Title of Document: THE ROLE OF PRICES AND INFORMATION IN RESIDENTIAL ENERGY CONSUMPTION AND INVESTMENT BEHAVIOR

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Good stewardship of the planet's natural resources is the central challenge of our age, and energy generation and usage has become an important dimension of the current debate about sustainability. Americans spend approximately 5% of household income on energy, and over the last few decades—and as recently as with President Obama's stimulus package of 2009--many government policies have been targeted at residential energy efficiency. Improving energy efficiency would reduce total energy usage, emissions associated with generation of power from fossil fuels, and reliance on imports of such fuels. In this dissertation, I analyze three key aspects of residential energy behavior and their impact on policy.

The first is elasticity of energy demand with respect to price. Earlier estimates span a wide range, due to the differing geographic coverage and time scales used in each study. In Chapter 3, I estimate a residential demand function for energy on a recent, nationwide panel of U.S. homes, and find higher price elasticities than previously documented. These results suggest that residential consumers *are* price

responsive in their energy consumption. *How* they respond to price is the topic of Chapter 4, where I estimate a series of demand functions for energy efficiency improvements, and focus on the role of moving on energy investment. I find that households that move within 2 years are 20% *less* likely to invest in heaters than those who do not move, suggesting that homeowners do not believe that energy efficiency is capitalized into the value of the home. Requiring disclosure about the energy efficiency of a home during the sales process may remedy this disincentive.

In Chapter 5, I use data from an original survey of households to examine how consumers value future savings from energy bills *vis-à-vis* money. I find that consumers apply a lower discount rate to energy savings than to money, suggesting that market failures, rather than consumer bias, may be responsible for a low rate of residential energy efficiency investment.

Taken together, these findings contribute a greater understanding of residential energy behavior, and underscore the potential for intelligent policy to achieve energy efficiency goals.

THE ROLE OF PRICES AND INFORMATION IN RESIDENTIAL ENERGY CONSUMPTION AND INVESTMENT BEHAVIOR

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Preface

Energy makes the world go round. The discoverers and exploiters of energy sources wrote the history of the modern world. Many of the actions and activities that humankind takes for granted, from the cars and trains that we travel in, to the warm rooms that we sleep in, to the computers that we type on; are directly manufactured, delivered, or enabled by the consumption of energy. In the United States and many parts of the world, energy is predominantly generated by fossil fuel combustion. Despite the specter raised by "peak oil" advocates, resource exhaustion is less of a threat to society than other impacts of the growth in consumption of fossil fuels: direct byproducts of combustion, such as carbon dioxide, alter and pollute the atmosphere, unleashing dramatic changes to the climate. Large-scale extraction inevitably results in leaks, spills, and the destruction of the local landscape. Implicit and explicit security guarantees necessary to insure continued delivery of imported fuel are costly and morally fraught. However, few alternatives seem to exist.

Those agitating for a transition away from fossil fuels seem all too often to ignore the economics. Hucksters hoping to profit from new subsidies make overly optimistic claims about their brand of renewable energy. Diehard vested interests go to great lengths to downplay and obfuscate the risks of continuing the status quo. With such large stakes and partisan players, objectivity and considered planning are a challenge. Yet, one solution does emerge, time and again, from reports and white papers by those great and good: energy efficiency. It is cost-effective, simple, can be done with existing technology, is domestically produced and locally sourced; in other words, it checks all of the right boxes. Increasing the efficiency of our energy consumption can *potentially* mitigate, reduce, and reverse many of the environmental and security issues described above. How do we realize this potential? How do we embark on this energy diet?

This dissertation contributes in a small way to this literature by exploring the 'who, what, and how' of residential energy efficiency. The conclusions are a reason for hope, but also an acknowledgement of the barriers and difficulty faced on the road ahead. Bring on the $20 bills!

