degree-days [HDD] and cooling degree-days [CDD]), and equipment type (see Equation 3.1 and Table 3.1):

$$\begin{aligned} ln(QD) = \alpha + \beta_1\, ln(PELEC) + \beta_2\, ln(PGAS) + \beta_3\, ln(income) + \beta_4\, ln(\#\ of\ rooms) \\ + \beta_5\, ln(HDD) + \beta_6\, ln(CDD) + \beta_7\, (appliance\ holding\ dummies) + u \end{aligned}$$

[Equation 3.1]

The short-run changes depend only on changes in consumption of energy services, whereas the long-run changes include greater alterations in the equipment's energy efficiency. Because the model controls for the equipment type with a set of dummy variables, the elasticity estimated by this equation is a short-run elasticity. Correlations among variables are presented in Appendix D.

Table 3.1 List of Variables of Models I and II

Variable Name	Description	Mean	S.D.	Min.	Max.
QD	Electricity consumption in each household (Btu/ year)	38,646	25,666	164	246,261
PELEC1	Average electricity price by census division ($/million Btu)	30.5	5.8	23.1	41.9
PELEC2	Average electricity price by household ($/million Btu)	31.2	13.9	9.1	127
PGAS1	Average natural gas price by census division ($/million Btu)	13.5	1.7	11.2	16.1
PGAS2	Average natural gas price by household ($/million Btu)	11.0	5.1	2.4	75
INCOME	Annual income	47,602	34,679	1,250*	120,000*
NROOM	Number of rooms	2.8	1.1	0	8
CDD	Cooling degree-days	1486.2	966.5	0	5518
HDD	Heating degree-days	4311.2	2180.8	0	11,465
EQUIPMENT	A set of dummy variables classifying equipment type	Table 3.2 provides descriptions of the dummy variables			

Number of observations = 4,382
*The maximum and minimum levels of income could not be found, because the lowest category is "below 1,250" and the highest category is "above 120,000."

McClung (1988) categorizes appliance holding alternatives into 1) gas space-and-water heating with no central AC, 2) gas space-and-water heating with central air, 3) electric space-and-water heating with central air, and 4) oil space-and-water heating without central air. Following McClung's classification of alternatives, the appliance holding types of this study are classified according to two criteria: the type of fuel used for heating and the type of AC equipment. The heating fuel types are categorized into natural gas, electricity, and other fuels, and the AC systems are classified into central, individual, and combination central and individual systems. Table 3.2 shows that the combination of electric heating and central AC is adopted by 19% of the sample households and that the combination of natural- gas-based heating equipment and central AC is used by 28% of them. The group of households that have electric heating and central AC is chosen as a reference group, because it is anticipated to spend the most electricity. The choice of the reference group facilitates the interpretation of regression results.

Table 3.2 List of Equipment Dummy Variables by Heating Fuel and AC Type

Variable Name	**Heating Fuel/AC Type**	**Frequency**	**%**
NGCEN	Natural gas/central AC	1,228	28.02
ELECCEN (Reference group)	Electricity/central AC	852	19.44
NGIND	Natural gas/individual AC	575	13.12
NG9	Natural gas/don't know AC type	465	10.61
OTHERIND	Other fuel type/individual AC	358	8.17
ELECIND	Electricity/individual AC	241	5.5
OTHERCEN	Other fuel type/central AC	231	5.27
OTHER9	Other fuel type/don't know AC type	190	4.34
ELEC9	Electricity/don't know AC type	127	2.9
NGBOTH	Natural gas/both central and individual AC	31	0.71
ELECBOTH	Electricity/both central and individual AC	19	0.43
DONTKNOWIND	Don't know heating fuel/individual AC	18	0.41
DONTKNOWCEN	Don't know heating fuel/central AC	6	0.14
OTHERBOTH	Other fuel type/both central and individual AC	6	0.14
NOANSWER	No answer	35	0.8
	Total	**4,382**	**100**

Model I: Elasticity Estimation with Census Division-level Average Energy Prices

As discussed in Chapter 3, Halvorsen (1975) simultaneously estimated price and demand with a two-stage model with the speculation that price and consumption interplay in the electricity market. In this study, model I includes only the demand function, because it uses the average price not the marginal price. This model assumes that price affects consumption, but not vice versa, because change in consumption of each household in a census division is very minimal so that it barely affects the change in the average division price. In other words, consumers in this model are price-takers. The average prices of electricity and natural gas to the residential consumers in each census division in 2005 were obtained from the EIA's NEMS dataset and matched to the RECS dataset according to where each house is located. Particularly for larger divisions, there is some unavoidable imprecision in the data. The RECS dataset, open to the public, provides a variable to indicate the respondent's census division of residence but no information about where the respondent lives within the census division. Consequently, the respondent is assumed to face the division-wide average prices of electricity and natural gas.

Table 3.3 shows that the own-price elasticity of residential electricity demand is found to be highly significant at –0.66 in the short run. It is in the range of the short-run price elasticities of residential electricity demand (from –0.97 to +0.57) collected by Dahl in 1993. This suggests that a 1% rise in price causes a reduction in demand by 0.66%. This interpretation of the estimated variable requires an assumption that the behavioral attributes of all of the households in the population are homogeneous. Reiss and White (2008) argued that short-run price elasticities of households in California are heterogeneous and that the differences are caused by the variety in appliance holdings. Since model I and Model II in this study controls the equipment variation by adding the appliance holding dummy variables, the homogeneity assumption is justified.

On the other hand, the cross-price (natural gas) elasticity is found to be 0.45. This means that when a 1% increase in the electricity price results in the increase in consumption of a competing good, natural gas use increases by 0.45%. This result suggests that a substitution relationship exists between electricity and natural gas in the residential sector. When electricity prices go up continuously or stay at a high level for a long time, consumers may consider replacing their electricity-based heating equipment with natural-gas-based equipment.

The income elasticity is estimated to be 0.12, which indicates that a 1% increase in income is associated with a 0.12% rise in consumption. When the total income of a household increases, the income elasticity should be distinguished from the concept of price elasticity at different income levels. While the former indicates how consumers change their consumption levels as their incomes increase, the latter shows how sensitively consumers at different income levels respond to price changes. The sensitivity of consumers at different income levels is analyzed with separate models.

Table 3.3 also shows that when HDD increase by 1%, electricity consumption goes up by 0.03%. With a 1% increase in the number of CDD, consumption rises by 0.08%. Compared to households that have electric heating and a central AC system (the reference group), households that have natural-gas-based heating systems use less electricity, as would be expected.

Table 3.3 Electricity Demand Parameter Estimates of Model I

Dependent Variable	ln(electricity use)	Coef.	Std. Err.	*t*	*P*>|*t*|
Price variables	ln(electricity price)	–0.663*	0.051	–13.010	0.000
	ln(natural gas price)	0.445*	0.076	5.870	0.000
Control variables *(Household and housing characteristics)*	ln(income)	0.119*	0.010	11.880	0.000
	ln(# of rooms)	0.627*	0.022	28.610	0.000
	ln(HDD)	0.032*	0.012	2.610	0.009
	ln(CDD)	0.077*	0.013	6.000	0.000
Control variables *(Appliance holding dummies)*	NGCEN	–0.415*	0.025	–16.710	0.000
	NGIND	–0.605*	0.031	–19.820	0.000
	NGBOTH	–0.393*	0.095	–4.120	0.000
	NG9	–0.768*	0.035	–21.950	0.000
	ELECIND	–0.046	0.040	–1.150	0.249
	ELECBOTH	0.167	0.121	1.380	0.167
	ELEC9	–0.156*	0.035	–4.470	0.000
	OTHERCEN	–0.155*	0.039	–3.960	0.000
	OTHERIND	–0.444*	0.036	–12.500	0.000
	OTHERBOTH	0.198	0.213	0.930	0.352
	OTHER9	–0.502*	0.045	–11.220	0.000
	Constant	9.161*	0.292	31.370	0.000

R-squared = 0.4326
Adjusted R-squared = 0.4304
Number of observations = 4271
*Significant at the 99% confidence level

In order to check if there are any model specification errors, this study performed the Ramsey regression specification error test (RESET) for omitted variables.

Ramsey RESET using powers of the fitted values of ln (electricity use)

Ho: model has no omitted variables

F(3, 4250) = 1.64

Prob > F = 0.1790

The p-value for the Ramsey RESET is greater than 0.05. This indicates that the Ramsey RESET failed to reject the null hypothesis that the model has no omitted variable. According to the test result, this study can conclude that the model is specified correctly.

In addition to the RESET, this study checked multicollinearity among variables with the variance inflation factor (VIF). As a rule of thumb, a variable whose VIF value is greater than 10 may merit further investigation. Table 3.4 indicates that there is no variable suspected to cause a multicollinearity problem.

Table 3.4 Variance Inflation Factor of Model I

Variable	VIF	1/VIF
NGCEN	2	0.499175
LNCD65	1.88	0.530669
NG9	1.76	0.569607
NGIND	1.69	0.591614
LNHD65	1.64	0.608153
OTHERIND	1.51	0.66304
LNELECPRICE	1.37	0.727977
LNNGPRICE	1.34	0.745137
OTHER9	1.33	0.753607
ELECIND	1.28	0.78342
LNHHINCOME	1.25	0.802227
OTHERCEN	1.25	0.802533
LNBEDROOMS	1.23	0.815073
ELEC9	1.23	0.81538
NGBOTH	1.04	0.96114
ELECBOTH	1.02	0.97969
OTHERBOTH	1.01	0.987143
Mean VIF	1.4	

One of the main assumptions for the OLS regression is the homogeneity of variance of the residuals. According to the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity, the null hypothesis that the variance of the residuals is homogeneous is rejected.

Breusch-Pagan/Cook-Weisberg test for heteroscedasticity

Ho: constant variance

Variables: fitted values of ln (electricity use)

$Chi^2(1) = 70.06$

$Prob>Chi^2 = 0.0000$

However, homoscedasticity tests are very sensitive to model assumptions such as the assumption of normality. Therefore, it is common practice to combine the tests with diagnostic plots to make a judgment on the severity of the heteroskedasticity and to decide if any correction is need for heteroscedasticity. If the model is well-fitted, there should be no pattern to the residuals plotted against the fitted values. This study then graphically checked the homoscedasticity of residuals. The plot in Figure 3.1 does not show any specific pattern. This means that there is no evidence to conclude that the residual variance is heteroscedastic. In other words, because no pattern is detected in the plot, this study concludes that the model satisfies the homoscedasticity assumption.

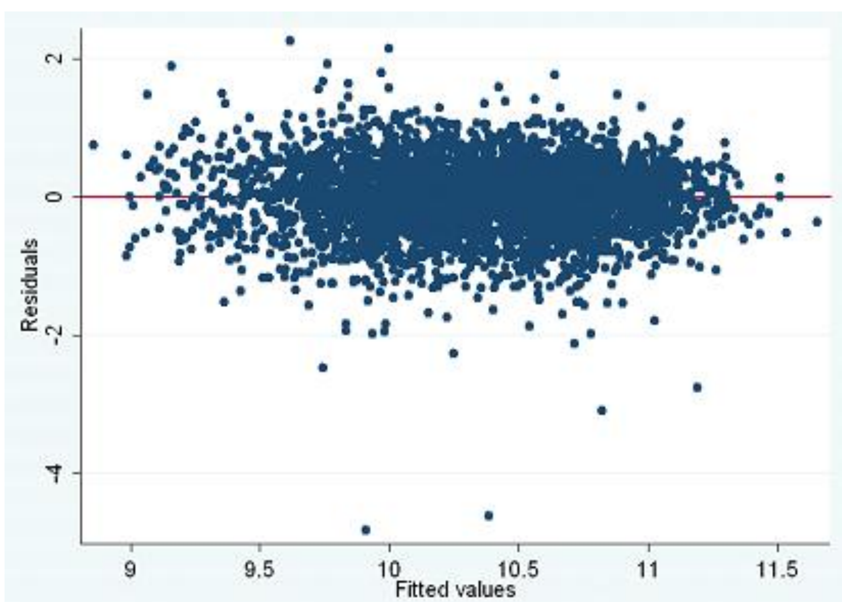

Figure 3.1 Checking Homoscedasticity of Residuals for Model I

Diverse income groups can have different behavioral responses to changes in fuel prices. Variations in price elasticity have been analyzed specially with gasoline demand for the transportation sector, whereas there have been few studies to analyze such research questions for the residential buildings sector. Two opposite groups of arguments about the diversity of price responsiveness across different income quintiles coexist. One argument states that lower-income households may be more sensitive to price changes and have a tendency to switch modes easily, resulting in a higher than average price elasticity (West and Williams, 2004). On the other hand, another argument states that lower-income households may already minimize their energy use because of their budget constraints, and for that reason, they may be unable to reduce their energy use further, resulting in a lower price elasticity than average (Kayser, 2000). Higher-income households may be less sensitive to price changes because the share of the electricity bill to their total expenditures would be relatively small, so they would care about electricity price increases less than low-income households (Robinson, 1969). However, higher-income households may have more options to reduce energy use because some portions of their consumption may be discretionary rather than necessary (Kayer, 2000). All of these various arguments suggest that substantial potential heterogeneity among income groups exists (Wadud et al., 2010).

This study includes an interaction term between price and income, *ln(electricity price) * ln(income)* to examine the heterogeneity in price elasticity among different income levels:

$$ln(\text{electricity use}) = \alpha + \beta_1\, ln(\text{electricity price}) + \beta_2\, ln(\text{natural gas price}) + \beta_3\, ln(\text{income}) + \boldsymbol{\beta_4\, ln(\text{electricity price}) * ln(\text{income})} + \beta_5\, ln(\#\text{ of rooms}) + \beta_6\, ln(HDD) + \beta_7\, ln(CDD) + \beta_8\, (\text{appliance holding dummies}) + u$$

[Equation 3.2]

Table 3.5 shows that heterogeneity in price elasticity across different income levels is not supported by the regression result (the p-value of the interaction term is 0.202).

Table 3.5 Heterogeneity in Price Elasticity of Electricity Demand

Dependent Variable	ln(electricity use)	Coef.	Std. Err.	*t*	*P*>|*t*|
Interaction term	ln(elec. price)*ln(income)	0.063	0.050	1.280	0.202
Price variables	ln(electricity price)	–1.321*	0.518	–2.550	0.011
	ln(natural gas price)	0.443**	0.076	5.840	0.000
Control variables *(Household and housing characteristics)*	ln(income)	–0.10	0.169	–0.570	0.568
	ln(# of rooms)	0.63**	0.022	28.560	0.000
	ln(HDD)	0.03**	0.012	2.660	0.008
	ln(CDD)	0.08**	0.013	6.030	0.000
Control variables *(Appliance holding dummies)*	NGCEN	–0.36**	0.023	–15.57	0.000
	NGIND	–0.51**	0.028	–17.82	0.000
	NGBOTH	–0.32**	0.089	–3.57	0.000
	NG9	–0.67**	0.032	–20.91	0.000
	ELECIND	–0.07	0.037	–1.870	0.062
	ELECBOTH	0.12	0.118	1.01	0.314
	ELEC9	–0.16**	0.032	–4.84	0.000
	OTHERCEN	–0.08*	0.037	–2.32	0.020
	OTHERIND	–0.30**	0.033	–8.97	0.000
	OTHERBOTH	0.24	0.196	1.18	0.236
	OTHER9	–0.35**	0.042	–8.35	0.000
	_Constant	5.12**	0.257	19.92	0.000

R-squared = 0.5051
Adjusted R-squared = 0.5031
Number of observations = 4240
*Significant at the 95% confidence level
** Significant at the 99% confidence level

However, there is a great difference in price elasticity between extremely low and extremely high income groups. To show how differently low- and high-income households react to price increases, this study estimated the price elasticity of the two income groups separately. Households that earn less than $10,000 a year are included in the low-income group, and those that earn greater than $100,000 per year are defined as the high-income group. Table 3.6 shows that the price elasticity of the low-income households (–0.67) is about three times greater than that of the high-income households (–0.21). This result supports Robinson's (1969) argument that wealthier households are less sensitive to price changes than low-income households.

Table 3.6 Elasticity Variations for Different Income Groups

Income Level	Annual Income Range	Price Elasticity	Number of Observations
Low income	Less than $10,000	–0.67	439 (bottom 10%)
High income	Greater than $100,000	–0.21	537 (top 12%)

In addition, this study conducted the same exercise with RECS 1997 data and found that the price elasticity was –0.96. Differences in economic situations would affect the difference between the elasticities of 1997 and 2005. Detailed results are provided in Appendix E.

Model II: Elasticity Estimation with Derived Observation-specific Average Prices

The price elasticity of demand was estimated with the derived observation-specific average electricity price by household. As mentioned previously, one concern of model I is that when estimating the elasticity with census division-level average prices, their variation is not sufficient to analyze the responsiveness of demand with respect to the prices. In order to solve this problem, model II uses household-level energy prices derived from annual energy expenditure in dollar (DOLLAREL[2] and DOLLARNG[3]) and

---

[2] Annual electricity expenditure in dollar
[3] Annual natural gas expenditure in dollar

annual energy consumption in Btu (BTUEL[4] and BTUNG[5]). The observation-specific price of electricity is derived by a calculation of the annual electricity bill divided by the annual electricity consumption. That of natural gas is derived from the same formula. Table 3.7 shows that using model II, the short-run price elasticity of residential electricity demand is found to be –0.81 at the 99% confidence level.

Table 3.7 Electricity Demand Parameter Estimates of Model II

Dependent Variable	**ln(electricity use)**	**Coef.**	**Std. Err.**	***t***	***P*>|*t*|**
Price variables	ln(electricity price)	–0.811*	0.028	–28.890	0.000
	ln(natural gas price)	–0.022	0.032	–0.690	0.492
Control variables *(Household and housing characteristics)*	ln(income)	0.136*	0.009	14.460	0.000
	ln(# of rooms)	0.566*	0.021	27.520	0.000
	ln(heating degree days)	–0.013	0.012	–1.140	0.255
	ln(cooling degree days)	0.104*	0.012	8.810	0.000
Control variables *(Appliance holding dummies)*	NGCEN	–0.356*	0.023	–15.570	0.000
	NGIND	–0.506*	0.028	–17.820	0.000
	NGBOTH	–0.317*	0.089	–3.570	0.000
	NG9	–0.675*	0.032	–20.910	0.000
	ELECIND	–0.069	0.037	–1.870	0.062
	ELECBOTH	0.119	0.118	1.010	0.314
	ELEC9	–0.156*	0.032	–4.840	0.000
	OTHERCEN	–0.086	0.037	–2.320	0.020
	OTHERIND	–0.297*	0.033	–8.970	0.000
	OTHERBOTH	0.235	0.199	1.180	0.236
	OTHER9	–0.351*	0.042	–8.350	0.000
	Constant	5.119*	0.257	19.920	0.000

R-squared = 0.5051
Adjusted R-squared = 0.5031
Number of observations = 4240
*Significant at the 99% confidence level

[4] Annual electricity consumption in Btu
[5] Annual natural gas consumption in Btu

As was done, this model was diagnosed in various ways. The RESET was performed for checking omitted variables and the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity. The heteroscedasticity is checked in a graphical way too. In addition, multicollinearity was checked with the VIF factor. The p-value for Ramsey's RESET is less than 0.05. This indicates that the Ramsey RESET rejects the null hypothesis that the model has no omitted variables. This means the model could be misspecified. The use of micro-level prices rather than macro-level prices in model specification basically means that the price affects each household's demand and that at the same time, a change in the demand has an impact determining the price that the consumer is given under the today's block pricing system. Halvorsen (1975) employed a simultaneous equation model to include the demand and price equations at the same time. He used marginal electricity prices in the demand equation and the prices influenced by the electricity generation and other market conditions of the area where each household is located. For that reason, he added the percentage of generation produced by publicly owned utilities, the cost of fuel per kilowatt-hour of generation, the percentage of population living in rural areas, the ratio of total industrial sales to total residential sales, and the cost of labor in the price equation. The RESET tests for Model I and Model II indicate that the use of division level average prices in the previous model fits the RECS data and the equation specified (Equation 3.1) better than the household level average prices.

In addition to the RESET, this study checked multicollinearity among variables with the VIF. The mean value of VIF was 1.36, which indicates that there is no variable suspected to cause a multicollinearity problem. As mentioned previously, the null hypothesis of the Breusch-Pagan/Cook-Weisberg test for heteroscedasticity is that the variance of the residuals is homogeneous. This is rejected at the 99% confidence level ($Prob>Chi^2 = 0.0000$). However, homoscedasticity tests are very sensitive to model assumptions such as the assumption of normality. Therefore, this study combined the test with diagnostic plots to make a judgment on the severity of the heteroscedasticity and to decide whether any correction is need for heteroscedasticity. This study graphically checked the homoscedasticity of residuals. The plot in Figure 3.2 shows no pattern of the data points. This indicates that there is no evidence to conclude that the residual variance is heteroscedastic. In other words, because no pattern is detected in the plot, this study concludes that the model satisfies the homoscedasticity assumption.

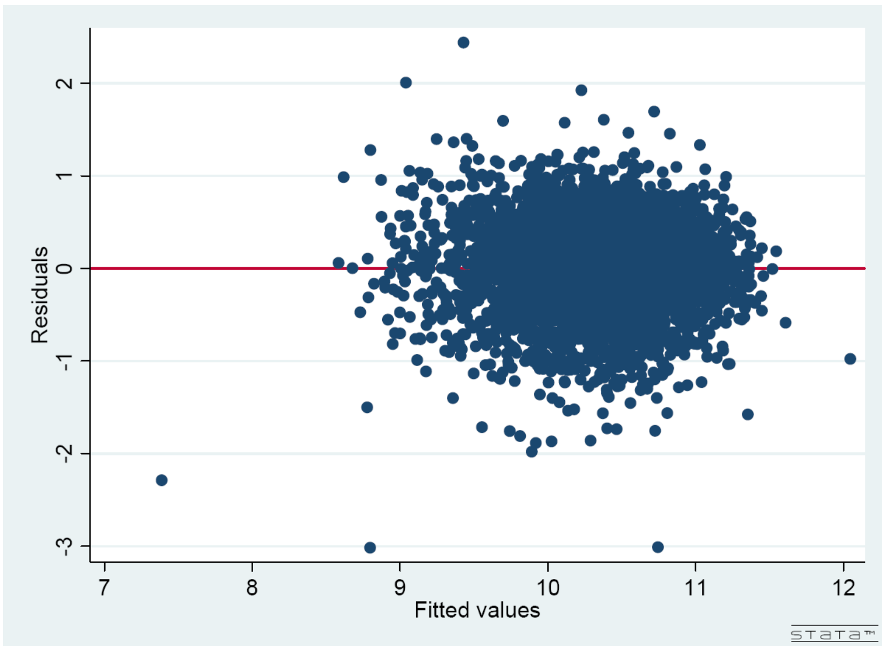

Figure 3.2 Checking Homoscedasticity of Residuals for Model II

3.3 Discrete/Continuous Choice Model (Model III)

This section specifies a unified model of the demand for electricity consistent with discrete choice of appliances in particular its ability to account for the interdependency between the appliance choice and the demand for residential electricity (Dubin & McFadden, 1984; Vaage, 2000). Many micro-simulation studies have attempted to model jointly the demand for appliances and the demand for electricity by the appliances (Dubin & McFadden, 1984).