"For the next few decades, energy efficiency is one of the lowest cost options for reducing US carbon emissions. ...Some economists, however, don't believe these analyses; they say there aren't 20-dollar bills lying around waiting to be picked up. If the savings were real, they argue, why didn't the free market vacuum them up? The skeptics are asking a fair question: why do potential energy efficiency savings often go unrealized? ... Regardless of what the skeptics may think, there are indeed 20-dollar bills lying on the ground all around us. We only need the will -- and the ways -- to pick them up."

Excerpt from an Op-Ed entitled "Energy Efficiency: Achieving the Potential, Realizing the Savings", by U.S. Energy Secretary Steven Chu, March 16, 2010, *Huffington Post*

Dedication

To Rebecca, for your patience and support.

To Mom and Dad, for the preparation and encouragement to make it this far.

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Student debt comes in many forms. From my six years at Maryland, I have accumulated a massive debt of gratitude to the many instructors, advisors, and colleagues who gave willingly of their time to further my education. With the understanding that this small bit of thanks is insufficient repayment of such a debt, I hereby seek to acknowledge a few of those individuals that stood out, and without whom this work would not have been impossible.

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My time at AREC was a whirlwind of learning and challenging courses, and I am grateful to the faculty for providing an environment so conducive to learning. I am especially thankful to have had the econometrics training provided by Professors Richard Just, Nerlove, and Alberini; the theoretical training of Professors Lars Olson and Bob Chambers, and the grounding in environmental economics provided by Professor Maureen Cropper and Erik Lichtenberg.

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Chapter 1: Introduction

In 1954, Lewis Strauss, head of the Atomic Energy Commission, boasted that nuclear power would usher in an era when people "will enjoy in their homes electrical energy too cheap to meter." This bit of hyperbole neatly captures the attitude of many Americans towards energy consumption today: not costly enough to worry about. Yet concerns are mounting about the reliance on fossil fuel and the attendant environmental and economic costs. Fossil fuel combustion, the primary means of electricity generation and heating, produces undesirable emissions that threaten human and environmental health.

In the US, energy usage in buildings accounts for a sizable fraction (30-40%) of total energy use and energy-related emissions (EIA, 2008). Buildings thus offer a natural target for policies that seek to reduce energy consumption and increase energy efficiency. Effective residential energy efficiency policies would help reduce $CO2$ and conventional pollutant emissions from (fossil-fuel) power generation, reduce dependence on imported fuels and vulnerability to supply shocks, and likely, create jobs (Wei *et al.*, 2010).

Building energy consumers can be broadly classified into two sectors: residential and non-residential. The latter group is comprised of institutional concerns, such as schools and government installations, commercial properties such as office buildings, stores and shopping malls, and industrial or manufacturing facilities. These non-residential demanders share a financial incentive for greater energy efficiency: energy is a costly production input, and profit can be increased (or costs reduced) by minimizing energy costs given a desired level of energy service provision. To that end, many companies and facilities employ professional energy managers to accomplish cost-effective energy efficiency.

By contrast, residential consumers tend to lack the resources and diligence (not to mention financial motivation) to expend comparable effort on energy optimization. For this reason – and because of its size – the residential sector offers a major opportunity to reduce energy usage, and, accordingly, has received considerable policy attention. The 2007 report of the Intergovernmental Panel on Climate Change, for example, states that significant carbon dioxide emission reductions are possible at low or no cost through energy efficiency improvements in buildings, including residential buildings (Levine *et al.*, 2007), but there remains significant skepticism as to whether consumers actually do spontaneously undertake energy efficiency investments and renovations at their home (Jaffe and Stavins, 1994; Golove and Eto, 1996).

Many government policies have been specifically targeted at buildings and residential energy usage over the last few decades. These include, among others, 1) aggressive pricing policies, 2) incentives for conservation and energy efficiency investments, and 3) regulations, including energy efficiency standards that must be met by appliances, new buildings, and building retrofits. Most recently, the 2009 American Recovery and Reinvestment Act ('The Stimulus Bill') allocated over $300 million to efficiency incentives in the home, and additional measures have been adopted by municipalities and states, and by utility companies at the behest of Public Utility Commissions. While these policies vary in terms of products (*e.g.,* lights, washing machines, wall insulation) and incentives (*e.g.,* low-interest loans, tax credits and rebates), their common goal is to enhance the energy efficiency of the building sector.[1] Despite the strength of policy support, however, evidence about the effectiveness of these measures is limited.

Some observers argue that if consumers knew what drives their energy consumption and were informed about opportunities for conservation and energy efficiency investments, they may undertake them spontaneously. Low-cost or free audits and informational campaigns are examples of policies based on these arguments. Energy Service Companies (ESCOs) are an example of a marketplace solution to the investment gap surrounding energy usage and energy efficiency.[2]

Residential consumers can reduce their consumption by engaging in conservation measures (such as moderating their heating or cooling demand) or by investing in more efficient equipment. Energy is a derived demand: consumers demand *services* (lighting, heating, washing) that are converted to a demand for energy through appliances and equipment. This has important consequences for residential energy usage behavior. Compared with rates of return from other assets, on average, residential energy consumers underinvest in energy efficiency. Many observers attribute this phenomenon to energy users having higher discount rates for energy savings than for non-energy investments, which results in lower rates of investment for energy efficiency projects. This energy-efficiency 'paradox' or 'gap,' (Jaffe and Stavins, 1994) has generated a lot of research and policy interest. Possible explanations include uncertainty (over future

[1] Regulatory approaches, such as building codes and appliances standards, have also been used to promote energy efficiency (see, e.g. CA CCR Title 24 at http://www.energy.ca.gov/title24/).

[2] An ESCO will undertake an investment on behalf of a facility, and perhaps even operate the new equipment. The ESCO then 'sells' the service back to the facility, and profits from the difference between the 'sale' price and the new, lower operating cost. In this way, an industry of middlemen has grown to exploit the many profitable energy efficiency opportunities.

energy prices), irreversibility (of the durable good), and information asymmetry (over the performance of the appliance), and/or institutional disincentives (owners versus renters).

Clearly, it is important to understand the determinants of energy consumption in buildings and among residential customers, and the responsiveness of consumers to pricing and other policies. The focus of this dissertation is on understanding the U.S. residential energy consumers, their usage of energy, and their decisions about energy efficiency home renovations and investments. I analyze three main facets of residential energy consumption and investment behavior.

First, in Chapter 3, I focus on estimating a residential demand function for electricity and natural gas. In that chapter, I ask two broad research questions: 1) what are the determinants of residential energy consumption, and 2) how do consumers respond to price? I use recent longitudinal household data drawn from the American Housing Survey, which reports information about the structural characteristics of a very large sample of homes in the US, along with utilities and energy expenditures, appliances, heating and cooling systems, and characteristics of the households residing in those homes. I develop a large, nationwide sample that follows homes from 1997 to 2007. I merge these data with weather data, since weather is an important determinant of energy demand, and with information about energy prices and the utilities serving each area covered by the sample.

I find that electricity and gas usage is well predicted by house characteristics, the type of heating and cooling system, tenure and ownership, weather and household characteristics. Importantly, my models allow me to identify both short-term and long-term price elasticities of demand, which are much more pronounced than previously appreciated. I estimate own-price elasticities of electricity and gas demand of approximately -0.7 and -0.6, respectively. Residential consumers *are* price responsive, and the long-term price elasticity is sufficiently strong to suggest that households do engage in renovations and replacement of appliances that improve energy efficiency, at least at locales or during periods when the prices are high.

These findings motivate the investigation in Chapter 4, where I specifically focus on residential investment in energy efficiency renovations and improvements. I ask two key research questions: 1) what are the determinants of energy efficiency investments in the home, and 2) how are energy efficiency investments affected by moving/staying decisions?