Since the 1908s, there have been some arguments that it is important to clarify the exogeneity of appliance dummy variables used in the conventional models. Because the demand for durables (appliances) and their uses are related decisions by the consumer, specifications that ignore this fact will lead to biased and inconsistent estimates of price elasticities (Dubin & McFadden, 1984). In the case of the purchase and the use of an air conditioner, an unobserved effect that is captured in the error term in the electricity demand equation (e.g., poor natural ventilation in a housing unit) may increase the electricity consumption. At the same time, the unobserved effect is likely to increase the probability of selection of the central AC system. In this case, OLS estimation of the electricity demand equation includes a classical bias due to correlation of an explanatory variable and the equation error. In order to solve this problem, this model uses a set of instrumental variables (IV)[6] that replace dummy variables that may not be exogenous and correlated with the error term in Equation 3.1. In this model, the probabilities for appliance portfolios to be selected by households are used instead of the appliance holding dummies. In other words, the expected probability for each alternative chosen by the household from the discrete choice model is used as an instrument for the appliance holding dummies used in the previous models. Appliance holding decisions are analyzed as if they are contemporaneous with usage decisions and do not involve inter-temporal considerations.

[6] An instrument is a variable that does not itself belong in the explanatory equation and is correlated with the endogenous explanatory variables, conditional on the other covariates.

Stage I: Heating and Cooling Equipment Choice (Discrete Choice) Model

In the discrete choice model, I specify that each household faces five different heating-cooling systems: ELECCEN, NGCEN, ELECIND, NGIND, and OTHERS.[7] The percentage shares for the different alternatives are 19%, 28%, 6%, 13%, and 34%, respectively. The heating-cooling system variable (nominal variable) is used as the dependent variable. Independent variables included in this discrete choice model are annual operating cost for heating and cooling, capital cost for heating and cooling equipment, average prices of electricity and natural gas by census division, and annual income. Table 3.8 gives the variables used in the choice model and their sample mean by alternative.

Table 3.8 Variables in the Heating-Cooling Choice Model

Description	Variable	Mean by Alternative				
		ELECCEN (Reference Group)	NGCEN	ELECIND	NGIND	OTHERS
Annual operating cost for heating ($)	HOPCOST*	564	855	437	989	678
Annual operating cost for cooling ($)	COPCOST	384	280	117	129	88
Capital cost for heating ($)	HKCOST	3,435	3,500	3,342	3,637	3,465
Capital cost for cooling ($)	CKCOST	2,574	2,574	511	511	1,454
Average price of electricity ($/million Btu)	AELECP	28	29	30	33	33
Average price of natural gas ($/million Btu)	ANGP	14	13	13	14	13
Annual income ($)	INCOME	47,565	59,474	29,979	35,478	45,345

* HOPCOST includes space heating and water heating together.

[7] ELECCEN = electric heating and central AC, NGCEN = natural-gas-based heating and central AC, ELECIND = electric heating and individual AC, NGIND = natural gas heating and individual AC, and Others = other heating-cooling systems.

As Vaage (2000) pointed out, an obvious limitation of the discrete/continuous model with cross-sectional data is lack of data on capital costs. The RECS data do not include the information about the initial capital costs spent to install heating and cooling systems in the houses when they are built, because the RECS questions were asked to the current residents in those houses, not to the builders who actually know installation cost information. The only information allowing inference of the capital costs of the heating and cooling equipment are the COOLTYPE and EQUIPM variables in the RECS. COOLTYPE explains what kind of air-conditioning equipment the home has: central AC, individual AC, or both. EQUIPM means the type of heating equipment that provides most of the heat for the home. EQUIPM is categorized into heat pump, central warm-air furnace, steam/hot water system with radiators, built-in electric units, built-in pipeless furnace, built-in heater burning wood/coal/coke, portable electric heaters, portable kerosene heaters, fireplace, cook stove, some other equipment, and no heating equipment.

To solve this data problem, this study assumed that real capital costs evolve slowly enough that contemporary real prices reflect costs at the date of acquisition, following McClung's (1988) assumptions. Average energy fuel prices by census division were used rather than marginal prices in the first stage of the discrete choice model, since it was assumed that when they purchase appliances, consumers consider today's energy price levels broadly rather than considering marginal price changes in the future thoroughly. A multinomial logit model with maximum likelihood estimation (MLE) was run to estimate the expected probability for each option chosen by the household. To identify the choice specific parameters, one of the alternatives was used as the base category; this study used ELECCEN because the electricity-based heating and the central AC system are the most electricity-intensive systems for heating and cooling.

Results from the estimation of the model are reported in Table 3.9. The coefficients show the change in the log-odds of being in each category of the dependent variable relative to the base category from a one-unit increase in each independent variable, holding the other variables constant. According to the straightforward interpretation of the coefficients, the estimated coefficients of the COPCOST for the ELECIND category, –0.00286, for instance, is interpreted as follows. When the operating cost for cooling increases by $1, the log-odds of the ELECIND category relative to ELECCEN decrease by 0.00286. When the operating cost for heating (HOPCOST) increases, the natural-gas-based heating systems (NGCEN and NGIND) are less likely to be chosen than the reference group (ELECCEN). When the operating cost for cooling (COPCOST) increases, ELECCEN becomes the most popular option among the five for heating and cooling. This is because every coefficient by alternative is negative for this variable. In other words, when the operating cost for cooling increases, it is more probable for a household to choose a central AC system over an individual AC system. As for the estimate average natural gas coefficient (ANGP), high natural gas prices appear to increase the probability of choosing ELECCEN as the heating and cooling equipment. AELECP for NGCEN, 0.05061, means that when the electricity price goes up, households are more likely to select natural-gas-based heating over the electric heating system. The INCOME coefficient for the NGCEN category shows that the natural-gas-based heating and the central AC system are popular among higher-income households. This fact is supported by Table 3.8 as well. The descriptive statistics in the table show that the annual income of the NGCEN category is highest among the five categories.

Table 3.9 Estimated Coefficients, the Discrete Appliance Choice of Model II
(Alternatives: ELECCEN (reference group), NGCEN, ELECIND, NGIND, and OTHERS)

Variable	Choice	Coefficient	Std. Err.	p-value
HOPCOST	NGCEN	–9.5E-05*	1.52E-05	0.000
	ELECIND	2.76E-06	3.33E-06	0.407
	NGIND	–8.5E-05*	1.29E-05	0.000
	OTHERS	–1.69E-07	1.75E-06	0.923
COPCOST	NGCEN	–0.00149*	0.000238	0.000
	ELECIND	–0.00286*	0.000969	0.003
	NGIND	–0.0033*	0.000888	0.000
	OTHERS	–0.00166*	0.000312	0.000
HKCOST	NGCEN	0.005932*	0.001278	0.000
	ELECIND	–0.0004	0.000306	0.187
	NGIND	–0.00025	0.000561	0.658
	OTHERS	–0.00046	0.000235	0.050
CKCOST	NGCEN	0.000916	0.000379	0.016
	ELECIND	–0.01424*	0.003015	0.000
	NGIND	–0.01502*	0.004376	0.001
	OTHERS	–0.0023*	0.000233	0.000
INCOME	NGCEN	5.79E-06*	2.18E-06	0.008
	ELECIND	–3.35E-06	4.33E-06	0.439
	NGIND	1.07E-05	4.65E-06	0.021
	OTHERS	4.54E-06	2.13E-06	0.033
AELECP	NGCEN	0.050601*	0.017423	0.004
	ELECIND	0.00133	0.022634	0.953
	NGIND	–0.01314	0.030029	0.662
	OTHERS	0.096108*	0.014758	0.000
ANGP	NGCEN	–0.17084*	0.048314	0.000
	ELECIND	–0.45572*	0.081959	0.000
	NGIND	–0.21107	0.116534	0.070
	OTHERS	–0.19063*	0.043995	0.000

Number of observations = 3386
LR $Chi^2(28)$ = 6415.26
Prob > Chi^2 = 0.0000
Pseudo R^2 = 0.6404

a. The choice-specific coefficients are relative to the base category, ELECCEN.
b. Likelihood Ratio (LR) test of Ho: all coefficients but the constant terms equal to zero.

Stage II: Electricity Consumption (Continuous Choice) Model

As model I and model II specified, observation-specific energy prices, income, number of rooms, HDD, and CDD are included in the continuous choice model. The main difference of this model from the previous two models is including the expected probability of each alternative (PRNGCEN[8], PRELECIND[9], PRNGIND[10], and PROTHERS[11]) rather than the set of dummy variables showing the current equipment holdings. The variables except the choice probability terms are transformed to logs. This model found that the price elasticity of residential electricity demand is –0.78. This value is between the estimates from the two previous OLS models (–0.66 and –0.81). Compared to the second OLS model using observation-specific energy prices (α = –0.81), this continuous/discrete choice model shows less elastic demand. Because the income variable is used both in the discrete choice model and in this continuous choice model, it is allowed to influence the energy demand directly; this is measured by their respective parameter estimates and indirectly through their effects on the selection terms. Finally the potential (direct) impact from income is tested in this model. Table 3.10 reports the estimated coefficients from this continuous choice model.

The reported elasticity is not the universally correct number, but it is noteworthy that it does not reject the hypothesis of long-term optimization. This model includes probability terms to take into account the possible impacts from the appliance choice on electricity demand. Because the assumption of joint optimization is proved to be correct by this model, the omission of this variable in the standard OLS models may imply a misspecification bias.

---

[8] The expected probability for the natural-gas heating and central AC to be selected for each household
[9] The expected probability for the electric heating and individual AC to be selected for each household
[10] The expected probability for the natural-gas heating and individual AC to be selected for each household
[11] The expected probability for other heating-cooling systems to be selected for each household

Table 3.10 Estimated Coefficients, the Conditional Energy Demand of Model III

ln(electricity use)	Coefficient	Std. Err.	*t*	p-value
ln(electricity price)	–0.777*	0.032	–24.630	0.000
ln(natural gas price)	0.086	0.034	2.500	0.012
ln(income)	0.150*	0.010	14.330	0.000
ln(# of rooms)	0.530*	0.022	23.590	0.000
ln(HDD)	0.000	0.016	0.020	0.981
ln(CDD)	0.172*	0.019	8.850	0.000
PRNGCEN	–0.593*	0.034	–17.530	0.000
PRELECIND	–0.145	0.063	–2.300	0.022
PRNGIND	–0.733*	0.038	–19.340	0.000
PROTHERS	–0.517*	0.067	–7.690	0.000
Constant	5.186*	0.328	15.820	0.000

Number of observations = 3315
Prob > F = 0.0000
R^2 = 0.5148
Adjusted R^2 = 0.5133
Root MSE = 0.45845

3.4 Comparisons among the Three Models

As mentioned previously in this chapter, the main purpose of estimating price elasticity in this study is to examine how the short-run demand responsiveness to changes in price influences the long-run demand projections. The short-run price elasticity basically reflects how consumers adjust to changes in price without any consideration of equipment shift. Because model I and model II controlled for the technology shift with the use of appliance holding dummies, they are interpreted as short-run price elasticities. Then, is the elasticity in the discrete/continuous choice model most naturally interpreted as a short- or long-term estimate? As discussed in Chapter 2, when the demand is limited (fixed) by the available stock of installation, the response to a price change is a short-run response. On the other hand, when the appliance has been optimally adapted to new conditions and the response to the price change is affected by the optimized new conditions, it is a long-term response (Vaage, 2000). The continuous/discrete choice model explicitly modeled the joint optimization of appliance and appliance use. Thus, the derived estimate must be interpreted as a long-term effect. Thus, either Model I or Model II should be used to estimate the short-run price elasticity for NEMS experiments in Chapter 6.

First of all, in terms of R^2, the continuous/discrete choice model (model III) shows the best fit to the data (Table 3.11). It was found that the electricity price (either census-division price or household-level price) the annual income and the number of rooms affect the determination of the level of electricity consumption significantly. The 2005 RECS data detailed information about American households' energy consumption. This rich source of micro-level data complements the existing econometric analysis based on time series data. Time series studies lack information concerning appliance stock, building characteristics, differences in climates, and demographic characteristics and are usually aggregates over the entire nation's or region's data. The use of this cross-sectional data, however, allows researchers to consider the interventions across the households; thus, the cross-sectional data was used for this analysis.

Last, model II and model III use observation specific energy prices, and they show relatively more elastic demand than the first model with average prices. This means that consumers are more responsive to prices they face on their bills rather than to regional average prices. However, it was found that there may be a misspecification problem in the use of observation-specific prices, as discussed in Section 3.2. To solve the misspecification problem, the involvement of the supply function or the price function including some information about the supply is required.

Model III includes probability terms to take into account the possible impacts from the appliance choice on electricity demand. Because the probability terms are statistically significant, this model shows that the assumption of joint optimization of appliance choice and appliance use is a legitimate assumption. However, the estimates from the conventional models are appropriate for the NEMS experiments in Chapter 6, because NEMS uses only short-term price elasticities to adjust its long-term forecasts. Puller and Greening (1999) also argue that they believe that their single continuous analysis is not without good foundation because many of the short-run adjustments are continuous choice only, although a more complete model would incorporate discrete choices. The first two OLS models do not allow changes in appliance choice of the households, so that they can be interpreted as short-run price elasticities needed for the next phase of this study. Considering the issue of possible misspecification error in model II, the short-run price elasticity estimated by model I is ultimately selected for the NEMS experiments.

Table 3.11 Summary of Estimated Electricity Demand Models

	Coefficients by Model		
Dependent Variable ln(electricity use)	**Model I: OLS with Average Prices**	**Model II: OLS with Observation-specific Prices**	**Model III: Continuous/ Discrete Choice Model with Observation-specific Prices**
Independent Variables			
ln(electricity price)	**–0.663***	**–0.811***	**–0.777***
ln(natural gas price)	0.445*	–0.022	0.086
ln(income)	0.119*	0.136*	0.150*
ln(# of rooms)	0.627*	0.566*	0.530*
ln(HDD)	0.032*	–0.013	0.000
ln(CDD)	0.077*	0.104*	0.172*
NGCEN	–0.415*	–0.356*	
NGIND	–0.605*	–0.506*	
NGBOTH	–0.393*	–0.317*	
NG9	–0.768*	–0.675*	
ELECIND	–0.046	–0.069	
ELECBOTH	0.167	0.119	
ELEC9	–0.156*	–0.156*	
OTHERCEN	–0.155*	–0.086	
OTHERIND	–0.444*	–0.297*	
OTHERBOTH	0.198	0.235	
OTHER9	–0.502*	–0.351*	
PRNGCEN			–0.593*
PRELECIND			–0.145
PRNGIND			–0.733*
PROTHERS			–0.517*
Constant	9.161*	5.119*	5.186*
R^2	**0.433**	**0.505**	**0.515**

*Significant at the 99% confidence level

CHAPTER 4
ENERGY CONSUMER BEHAVIOR

Economics as well as other behavioral sciences such as psychology and sociology have suggested various and interesting views of energy consumer behavior. A broader approach to energy efficiency and conservation policy could motivate consumers to save residential energy. Some behavioral scientists argue that small changes in the context, so called "nudges," could affect as much as large price changes. This suggests a potential role for non-price intervention. Insights from economic and non economic behavioral sciences may contribute to developing informational programs for energy conservation. Recently, utility companies and public agencies have utilized the behavioral science research for shifting electricity loads, conserving energy, and enhancing technological innovation.

The behavioral scientists have been interested in not only the rational but also the irrational side of human behaviors. They point out that people sometimes procrastinate and that their attention and interests wander (Allcott and Mullainathan, 2010). These peripheral factors subconsciously influence consumers' perceptions and decisions, which influence real-world outcomes. Many previous studies suggest that people fail to adopt advanced technologies that would save them money by using less energy, such as better insulation, fuel-efficient vehicles, and efficient appliances and lighting. It is because people often resist actions that have clear long-term benefits if they perceive them unpleasantly in the short run. Allcott and Mullainathan (2010) explains this phenomenon with an interesting example like follows. People do not exercise regularly because of the short-term inconvenience or discomfort even though they know the regular work-out would turn out a healthy and well-shaped body in the end. A recent *New York Times* article shows an interesting behavior of consumers (in terms of energy savings) in the home electronics market:

> Each year millions of Americans with old, inefficient refrigerators in their kitchens buy new, energy-saving ones. That may sound like an efficiency boon, but what's vexing efficiency advocates is that an increasing number of consumers don't actually get rid of the old fridge. A large number of older refrigerators still remain on the grid, even when swapped for more energy-efficient models. Unplugging the 29.6 million secondary units nationwide that are candidates for retirement would save 25 million megawatt hours of electricity, or about $2.8 billion, the energy department study reported (Vestel, 2010).

The Scenarios for a Clean Energy Future study (Brown et al., 2001) show that the U.S. economy could reduce residential energy consumption by up to 20 percent in 2020 solely by adopting energy-efficient and clean technologies. Similarly, a McKinsey report released in 2009 points out that many households and businesses in the U.S. are not energy efficient, even though they could reduce energy consumption by 23% from the baseline by making them so. The amount of saved energy is equivalent to $1.2 trillion at an upfront cost of $520 billion (Granade et al., 2009). Of course, various factors affect this phenomenon, and more evidence is needed, but some barriers may come from insufficient information about energy efficiency and the imperfect rationality of consumers. Nolan and his colleagues (2008) argue that households could reduce their electricity consumption by 3% on average and lower carbon dioxide emissions from electric power by 0.5% only if they were provided with home energy-use reports to inform them of tips for saving energy.

This chapter discusses economic, psychological, and sociological concepts underlying consumer behavior in energy efficiency and conservation. Market and behavioral failures, psychological nudges, information problems relevant to energy efficiency are the main themes of the discussion.

4.1 Energy Market Failure

Energy market failure can be explained with the "energy efficiency gap" between the observed level of energy efficiency and some notion of optimal energy use (Hirst and Brown, 1990; Jaffe et al., 2004; Gillingham et al., 2009). Maximizing economic efficiency, which is generally considered as maximizing the net benefits to society, does not imply maximizing physical energy efficiency (Gillingham et al., 2009). One of the reasons the socially optimal level of efficiency will not be achieved is that implicit discount rates for consumers are higher than actual discount rates in the market. Thus, consumers weigh present and visible cash flows against uncertain future flows. The gap between economic energy efficiency and technical (physical) energy efficiency could occur as a result of hidden costs, such as search costs (Jaffe et al., 2004), or with the irreversibility of energy efficiency investments (Hassett and Metcalf, 1993, 1995; van Soest and Bulte, 2000).

Energy market failure can be explained from other concepts of environmental externalities and imperfect information that lead to deviations from benefit maximization (or cost minimization). The main theme in energy market failures is that energy prices could not convey the true marginal social cost of energy consumption correctly because of environmental externalities and average-cost pricing (Gillingham et al., 2009). When a scarce environmental good, such as cleanliness of air, is considered as a public good and not a common good which is traded in the market, an externality occurs. The externality leads to an underinvestment in energy efficiency and hence results in an overuse of energy. To the extent that electricity prices do not internalize the externalities related to greenhouse gas emissions and water pollution from the electric power sector, the rate of energy efficiency adoption would be lower than the socially optimal level. In addition to unpriced environmental externalities, imperfect or missing information of products' energy intensity would tend to lower the relative price of energy (fuels) to technology adoption in energy production in a household[12], leading finally to choices of low energy efficiency.

On the other hand, there exist positive externalities associated with learning by using, and the experience and knowledge absorbed by consumers motivates them to adopt additional efficient equipment or for non-participants to join energy-efficiency programs and purchase energy-efficient appliances (Gillingham et al., 2009). Program spillovers occur when participating households install additional energy-efficient products voluntarily, and without any additional rebates, as a result of the knowledge and experience they have absorbed through participating in the program. An early adopter of a new energy-efficient product builds knowledge about the product through its use, and others benefit from the information about the existence, attributes, and performance of the products. Customer reviews available online are a good example of these positive externalities. Some studies have named learning-by-doing spillovers as “free drivers” in the context of demand-side management programs (Blumstein and Harris, 1993; Eto et al., 1996). Free drivers are nonparticipants who purchase and install energy-efficient products as a result of hearing about them from program participants.

4.2 Behavioral Failure

The psychology, sociology, and even economics literatures have drawn attention to several systematic biases in consumer decision making in energy use and investment in energy efficiency. Arguments about behavioral failure depart from the neoclassical economic assumption about consumers: perfect rationality. Thus, the crucial and main question is whether the deviations from the perfect rationality lead to significant

---

[12] The conception of relative price of energy (fuels) to technology adoption is explained in Figure 2.1 in Chapter 2.

systematic biases in energy efficiency decision making and, if so, whether these biases lead to under- or overinvestment in energy efficiency (Gillingham et al., 2009).

Bounded rationality suggests that consumers are rational but face cognitive constraints in processing information, which leads to deviations from rationality in certain circumstances (Simon 1959, 1986). Empirically testing the bounded rationality of energy consumers is difficult in that there are limited models of bounded rationality applicable to energy decision making (Sanstad and Howarth, 1994; Gillingham et al., 2009). Kempton and Montgomery (1982) argue that consumers tend to use a simple payback measure derived from a simple calculation: the total investment cost divided by the future savings, calculated using the energy price at the moment of the calculation rather than the price at the time of the actual savings. According to this argument, consumers ignore future changes in real fuel prices for convenience in calculation. Kempton et al. (1992) empirically find that consumers systematically miscalculate payback for air conditioner investments, and the miscalculation results in overconsumption of electricity. Yates and Aronson (1985) point out that there is a salience effect in decision making. The salience effect means that consumers attach disproportionate weight to the most psychologically vivid and currently observable factors among various determinants. The salience effect may explain bounded rational behaviors in energy efficiency decisions, such as an overemphasis on the initial cost of an energy-efficient purchase, which leads to an underinvestment in energy-efficient equipment (Wilson and Dowlatabadi, 2007).

Heuristic decision-making theory basically assumes bounded rationality and explains a variety of decision-making strategies different from critical ways used in conventional utility maximization. According to this theory, consumers use simple heuristic techniques to determine their energy consumption levels in order to reduce the cognitive burden, and this behavioral feature systematically leads to an underinvestment in energy efficiency. Tversky (1972) argues that consumers use a sequential decision-making process by which they first narrow their full choices down to a smaller set by eliminating products that cost above a certain level.

Furthermore, there have been some controversies around the effectiveness of the energy efficiency policies. Some people argue that the policies for reducing carbon emissions and for saving energy might actually increase overall energy consumption—a side effect called the "rebound" or "takeback" effect, which might be caused either by unintended wastes or by energy consumers' behavioral changes (Dinan, 1989; Laitner, 2000). The demand for energy services may increase in response to the declined marginal cost for operating the efficient equipment. As the efficiency of heating equipment and housing structures improves, homeowners may choose to maintain higher indoor temperature levels because the price of heating becomes relatively less due to the improved efficiency.

4.3 Information Problems

There has been a skeptical view of informational and educational programs in that there have been very few studies empirically measuring the exact magnitude of their effectiveness. Moreover, the evidence of their effectiveness is mixed because the programs vary in implementation and evaluation. Weil and McMahon (2003) argue that product labeling requirements are successful in increasing energy-efficient investments and offered anecdotal evidence. Newell and his colleagues (1999) empirically find that the responsiveness of energy efficiency innovation to energy prices had grown substantially since product labeling was required, whereas Levine and his colleagues (1995) argue that the Energy Guide product labeling requirements were fairly ineffective.