I examine the home renovations and improvements documented in the American Housing Survey from 1997 to 2009 (up to 9 waves). Briefly, I find that households that move within 2 years are 20% less likely to invest in heater renovations or replacements, but that there is no statistically significant relationship between moving or staying and other classes of investment, such as kitchen renovations or yard repairs. This result suggests that homeowners do not believe that energy efficiency is capitalized into the value of the home, and therefore forego efficiency upgrades prior to moving. This has very important policy implications: Requiring disclosure about the energy efficiency of a home when selling it/buying may be the remedy to this disincentive. Indeed, recent evidence (Brounen and Kok, 2011; Eichholtz *et al.,* 2010) suggests that signals about the energy efficiency of a building tend to raise it selling price.

Neither the American Housing Survey, which I used in my empirical analyses of chapter 3 and 4, nor other government-conducted data collection efforts (*e.g.*, the

Department of Energy's Residential Energy Consumption Survey), however, elicit any information about consumer response to energy-efficiency incentives or explicit tradeoffs between appliance prices and energy savings when purchasing appliances. To study these issues, which are extremely important in energy economics and policy, I developed my own survey questionnaire, which I administered to a sample of Maryland households.

In Chapter 5, I use data from this original survey of households to examine how consumers value future savings from energy bills *vis-à-vis* money. I ask whether their rate of time preference in the energy savings context differs from that exhibited in the 'money now versus money later' context. Briefly, I find that the discount rate for energy savings is significantly lower than the discount rate for money. This result stands in contrast to the literature on the energy efficiency paradox, and suggests that low diffusion of energy efficiency appliances may be attributable to market failures rather than consumer preferences or bias.

By combining novel, comprehensive, and contemporary data, and extensive empirical testing and checks for robustness, my work is a contribution to understanding residential energy consumption and investment behavior, and to designing and developing policies that seek to influence this behavior to advance energy efficiency and other goals.

Chapter 2: Review of the Literature

Many factors contribute to residential demand for energy. Structural characteristics of the home, appliances, and external climate factors interact with household preferences and habits to determine the total demand for energy. In the economics literature, however, the demand driver that has received the most devoted attention is the price of energy.

As an economic good, energy is priced at equilibrium between the supply curve of electricity generators or fuel suppliers, and the demand curve for home energy users. The simplicity of this relationship is distorted by the nature of the predominant residential energy fuel – electricity – and the institutions of the energy supply sector. Electricity is difficult to store, so electricity supply must vary to meet a fluctuating demand. The combination of work and school schedules and changes in weather leads to a highly variable demand for electricity from an individual home over the course of a single day. When aggregated up to the level of a city, the difference between 'peak' and 'off-peak' demand can be as much as 300% or more.

This fluctuation has several consequences. For one, it complicates pricing. In a residential setting, it is impractical that the price of electricity be allowed to vary wildly with surges in demand, so many electric utilities bi-modally segment demand into peak and off-peak regimes for the purposes of customer pricing. As an operational consequence, spare supply capacity must be available to balance the system load. Some of this spare capacity remains unutilized, acting as costly insurance to consumers. In addition, the electric power utility companies, and, to a lesser extent, the fuel delivery (*e.g.,* natural gas) utility companies are heavily regulated. The price for energy and the structure of the tariff (energy purchase contract between the utility and residential customer) is complex and tightly delimited.

For these reasons, although energy is a commonly traded commodity, institutional barriers, customer ignorance, and perverse incentives lead to a host of economic inefficiencies and market failures. This makes a study on price both an interesting research endeavor and a worthwhile policy contribution.

A. The Role of Price

There is a debate in the literature about the most relevant price for energy consumers. Standard economic theory posits that what matters in the household's energy demand is marginal price. If price is constant with respect to quantity and there is no fixed fee, the marginal price is constant and equal to the average price. In practice, this is seldom the case. For starters, many utilities charge a fixed fee in each billing period on top of the metered amount, which makes the marginal and average price per unit of energy different. Moreover, most utilities apply block pricing schemes, which result in marginal prices that depend on the quantity consumed, but do not vary smoothly with it. The budget constraint will be piecewise linear, and for most households the marginal and the average price will be different. Even more important, marginal block price and consumption are simultaneously determined (Burtless and Hausman, 1978).