Whether they support the effectiveness of the informational programs or not, experts and scholars have agreed on that information problems are the primary explanations for the energy-efficiency gap (Sanstad et al., 2006). Gillingham and his colleagues (2009) point out that consumers' lack of information about the availability of and savings from energy-efficient products and principal-agent (split-incentive) problems are often given as reasons why consumers systematically under-invest in energy efficiency. The main idea is that consumers often do not have sufficient information about new and efficient equipment or about the differences in future operating costs between existing and newly introduced products in the market, even though such information is necessary to make proper investment decisions (Howarth and Sanstad, 1995). These information problems can be lightened by labeling and other information programs. Ek and Soderholm (2010) find that costs, environmental attitudes, and social interactions are important determinants of electricity saving activities within Swedish households. They test a hypothesis that information about available savings measures that is presented in a more concrete and specific way is more likely to affect behavior than is more general information.

Economic theories about principal-agent problems are often involved to explain that the split incentive causes underinvestment in energy efficiency. The agent, such as a builder or landlord, decides the level of energy efficiency in a building, while the principal, such as the purchaser or tenant, pays the energy bills. Because the person who installs energy efficient technologies could not be the same person who uses them, it is possible that information asymmetry about the energy efficiency of the building exists. Thus, the agent may not be able to get back the costs of energy efficiency. Similarly, many builders hesitate to adopt green building practices because they know that higher up-front expenditures would raise the sales values. Builders under-emphasize operating and maintenance costs and under-invest in energy efficiency relative to the social optimum because they know that some homeowners are not able to see beyond the relatively high initial costs of energy-efficient appliances and building construction practices (Jaffe and Stavins, 1994). Even though builders or landlords have enough knowledge and information about energy-efficient insulation or the necessary home electronics, they may not adopt new and advanced technologies because the installation costs reflect in the price or the rent of the house and they know that tenants and home buyers are more interested in lower prices and rents than in the bill savings they might expect in the future.

Time-dependent pricing systems also can solve the imperfect information problem by correcting price signals estimated based on information about the current marginal cost of electricity generation and transmission updated hourly or even more frequently. Since most of the electricity companies commonly use average-cost pricing systems under utility regulations, consumers are given retail prices that may not reflect marginal social costs. The average-cost prices normally depend on the average cost of the mix of generators used to produce electricity over a year or a season. When the average costs are below marginal cost, consumers face a price below the economically optimal price and are motivated to use electricity more than the optimal level. This market failure can be solved by market-based pricing systems that provide daily or hourly information. Pilot programs of alternative pricing schemes, such as time-of-use (TOU) pricing, peak and off-peak pricing (PTR), and critical-peak pricing (CPP), have proven that these time-variant pricing systems have significant impacts on reduction in energy consumption and load shifting (Faruqui and Sergici, 2009).

4.4 Policy Discussions from the Energy Consumer Sciences

The various arguments from economics and other behavioral sciences can shed a light on policy designs for energy efficiency improvement and energy conservation. First, governments can educate consumers and encourage them to make their energy-use habits more efficient and can also adjust their sensitivity to changes in price and policy by providing various tips for saving energy. In addition, various incentive systems using price differentials might motivate households to respond more sensitively to price changes. Rigorous consumption-recording and -monitoring systems, such as smart meters could promote the effectiveness of the incentive systems. Consumers could recognize how much energy they spend, and when they spend the most, based on the monitored energy-consumption record, and the information might help them to plan rationally for their own energy consumption. The number of installed smart meters has gradually grown, and 6.7 million smart meters were installed in 2008. However, 95 percent of residential buildings still remain unequipped (FERC, 2008). Ongoing R&D is expected to bring the cost down further, and a broad public advertisement would familiarize consumers with the monitoring system. When combined with enabling technology, energy conservation can be expedited (Brown et al., 2009).

Second, governments can establish potentially high-impact behavioral research programs as part of their broader energy innovation programs. The behavioral programs support research on consumers' rational or irrational behavioral attributes, such as their conceived discount rate for energy efficiency. The research could contribute to developing reasonable and effective incentive systems. Criteria for funding such behavioral research should be similar to those used for allocating resources to engineering and basic science research (Allcott and Mullaninathan, 2010). As they support technological R&D projects to develop theories and their applications, governments can provide funding for social sciences to scientifically measure and analyze consumers' psychology and behavior in energy consumption and efficiency adoption through both theory-driven and empirical study. For instance, even though the results of recent real-time pricing (RTP) and critical-peak pricing (CPP) pilots demonstrate that consumers can and will adjust electricity usage in response to price changes, policy makers and pricing plan designers are still skeptical of the impact of large-scale implementation because there is no consensus on the degree to which consumers will respond to price changes. As a result, there is no concurrence on which pricing plan or plans should be adopted (Neenan and Eom, 2008). Rigorous theory-driven social science research to measure the degree of the policy impact and to probe the mechanism of consumers' behavior by income level or other demographic differences will be required in order to design a more effective pricing system. A bill under consideration in the U.S. House of Representatives, HR 3247, would establish a behavioral research program at the DOE to understand behavioral factors that affect energy conservation and accelerate the adoption of promising initiatives.

Third, expanded informational programs can support consumers to save their energy. The educational programs can be utilized more successfully in the following ways. First of all, they can provide detailed and customized energy-saving tips to households and promote changes in energy-consuming habits more effectively. For example, the programs can give information on the differences between off-peak and high-peak prices and on how much money can be saved simply by rearranging the times that electricity is used. This could improve the short-run price elasticity of electricity demand. The improved responsiveness could contribute to conserving energy and redistributing the load so as not to overload the grid, generator, and transmission. In addition, the programs can "nudge" consumers to make better choices in adopting energy-efficient products. Only through providing and educating about the kind of financial supports the government offers, such as tax credits, the U.S. could expect significant energy savings. These informational programs should be effectively designed with careful consideration given to behavioral factors in the disclosures they control because the effect of information on choices depends critically on how the information is conveyed (Allocott and Mullaninathan, 2010).

Of course, the success of disclosure depends on the quality and consistency of information provided and the extent of public understanding. Information barriers occur when decision-makers do not have enough practical information to make investments in their own best interests. Consumers have been found not to be clearly aware of the relationships between their lifestyles, energy consumption, and the environment (Garrett and Koontz, 2008). Numerous facts and data are available to consumers, but they are regarded as useless information when information barriers are compounded by a lack of trusted and actionable guidelines. Information is often presented in terms that are not specific enough to drive consumer change (Gillingham, 2009). For that reason, more detailed and customized information is required to influence consumers efficiently. Even a simple feedback system accompanied by public information or education campaigns could have a great impact. For smart meters, there could be an online component to provide a customized electricity usage plan for each household based on their energy consumption and performance information. Consumers could be provided the specific rating scheme along with estimated benefits and costs of greater-efficiency units and retrofits. In addition, collecting feedback from various households could help to analyze more detailed behavioral characteristics of each household. A California case study demonstrated that, in most cases, consumer understanding of the meaning and usefulness of home energy performance data was a necessary prerequisite for interest in home energy performance (TecMarket Works, 2004).

This chapter casts a light on that the wide understanding the energy consumer behavior and the empirical evidences provided by the various energy consumer sciences can assist policy makers to design and implement effective energy policies.

CHAPTER 5
ENERGY POLICY AND RESIDENTIAL ELECTRICITY MARKET

Whether an energy policy is aimed to directly affect electricity price or not, it influences the market, utilities, and consumers and ultimately results in changes in price. This chapter reviews three major energy policies—energy efficiency, climate, and electricity pricing—that would have a potentially large impact on price changes. First, this chapter discusses carbon cap and trade and renewable electricity standard, and predicts how residential electricity price and consumption would under the scenario of a national carbon tax system and national renewable electricity standards. The price and consumption projections in this chapter are rough and preliminary estimations, but provide initial ideas for simulation experiments conducted in Chapter 6. Secondly, the effectiveness of two representative energy efficiency programs, ENERGY STAR and PATH, and their loopholes are discussed. In the last section, time-dependent electricity pricing systems with economic theories of consumer behavior are discussed.

5.1 Climate Policies

National and international climate policies are anticipated to affect electricity consumption and prices in the future. This section reviews two major climate policies, the national carbon tax and the national Renewable Electricity Standard (RES), and predicts changes in future electricity consumption and prices. To assess the potential impacts of the two energy and climate policies currently being debated in the U.S. Congress, this study modifies the third version of AEO2009-NEMS with the Economic Stimulus Package. This study names it GT-NEMS in order to emphasize that energy projections from the GT-NEMS could be different from projections from the original NEMS.

National Carbon Cap and Trade System

Putting a price on greenhouse gas (GHG) emissions and creating a market for trading the carbon credits can be accomplished with various policies, including energy and carbon taxes and cap-and-trade systems. Ten northeastern states—Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island, and Vermont—are participating in the Regional Greenhouse Gas Initiative (RGGI), which is the first mandatory, market-based CO_2 emissions reduction program in the United States (see the states marked in black in Figure 5.1). The signatory states to the RGGI agreement have capped CO_2 emissions from the power sector and will require a 10-percent reduction in these emissions by 2018. Twelve western states have formed the Western Climate Initiative (WCI) to implement a joint strategy to reduce GHG emissions. The WCI cap and trade program aims to reduce GHG emissions by 15 percent below the 2005 level by 2020. The nine states in the Midwest signed their own GHG reduction accord. The Midwestern GHG Reduction Accord advisory group has finalized their recommendation. The governors are now reviewing the recommendations to offer their input on next steps to be taken in the region and at the federal level. The recommendations have not been endorsed or approved by individual governors. In the South, there is no regional program yet. This variety of divergent policies is particularly challenging to stakeholders who are striving to develop national markets. In recent years, the U.S. Congress has proposed hundreds of climate-related initiatives (Congressional Budget Office, 2009), and the pace of climate policy activity appears to be accelerating. Keeping step with the trend, an increasing number of U.S. companies has been participating in voluntary GHG emissions reduction programs and registries partly to prepare for eventual federal regulations (Southworth, 2009). Given the importance of placing a cost on carbon and the problems associated with the diversity of regional approaches that exists today, there is great momentum to establish a national policy of carbon constraints (Brown and Baek, 2011). The National Commission on Energy Policy

(NCEP, 2004) provides key design features of a cap-and-trade program pertaining to emission targets, point of regulation, price ceiling and floor, offsets, banking and borrowing, and allocation of allowances. It has been pointed out that having an effectively designed instrument is more important than the choice of policy (Aldy et al., 2009; Goulder, 2009), since there have been some concerns about how the costs of the national policy would be distributed fairly across regions and income groups.

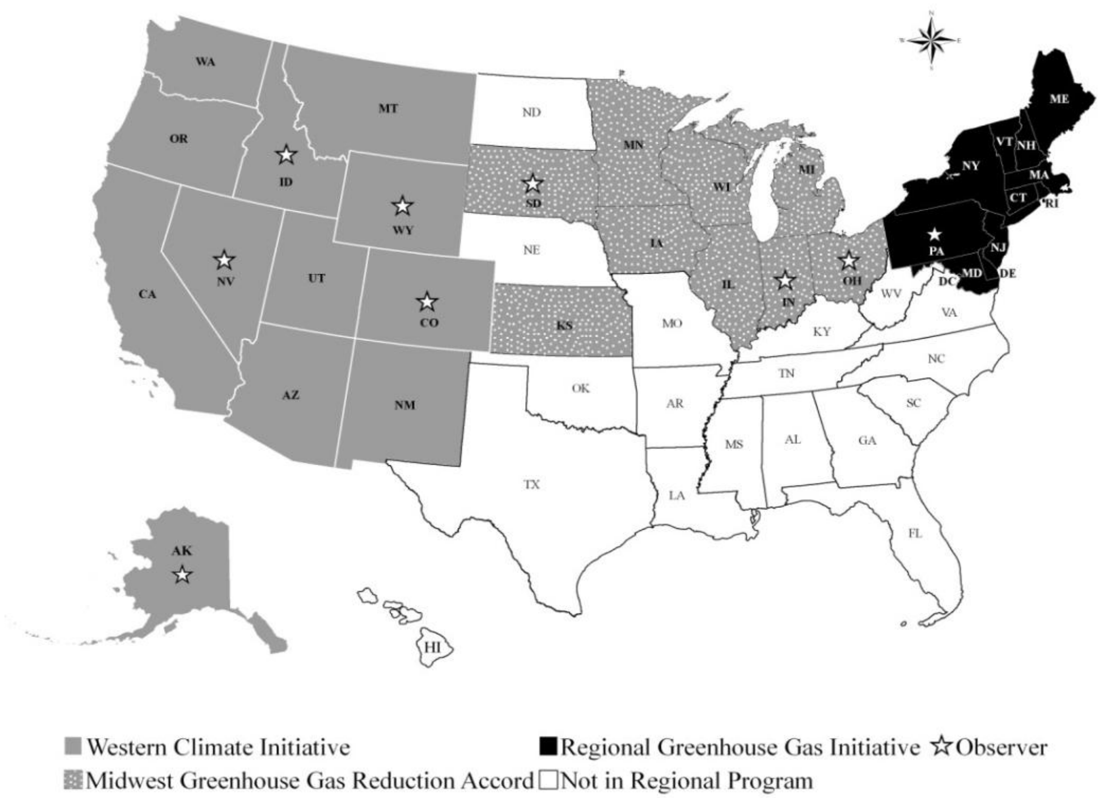

Figure 5.1 Regional Carbon Cap-and-Trade Initiatives

(Data Source: Database of State Incentives for Renewable Energy, http://www.dsireusa.org/)

Energy policy makers are aware of the importance of the policy and claim to be taxing polluters, not electricity consumers. Once the government creates a scarce new commodity, the costs would inevitably be passed on to the electricity prices. Peter Orszag, President Obama's budget director, told Congress last year that "Those price increases are essential to the success of a cap-and-trade program." The Congressional

Budget Office (2007) estimates that the price hikes to reduce emissions by 15% would cost the average household in the bottom-income quintile about 3.3% of its after-tax income every year—the equivalent of $680, not including the costs of reduced employment and output. The three middle quintiles would see their paychecks cut between $880 and $1,500, or about 2.7 percent of their income. The rich would pay 1.7% (CBO, 2007).

This study analyzes the potential impact of a national policy of carbon constraints on residential electricity and consumption by changing several parameters in GT-NEMS. First, based on examinations of the allowance price projections estimated by the Energy Information Administration (EIA), Congressional Budget Office (CBO), Environmental Protection Agency (EPA), and Natural Resources Defense Council (NRDC), the annual schedule of carbon tax prices was estimated. This study models a carbon tax policy starting at $15 per ton of carbon dioxide (in 2005 dollars) in 2012, growing at 7% annually and reaching $51 per ton in 2030. In addition, an allowance redistribution system is implemented in GT-NEMS. It gives 90% of allowances to electricity-load-serving entities and 10% to generators. The allowances given to the load-serving entities are assumed to be passed along to consumers and subdue the increase in retail electricity prices.

A national carbon tax would raise the residential electricity price by 2% in 2020 and 17% in 2030. The price inflation is forecast to be considerably higher than the price increase under a national electricity standard (see Figures 5.2). With the short-run elasticity of -0.15 in the model, there would be no significant change in consumption (Figure 5.3). With a higher short-run elasticity, a reduction in future demand is expected.

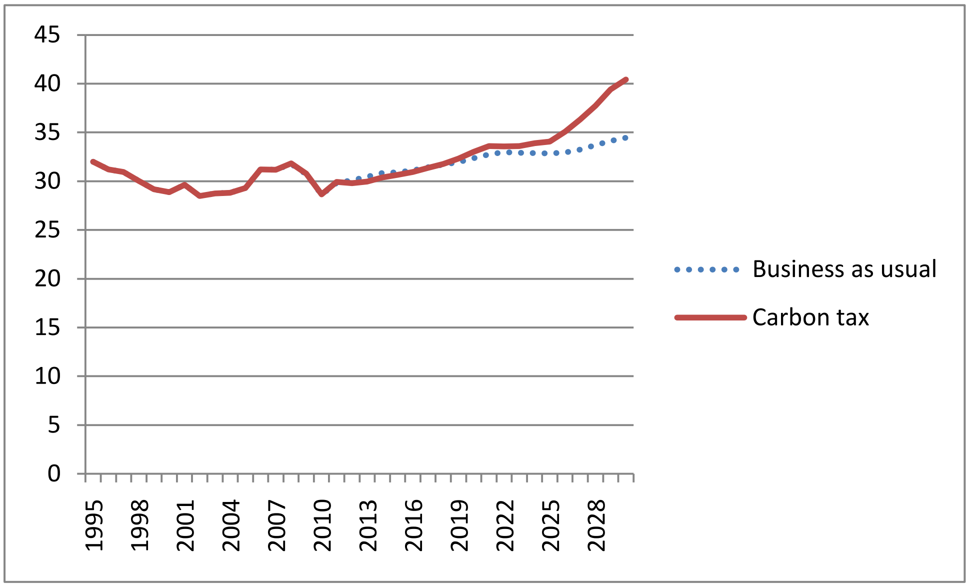

Figure 5.2 Residential Electricity Price Projections with a National Carbon Tax

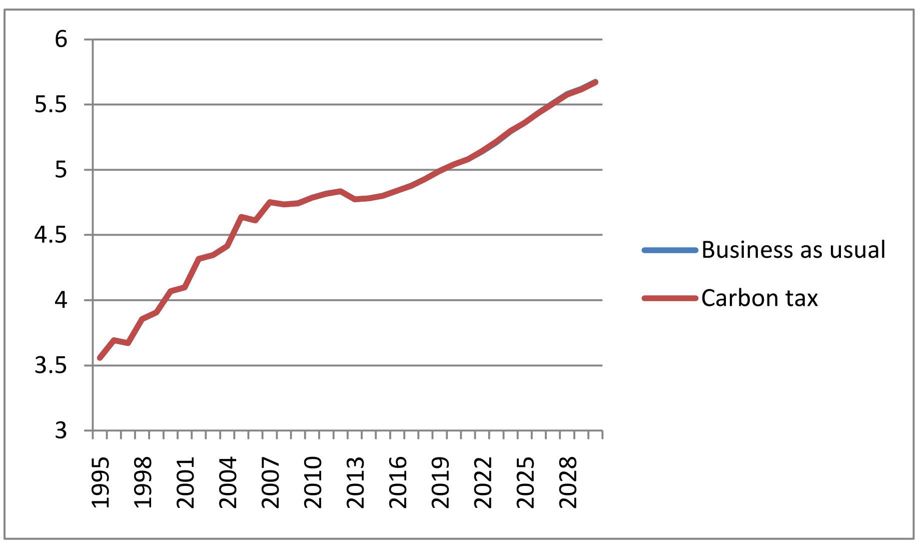

Figure 5.3 Residential Electricity Demand Projections with a National Carbon Tax

Renewable Electricity Standard (RES)

A renewable electricity standard (RES) is a legislative mandate requiring electricity suppliers in a given geographical area to employ renewable resources to generate a certain amount or percentage of renewable power by a target year (e.g., California will generate 20 percent of its electricity from renewables by 2010). Typically, electricity suppliers can either produce their own renewable energy or buy renewable energy credits. Therefore, this policy blends the benefits of a "command and control" regulatory paradigm with a free market approach to environmental protection. Renewable portfolio standards are currently mandated on a state-by-state basis. Currently, 36 states (including the District of Columbia) have some kind of RPS system in place, six of which set voluntary goals as opposed to strict requirements (Beck, 2009). Contrary to enabling a well-arranged national renewable energy market, however, inconsistencies between states over what counts as renewable energy, when it has to come online, how large it has to be, where it must be delivered, and how it may be traded clog the renewable energy market (Figure 5.4).

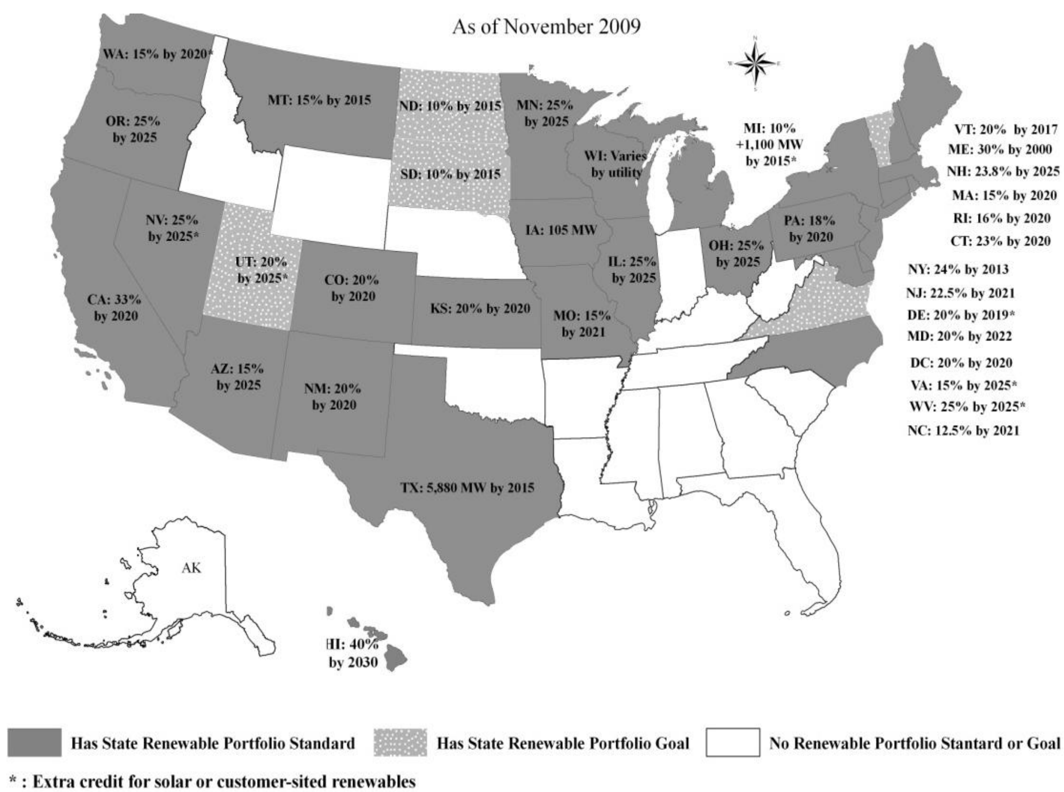

Figure 5.4 State renewable electricity standards

(Source: Database of State Incentives for Renewable Energy, http://www.dsireusa.org/)

To reduce state-by-state inconsistencies and further accelerate the growth of renewable power production, the U.S. Congress is considering implementation of a national standard. Recent Congressional proposals tend to be consistent with President Obama's campaign platform in 2008, which included a commitment to 25% renewable electricity production by 2025. Responding to requests from Chairman Edward Markey for an analysis of a 25% Federal RES, the EIA released the report "Impacts of a 25-Percent Renewable Electricity Standard as Proposed in the American Clean Energy and Security Act Discussion Draft" in 2009.

This study examines the nominal target share for renewables requiring not only major utility companies but also small retailers to meet the aggressive national RES target in order to estimate the maximum impact of the aggressive national RES on industrial electricity and biomass markets. This study modeled an RES goal equivalent to the one pledged by President Obama in 2008. Specifically, the RES specifies that at least 10 percent of U.S. electricity would come from renewable sources by 2012, and 25 percent by 2025. It took into account the possible technological advancement in renewable energy technologies and updated the supply curves of the renewable energy sources.

Figure 5.5 shows that a national RES would raise the prices by 2% in 2020 and 4% in 2030. This finding is replicated by other studies. The National Renewable Energy Laboratory (NREL, 2009) analyzed the potential impact of proposed national RES legislation by using the Regional Energy Development System (ReEDS) model and found that all of the RES bills, including Waxman-Markey, would have a modest impact on consumer electricity prices at the national level. Differences between average national electricity prices in the RES cases and the base case are less than 5%.