In the presence of block pricing, which should be entered in the econometric model of consumption—marginal or average price? Howe and Linaweaver (1967) argue that the relevant variable is marginal block price. Taylor (1975) and Nordin (1976) include marginal price and a "difference" variable meant to account for the lump sum transfers implied by block rates, and propose ways to test the marginal price versus average price model.

Later studies used instrumental variable estimation techniques to address the simultaneity of marginal price, quantity consumed, and "difference". Wilder and Willenberg (1975) instrument for observed marginal block price and the "difference" variable using exogenous variables such as housing and household characteristics, and the block prices themselves. McFadden *et al.* (1977) present an alternative IV approach, whereby observed usage is regressed on dwelling and household characteristics and the typical bills that would be incurred at specified levels of consumption. The predicted quantities and the rate schedule are used to form the predicted price variable, which serves as an instrumental variable for marginal prices in the second stage of estimation.

Terza (1986) points out that this approach may introduce spurious correlation between observed marginal price and the econometric error term, making the correlation problem appear to be more severe that it truly is. Moreover, McFadden *et al.* did not have the actual rate schedules. Nieswiadomy and Molina (1989) implement an approach similar to McFadden *et al*. (1977), but in the first stage they regress actual usage on the actual marginal prices that a household would face at different levels of demand (and other exogenous variables).

Hewitt and Hanemann (1995) use maximum likelihood estimation in the presence of block pricing. Reiss and White (2005) focus on the California households in the Residential Energy Consumption Survey (RECS), match each household with the block pricing structure applied by the utility that serves the area, and estimate a model of choice of block and consumption levels by GMM. Reiss and White (2005) posit that what matters is marginal price, yet there is evidence that marginal price is not salient to consumers. In two working papers, Borenstein (2008, 2009) finds that customers do not respond to marginal price. In Borenstein (2009), household level data from California were used to model customer response to marginal price, expected marginal price, and average price. To optimally consume under increasing block pricing, the consumer must know the timing of exogenous demand shocks (*e.g.,* extremely hot days) at the beginning of the billing period. These informational requirements motivate Borenstein's formulation of expected marginal price.

Shin (1985) argues that households respond to average price, which is easily calculated from electricity bill, rather than actual block marginal price, because it costly to determine the latter. Borenstein (2009) echoes that result: he finds that many of the consumers respond to an average price, rather than a marginal or expected marginal price, suggesting that informational or educational campaigns could improve understanding of non-linear pricing schedules. An additional concern is whether usage decisions depend on the price in the current (billing) period, on that of earlier periods, or a moving average of the prices of recent periods (Poyer and Williams, 1993).

Non-linear tariffs usually exist as a mechanism to discourage overconsumption of a good when technology or regulatory authority is lacking to impose more direct scarcity rents. Yet there is often a cognitive cost to the consumer associated with observing and responding to non-linear tariffs that limits their effectiveness. There may be other reasons for consumers to prefer flat tariffs. Herweg and Mierendorff (2011) develop a model which indicates that loss-aversion in a setting with uncertainty of demand may result in 'tariff bias,' or preference for a flat rate. They show that consumers will select a flat-rate tariff because of the implicit insurance provided (in the event that they exceed their demand estimate), even if they could minimize costs by choosing a metered tariff. In such a setting, it may be optimal for firms to offer a flat rate schedule, even though the existence of such a tariff is economically inefficient in light of non-zero marginal provision costs and low transaction/monitoring costs. This effect has been documented before for tariffs in telecommunications (*e.g.,* Lambrecht and Skiera 2006), but the logic applies to energy usage. A high cognitive cost of energy monitoring may actually lead consumers towards a more *inefficient* tariff.