Like a national carbon tax, there was no significant change in consumption with the short-run elasticity of -0.15 in the GT-NEMS model (Figure 5.6). With a higher short-run elasticity, a reduction in consumption is expected.

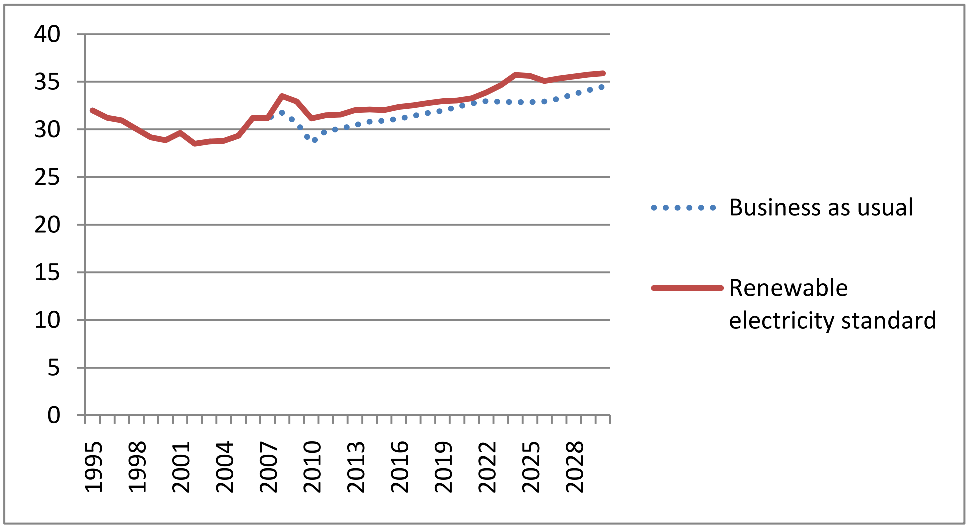

Figure 5.5 Residential Electricity Price Projections with a National RES

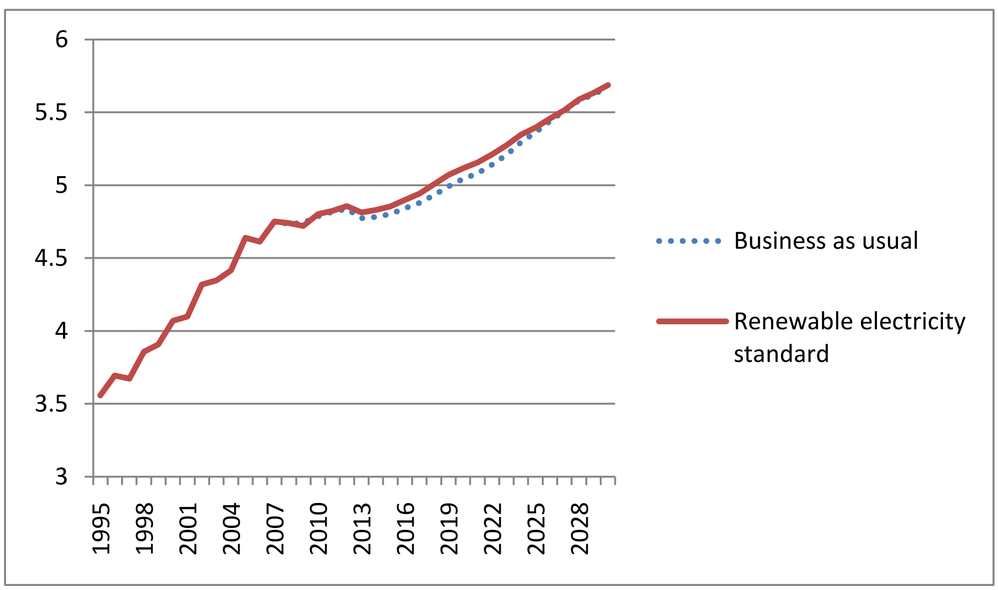

Figure 5.6 Residential Electricity Demand Projections with a National RES

5.2 Energy Efficiency Programs for Residential Buildings

Financial incentives for purchasing energy-efficient appliances and equipment have been regarded as one of the most effective policies for expediting advanced technologies' penetration of the market. Among these, tax credits could provide significant savings to households and builders, in that, while a tax deduction reduces just the amount of income subject to tax, a tax credit directly reduces the total amount of tax paid. Most of the residential tax credits, except for those applied to solar water heaters and panels, were expired as of December 31, 2007, but in the following year, the House passed 18.1 billion dollars in renewable energy tax incentives (HR 5351), including an extension of the tax credit for energy-efficient home improvements (Energy Star, 2008). In addition, the Department of Energy still calls for additional provisions of financial incentives to retailers selling large quantities of "best-in-class" appliances per the American Clean Energy and Security Act of 2009.

Two representative efficiency programs in the residential buildings sector are Energy Star and the Partnership for Advancing Technology in Housing (PATH). Energy Star is a joint program of the U.S. Environmental Protection Agency (EPA) and the U.S. Department of Energy (DOE) to help people save money and protect the environment through promoting energy-efficient products and practices. Consumers are estimated to have saved 16 billion dollars on their utility bills through the purchase of Energy Star equipment in 2007. Converted to carbon emissions, the savings are equivalent to those from 27 million cars (Energy Star, 2008). In particular, Energy Star labels appear to have achieved significant savings by inducing consumers to adopt greater energy efficiency (Webber et al., 2000). The voluntary Green Lights program and Energy Star office products program have been effective in increasing energy-efficiency investments by increasing access to information (Howarth et al., 2000).

On the other hand, PATH was initiated to speed up the development and use of building technologies that improve the quality, durability, energy efficiency, environmental performance, and affordability of America's housing. It is a voluntary partnership among leaders of homebuilding, material manufacturing, insurance and financial industries, and federal agencies related to housing. The PATH program incentivizes homebuilders with a 2,000-dollar tax credit for each energy-efficient house built.

However, not all Energy Star qualified homes and products are eligible for a tax credit. These tax credits are available only for limited products at the highest efficiency levels, which cost more than standard products. In addition, builders must build houses whose heating and cooling load efficiency exceeds the level indicated by the Internal Energy Conservation Code (IECC) by 50 percent in order to qualify for the PATH tax credit. Foss (2007) points out that meeting the requirement is not an easy task:

> Code minimum requirements include a 13-seer air conditioner and 13-seer, 7.7-HSPF heat pump. But the tax credit does not allow [homebuilders] to achieve the 50 percent heating and cooling reduction target through HVAC upgrade alone. [They] must improve the energy efficiency of the building envelope enough to reduce heating and cooling loads by at least 10 percent compared to 2004 IECC. In particular, builders should focus on air-sealing, window performance and insulation levels.

Energy efficiency retrofits of older homes and improved home construction practices are considered the most cost-effective strategies for cutting energy costs and curbing carbon emissions (Granade et al., 2009). However, various market failures and barriers impede investments in these opportunities. The first of these is the diverse and fragmented nature of the buildings industry. Multiple participants influence the decision-making process of a single house according to distinct interests, affecting the process at different points during design, construction, and use, and they often act as "decision-making intermediaries" who do not represent the long-term interests of the building owners or occupants who pay the energy bills (Brown et al., 2009; Jaffe and Stavins, 1994). The involvement of intermediaries in the purchase of energy technologies leads to an under-investment in energy efficiency. Even if there is no deviation in the process, homeowners themselves could weigh present and visible cash flows over uncertain flows in the future. Empirical evidence has been found in previous studies; the implicit discount rates range from 25% to over 100% (Sanstad et al., 2006; Train, 1985).

Furthermore, outdated building codes and appliance standards could be barriers to energy-efficient buildings, in spite of their numerous positive influences. Since codes and standards take a long time to be implemented and updated, the best performing materials and technologies in the market are not readily deployed, thereby inhibiting innovation and encouraging obsolete technology (Brown et al., 2009). Even when states improve older building codes, the code compliance is often limited because many of them lack consistent code enforcement and support programs to improve the compliance rate (Yang, 2005).

In addition, there have been some controversies around the effectiveness of certain energy-efficiency policies. Some people argue that the policies for reducing carbon emissions and for saving energy might actually increase overall energy consumption—a side effect called the "rebound" or "takeback" effect, which might be caused either by unintended wastes or by energy consumers' behavioral changes (Dinan 1989; Laitner 2000). As the efficiency of heating equipment and housing structures improve, homeowners may choose to maintain higher indoor temperature levels because the price of heating becomes relatively less due to the improved efficiency. Through an empirical study on a retrofit homes program in Hood River, Oregon, Dinan (1989) found that retrofitted homes maintained an average 0.5 degree Fahrenheit increase in residential temperature level. She also found that the gap between the actual and expected levels of temperature by the retrofit program is wider among lower-income households (Dinan

1989). In addition, Laitner (2000) found that the rebound effect might reduce overall energy savings by about 2 to 3 percent, depending on the assumptions for income, price elasticities, and supply-demand interactions.

Governments can improve the existing building codes and appliance standards so as to motivate electricity consumers to adopt energy-efficient technologies in the long run. Outdated building codes and appliance standards could be regulatory barriers to energy-efficient residential buildings. Since codes and standards take a long time to be implemented and updated, the best performing materials and technologies in the market are not readily deployed, thereby inhibiting innovation and encouraging obsolete technology (Brown et al., 2009). Even when states improve older building codes, the code compliance is often limited because many of them lack consistent code enforcement and support programs to improve the compliance rate (Yang, 2005). In addition, principal-agent problems between builders and building owners could impede the adoption of active energy-efficiency measures. In order to overcome the latent problems in the existing policies, a consistent financial support for code enforcement and maintenance would be required.

5.3 Time-dependent Electricity Rates and Smart Meters

Most households are given electricity prices that may not reflect marginal social costs since average-cost pricings under utility regulation are common. The retail prices typically reflect the average of these marginal costs over a period of months. The average-cost prices normally depend on the average cost of the mix of generators used to produce electricity. When the average costs are below the marginal cost, consumers face a price lower than the economically optimal price and are encouraged to use more electricity than the optimal level. On the other hand, market-based pricing provides daily or even hourly wholesale prices that reflect changes in market demand and operating costs. For that reason, time-variant pricing systems, such as time-of-use (TOU) prices and real-time pricing (RTP), can shift demand from peak time to off-peak so as to stabilize the market. The TOU prices vary by time of day or season, whereas the RTP directly reflects information about the current marginal cost of generation and transmission and is updated hourly or even more frequently. RTP and, to a lesser degree, TOU pricing have the potential to alleviate the market failure caused by average-cost pricing (Gillingham et al., 2009).

To make electricity demand responsive to price changes, rigorous recording and monitoring systems should precede incentive systems through price differentials. The term "smart meter" refers to meters that record the consumption of electricity as well as natural gas and water hourly or more frequently and output the information through an in-home device or on-line tool. The number of installed smart meters gradually grows and 6.7 million smart meters were installed in 2008. However, 95 percent of residential buildings still remain unequipped (FERC, 2008). Ongoing R&D is expected to bring the cost down further and a broad public advertisement would make consumers familiar with the monitoring system. When combined with enabling technology such as smart meters, energy conservation can be accelerated (Brown et al., 2009).

The potential for energy savings from time-dependent pricing is significant. Pfannenstiel and Faruqui (2008) found that the technical potential of the pricing system is 25 percent, the economic potential 12 percent, and the market achievable potential 5 percent during peak hours. Energy savings from smart meter technologies alone or in combination with alternative pricing have occurred both as load shifting and energy savings. Darby (2006) summarized that the energy savings caused by the direct feedback from meters in home displays ranged from 5 to 15 percent over several studies. Faruqui and Sergici (2009) argued that reducing the peak demand by five percent could lead to nationwide savings of $66 billion. The range of savings depends on uncertainties associated with combinations of different TOU rates and smart meters. Thus, research for optimizing the design of smart meter and TOU pricing policies, including evaluation of pilot programs, is required. Faruqui and Sergici (2009) summarized the potential savings from the pilot programs (Table 5.1).

Table 5.1 Summary of savings from pilot time-dependent-pricing programs

% of Savings	Minimum	Average	Maximum
Time of Use (TOU) Rate	2	4	6
TOU with Technology	21	26	31
Peak Time Rebates (PTR)	9	13	18
Critical Peak Pricing (CPP)	12	18	24
CPP with Technology	17	36	51

*Source: Faruqui and Sergici (2009)

5.4 Ex Ante Evaluation of Policy Options

Each of the policies discussed in this chapter have multiple policy options implementation. The impact of the policies discussed in this section could be evaluated differently depending on which criteria and assumptions are applied to the evaluation. Brown and her colleagues (2009) suggest eight criteria for evaluating energy policy options: 1) federal role, 2) applicability, 3) potential benefits, 4) non-R&D, 5) cost-effectiveness, 6) administrative practicability, 7) additionality, and 8) time to savings. Table 5.2 shows the description of each standard. This study develops discussions of social welfare estimation according to the two of the potential benefits and the time to savings out of the eight criteria.

Table 5.2 Criteria for Evaluating Policy Options (Brown et al., 2009)

Criteria	Description
Federal Role	Many of the more effective policies and measures in this area require state or local action. Must be clear regarding the appropriateness of the Federal role.
Applicability	Since the number of policies and measures to be analyzed is small, those selected for analysis should have broad applicability across the national scene.
Potential benefits	Policies and measures with significant and early quantitative benefits are to be favored over those with later and less.

Criteria	Description
Non-R&D	The policies and measures selected should address barriers and/or risks of mainly an institutional, policy, or non-technical nature.
Cost-effectiveness	Consideration should be limited to those that would be expected to have both reasonable costs, and a strong social benefit to cost ratio.
Administrative Practicability	Policies need to be capable of being fairly easily established and, if necessary, managed and/or enforced.
Additionality	The collection of selected policy options should be diverse, such that each option represents a somewhat different approach to a barrier or to different barriers.
Time to Savings	The shorter the time horizon required to achieve significant energy savings, the better.

This study discuss ex ante evaluation of a carbon tax as an example in the following section. How differently the short-run consumer's responsiveness affects the evaluation of the policy impacts of the tax is discussed in Chapter 7.

CHAPTER 6
LONG-RUN DEMAND MODEL: NEMS EXPERIMENTS

6.1 National Energy Modeling System

Using the value of the short-run price elasticity estimated in Chapter 3, this chapter examines the sensitivity of the long-run U.S. residential electricity demand to various short-run elasticity settings. To forecast consumers' responsiveness in the long-run, this study uses the National Energy Modeling System (NEMS), a computer-based, energy-economy modeling system of U.S. energy markets developed by the Energy Information Administration (EIA). It predicts the supplies, demands, and prices of various energy resources subject to macroeconomic factors, world energy market indicators, resource availability, technological advancement, and regional characteristics. It is typically used by the EIA as well as other parties in order to forecast the energy, economic, environmental, and security impacts on U.S. alternative energy policies and to conduct sensitivity analyses. The modeling system includes regional details based on the nine U.S. census divisions and is able to project regional variations in energy costs, policies, and resource availabilities. NEMS consists of four supply modules, four demand modules, two conversion modules, two exogenous modules, and one integrating module (see Figure 6.1). Each module of NEMS assumes various cases of economic growth in the U.S. and in the world energy market, particularly world oil prices. To embody the assumptions, it represents a scenario for each of the following cases: a reference case, high and low economic growth cases, and high and low world oil price cases. The reference case is set by assuming a business-as-usual-scenario (EIA 2003).

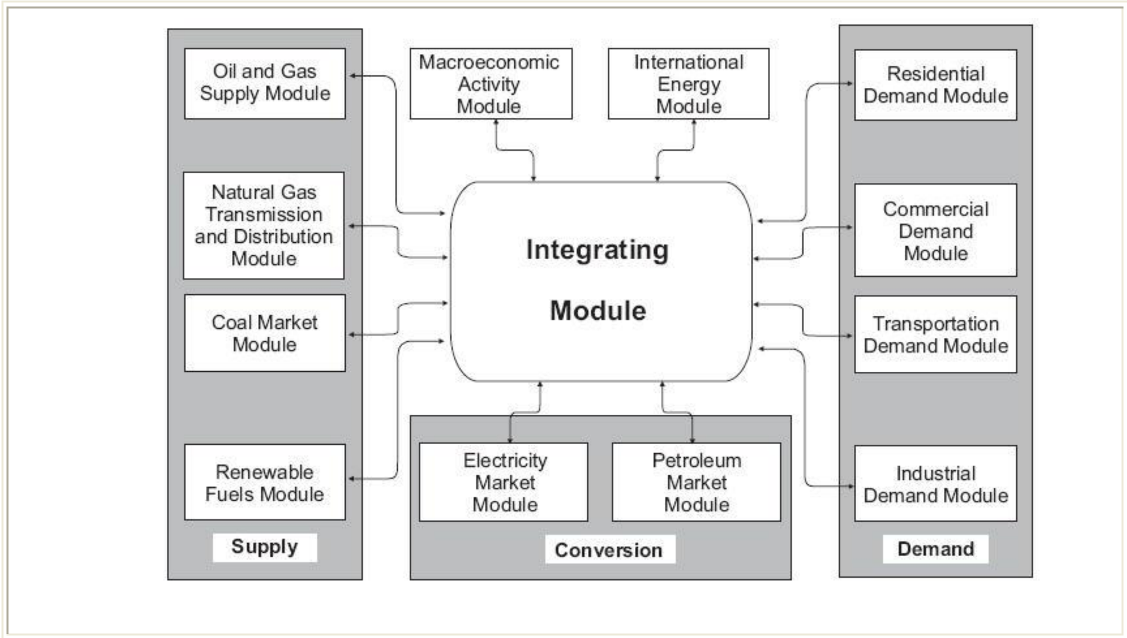

Figure 6.1 National Energy Modeling System (NEMS)

(Source: National Energy Modeling System: An Overview of 2003, EIA 2003)

Among the 13 different modules, this study focuses especially on the Residential Demand Module (RDM). The RDM is built based on the EIA's Residential Energy Consumption Survey (RECS) collected in 2005. The RDM projects annual residential-sector energy demand, appliance stocks, and market shares of the entire U.S. by nine census divisions, fuel type, and service based on accounting principles and residential consumer behaviors (EIA, 2007). In other words, the RDM provides national residential energy demands at the macro level. For that reason, it is regarded as the housing and equipment stock model. The residential energy demand of the entire U.S. is influenced by residential housing stock and energy consuming equipment, especially by building shell efficiency (EIA 2003): "… in the residential building model, price-induced increase in building shell efficiency such as insulation, caulking, and thermally-efficient windows persist longer than other equipment purchase decisions because adjustments to the shell are assumed to retire only when the housing unit decays from the stock" (Wade, 2003).

The RDM generates projections of residential energy demand through six sequential steps; these steps produce information on housing stocks, technology choices, appliance stocks, building shell integrity, distributed power generation, and energy consumption. First, the RDM generates a projection of housing stock, accounting for the retirement of existing housing stock and the addition of new construction. Second, the module estimates vintage equipment stock based on the number of housing demolitions and additions. Third, the market shares of equipment by service are estimated. Fourth, the weighted average efficiencies are calculated based on market shares. Finally, the RDM calculates energy consumption by fuel using the unit energy consumption data and the weighted efficiencies (EIA, 2007).

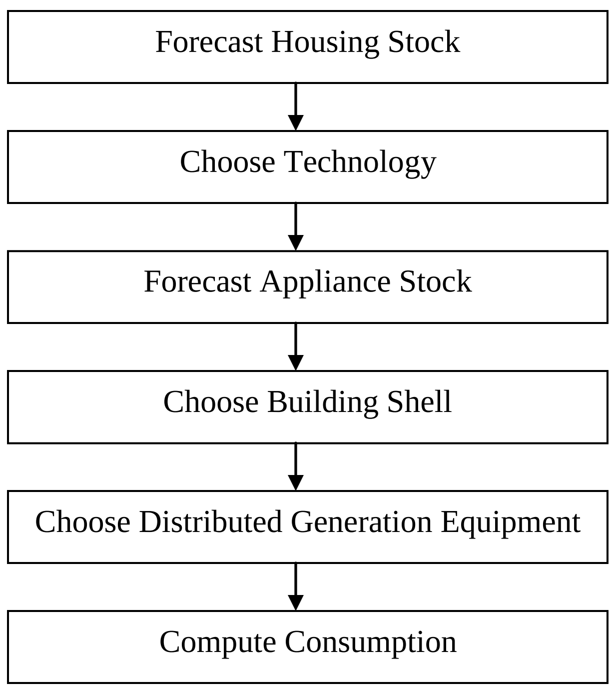

Figure 6.2 Structure of the Residential Demand Module (RDM)

(Source: Model Documentation Report: RDM of the NEMS, EIA 2007)

The RDM applies various research findings from academic, industrial, and government studies to the model, beginning with implementing the short-run price elasticity of demand by end-use service. EIA has applied the rebound effect[13] to the RDM, because many empirical studies have revealed the effect of efficiency policies on energy consumption. The module assumes a 0.15 percent increase in consumption for a 1 percent increase in efficiency. Furthermore, a discrete building shell module has been added in order to characterize several efficiency programs sponsored by the DOE and EPA, such as Energy Star and PATH. The choice of Energy Star and PATH homes is modeled on the basis of tradeoffs between increased construction costs and reduced energy costs. (EIA, 2003; Wade, 2003; EIA, 2007).

With the growing appreciation of how energy consumption impacts environmental quality and national security, future consumer behavior could further enlarge the savings estimate as the demand for energy-efficient technologies grows. The inclusion of additional behavioral effects would provide a more precise estimate of efficiency potential.

6.2 Distributed Short-run Elasticity Calculation Function

The source codes of the RDM are thoroughly reviewed to figure out how the short-run price elasticity parameter (alpha) is utilized in NEMS long-run demand forecast. The actual Fotran codes are shown in Appendix F. First of all the RDM define three distributional shares for the short-run elasticity effects of EF1, EF2, and EF3. They are used as lag weights that redistribute the impact of alpha into three consecutive years. Therefore, the sum of the three should be equal to 1. Then, the RDM defines a distributed short-run elasticity function, RSELAST as a function of EF1, EF2, and EF3, and alpha.

---

[13] The rebound effect in energy consumption is discussed in the section of behavioral failure in Chapter 4 and in the section of the effectiveness of energy efficiency programs for residential buildings in Chapter 5.

To link EF1, EF2, and EF3 to RSELAST, the RDM defines three intermediate parameters of FAC1, FAC2, and FAC3 which are computed like as follows:

If current year ≥ RECS year+1,

$$FAC1 = \left(\frac{Prices\ (F,R,current\ year)}{Prices\ (F,R,RECS\ year)}\right)^{(alpha*EF1)}$$

If current year ≥ RECS year+2,

$$FAC1 = \left(\frac{Prices\ (F,R,current\ year-1)}{Prices\ (F,R,RECS\ year)}\right)^{(alpha*EF2)}$$

If current year ≥ RECS year+3,

$$FAC1 = \left(\frac{Prices\ (F,R,current\ year-2)}{Prices\ (F,R,RECS\ year)}\right)^{(alpha*EF3)}$$

[Equation 6.1]

Then, RSELAST is ultimately defined as:

RSELAST = FAC1*FAC2*FAC3

[Equation 6.2]

The RSELAST is used to adjust the computed annual energy consumption by fuel and end use from the sequential calculations listed in Figure 6.2.