Ito (2010) summarizes alternative models of consumer behavior in the presence of block pricing, showing that people will invest effort in finding out the price of energy only to the point in which the gains from re-optimizing consumption decisions exceed the cost of the effort spent monitoring and investigating prices. He reasons that the monthly billing structure of most utility bills, combined with the presence of non-linear pricing schemes, means that consumers must have knowledge of their cumulative (since the beginning of the billing period) consumption as well as their actual price schedule in order to determine (i) which section of the price schedule they face, and (ii) the magnitude of the prices. Only then might they estimate their true marginal cost of consumption. Without specialized devices or costly effort, it is unlikely that consumers are capable of calculating marginal price. Ito calculates a maximum potential savings of $2 monthly from optimizing consumption to marginal, instead of average price: Such small savings wouldn't make the cost of monitoring worthwhile.

Relatedly, there is an emerging literature about the cognitive cost of monitoring energy usage (and price). In non-energy settings, Chetty *et al.* (2007) and Finklestein

(2009) find that consumers do not always account for tax in their consumption, and that demand reduces significantly when they do. Given the complexity of most energy bills, and the inherent fluctuations in usage, it might be expected that a similar effect exists in energy consumption. Recently, Shultz *et al.* (2007) find that the simple reporting of average monthly energy consumption relative to the neighborhood (i.e. 'more' or 'less') can affect energy consumption.

Bushnell and Mansur (2005) study residential energy consumption behavior during the California energy crisis of 1999 and 2000, a period of extreme price volatility in the San Diego market, and find strong evidence that consumers respond to lagged, rather than contemporaneous, electricity price. Their study uses aggregate market-level data in which all customers experienced dramatic exogenous rate changes. Using a difference-in-difference estimation technique, they find more explanatory power in a model using a five-week price lag than with one using a contemporaneous price specification. This suggests that, for the majority of consumers, the cognitive cost of real-time price monitoring was sufficiently high, or the returns sufficiently low, that they simply did not monitor.

B. Price Elasticity of Demand

Knowing the responsiveness of energy demand to the price allows analysts to predict the effects of price changes or policies that result in price changes—for example, general energy taxes, taxes on carbon emissions, or mandates on the share of renewable energy. Earlier research has produced a wide range of estimates of the price elasticity of demand in the residential sector, possibly because of the diverse types of data used (time-series, cross-sections, and panel), level of geographical and jurisdictional aggregation (local, state, or national), extent of the observed variation in price, and time periods covered.

Selected studies that estimate price elasticity are summarized in table 2.1. These include studies based on annual time-series aggregates for the entire US, such as Dergiades and Tsoulfidis (2008), who estimate the short- (long-) run own-price elasticity of residential electricity consumption to be -0.386 (-1.06), and Kamerschen and Porter (2004), where the elasticities range from -0.94 to -0.85. Studies based on recent state-level panel data, such as Bernstein and Griffin (2005), Paul *et al.* (2008), and Alberini and Filippini (2010), have often found that the demand is relatively insensitive to price, at least in the short term, and that the estimates of the long-run elasticity are very sensitive to the specific estimation procedure.[3] Garcia-Cerrutti (2000) uses county-level data from 44 California counties for 1983-1997, estimates the own-price elasticity of electricity demand to be -0.17 in the short run and -0.19 in the long run, and uncovers significant variation between counties.

[3] For example, Alberini and Filippini (2010) use annual state-level data in the U.S. from 1995 to 2007, and attempt to get consistent estimates of the long-run elasticity by using a bias correct "within" estimator (Kiviet, 1995) and the Blundell-Bond (1998) approach. The short-run own price elasticities of electricity range from -0.15 to -0.08, and their long-run counterparts range from -0.78 to -0.44.

Table 2.1 Selected empirical studies and price elasticity estimates

Study	Type of Data Coverage	Estimate, Fuel Demand
Dergiades and Tsoulfidis (2008)	Nationwide total, time series, 1965-2006	-0.386 *short-run* (-1.06 *long-run*) electricity
Kamerschen and Porter (2004)	Nationwide total, time series, 1973-1998	Long-run: -0.94 to -0.85 electricity
Alberini and Filippini (2010)	State-level, panel data, 1995-2007	-0.15 to -0.08 (-0.78 to -0.44) elect.
Bernstein and Griffin (2005)	State-level, panel data, 1997-2004	-0.243 (-0.32) electricity
Paul *et al*. (2008)	State-level, panel data, 1990-2006	-0.13 (-0.36) electricity
Maddala *et al*. (1997)	State-level, panel data, 1970-1990	-0.19 to -0.21 (-0.56 to -1.03) elect; -0.09 to -0.18 (0.24 to -1.36) gas
Garcia-Cerrutti (2000)	California county-level, panel data, 1983-1997	Long-run: -0.17 electricity; -0.11 gas
Quigley and Rubinfeld (1989)	AHS household-level, cross section, 1980	-0.1 energy
Fell, Li, and Paul (2010)	CEX and RECS household-level, 2004-2006	-0.82 to -1.02 electricity
Metcalf and Hassett (1999)	RECS household-level, panel data, 1984, 1987 and 1990	-0.78 to -1.11 electricity; -0.48 to -0.71 gas
Reiss and White (2005)	California RECS, household-level, multi-year cross sections, 1993 and 1997	-0.85 to -1.02 electricity
	Studies Outside the U.S.	
Meier and Rehdanz (2010)	UK, household-level, panel data, 1991-2005	-0.4 to -0.49 oil -0.34 to -0.56 gas
Rehdanz (2007)	Germany household-level panel, 1998 and 2003	-2.03 to -1.68 oil; -0.63 to -0.44 gas
Leth-Petersen and Togeby (2001)	Denmark panel data, 1984-1995	-0.08 oil; -0.02 district heating
Bernard *et al*. (2010)	Quebec household-level, multi-year cross-sections, 1989-2002	-0.51 (-1.32) electricity
Nesbakken (1999)	Norway household level, multi-year cross-sections, 1990-1992, 1994-1995	-0.33 (-0.66) electricity

Most household-level data studies are limited in either time coverage or geographic scale. Quigley and Rubinfeld (1989) use a cross-section from the 1980 American Housing Survey and find evidence of low elasticity of energy demand (-0.1 in the short run). Metcalf and Hassett (1999) use the 1984, 1987 and 1990 waves of the

Department of Energy's Residential Energy Consumption Survey (RECS) to examine homeowners' insulation investments, finding price elasticities of electricity ranging from -0.73 to -1.16.

Bernard *et al.* (2010) have multi-year cross-sections about electricity and gas consumption and prices in Quebec from 1989-2002, estimate the short-run and long-run elasticity to be -0.51 and -1.32, respectively, and conclude that electricity and natural gas are substitutes. Studies outside of North America tend to produce price elasticity ranges similar to those for North America. Nesbakken (1999) focuses on the choice of heating and residential energy consumption in Norway, reporting that short- and long-term price elasticities (in the range of -0.33 to -0.66) are remarkably stable across the 1990-1995 period, with the only exception of 1993. In contrast to other papers, responsiveness to price is more pronounced at higher levels of income. Rehdanz (2007) examines expenditures for residential space heating in Germany, and Meier and Rehdanz (2010) use a 15-year panel of residential heating expenditures in Great Britain. Using a log-linear specification with year and regional effects, they obtain gas price elasticities between -0.4 and -0.49, which fall in the range of -0.2 to -0.57 from the comparable literature. They obtain different elasticities for homeowners and renters. Leth-Petersen and Togeby (2001) find much lower price elasticities in heating fuels (on the order of -0.1) based on a panel dataset from Denmark and a conditional logit fixed-effect model. Reiss and White (2005) focus on the California households in RECS, match each household with the block pricing structure applied by the utility that serves each area, and estimate a model of choice of block and consumption levels using Generalized Method of Moments (GMM).