On balance, the internal source codes indicate that the NEMS applies a lagged structure of demand and distribute of the impact of short-run consumer's responsiveness into multiple years. This means that when price shocks occurs, consumer gradually adjust to the price changes for three years rather than responding to them immediately in NEMS.

6.3 Technology Choice

The production function theory in economics can explains how market forces and technological innovation affect consumers' choice of energy efficiency. This framework views capital and energy as two inputs for producing energy services. Along an isoquant curve depicting a given level of indifferent energy services, the cost-minimizing level of energy efficiency (capital) and energy use are found at the point of tangency where the marginal increase in capital cost with respect to energy reduction is equal to their relative price (in present-value terms) (Figure 6.3). The relative price depends on the capital cost of efficiency improvements, the discount rate, expected energy prices, equipment utilization, and decision-time horizon. This framework is applicable not only to the household but also to the broad sectoral or national level where energy and capital are used to produce energy services.

Figure 6.3 and Figure 6.4 show two different ways for market forces to drive greater energy efficiency within this production function framework. First, households could move along the energy services isoquant by substituting capital for energy input in response to a change in relative price. Figure 6.3 describes a situation when the relative price between capital and energy changes from P_0 to P_1. Second, technological change (innovation) that shifts the isoquant in a way favoring greater energy efficiency could change the production possibilities available to households. Figure 6.4 describes a situation that technological innovation shifts the isoquant curve itself and make it possible for consumers to produce the same level of energy services with a smaller level of energy input. In contrast, energy conservation not driven by energy efficiency improvement would be associated with a lower level of energy-service production.

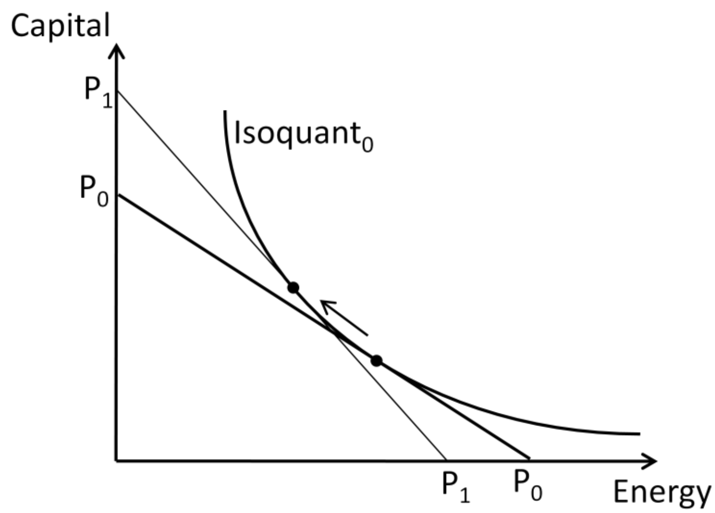

Figure 6.3 Substitution between Energy Use and Capital Investment

(Source: Gillingham et al., 2009)

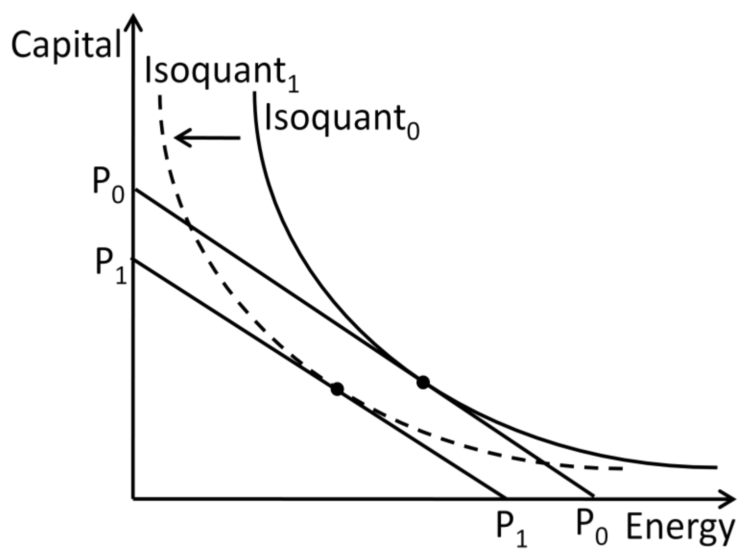

Figure 6.4 Technological innovation

(Source: Gillingham, 2009)

Gillingham et al. (2009) argue that market failures can be explained within this framework as a divergence of the relative prices used for private decisions from the economically efficient prices. Both unpriced environmental externalities and missing information about the energy intensity of product use result in a lower relative price of energy. The underestimated price of energy leads to choices of inefficiently low energy efficiency (e.g. P_0 compared with P_1 in figure 6.4).

In the RDM in NEMS, consumers are allowed to choose their technology level among the various levels of cost and efficiency for a given class of equipment. Electric heat pump is an example of an equipment class for heating. Equipment type refers to different efficiency ratings in a class of equipment (e.g., high- vs. low-efficiency electric heat pumps). The RDM employs a time-dependent function for computing the installed capital cost of equipment in new construction and the retail replacement cost of equipment in existing housing. Energy efficiency (technology) choices fundamentally involve investment decisions with consideration of trade-offs between higher initial capital costs in the present and uncertain lower operating costs in the future. The decision of whether to invest in energy-efficient equipment requires comparing the initial capital cost to the expected cumulative future savings. From an economic perspective, rational consumers assess the future savings considering future energy prices, operating costs expected from the efficient equipment, intensity of the use of the product, and equipment lifetime. They compare these expected future cash flows against the initial cost, discounting the future cash flows to present values. A privately optimal decision entails choosing the level of energy efficiency to minimize the present value of private costs, whereas economic efficiency at a societal level would require minimizing social costs (Gillingham et al., 2009).

Energy market prices influence consumer decisions regarding how much energy to consume and whether to invest in energy-efficient equipment. A persistent energy price increase affects energy efficiency adoption. Many previous studies analyzed which factors influence technology adoption and found that higher energy prices are associated with significantly greater adoption of energy-efficient equipment (Anderson and Newell, 2004; Hassett and Metcalf, 1995; Jaffe et al., 1995). The concept of “price induced technology change” is included in the formulation of capital costs of the RDM in NEMS to reflect this effect. This concept allows future technologies to be diffused into the marketplace faster if fuel prices increase markedly and remain high over a multiple-year period. The Technology Choice Submodule (TCS) uses a log-linear function to adjust technology market shares. The module adjusts the current market shares based on consumer behavior as a function of capital costs, operating costs, and efficiency.

First, the TCS compares the average fuel price for a given fuel (electricity, in this study) over a three-year period to the price observed in the base year:

$$PRICEDELTA_{y,f} = \frac{.334*(PRICE_{y,f}+PRICE_{y-1,f}+PRICE_{y-2,f})}{PRICE_{base\ yr}} \qquad \text{[Equation 6.3]}$$

Where,

$PRICEDELTA_{y,f} =$

$relative\ price\ of\ consecutive\ three\ years\ to\ the\ price\ of\ the\ base\ year$

(y = current year, f = fuel type)

Shifts from 0 to 10 years are allowed in the current model formulations. Technological shifts in a relatively short term are limited by the algorithm in order to ensure that over-shifting does not occur. In other words, future technologies cannot become available before a persistent price change is projected to occur for at least three years. The formulation allows technologies potentially to shift toward earlier availability, and once shifted, they never shift back. This shift is represented as:

$$SHIFTYEARS_t = \frac{(PRICEDELTA_{y,f}-1.0)}{0.10} \qquad \text{[Equation 6.4]}$$

subject to the constraints listed in Appendix C. Operational and capital costs of technology data presented in equations [Equation C.1] and [Equation C.2] in the appendix are adjusted according to the results obtained in equation [Equation 6.3].

For instance, when y = 2007and f = electricity,

If $PRICEDELTA_{2007,electricity} = 1$, there is no technological shift

If $PRICEDELTA_{2007,electricity} = 2$, the most advanced technologies in 10 years from 2007 come forward to the current year.

The TCS assumes that if a "persistent" doubling of electricity prices exists, the most advanced equipment available in 10 years from today will be selected.

The TCS module also includes the option to use life-cycle costing to adjust market shares. The life cycle cost calculation is:

$$\mathrm{LFCY}_{y,es,b,r,v} = \mathrm{CAPITAL}_{es} + \mathrm{OPCOST}_{y,es,b,r,v} * \left(\frac{1-(1+\mathrm{DISRT})^{-\mathrm{HORIZON}}}{\mathrm{DISRT}}\right)$$ [Equation 6.5]

where,

$LFCY_{y,es,b,r,v}$ is the life cycle cost of an equipment type by forecast year, housing type, and Census Division, and vintage; $CAPITAL_{es}$ is the installed capital cost of an equipment type based on *EQCOST* with *RTEQCOST1es*; $HORIZON$ is the number of years into the future used to compute the present value of future operating cost expenditures, presently set to seven years; and *DISRT* is the discount rate applied to compute the present value of future operating costs, presently at 20 percent.

6.4 Long-run Demand Forecast

The original NEMS employs price elasticities of demand that result in limited demand sensitivity for some technologies. It employs a price elasticity of 0 for clothes washers, dishwashers, stoves, refrigerators, and freezers. The price elasticities of the remaining residential technologies, such as TVs and computers, are set at -0.15. This set of modeling assumptions may accurately reflect past consumer behavior from the 1970s to 1990s, but it might not accurately reflect consumer behavior in the present or future when electricity prices should continue to rise in real terms (Brown et al., 2010). To figure out today's consumer behavior, this study estimated the short-run price elasticity of residential electricity demand with the EIA's RECS survey data collected in 2005. The econometric analysis found that the short-run price elasticity of residential electricity demand is -0.66.

Of course, it would be somewhat hasty to argue and conclude that today's consumers are almost 5 times more responsive to price changes than past consumers. Since the variables for short-run price elasticities of the original NEMS are set based on the meta-analysis conducted by Dahl in the 1990s, differences in methodology and data could explain part of the gap. The meta-analysis incorporates research results from previous studies conducted from the late 1970s to early 1990s, which applied a variety of methods to estimate elasticity values. On the other hand, the estimated short-run elasticity in this study is derived from the 2005 Residential Energy Consumption Survey and employs a specific log linear function and the OLS estimation technique. However, even if some portion of the difference in the short-run elasticity values is attributed to differences in method and data, it seems that today's consumers react to changes in price and policy more sensitively than those in the past. Public appeals and education through mass media might have led consumers to change their behaviors in energy consumption.

This section analyzes how changes in short-run behavioral characteristics affect changes in long-run electricity demand.

Experiments with GT-NEMS and long-run price elasticity calculation

The distinction between the short-run and long-run elasticities is critical in understanding energy markets. Responsiveness of energy demand to price change could vary depending on the time span of the analysis. In economics theory, the short run is defined as a period of time in which the quantity of at least one input is fixed and the quantities of the other inputs can be varied. The long run is a period of time in which the quantities of all inputs can be varied. Thus, there is no fixed period of time to separate the short run from the long run. By responding to a price movement, the short-run elasticity measures immediate consumer response, such as changing energy-consuming habits, and the long-run elasticity measures total response, including technology shifts such as appliance changes.

To assess the potential impacts of future electricity price increases on demand, this study employs the National Energy Modeling System (NEMS). The study named the modified model GT-NEMS in order to emphasize that energy projections from this model could be different from projections derived from the original NEMS.

EIA and other research parties have conducted various experiments with the original NEMS simulation. Hadley and his colleagues analyzed the contribution of five potential building technologies (solid-state lighting, advanced geothermal, integrated energy equipment, efficient operations technologies, and smart roofs) to estimate energy savings and building efficiency improvement (Hadley, MacDonald, et al. 2004). Wade (2003) conducted several experiments on price responsiveness with the residential and commercial buildings sector models in the AEO2003-NEMS. He derived own-price and cross-price elasticities with both short-run and long-run models. He doubled the current price level and entered the artificially created price as a price shock in the simulation model and then observed how the electricity and natural gas demand finally reached a new point of equilibrium. He manipulated two different situations: temporary and permanent shock situations. He also created a sudden shock lasting one year and a permanent price inflation lasting multiple years and then examined the differences in their price adjustment behaviors. With the initial demand level and the new equilibrium level, he calculated the price elasticities of electricity and natural gas demand, respectively.

Following the methodology used by Wade (2003), this study conducts a quasi-experimental analysis to estimate the long-run price elasticity of energy demand in the residential sector with the NEMS developed for publishing the Annual Energy Outlook 2009 (AEO2009). The default values of the short-run price elasticities of heating and cooling (alpha = -0.15) are replaced with the new elasticity value (-0.66) estimated by this study. The elasticity values derived from the econometric analysis with the 2005 RECS survey are plugged into the NEMS model, and then the difference in output between the two is observed. The advantage of using the elasticity value derived directly from the RECS survey is that the Residential Demand Module (RDM) of the NEMS is modeled using the same survey data to estimate technology choices and annual appliance stocks. To estimate responses to energy price changes, a series of alternative simulations is made based on adjustments to the energy price paths from the AEO 2009. The adjustments model permanent price inflations by 10%, 30%, and 50% beginning in 2010 and continuing through the end of the model run, 2030 (Figure 6.5).

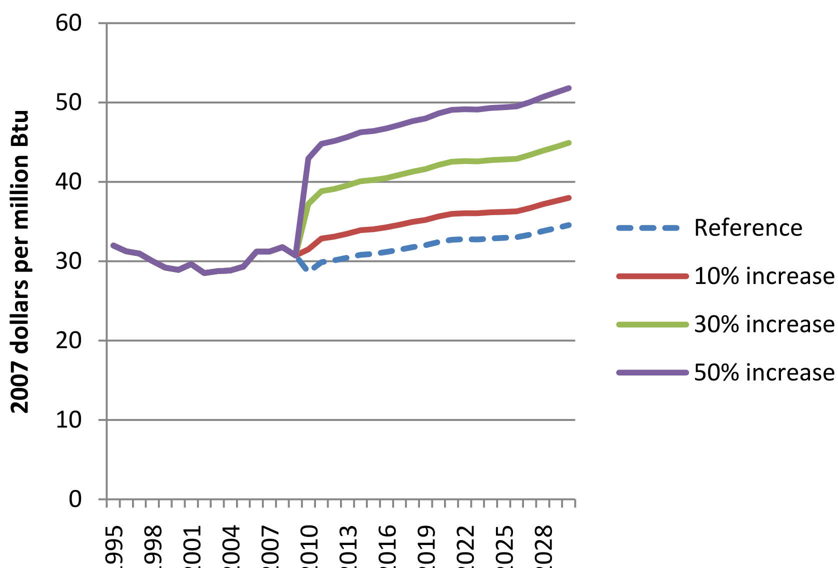

Figure 6.5 Permanent Price Inflations by 10%, 30%, and 50%

Figure 6.6 shows that the initial reduction in consumption rapidly widens the gap between a reference and modified scenarios by 2013. It is because the internal source codes of NEMS applies a lagged structure of demand and distribute of the impact of short-run consumer's responsiveness, but it just considers only the three years from the year when the shock occurs. Then, the consumption projections are stabilized until 2030. As predicted, scenarios having the more elastic short-run demand function (alpha = -0.66) respond to price inflations more sensitively than those with default elasticity values (alpha = -0.15) of the original NEMS. According to the consumption projections under the various price inflation and price elasticity scenarios, the scenario with a 30% price increase and alpha = -0.66 shows a greater consumption reduction than that with a 50% price increase and alpha = -0.15. This consequence means that pricing programs designed to achieve a specific level of consumption reduction during specified periods could be achieved at around half of the price increase under the scenario of more elastic demand. Also, the result suggests that benefits from price policies could be calculated differently under different elasticity assumptions. When consumers become more elastic to price changes, price policies can be more effectively implemented, giving consumers more benefits. The potential reductions are forecasted based on the assumption that all consumers are rational decision makers.

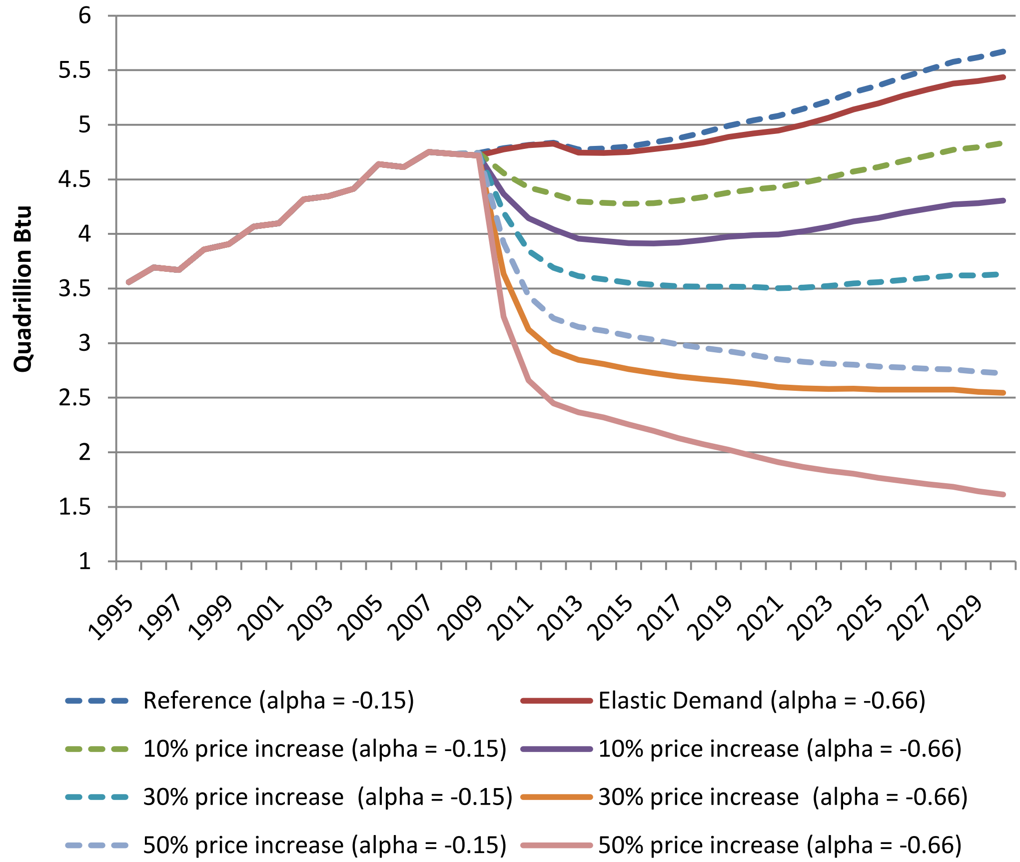

Figure 6.6 Electricity Consumption Projections in the Residential Sector

In addition, the long-run price elasticities of the original NEMS and modified NEMS (GT-NEMS) are calculated based on the outputs of the NEMS experiments. As McClung (1988) points out that elasticity values from micro data are estimated to be smaller than those derived from macro data, this study similarly finds that long-run demand functions are more elastic than short-run demand functions. The long-run elasticity of electricity demand in the residential sector is found to be -2.44 ~ -2.99 under the scenario with alpha = -0.66 (Table 6.1). Because electricity competes with natural gas as fuel for heating, when electricity price goes up, the natural gas demand increases accordingly (Figure 6.7). With the increase in electricity price and the change in natural gas, this study estimated cross-price elasticities: 0.15 ~ 0.28 (with alpha = - 0.15) and 0.15 ~ 0.34 (with alpha = -0.66).

Table 6.1 Long-run Price Elasticities*

	Original NEMS (with SR-elasticity of -0.15)	GT-NEMS (with more elastic SR-elasticity of -0.66)
Own-Price Elasticities	-1.67 ~ -0.81	-2.44 ~ -2.99
Cross-Price Elasticities**	0.15 ~ 0.28	0.15 ~ 0.34

* Elasticities are measured using the logarithmic percentage change formula give by: *elasticity* = $ln(q_1/q_0)/ln(p_1/p_0)$, where p_0 and q_0 are base prices and quantities and p_1 and q_1 represent an alternate price-quantity combination.
**Cross-price elasticities show changes in demand of competing goods (in this case, natural gas consumption) when the electricity prices change.

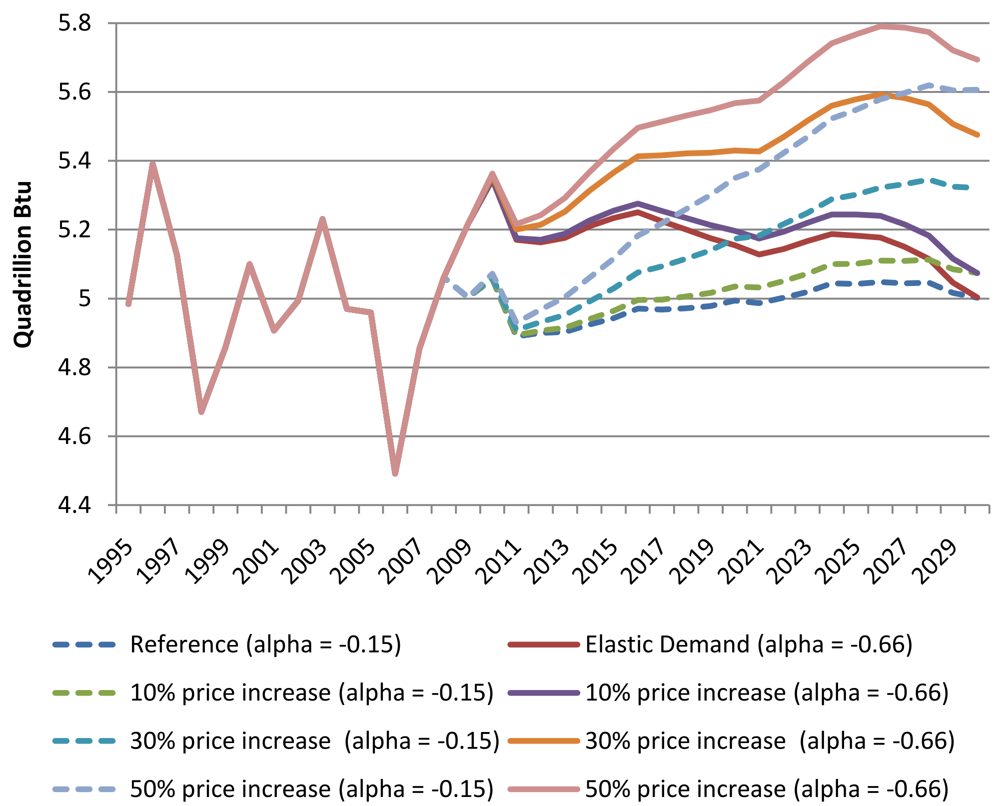

Figure 6.7 Natural Gas Consumption Projections in the Residential Sector

Comparison with Other Studies

The absolute values of long-run price elasticities derived from the GT-NEMS are greater than those of the previous studies summarized in Table 6.2. Wade (2003) estimated the long-run price elasticities with the AEO2003 and AEO99 and found that the own-price elasticity was -0.49 with the AEO2003 and -0.31 with the AEO99. The cross-price elasticity estimated from AEO2003 was 0.13, and that from AEO99 was 0.08. Both of AEO2003 and AEO2009 assumed short-run elasticities at -0.15 for their energy consumption projections. This analysis finds that households respond to price changes more sensitively compared to those in the 1970s and the 1980s.

Table 6.2 Elasticities from other studies

Author	Data Type	Model Type	**Long Run Elasticity**	
			Price	Income
Halvorsen (1975)	State level Aggregate Data	Static	**-1.15**	0.51
Houthakker et al. (1980)			**-1.18**	1.39
Houthakker (1980)		Dynamic	**-1.42**	1.78
McClung (1988)	Micro Data (RECS)	Static	**-0.42**	0.15

Impacts of SR-elasticity assumption on Electricity Market Forecast

This section provides an empirical analysis showing how price and consumption would change under different assumptions of price elasticity of demand. A set of NEMS experiments are conducted to show how the difference in short-run price elasticity influences the electricity prices and consumption levels in the future. A Carbon Cap and Trade system is commonly expected to increase electricity prices. The electricity price increase is observed in a preliminary NEMS forecast shown in Chapter 5. Figure 6.8 indicates that the magnitude of the price escalation would be estimated larger with an assumption of less elastic short-run demand (alpha = -0.15), at the same time, the magnitude of reduction in electricity use would be smaller. While a model with alpha = -0.15 forecasted that the policy would increase the residential electricity price by 17% in 2030, another model with alpha = -0.66 predicts that the price would go up by only 12% in the same year. The consumption is anticipated to shrink by 4% with alpha = -0.15, whereas the consumption is forecasted to decrease by 9% with alpha = -0.66. If consumers are assumed to be more sensitive to price changes, the change in consumption caused by a policy would be estimated relatively larger. Thus, the price escalation would be estimated relatively smaller. The initial market equilibrium points are altered as a result of the higher elasticity of demand.

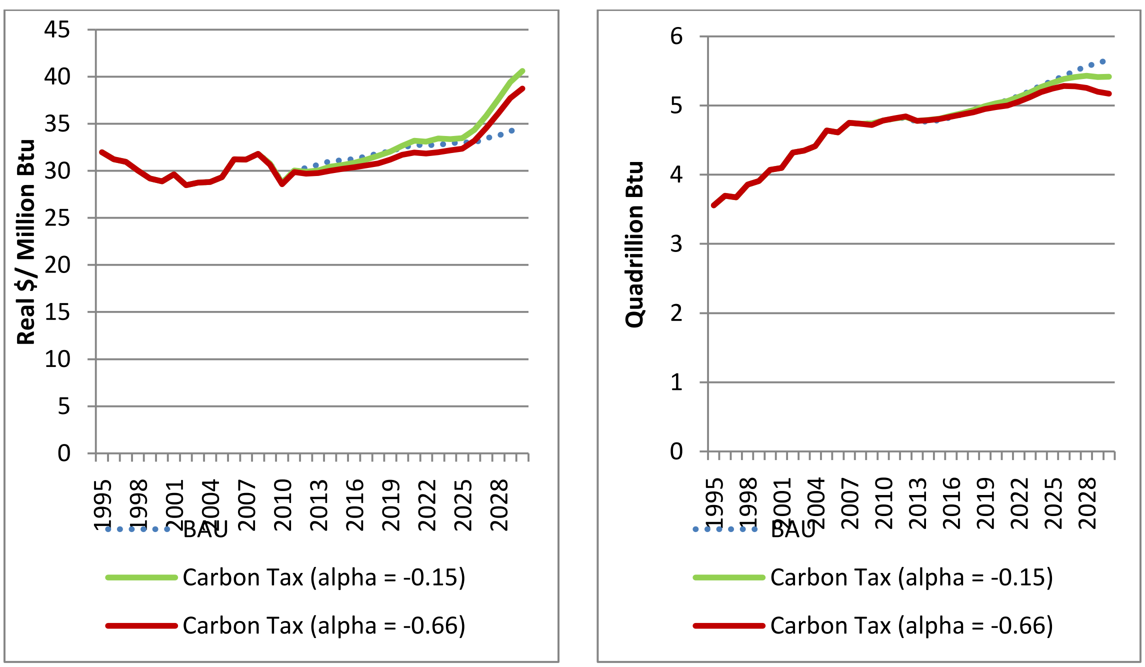

Figure 6.8 Price and Consumption Projections under the Carbon Tax Scenario

(Residential Electricity)

The impact of the RPS policy on price and consumption is anticipated be smaller than that of the CCT, but the directional change was the same (Figure 6.9).

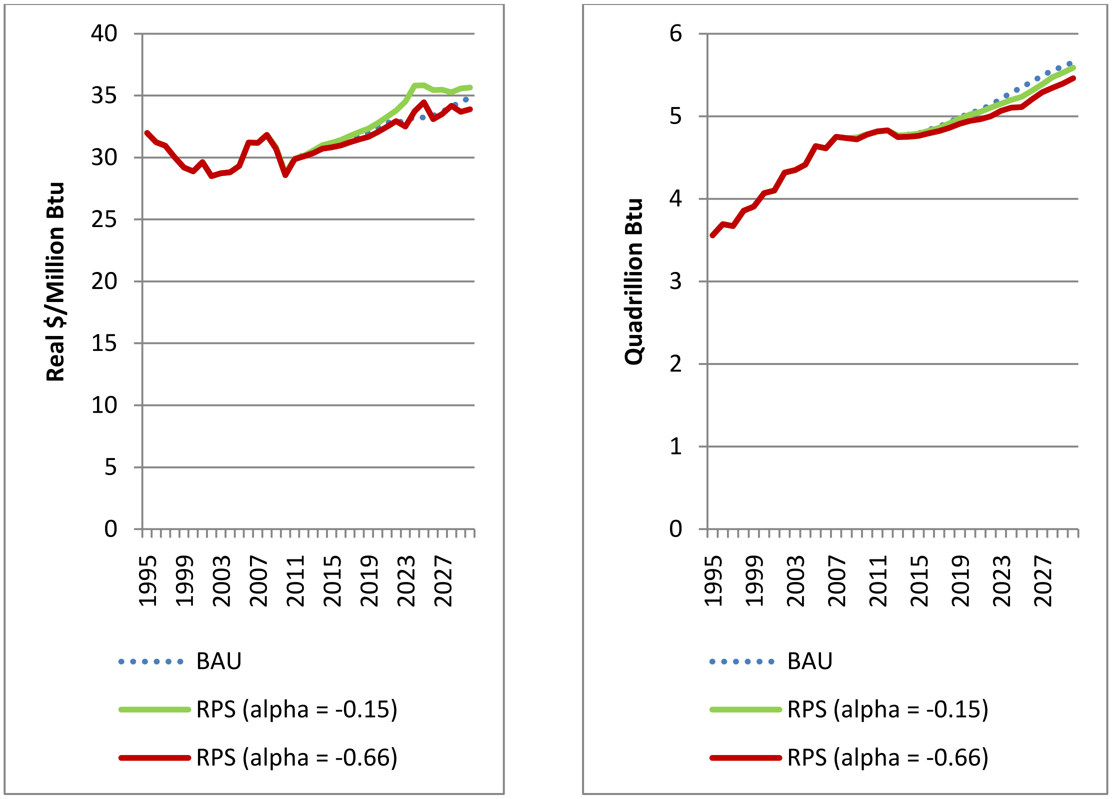

Figure 6.9 Price and Consumption Projections under the RES

(Residential Electricity)

CHAPTER 7
POLICY IMPLICATIONS AND CONCLUSIONS

7.1 Policy Implications

Impacts of SR-elasticity assumption on Electricity Market Forecast

Based on the price and demand changes, it estimates how much social welfare gain the U.S. might expect if households are more responsive to changes in price and policy. Consumer surplus is defined as the amount by which consumers' willingness to pay for a commodity exceeds the sum they actually have to pay. Changes in social welfare expected from more elastic demand could be estimated with the concept of consumer surplus. Shown in Figure 7.1, consumer surplus is measured by the area under the demand curve and above a horizontal line at the market price. Thus, when price is P_0, consumer surplus is triangle *abc* (Figure 7.1). When the price of electricity increases to P_1 because of an energy policy such as carbon tax, consumer surplus is the area under the demand curve and above a horizontal price line at the increasing price, but because the price is now P_1, the relevant area is triangle *ade*. Consumer surplus has decreased by the difference between areas *ecg* and *ebd* (i.e., area *dbce*). Policy-makers can estimate the shape of the demand curve, and the policy's benefits can be measured.

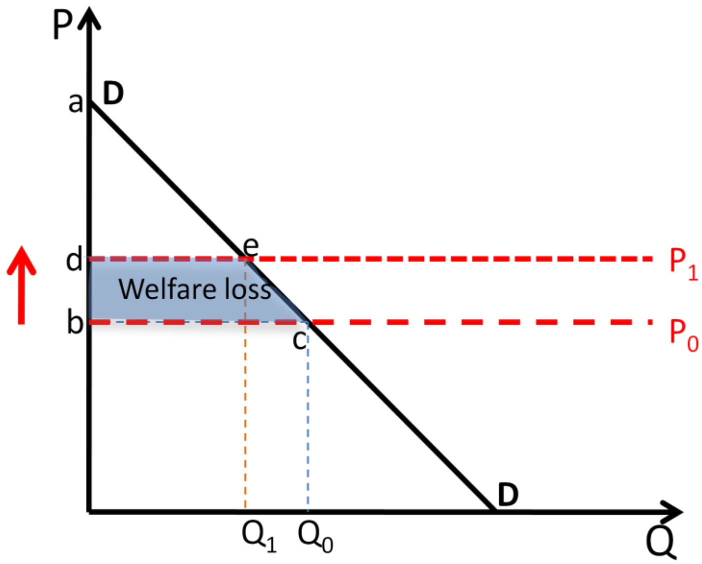

Figure 7.1 Measuring the Change in Consumer Surplus

The welfare gain or loss from price changes varies with the absolute value of the slope of the demand curve. In the case of a price increase, the less steep the demand curve (i.e., the more price-responsive the demand), the less steep the demand curve (i.e., the more price-responsive the demand), the less is the welfare loss. When the price of a commodity increases due to a tax policy, consumers who are more sensitive to price changes will substitute the good with another or will reduce the consumption level so as to escape the tax burden. If consumers are assumed to be more elastic to the price changes than the BAU case, the magnitude of social welfare changes will be estimated greater.

Economists argue that a flexible demand will help balance fluctuations in supply, improve market efficiency, reduce price volatility, and create a welfare gain. Suppose that the original demand curve is $D'D'$ (Figure 7.2). With a price increase from P_0 to P_1, the amount of loss in consumer surplus is area *fghi*. On the other hand, with a more elastic demand curve, $D''D''$, the social welfare loss is area *fkhi*. The gap between the two areas (= area *kgh*) is the welfare gain we can expect from the more elastic demand curve.

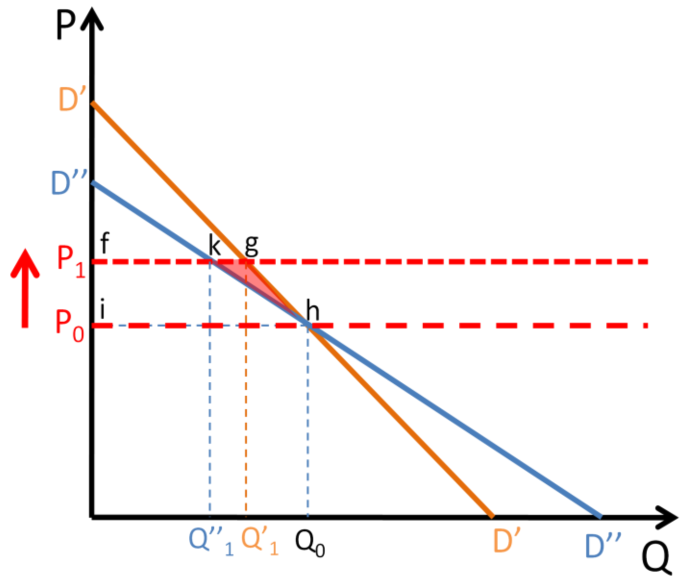

Figure 7.2 Social Welfare Change among Different Elasticities

Suppose that the residential electricity price increases by 10% (compared to a BAU scenario) in 2030 because of an energy policy, such as a new carbon tax. The market equilibrium (price, quantity) under the BAU scenario of AEO 2009 with no carbon tax policy is $34.5 per million Btu and 5.7 quadrillion Btu. When the price increases by 10% from $34.5 to $38.0 per million Btu, the optimal quantity will decrease from 5.7 to 4.8 quadrillion Btu. The social welfare loss caused by the price increase will be $18.4 billion (equivalent to area *fghi*).

If the demand is more elastic (alpha = -0.66) than the reference case (alpha = -0.15), the social welfare loss will be smaller than the reference case. The loss would be $ 17.5 billion (equivalent to area *fkhi*). Thus, the difference in welfare estimate is $900 million (=$18.4 billion - $17.5 billion) a year (Figure 7.3).

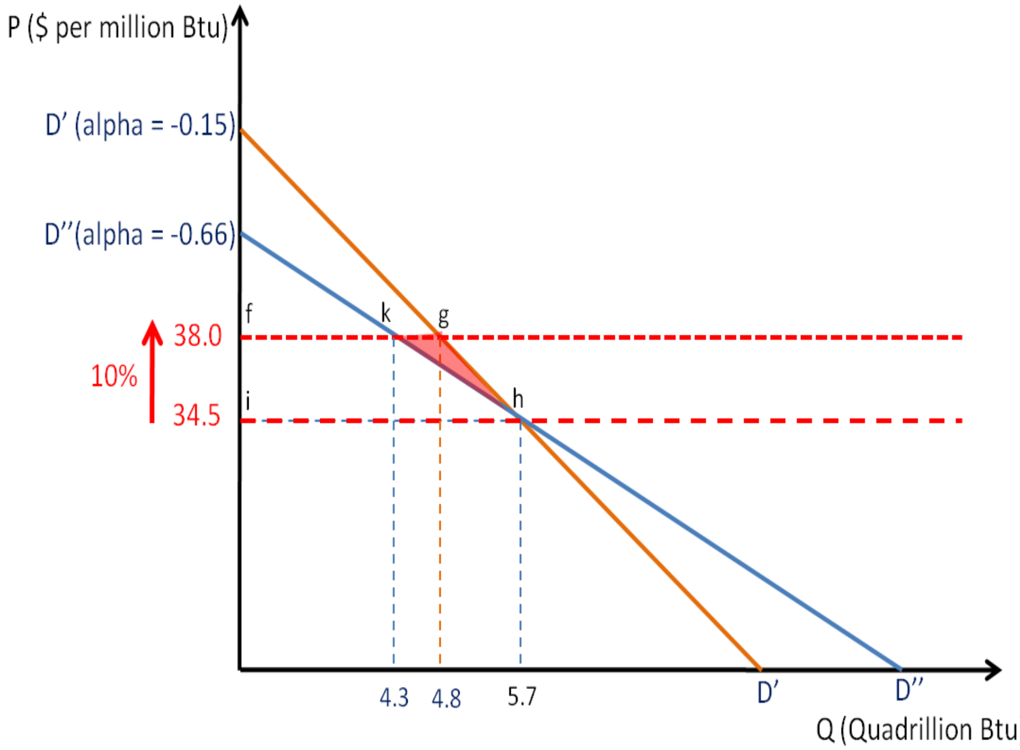

Figure 7.3 Social Welfare Calculations with Actual Numbers from AEO2009

This study calculated changes in quantity of residential electricity demand, welfare losses due to electricity price increases. Table 7.1 shows that the assumption of more elastic demand (alpha= -0.66) leads to a greater reduction in electricity consumption and a smaller welfare loss than that of less elastic demand (alpha=-0.15). The greater the price inflation, the larger the difference in social welfare estimate. When the retail electricity price increases by 10% the difference in social welfare estimation is $ 0.9 billion. With a 50% increase in price, the gap reaches $9.6 billion. In addition to the impact on consumer surplus, the difference in elasticity affects the impact on the change in quantity.

Table 7.1 Social Welfare Calculations in 2030

Price in 2030 ($/million Btu)	% increase in price	Reduction in quantity (alpha = -0.15)	Reduction in quantity (alpha = -0.66)	Difference in quantity reduction	Welfare loss due to price increase under the less elastic demand (alpha = -0.15)	Welfare loss due to price increase under the more elastic demand (alpha = -0.66)	Difference in social welfare estimation
34.5 (BAU)	0%	0%	0%	0%	$0	$0	$0
38.0	10%	16%	25%	9%	$18.4 billion	$ 17.5 billion	$0.9 billion
44.9	30%	36%	48%	12%	$48.4 billion	$42.6 billion	$5.8 billion
51.8	50%	52%	62%	10%	$72.7 billion	$63.1 billion	$9.6 billion

Overall Policy Implications

Policy is basically designed and intended to motivate members of a society to change their behavior and achieve a goal collectively. Thus, setting assumptions about human behavior need to be treated most carefully in policy modeling. This study probed the responsiveness of residential electricity demand to price changes from various angles. Behavioral characteristics responding to the electricity market are affected by various factors such as income, housing, climate, appliance holdings, and even psychological factors. A series of the analyses presented in this study suggests important policy implications to energy policy makers.

First, federal and state governments need to periodically understand how consumers respond to price signals when they determine their electricity consumption levels. Governments might benefit from supporting academic studies on price elasticities. The comprehensive understanding of the price elasticities can assist policy analysts and makers to forecast future electricity demand, which can be used to set policy goals for energy conservation programs and demand control programs. Employing a conventional econometric approach, this study estimated the price elasticity of residential electricity demand with 2005 RECS data, which is collected by the DOE and is open to the public. Employing a conventional econometric model and a discrete/continuous choice model, this exercise revealed that the price elasticity derived from the current cross-sectional gives a range of the price elasticity of demand of - 0.81 ~ - 0.66, which indicates pretty elastic demand[14]. The model used in this study also showed that income, climate, number of rooms, price of competing goods, and appliance holdings significantly affect the price elasticity of demand. The estimate could vary depending on the estimation methods and techniques. Periodical meta-analyses supported by government agencies would provide very useful information for those creating government policies and for those conducting academic studies as well. This study introduced two representative meta-analyses conducted in the 1990s and 2000s. The meta analyses of the elasticity estimates provide guidelines for determining what the important variables are for estimating elasticity and how the estimates might be adjusted when they are derived with unfavorable data. For scientific policy analyses, the application of the elasticity to policy evaluation is as important as the accurate estimation of elasticity.

Second, the price elasticity should be seriously considered in the ex ante evaluation of electricity demand control programs and other energy policies. In particular, the price elasticity of demand is considered as an important factor in the ex ante evaluation of alternatives of the time of use rate and smart meters. Demand forecasting is crucial to the ex ante evaluation of energy conservation programs. The ex ante evaluation of a policy is generally a necessary process in policy design prior to its implementation. In this process, policy analysts review all the alternatives that stakeholders and policy makers reasonably care about. Projecting the outcome of each alternative often requires forecasting not only the directional change but also the magnitude. Predicting a directional change for a policy

[14] This statement is justified by the current meta-analysis of price elasticities of residential electricity demand conducted by Espey and Espey (2004).

is relatively simple. However, forecasting the magnitude is regarded as the most difficult step in policy analysis (Bardach, 2000). The Energy Information Administration (EIA) of the DOE releases the Annual Energy Outlook (AEO) to provide energy market forecasts under the energy policies effective every year. The National Energy Modeling System (NEMS) has been developed by the EIA to make it possible to estimate the impact of a policy on energy supply, demand, and price. Many policy studies have been conducted with NEMS, and their quantitatively presented outcomes actually have been used in Congress. The forecasts depend on thousands of input variables used in the modeling system, such as technological characteristics and macroeconomic indicators. The previous section showed how different settings on the short-run elasticity affect not only the demand forecasts but also social welfare estimates. Under a Carbon Tax scenario that raises the electricity price by 10%, the social welfare loss is estimated at $17.5 billion under an elastic demand function (alpha = -0.66) and at $18.4 billion under a reference (alpha = -0.15). In addition, a further 9% reduction in consumption could be expected under the elastic demand. The goals of the energy efficiency policy and climate change policy are to conserve energy and reduce greenhouse gas emissions. The goal of a carbon tax or cap and trade is generally set as a percentage below 1990 levels in certain years. Brown and her colleagues (2009) suggested eight criteria for evaluating energy policy options such as 1) potential benefits, 2) cost-effectiveness, 3) time to savings, 4) applicability, 5) additionality, 6) administrative practicability, 7) non-R&D, and 8) federal role. The common measures for judgment of the effectiveness of a policy are benefit-to-cost ratios, social welfare estimates, and the absolute amount of reduction of target pollutants and energy savings. The previous section showed how the policy outcomes could be predicted differently depending on the assumption of human behavior. If people are assumed to be more elastic to price signals, the time it takes for a policy to accomplish its goal could be shorter.

The variation among elasticity estimates is not a problem when policy makers and researchers apply them to policy designs and analyses, if they correctly understand what causes the variation and how the variation affects price and demand forecasts as well. This study discussed how the different assumptions of price elasticity influence the projections of price and consumption and the estimates of social welfare change. When policy makers and governors design energy efficiency policies aimed at saving energy, they can use relatively high elasticity values for their ex ante evaluation if they assume that more informational programs would be implemented to educate consumers to be sensitive to price signals and tips for improving energy efficiency levels.

Given the variety of energy sources used to generate electricity, the continuous expansion of urban areas in the United States, and the uncertainty of national and international energy markets, understanding consumers' responsiveness to electricity price changes is necessary for municipalities, utility companies, and policy makers to predict future energy needs and design pricing and taxation policies (Espey and Espey, 2004). In addition to designing monetary incentives relevant to electricity prices, decisions about new sources of electric power, the construction of new power plants, or the creation of new interstate transmission lines also requires an accurate understanding of the price elasticity of demand. Even though the importance of understanding price elasticities in policy design and analysis is widely recognized among policy analysts, it is still true that there are confusions and often contradictory results of residential elasticity estimates. At present, utilities and utility commissions tend to use an approximate value of short-run elasticity in the range of -0.4 to -0.2; the EIA uses -0.15 for analyzing the residential electricity market; this study estimated it at -0.66; the median value of Espey and Espey (2004)'s study is -0.35.

On balance, this study shows that how the residential electricity market would be affected by policies depends highly on the price elasticity of demand. The relationships among price, consumption, and policy are interconnected, and the price elasticity of demand is an important factor characterizing the relationship. As noted in the previous section about social welfare impact, the duration of a policy can be adjusted depending on the price elasticity assumption.

7.2 Conclusions

In order to understand consumers' behavioral responsiveness to changes in price and policy at both the micro and macro levels over the short and long runs, this study employed a hybrid method of conventional econometric analyses and energy market simulations with the National Energy Modeling system (NEMS). The econometric analysis with individual household survey data contributed to setting new assumptions on short-run demand functions of residential households in the NEMS. Prior to the NEMS experiments with the adjustments of short-run price elasticities and the price shocks, this study examined how energy policies would have a potentially large impact on electricity prices in the future. When climate policies are implemented nationally, electricity prices are estimated to increase in 2030 by 17% with a carbon cap and trade initiatives and 4% with Renewable Electricity Standards. Once the federal government creates a scarce new commodity such as cleanliness of air, some portion of the costs for generating clean electricity would unavoidably be passed on to retail electricity prices. The increased prices could be considered as positive signals for conserving energy and reducing greenhouse gas emissions. Those price increases may be essential to the success of a cap-and-trade program. However, the price signals could be used effectively only when the public responds to the signals sensitively. If electricity demand is inelastic to changes in price and policy, it would be inevitable that some portion of the tax burden be passed on to consumers.

Employing the conventional econometric model and the discrete/continuous choice model, this study estimated the price elasticity of residential electricity demand with the most recent Residential Energy Consumption Survey data collected in 2005. The short-run elasticity of demand was found to be in the range of - 0.81 ~ - 0.66, which is greater than the current NEMS assumption of -0.15 in absolute value. The 2005 RECS data detailed information about American households' energy consumption. This rich source of micro-level data complements the existing econometric analysis based on time series data. Time series studies lack information concerning appliance stock, building characteristics, differences in climates, and demographic characteristics and are usually aggregates over the entire nation's or region's data. The use of this cross-sectional data, however, allows researchers to consider the interventions across the households; thus, the cross-sectional data was used for this analysis. The value of - 0.81 was estimated by the discrete/continuous choice model and interpreted as a long-run price elasticity of demand. The difference in short-run price elasticity would lead to a difference in social welfare estimates of energy policies and energy market forecasts. This study found that the estimate of social welfare loss caused by electricity price increases would be overestimated if an energy market model assumes elasticity less than the actual responsiveness. The original NEMS employs a short-run price elasticity of -0.15 for heating and cooling equipment, dryers, standard lighting, PCs, and TVs. The price elasticities of the remaining residential technologies are set at zero. These modeling assumptions may accurately reflect past consumers' behavioral characteristics in periods of energy price volatility, but they might not accurately reflect those in the present or future when prices continue to rise in real terms (Brown et al., 2010). On the other hand, in the long run, higher energy prices are associated with significantly greater adoption of energy-efficient equipment (Anderson and Newell, 2004; Hassett and Metcalf, 1995; Jaffe et al., 1995). The increased adoption of energy-efficient technologies would result in a more elastic demand in the long run, as this study showed in Chapter 6. On balance, Supposing that 1) the short-run elasticity of -0.66 reflects the actual consumers' responsiveness to price changes in the present and future and 2) retail electricity prices permanently increase by 10%, the welfare loss caused by the price increases would be estimated 0.9 billion dollars less than the current estimates with the elasticity of -0.15.

In addition to assessing potential savings expected from consumers' behavioral changes with the concept of price elasticity of demand in neoclassical economic theory, this study conducted a broader review of theories about behavioral features of energy consumers, and discussed how existing information programs could be improved. To motivate households to change their energy-use habits in the short run, well-designed information and training programs reflecting their needs and feedback are required. The effect of information on consumers' choices depends on how the information is transferred. Thus, government agencies should carefully consider behavioral factors in the disclosures they control (Allcott Mullainathan, 2010). Developing psychological nudges to make consumers move toward an energy-efficient lifestyle also could make people more sensitive to price changes and eventually conserve more energy in the short run. Some psychological cues typically cost very little as compared with other financial incentives. When combined with consumption-monitoring systems such as smart meters, these changes could be expedited.

To enhance the long-run responses, on the other hand, governments can increase the energy efficiency basically through some monetary incentives for installing new technologies, such as tax credits and subsidies. In addition, disclosing useful information about the performance of new equipment could help consumers to adopt new technologies so that they actively respond to price changes. The informational programs for energy-efficient technologies could lower the gap between the socially optimal level of efficiency and actual observed efficiency. Governments can also utilize positive externalities associated with learning by using for accelerating the adoption of new and efficient technologies. The experience and knowledge absorbed to consumers motivate only themselves to buy additional energy-efficient equipment, but also non-participants to join the energy efficiency program. The more the equipment resale market is activated, the more consumers would be willing to change their stock of appliances.

On balance, this study suggests that rigorous empirical studies on consumers' behavioral attributes are prerequisite for the effective program design. Governments can establish potentially high-impact behavioral research programs as part of their broader energy innovation programs to analyze consumers' behavior scientifically and continuously. The research programs should include careful testing protocols of their impacts. Additionally, behavioral interventions should have clearly measurable outcomes in order to be evaluated as effective policy options.

APPENDIX A

SUMMARY OF RANGES OF RESIDENTIAL ELASTICITIES FROM DAHL (1993)

Survey Source	**Fuel**	**Data Type**	**Model Class**	**Short Run**	**Intermediate Run**	**Long Run**
Taylor (1977)	Electricity	Grouped	Grouped	-0.07 to -0.61	-0.34 to -1.00	-0.81 to -1.66
	Natural Gas	Aggregate		0.00 to -0.16		0.00 to -3.00
Bohi (1981)	Electricity	Aggregate	Static	-0.08 to -0.45		-0.48 to -1.53
	Electricity	Aggregate	Dynamic	-0.03 to -0.49		-0.44 to -1.89
	Electricity	Aggregate	Structural	-0.16		0.00 to -1.28
	Electricity	Aggregate	Other	-0.18 to -0.54		-0.72 to -2.10
	Electricity	Household	Dynamic	-0.16		-0.45
	Electricity	Household	Static	-0.14		-0.7
	Electricity	Household	Structural	-0.25		-0.66
	Natural Gas	Aggregate	Static			-1.54 to -2.42
	Natural Gas	Aggregate	Dynamic	-0.15 to -0.50		-0.48 to -1.02
	Natural Gas	Aggregate	Structural	-0.3		-2
	Natural Gas	Household	Dynamic	-0.28		-0.37
	Natural Gas	Household	Static			-0.17 to -0.45
Bohi & Zimmerman (1984)	Electricity	Aggregate	Static		0.00 to -1.57	-0.18 to -0.52
	Electricity	Aggregate	Dynamic	0.00 to -0.35		-0.26 to -2.50
	Electricity	Household	Structural	-0.20 to -0.76		
	Electricity	Household	Static		-0.55 to -0.71	-0.05 to -0.71
	Electricity	Household	Structural	+0.04 to -0.67		-1.40 to -1.51
	Natural Gas	Aggregate	Dynamic	-0.23 to -0.35		-2.79 to -3.44
	Natural Gas	Aggregate	Dynamic	-0.03 to -0.05		-0.26 to -0.33
	Natural Gas	Household	Static			-0.22 to -0.60
Dahl (1993) Prior Surveys	Fuel Oil	Grouped	Grouped	0.00 to -0.70		0.00 to -1.50
Dahl (1993) New Studies	Electricity	Aggregate	Grouped	+0.57 to -0.80	-0.11 to -1.11	+0.77 to -2.20
	Electricity	Household	Grouped	-0.02 to -0.97	-0.05 to -0.97	-0.38 to -1.40
	Natural Gas	Aggregate	Grouped	+0.02 to -0.35	1.86 to -2.41	1.56 to -3.44
	Natural Gas	Household	Grouped	-0.63 to -0.88	-0.08 to -1.80	-1.09 to -1.49
	Fuel Oil	Aggregate	Grouped	-0.10 to -0.59	-0.77 to -1.22	
	Fuel Oil	Household	Grouped	-0.18 to -0.19	-1.09 to -1.56	-0.62 to -0.67

Source: C. Dahl, A Survey of Energy Demand Elasticities in Support of the Development of the NEMS, Contract No. DE-AP01-93EI23499 (Washington, DC, October 1933)

APPENDIX B

DESCRIPTIVE STATISTICS OF THE SAMPLE OF ESPEY AND ESPEY (2004)*

Variable	**Short-run Price**	**Long-run Price**	**Short-run Income**	**Long-run Income**
Elasticity	-0.35	-0.85	0.28	0.97
Demand Specification				
Reduced form	0.77	0.85	0.74	0.86
Structural	0.23	0.16	0.26	0.14
Static	0.60	0.56	0.55	0.56
Dynamic	0.40	-	0.45	0.44
Lag dependent variable	-	0.34	-	-
Other lag	-	0.10	-	-
Stock included	0.61	0.13	0.55	0.12
Substitute included	0.54	0.46	0.68	0.44
Temperature included	-	-	0.76	-
Household Size	-	-	-	0.17
Double log model	0.53	0.92	0.58	0.92
Non-double log model	0.47	0.08	0.42	0.08
Data characteristics				
Household level	0.49	-	-	-
Time series	0.11	0.56	0.14	0.56
Cross sectional	0.30	0.11	0.21	0.14
Cross sectional time series	0.59	0.33	0.65	0.30
Monthly	0.41	0.08	0.44	0.06
Annual	0.59	0.92	0.56	0.94
Average (price)	0.36	0.70	0.39	0.71
Marginal (price)	0.64	0.27	0.61	0.29
Increasing block (price)	0.07	-	-	-
Decreasing block (price)	0.39	0.60	0.42	0.58
Time and location				
Aggregate	0.36	0.26	0.50	0.25
Regional	0.64	0.74	0.50	0.75
United States	0.95	0.92	0.92	0.94
Non-United States	0.05	0.08	0.08	0.06
Pre-1972	0.34	0.82	0.40	0.81
1972-1981	0.85	0.82	0.81	0.79
Post-1981	0.11	0.11	0.11	0.15
Estimation Technique				
Ordinary least squares	0.37	0.08	0.32	0.09
Non-ordinary least squares	0.63	0.92	0.68	0.91

* Espey and Espey (2004) Turning on the Lights: A Meta-Analysis of Residential Electricity Demand Elasticities

APPENDIX C

TECHNOLOGY CHOICE COMPONENT OF RDM IN NEMS

(Source: EIA, Model Documentation Report: Residential Sector Demand Module of the National Energy Modeling System , April 2007)

The Technology Choice Component uses a log-linear function to estimate technology market shares. The module is able to calculate market shares based on consumer behavior as a function of bias, capital costs, and operating costs or as a function of life-cycle costs. New equipment operating costs are computed by the expression,

$$\mathrm{OPCOST}_{y,es,b,r,v} = \mathrm{PRICE}_{f,r,y} * \mathrm{EQCUEC}_{y,eg,b} * \mathrm{HDDFACT}_{r,y} * \mathrm{RTEFFAC}_{eg,v} * \mathrm{HSHSELL}_{y-1,r,v}$$

where,

$\mathrm{OPCOST}_{y,es,b,r,v}$ is the operating cost for the specific equipment type by year, housing type, and Census Division, and vintage;

$\mathrm{PRICES}_{f,r,y}$ is the fuel price for the equipment by fuel, by region and forecast year;

$\mathrm{EQCUEC}_{r,eg,b}$ is the unit energy consumption by Census Division, equipment class and housing type;

$\mathrm{HDDFACT}_{r,y}$ is a factor, the ratio between heating degree days in the current year and in the base year, for adjusting for abnormal weather in either the base year or in the current year;

$\mathrm{RTEFFAC}_{eg,v}$ is the efficiency adjustment for the general equipment class and vintage; and $\mathrm{HSHELL}_{y\text{-}1,r,v}$ is the shell efficiency adjustment to account for building shell improvements over time (which reduce heating loads).

For newly constructed homes, operating cost is a function of both the heating and cooling operating costs, with the shell efficiency also accounted for as shown:

$$OPCOST_{y.es.b.r.hvac} = PRICE_{f,r,y} * EQCUEC_{y,heating,b} * HDDFACT_{r,y} * RTEFFAC_{heating,v} * HTSHELL_{eg,r,b} + PRICE_{f,r,y} * EQCUEC_{y,cooling,b} * CDDFACT_{r,y} * RTEFFAC_{cooling,v} * CLSHELL_{eg,r,b}$$

[Equation C.1]

where,

$HTSHELL_{eg,r,b}$ is the heating shell efficiency factor for the HVAC system; $CDDFACT_{r,y}$ is the cooling degree-day adjustment; and $CLSHELL_{eg,r,b}$ is the cooling shell efficiency factor for the HVAC system.

The consumer is allowed to choose among the various levels of cost and efficiency for a given class of equipment. Electric heat pumps are an example of an equipment class (denoted by eg). Equipment type (denoted by es) refers to the same class of equipment with different efficiency ratings (e.g., high vs low efficiency electric heat pumps).

EQCOST is a time-dependant function for computing the installed capital cost of equipment in new construction and the retail replacement cost of equipment in existing housing. It is called if the cost trend switch COSTTRSW = 1 in COMMON RTEK (which is the default). Its mathematical description is as follows:

$$EQCOST_{es,y\ CAP} = RTEQCOST_{es}, \text{if } RTMATURE_{es} = MATURE$$

$$EQCOST_{es,y\ RET} = RTEQCOST_{es}, \text{if } RTMATURE_{es} = MATURE$$

$$EQCOST_{es,y\ CAP} = \frac{RTEQCOST * 2 * d}{1 + (\frac{y - y_1}{y_0 - y_1})^y} + (1 - d) * RTEQCOST_{es}, \text{if } RTMATURE_{es} = ADOLESCENT$$

$$EQCOST_{es,y\ RET} = \frac{RTEQCOST * 2 * d}{1 + (\frac{y - y_1}{y_0 - y_1})^y} + (1 - d) * RTEQCOST_{es}, \text{if } RTMATURE_{es} = ADOLESCENT$$

$$\mathrm{EQCOST}_{\mathrm{es,y\ CAP}} = \frac{\mathrm{RTEQCOST} * \mathrm{d}}{1 + (\frac{\mathrm{y} - \mathrm{y}_1}{\mathrm{y}_0 - \mathrm{y}_1})^{\mathrm{y}}} + (1 - \mathrm{d}) * \mathrm{RTEQCOST}_{\mathrm{es}}, \text{if } \mathrm{RTMATURE}_{\mathrm{es}} = \mathrm{INFANT}$$

$$\mathrm{EQCOST}_{\mathrm{es,y\ RET}} = \frac{\mathrm{RTEQCOST} * \mathrm{d}}{1 + (\frac{\mathrm{y} - \mathrm{y}_1}{\mathrm{y}_0 - \mathrm{y}_1})^{\mathrm{y}}} + (1 - \mathrm{d}) * \mathrm{RTEQCOST}_{\mathrm{es}}, \text{if } \mathrm{RTMATURE}_{\mathrm{es}} = \mathrm{INFANT}$$

[Equation C.2]

where,

$EQCOST_{es,y,ctype}$ is time-dependant installed capital cost of equipment in new construction or the retail replacement cost of equipment in existing housing;

ctype tells function type of equipment cost to return;

CAP = Return installed capital cost in new construction;

RET = Return retail replacement cost in existing housing;

$RTMATURE_{es}$ Technology maturity description;

MATURE = No further equipment cost reductions expected;

ADOLESCENT = Major cost reductions occurred before base year;

INFANT = All cost reductions expected after first year available;

$RTEQCOST_{es}$ Installed wholesale capital cost in $2004 per unit for new homes, remains constant for MATURE technologies only (used when ctype = CAP);

$RTRECOST_{es}$ Retail capital cost in $2004 per unit for replacements, remains constant for MATURE technologies only (used when ctype = RET);

y_0 is the year of inflection of cost trend; RTINITYRes if ADOLESCENT; RTCOSTP1es if INFANT;

y_1 is the year cost decline began; RTCOSTP1es if ADOLESCENT; RTINITYRes if INFANT;

d is the total possible proportional decline in equipment cost, RTCOSTP3es, from y0 onward if ADOLESCENT, from y1 onward if INFANT;

r is the logistic curve shape parameter, RTCOSTP2es.

For newly constructed homes, the costs shown above also include the cooling system and shell efficiency measures.

APPENDIX D

CORRELATION TABLE

Correlation	Electricity use	Electricity price	Natural gas price	Income	# of rooms	HDD	CDD	ngcen	ngind	ngboth	ng9	eleccen	elecind	elecboth	elec9	othercen	otherind	otherboth	other9
Electricity use	1.00																		
Electricity price	-0.25	1.00																	
Natural gas price	0.11	0.32	1.00																
Income	0.26	0.03	-0.03	1.00															
# of rooms	0.38	-0.05	-0.02	0.38	1.00														
HDD	-0.18	0.21	-0.02	0.00	0.04	1.00													
CDD	0.28	-0.25	0.13	-0.04	-0.01	-0.73	1.00												
ngcen	0.04	-0.17	-0.17	0.21	0.19	0.02	0.02	1.00											
ngind	-0.20	0.15	0.02	-0.13	-0.10	0.12	-0.08	-0.24	1.00										
ngboth	0.01	-0.05	-0.04	0.04	0.05	-0.01	0.01	-0.05	-0.03	1.00									
ng9	-0.23	0.07	-0.19	-0.01	-0.05	0.07	-0.25	-0.22	-0.13	-0.03	1.00								
eleccen	0.37	-0.23	0.21	0.00	-0.02	-0.36	0.40	-0.31	-0.19	-0.04	-0.17	1.00							
elecind	0.00	-0.02	0.00	-0.12	-0.18	0.00	-0.02	-0.15	-0.09	-0.02	-0.08	-0.12	1.00						
elecboth	0.08	-0.03	0.00	0.00	0.04	-0.05	0.06	-0.04	-0.03	-0.01	-0.02	-0.03	-0.02	1.00					
elec9	-0.04	0.01	-0.09	-0.04	-0.05	-0.06	-0.01	-0.17	-0.11	-0.02	-0.10	-0.14	-0.07	-0.02	1.00				
othercen	0.09	-0.03	0.02	0.03	0.07	0.06	-0.03	-0.15	-0.09	-0.02	-0.08	-0.12	-0.06	-0.02	0.08	1.00			
otherind	-0.08	0.25	0.18	-0.06	0.01	0.17	-0.11	-0.19	-0.12	-0.03	-0.10	-0.15	-0.07	-0.02	0.08	-0.07	1.00		
otherboth	0.04	0.02	0.02	0.01	0.03	0.01	0.00	-0.02	-0.01	0.00	-0.01	-0.02	-0.01	0.00	0.06	-0.01	-0.01	1.00	
other9	-0.09	0.18	0.07	-0.02	-0.01	0.20	-0.17	-0.13	-0.08	-0.02	-0.07	-0.10	-0.05	-0.01	0.13	-0.05	-0.06	-0.01	1.00

APPENDIX E

PRICE ELASTICITY OF DEMAND ESTIMATED FROM RECS1997

lnelecuse	Coefficient	Std. Err.	t	P>|t|
lnelecprice	-0.955	0.052	-18.310	0.000
lnngprice	0.279	0.056	4.950	0.000
lnhhincome	0.102	0.009	11.750	0.000
lnrooms	0.683	0.017	40.360	0.000
lnhdd65	0.070	0.012	5.890	0.000
lncdd65	-0.001	0.013	-0.050	0.958
ngcen	-0.576	0.023	-25.110	0.000
ngind	-0.737	0.026	-28.860	0.000
ngboth	-0.541	0.124	-4.370	0.000
ng9	-0.936	0.026	-36.220	0.000
elecind	0.008	0.034	0.250	0.806
elecboth	-0.355	0.117	-3.030	0.002
elec9	-0.099	0.035	-2.830	0.005
othercen	-0.392	0.038	-10.450	0.000
otherind	-0.595	0.030	-19.530	0.000
Otherboth	-0.501	0.180	-2.790	0.005
other9	-0.726	0.031	-23.510	0.000
_cons	11.203	0.239	46.870	0.000

R-squared = 0.5024
Adj R-squared = 0.5009
Number of obs = 5801

APPENDIX F

SOURCE CODES FOR DISTRIBUTED SHORT-RUN ELASTICITY CALCULATION FUNCTION

```
!==================================================================
!     DISTRIBUTED SR ELASTICITY CALCULATION FUNCTION
!==================================================================
     REAL FUNCTION RSELAST (F,R,ALPHA,EF1,EF2,EF3,RECSYEAR)
     IMPLICIT NONE
     REAL*4 EF1,EF2,EF3
     REAL*4 ALPHA
     INTEGER F,R,RECSYEAR
     REAL*4 FAC1,FAC2,FAC3

  !    NOTE EF1+EF2+EF3 SHOULD SUM TO 1.0 -- THEY ARE DISTRIBUTIONAL
SHARES FOR THE SHORT RUN ELASTICITY EFFECTS

           FAC1=1.  ;  FAC2=1.  ;  FAC3=1.   !INITIALIZE

     IF
(CURCALYR>=RECSYEAR+1)FAC1=(PRICES(F,R,CURCALYR  )/PRICES(F,R,RECSYEA
R))**(ALPHA*EF1)
     IF (CURCALYR>=RECSYEAR+2)FAC2=(PRICES(F,R,CURCALYR-
1)/PRICES(F,R,RECSYEAR))**(ALPHA*EF2)
     IF (CURCALYR>=RECSYEAR+3)FAC3=(PRICES(F,R,CURCALYR-
2)/PRICES(F,R,RECSYEAR))**(ALPHA*EF3)

     RSELAST=FAC1*FAC2*FAC3
 !     write(DGDAT,*)
"rselast=",rselast,CURCALYR,PRICES(F,R,CURCALYR),RECSYEAR,prices(f,r,recsyear)!pro
duces copious output in rdgenout
     RETURN
     END FUNCTION RSELAST

                       END SUBROUTINE RESD   ! CLOSES THE CONTAINS STRUCTURE
```

APPENDIX G

MATHEMATICAL MODEL OF DUBIN AND MCFADDEN (1984)

Several econometric models consistent with utility maximization which could be used to describe appliance choice and electricity consumption are outlined first. In the present analysis, block rate structure is ignored, and electricity treated as a commodity available in any quantity at a fixed marginal (=average) price. Also, appliance holding decisions is analyzed as if they are contemporaneous with usage decisions, and do not involve intertemporal considerations. The approach combines the method of development of discrete choice models from conditional indirect utility functions employed in McFadden (1981) and the method developed by Hausman (1979) for recovery of indirect utility functions from econometric partial demand systems.

The consumer face a choice of *m* mutually exclusive, exhaustive appliance portfolios, which can be indexed $i = 1, \ldots, m$. Portfolio *i* has a rental price (annualized cost) r_i. Given portfolio *i*, the consumer has a conditional indirect utility function.

$$\mathrm{u} = \mathrm{V}(\mathrm{i}, \mathrm{y} - \mathrm{r_i}, \mathrm{P_1}, \mathrm{P_2}, \mathrm{S_i}, \mathcal{E}_i, \eta) \ (1)$$

where P_1 is price of electricity, P_2 is price of alternative energy sources, *y* is income, S_i is observed attributes of portfolio *i*, $\mathcal{E}_i$ is unobserved attributes of portfolio *i*, r_i is price of portfolio i, η is unobserved characteristics of the consumer, and all prices and income are deflated by an index of nonenergy commodity prices. Electricity and alternative consumption levels, given portfolio i, are (by Roy's identity)

$$x_1 = \frac{-\partial V(i, y-r_i, P_1, P_2, S_i, \mathcal{E}_i, \eta)/\partial P_1}{\partial V(i, y-r_i, P_1, P_2, S_i, \mathcal{E}_i, \eta)/\partial y} \quad (2)$$

$$x_2 = \frac{-\partial V(i, y-r_i, P_1, P_2, S_i, \mathcal{E}_i, \eta)/\partial P_2}{\partial V(i, y-r_i, P_1, P_2, S_i, \mathcal{E}_i, \eta)/\partial y} \quad (3)$$

The probability that portfolio *i* is chosen is

$$P_i = \mathrm{Prob}\{(\mathcal{E}_1, \dots, \mathcal{E}_m, \eta) : V(i, y - r_i, P_1, P_2, S_i, \mathcal{E}_i, \eta) > V\big(j, y - r_j, P_1, P_2, S_j, \mathcal{E}_j, \eta\big) \, for\ j \neq i\} \quad (4)$$

Any function *V* with the necessary and sufficient properties of an indirect utility function can be used to construct econometric forms for joint discrete/continuous choice.

A second method of obtaining a discrete/continuous demand system is to start from a parametric specification of the unit electricity consumption (UEC) equation, treat Roy's identity as a partial differential equation whose solution defines a conditional indirect utility function, and then define the discrete choice probabilities from the indirect utility function. This procedure can be carried through for functions in which UEC levels exhibit some income elasticity. First consider systems in which the UEC equation is linear in income,

$$x_1 = \beta_1(y - r_i) + m^i(P_1, P_2) + \nu_{1i} \quad (5)$$

with m^i linear in parameters and the distribution of ν_{1i} depending in general on discrete choice *i*. A general solution for an indirect utility function yielding this demand equation is

$$u = \psi(\left[M^i(P_1, P_2) + y - r_i + \frac{\nu_{1i}}{\beta_i}\right] e^{-\beta_i P_1}, P_2, \nu_{2i}) \quad (6)$$

where

$$M^i(P_1, P_2) = \int_{P_1}^{0} m^i(t, P_2) e^{\beta_i (P_1 - t)}\, dt \quad (7)$$

And ψ is a function which is increasing in its first argument. The demand for substitute energy satisfies

$$x_2 = -M_2^i(P_1, P_2) - e^{-\beta_i P_1}\, {\psi_2}/{\psi_1} \quad (8)$$

where $M_2^i = {\partial M^i}/{\partial P_2}$ and ${\psi_2}/{\psi_1} = ({\partial \psi}/{\partial P_2})/({\partial \psi}/{\partial P_1})$ is evaluated at the arguments in (6). Consider a special case of (6) in which $\nu_{2i} = \nu_{21}$ is the same for all *i*. The discrete choice probabilities satisfy

$$P_i = \mathrm{Prob}\{\left[M^i(P_1, P_2) + y - r_i + {\nu_{1i}}/{\beta_i}\right] e^{-\beta_i P_1} \geq$$

$$\left[M^j(P_1, P_2) + y - r_j + {\nu_{1j}}/{\beta_j}\right] e^{-\beta_j P_1} for j \neq i\} \quad (9).$$

A special case of this system which yields simple functional form is

$$u = \ln\left\{\left[\alpha_0^i + \frac{\alpha_1^i}{\beta} + \alpha_1^i P_1 + \alpha_2^i P_2 + \beta(y - r_i) + \nu_{1i}\right] e^{-\beta P_1}\right\} - \alpha_5 ln P_2 \quad (10)$$

with $\beta_i = \beta$ common across alternatives, and

$$x_1 = \alpha_0^i + \alpha_1^i P_1 + \alpha_2^i P_2 + \beta(y - r_i)\nu_{1i} \ (11)$$

$$x_2 = \frac{\alpha_2^i}{\beta}(\alpha_5 - 1) + \frac{\alpha_5}{\beta}\left(\alpha_0^i + \frac{\alpha_1^i}{\beta}\right)\frac{1}{P_2} + \frac{\alpha_5\alpha_1^i}{\beta}\frac{P_1}{P_2} + \alpha_5\frac{(y - r_i)}{P_2} + \frac{\alpha_5\nu_{1i}}{\beta P_2} \ (12)$$

Alternatively, consider the special case of (6) in which $\nu_{1i} = \eta$ and

$$u = \left[M^i(P_1, P_2) + y - r_i + {}^{\eta}/_{\beta_i}\right] e^{-\beta P_1} + \nu_{2i} \ (13)$$

Analogously to (10) define

$$u = (\alpha_0^i + \frac{\alpha_1^i}{\beta} + \alpha_1^i P_1 + \alpha_2^i P_2 + \beta(y - r_i) + \eta)e^{-\beta P_1} - \alpha_5 lnP_{2+}\nu_{2i} \ \ (14).$$

The UEC equation is then

$$x_1 = \alpha_0^i + \alpha_1^i P_1 + \alpha_2^i P_2 + \beta(y - r_i)\nu_{1i} + \eta \ (15)$$

And the choice probability satisfy

$$P_i = Prob(\nu_{2j} - \nu_{2i} < W_i - W_j \text{ for } j \neq i) \ (16)$$

With

$$W_i = V_i e^{-\beta P_1} = (\alpha_0^i + \frac{\alpha_1^i}{\beta} + \alpha_1^i P_1 + \alpha_2^i P_2 - \beta r_i)e^{-\beta P_1} \ (17)$$

Econometric studies of UEC have in most cases assumed, implicitly or explicitly, statistical independence of appliance portfolio choice and the additive error in the UEC equation and have proceeded to estimate the UEC equation by OLS.

REFERENCES

Alberini, A. and M. Filippini. (2010). Response of Residential Electricity Demand to Price: The Effect of Measurement Error. CEPE Working Paper 75, Centre for Energy Policy and Economics, ETH Zurich, July (available at http://www.cepe.ethz.ch/publications/workingPapers/CEPE_WP75.pdf).

Alberini, A., W. Gans, and D. Velez. (2010). Residential Consumption of Gas and Electricity in the U.S.: The Role of Prices and Income. CEPE Working Paper 77, Centre for Energy Policy and Economics (CEPE). ETH Zurich, November. Available at http://www.cepe.ethz.ch/publications/workingPapers/CEPE_WP77.pdf.

Aldy, J. E. et al. (2009). Designing Climate Mitigation Policy (Cambridge, MA: National Bureau of Economicaaa Research), Working Paper 15022, June. www.nber.org/papers/w15022.

Allcott, H. and S. Mullainathan. (2010). Behavior and Energy Policy. Science Vol.327 (March) pp. 1204-1205.

Anderson, S. and R. Newell. (2004). Information programs for technology adoption: the case of energy efficiency audits. Resource Energy Economics 26:27-50.

Atakhanova, Z. and P. Howie. (2007). Electricity demand in Kazakhstan. Energy Policy. 35(2007):3729-3742.

Athukorala ,W. and C. Wilson. (2010). Estimating short and long-term residential demand for electricity: New evidence from Sri Lanka. Energy Economics 32 S34-S40.

Baht, C. R. (1994). Imputing a continuous variable from grouped and missing income observations. Economics letters. 46:311-319.

Bardach, E. (2000). A Practical Guide for Policy Analysis, Seven Bridges Press, LLC, New York.

Beck, M. J. (2009). Renewable Portfolio Standards. Cherry Hill, NJ: M.J. Beck Consulting, March. http://mjbeck.emtoolbox.com/?page=Renewable_Portfolio_Standards.

Bernstein, M. and J. Griffin. (2006). Regional Differences in the Price-Elasticity of Demand for Energy. NREL. Available at http://www.nrel.gov/docs/fy06osti/39512.pdf.

Blumstein C. and Harris J. (1993). The cost of energy efficiency. Science 261:970.

Bohi, D. R. (1981). Analyzing the Demand Behavior: A Study of Energy Elasticities. Johns Hopkins University Press, Baltimore, Md.

Borenstein, S. (2008). Equity Effects of Increasing-Block Electricity Pricing. CSEM Working Paper 180, University of California, Berkeley, April.

Brown, F. L., L. Hoffman, and J. D. Baxter. (1975). New Way to Measure Price Elasticity. Electrical World. pp. 184:52-54.

Brown, M. A. and Y. Baek. (2011). The Forest Products Industry at an Energy/Climate Crossroads. Energy Policy. 38:7665–7675.

Brown, M. A., E. Gumerman, X. Sun, Y. Baek, J. Wang, R. Cortes, and D. Soumonni. (2010). Energy Efficiency in the South, Retrieved from http://www.seealliance.org/.

Brown, M. A., J. Chandler, M. Lapsa, and M. Ally. (2009). Making Homes Part of the Climate Solution. Oak Ridge National Laboratory, ORNL/TM-2009/104, June, http://www.ornl.gov/sci/eere/PDFs/CCTP_PolicyOptions_200906.pdf.

Brown et al. (2001). Scenarios for a Clean Energy Future. Energy Policy 29 (2001) 1179-1196.

Burtless, G. and J. A. Hausman. (1978). The Effect of Taxation on Labor Supply: Evaluating the Gary Negative Income Tax Experiment. Journal of Political Economy. 86(6):1103-1130.

Carter, D. W. and J. W. Milon. (2005). Price Knowledge in Household Demand for Utility Services. The Rand Economics 81(2):265-283.

Congressional Budget Office (CBO). (2009). The Economic Effects of Legislation to Reduce Greenhouse Gas Emissions. Washington, DC.

Congressional Budget Office (CBO). (2007). Trade-Offs in Allocating Allowances for CO_2 Emissions. Washington, DC.

Dahl, C. (1993). A Survey of Energy Demand Elasticities in Support of the Development of the NEMS. Washington, D.C. Contract No. DE-AP01-93EI23499.

Dahl, C. A. (1979). Consumer Adjustment to a Gasoline Tax." The Review of Economics and Statistics 61(3): 427.

Dergiades, T. and L. Tsoulfidis. (2008). Estimating Residential Demand for Electricity in the United States, 1965-2006. Energy Economics. 30(2008); pp. 2722-2730.

Darby, S. (2006). The effectiveness of feedback on energy consumption: A review for DEFRA of the literature on metering, billing and direct displays, Environmental Change Institute, University of Oxford, Oxford.

Deaton, A. and J. Muellbauer (1980). Economics and Consumer Behavior. Cambridge University Press.

Dinan, T. M. (1989). Temperature Takeback in the Hood River Conservation Project. Energy and Buildings 13: 39–45.

Dubin, J. A. and D. L. Mcfadden. (1984). An econometric analysis of residential electric appliance holdings and consumption, econometrica (pre-1986); Mar 1984;52,2;ABI/INFORM Global, pg. 345.

Ek, K. and P. Soderholm. (2010). The devil in the details: Household electricity saving behavior and the role of information. Energy Policy. Volume 38, Issue 3, March 2010, Pages 1578-1587.

Energy Information Administration EIA. (2007). Model Documentation Report: Residential Sector Demand Module of the National Energy Modeling System. Washington, D.C., DOE.

Energy Information Administration (EIA). (2003). National Energy Modeling System: An Overview, 2003. Available at http://www.eia.doe.gov/oiaf/aeo/overview/introduction.html.

Energy Star. (2008). Energy Star Homes. Retrieved July 21, 2008, from www.energystar.gov.

Espey, J. A. and M. Espey. (2004). Turning on the Lights: A Meta- Analysis of Residential Electricity Demand Elasticities, Journal of Agricultural Economics; 36,1(April 2004):65-81.

Eto J, et al. (1996). The total cost and measured performance of utility sponsored energy-efficiency programs. Energy J. 17:31-52.

Faruqui, A. and S. Sergici. (2009). Household Response to Dynamic Pricing of Electricity – A Survey of The Experimental Evidence. The Brattle Group. http://www.hks.harvard.edu/hepg/

Federal Energy Regulatory Commission (FERC). 2008. Assessment of Demand Response and Advanced Metering. Staff Report. Washington, DC.

Fell et al. (2010). A New Look at Residential Electricity Demand Using Household Expenditure Data. RFF Discussion Paper. pp. 10-57. Washington, DC. October.

Filippini, M. and S. Pachauri. (2004). Elasticities of electricity demand in urban Indian households, Energy Policy 32(2004) 429-436.

Foss, A. (2007). Tax Credit Helps Builders. PATH Report.

Foster, H. S. Jr, and B. R. Beattie. (1981). Urban Residential Demand for Water in the United States: Reply. Land Economics 57 (may): 257-65.

Garcia-Cerrutti, L. M. (2000). Estimating Elasticities of Residential Energy Demand from Panel County Data Using Dynamic Random Variables Models with Heteroskedastic and Correlated Error Terms. Resource and Energy Economics. 22(2000):355-366.

Garrett, V. and T. M.Koontz. (2008). Breaking the cycle: Producer and consumer perspectives on the non-adoption of passive solar housing in the US. Energy Policy. 36(4) p. 1551.

Gillingham, K., R. G. Newell, K. Palmer. (2009). Energy Efficiency Economics and Policy, SSRN Working Paper Series. Rochester: June 2009.

Goulder, L. H. (2009). Carbon Taxes versus Cap-and-Trade. Working Paper. Stanford, CA: Department of Economics, Stanford University.

Granade. H. C. et al. (2009). Unlocking Energy Efficiency in the U.S. Economy, Mckiney &Co, New York.

Greene, D. and P. Hu. (1986). A Functional Form Analysis of the Short-Run Demand for Travel and Gasoline by One-Vehicle Households. Transportation Research Record. T. R. Board. Washington, D.C., National Research Council. 1092: 10–15.

Haas, R. and L. Schipper. (1998). Residential energy demand in OECD-countries and the role of irreversible efficiency improvements. Energy Economics 20, pp. 421-442.

Hadley, S. W., J. M. MacDonald, et al. (2004). Emerging Energy-Efficient Technologies in Buildings: Technology Characterizations for Energy Modeling. Engineering Science and Technology Division. Oak Ridge, Tennessee, ORNL.

Halvorsen, R. (1975). Residential Demand for Electric Energy. Review of Economics and Statistics February 1975(57): 12–18.

Hausman, J. (1979). Exact Consumer's Surplus and Dead weight Loss. American Economic Review. 71(1979), pp. 663-676.

Hassett, K. A. and G. E. Metcalf. (1995). Energy tax credits and residential conservation investment: evidence from panel data. Journal of Public Economics. 57:201-217.

Hassett, K.A. and G. E. Metcalf. (1993). Energy conservation investment: Do consumers discount the future correctly? Energy Policy 21:710-716

Hirst, E. and M. A. Brown. (1990). Closing the Efficiency Gap: Barriers to the Efficient Use of Energy. Resources, Conservation and Recycling, 3(1990) 267-281.

Holtedahl, P. and F. L. Joutz. (2004). Residential electricity demand in Taiwan. Energy Economics. 26(2004):201-224.

Hondroyiannis, G. (2004). Estimating residential demand for electricity in Greece. Energy Economics. 26(2004):319-334.

Horowitz, M. (2007). Changes in Electricity Demand in the United States from the 1970s to 2003. The Energy Journal; 2007; 28, 3 pg. 93.

Houthakker, H. S. (1980). Residential Electricity Revised. The Energy Journal 1980(1): 29–41.

Houthakker, H. S., P. K. Verleger, et al. (1974). Dynamic Demand Analyses for Gasoline and Residential Electricity. American Journal of Agricultural Economics May 1974(56): 412–418.

Howarth, R. B. et al. (2000). The economics of energy efficiency: insights from voluntary participation programs. Energy Policy 28:477-86.

Howarth, R. B. and A. H. Sanstad. (1995). Discount Rates and Energy Efficiency. Contemporary Economic Policy 13:101-109.

Hsing Y. (1994). Estimation of Residential Demand for Electricity with the Cross-sectionally Correlated and Time-wise Autoregressive Model. Resource Energy Economics 16:255-263

Hughes, J. E. et al. (2008). Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand. The Energy Journal. 29(1): 113.

International Energy Agency. (IEA). (2005a). Saving Electricity in a Hurry: Strategies to Deal with Temporary Short falls in Electricity Supplies. Paris International Energy Agency.

International Energy Agency. (IEA). (2005b). Saving Oil in a Hurry: Measures for Rapid Demand Restraint in Transport. Paris: International Energy Agency.

Jaffe, A., R. Newell, and R. Stavins. (2004) The economics of energy efficiency. In Encyclopedia of Energy. C. Cleveland (ed.). pp. 79-90. Amsterdam: Elservier

Jaffe A., R. Stavins, R. Newell. (1995). Dynamics Incentives of Environmental Regulations: the Effects of Alternative Policy Instruments on Technology Diffusion. Journal of Environmental Economics and Management 29:S43-63.

Jaffe, A. and R. Stavins. (1994). The energy efficiency gap: What does it mean? Energy policy 22:804-10.

Jakajima, T. and S. Hamori. (2010). Change in Consumer Sensitivity to Electricity Prices in Response to Retail Deregulation: A Panel Empirical Analysis of the Residential Demand for Electricity in the United States. Energy Policy 38(2010) 2470-2476.

Jung, T.Y. (1993). Ordered logit model for residential electricity demand in Korea. Energy Economics. 15(3), pp. 205-209.

Kayser, H. A. (2000). Gasoline demand and car choice: estimating gasoline demand using household information. Energy Economics. 22:331-348.

Kempton, W., D. Feuermann, A. McGarity. (1992). I always turn it on "super": user decisions about when and how to operate room air conditioners. Energy and Buildings. 18:177-91.

Kempton, W. and L. Montgomery. (1982) Folk quantification of energy. Energy. 7:817-27.

Kennedy, P. (2008). A Guide to Econometrics, 6th Edition. Blackwell Publishing. MA, USA.

Laitner, J. A. (2000). Energy Efficiency: Rebounding to a Sound Analytical Perspective. Energy Policy. 28(6–7): 471.

Leth-Petersen, S. (2001). Micro evidence on household energy consumption. AKF Memo. Danish Energy Agency, Denmark.

Levine, M., J. Koomey, J. McMahon, A. Sanstad, E. Hirst. (1995). Energy Efficiency Policy and Market Failures. Annual Review of Energy and the Environment 20: 535–55.

McClung, B. (1988). Estimation and Interpretation of Competing Models of Electricity Demand Using the Residential Energy Consumption Survey Microdata Sets. Dept. of Economics, Texas A&M University. Dissertation.

McFadden, D. L. (1981). Econometric Models of Probabilistic Choice. Structural Analysis of Discrete Data (ed. By P. Zarembka). New York: Academic Press. 1973.

McFadden, D., D. Kirschner, and C. Puig. (1978). Determinants of the Long-run Demand for Electricity. In Proceedings of the American Statistical Association, 1978.

Metcalf, G. and K. A. Hassett. (1999). Measuring the Energy Savings from HomeImprovement Investments: Evidence from Monthly Billing Data. The Review ofEconomics and Statistics. 81(3) 516-528.

Nakajima, T. and S. Hamori. (2010). Change in consumer sensitivity to electricity prices in response to retail deregulation: A panel empirical analysis of the residential demand for electricity in the United States. Energy Policy. 38(2010):2470-2476.

Narayan, P. K. and R. Smyth. (2005). The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration. Energy Policy. 33(2005):467-474.

National Commission on Energy Policy (NCEP). (2004). Ending the Energy Stalemate (Washington, DC: National Commission on Energy Policy), December.

National Renewable Energy Laboratory (NREL). (2009). Comparative Analysis of Three Proposed Federal Renewable Electricity Standards (Golden, CO: NREL).

Neeland, H. (2009). The Residential Demand for Electricity in the United States. Economic Analysis and Policy. Vol. 39 No.2, September 2009. pp. 193-203.

Neenan, B. and J. Eom. (2008). Price Elasticity of Demand for Electricity: A Primer and Synthesis, An EPRI White Pater for the Energy Efficiency Initiative.

Newell, R., A. Jaffe, and R. Stavins. (1999). The induced innovation hypothesis and energy-saving technological change. Quarterly Journal of Economics. 114:941-75.

Nolan, J. M. et al. (2008). Normative social influence is under-detected. Personality and Social Psychology Bulletin. 34(7): 913-923.

Pfannenstiel, J. and A. Faruqui. (2008). Mandating Demand Response: California's load-management experience argues for formal DR standards. Public Utilities Fortnightly, 146(1): 48-54.

Puller, S. L., and L. A. Greening. (1999). Household Adjustment to Gasoline Price Change: An Analysis Using Nine Years of U.S. Survey Data. Energy Economics 21(1): 37

Rajeev, G. K. (1994). Quasi-experimental Taxation Elasticities of U.S. Gasoline Demand. Energy Economics 16(2): 133.

Rajeev, G. K., and M. J. Morey. (1993). Effect of the 1973 Oil Price Embargo: A Non-parametric Analysis. Energy Economics. 15(1): 39.

Reiss, P. and M. White. (2008). What changes energy consumption? Prices and public pressures. The Rand Journal of Economics. Autumn 2008;39,3;ABI/INFORM Global pg.636.

Reiss, P. and M. White (2005). Household Electricity Demand, Revisited. The Review of Economic Studies. Vol. 72: pp. 853-883.

Robinson, J. (1969). The economics of imperfect competition. London: MacMillian.

Sanstad,A, M. Hanemann, M. Auffhammer. (2006). End-use Energy Efficiency in a "Post-Carbon" California Economy: Policy Issues and Research Frontiers. The California Climate Change Center at UC-Berkeley, Berkeley, CA.

Sanstad, A. H. and R. B. Howarth. (1994). Consumer rationality and energy efficiency. Working paper prepared for ACEEE 1994 Summer Study, Berkeley, CA.

Shin, J. (1985). Perception of Price When Price Information Is Costly: Evidence from Residential Electricity Demand. The Review of Economics and Statistics. 67, 4(November 1985):591-598.

Simon, H. (1959). Theories of decision-making in economics and behavioral science. American Economics Review 49:253-283.

Simon, H. (1986). Rationality in psychology and economics. Journal of Business. 59:209-24.

Southworth, K. (2009). Corporate Voluntary Action: A Valuable but Incomplete Solution to Climate Change and Energy Security Challenges. Policy and Society. 27:329-350.

Taylor, L. D. (1975). The Demand for Electricity: A Survey. The Bell Journal of Economics, 6(1), 74-110.

TecMarket Works (2004). The California Evaluation Framework. Prepared for the California Public Utilities. June 2004. Project Number: K2033910. Available at http://www.calmac.org/publications/California_Evaluation_Framework_June_2004.pdf.

Train, K. (1985). Discount rates in consumers' energy-related decisions: a review of the literature. Energy. 10:243-53.

Tversky, A. (1972). Elimination by aspects: A theory of choice. Psychological Review. 79:281-99.

Vaage, K. (2000). Heating technology and energy use: a discrete/ continuous choice approach to Norwegian household energy demand. Energy Economics 22(2000) 649-666.

van Soest, D. P. and E. Bulte. (2000). Does the energy-efficiency paradox exist? Technological progress and uncertainty. Environmental Resource Economics. 18:101-112.

Vestel, R. B. (2010). Consumers Buy More Efficient Refrigerators, but Keep the Old Ones Humming, The New York Times (March 19, 2010).

Wade, S. H. (2003). Price Responsiveness in the AEO2003 NEMS Residential and Commercial Buildings Sector Models. EIA.

Wadud et al. (2010). Gasoline Demand with Heterogeniety in Household Responses. The Energy Journal. 31,1; ABI/INFORM Global. pg. 47.

Webber et al. (2000). Savings estimates for the ENERGY STAR voluntary labeling program. Energy Policy 28:1137-49.

Weil, S. and J. McMahon. (2003). Governments should implement energy-efficiency standards and labels-cautiously. Energy Policy 31:1403-15.

West, S. and R. C. Williams III. (2004). Estimates from a Consumer Demand System: Implications for the Incidence of Environmental Taxes. Journal of Public Economics. 88:735-757.

Westoby, R. and D. Pearce. (1984). Energy Consumption in Eastern Europe: A Cross-sectional analysis, Energy Economics. Vol. 6(1), pages 2-4, January.

Wilson, C. and H. Dowlatabadi. (2007). Models of decision making and residential energy use. Annual Review of Environmental Resources. 32:169-203.

Yang, B. (2005). Residential Energy Code Evaluations: Review and Future Directions. (Building Code Assistance Program) A Joint Project of The Alliance to Save Energy, American Council for an Energy-Efficient Economy, Natural Resources Defense Council.

Yates, S. and E. Aronson. (1985) Social Psychological Aspects of Energy Conservation AIP Conference Proceedings. 135:81-91.

Yoo, S. H. et al. (2007). Estimation of residential electricity demand function in Seoul by correction for sample selection bias. Energy Policy. 35(2007):5702-5707.

Zarnikau, J. (2003). Functional Forms in Energy Demand Modeling. Energy Economics 25 (2003) 603-613.