One concern when examining the responsiveness of electricity use with respect to price is that the data contain sufficient price variation. Such variation is usually attained by selecting a broad geographic area and/or a sufficient long period of time. In some cases, identification is made possible by abrupt changes in prices due to supply conditions. Reiss and White (2008) and Bushnell and Mansur (2005) exploit the energy crisis and rapidly growing electricity rates in California in 2000 and 2001, and document relatively large reductions in energy usage induced by such price increases. Haas and Schipper (1998) argue that energy-saving investments spurred by raising prices are likely to remain in place even in periods of declining energy prices, but in practice there is reason to question the external validity of findings based on unusual market circumstances at specific locations. In Chapter 3, I estimate the price elasticity of demand for electricity and natural gas using nationwide household-level panel data. This provides sufficient geographic and time variation to identify the demand parameters while ensuring a result generalizable to the entire U.S.

C. Energy Efficiency Paradox

Despite repeated assertions of the enormous potential for efficiency-enabled energy savings in the residential sector (National Academy of sciences, 2010, EPRI 2009, Granade *et al.,* 2009) the rate of adoption and diffusion of apparently cost-effective technology is lower than can be explained by price alone. This so-called "energy efficiency paradox" (Jaffe and Stavins, 1995), has been interpreted to imply high discount rates for energy efficiency, and has been explained as the result of high switching costs (Mulder *et al.,* 2003), irreversibility and lost option value (Metcalf and Rosenthal, 1995, Hassett and Metcalf, 1993), or simply liquidity constraints (Hausman, 1979). Golove and Eto (1996) provide a useful synopsis of this literature.

Recent research has highlighted some alternative reasons for lack of investment in energy efficiency. Nair *et al.* (2010) use a 2008 survey of Swedish homeowners and find that a host of personal and 'contextual' factors may affect adoption of energy efficient technology, such as awareness about energy efficiency measures or perception of cost. Ek and Söderholm (2010) use a separate survey of Swedish households to assess the stated willingness of consumers to take general conservation steps, which may include adopting new technology. They find an increasing willingness with age, which they attribute to a greater stock of conservation knowledge from past awareness campaigns.

Metcalf and Hassett (1999) suggest that people do not invest more readily in energy efficient technology because they do not believe the energy savings predicted by engineering estimates. They estimate a model that shows that people make investments in energy efficiency in homes at an internal rate of return comparable to market interest rates. This result suggests a greater role for government education and awareness campaigns may be effective.

Some people may not invest or take conservation steps because they simply do not like to change. Hartman, Doane, and Woo (1991) use a survey of electric customers in California to investigate the value of electricity reliability – not consumption itself, but something that would affect the utility of consumption. They find strong evidence of a status quo bias using a contingent valuation survey of electric consumers. In some instances, they find the effect to be so strong that consumers must actually be compensated to switch to more reliable service (with fewer disruptions).

Others have suggested that ignorance explains the energy efficiency paradox, and that educational awareness campaigns can alleviate it. The empirical evidence for this "uninformed consumer hypothesis" is mixed. Brill *et al.* (1999) find that factors such as home age and size, weather, air conditioning, and fuel price are important in explaining insulation investment. Education level (a proxy for awareness about energy efficiency), however, has either no impact or a negative impact. Similarly, Jakob (2007b) finds no evidence of systemic ignorance, but instead identifies building extension or repair considerations, rather than efficiency, as the dominant consideration when making renovation decisions. In contrast, using a survey on 517 Swiss renters and homeowners, Banfi *et al.* (2008) find evidence that the WTP for building efficiency enhancements generally exceed the cost of implementing these measures, and suggest that lack of information on the advantages and potential cost savings from energy efficiency measures explains the underinvestment.

Hassett and Metcalf (1993) show that it is possible to get substantially different discount rates for energy investments due to price uncertainty.[4] In Chapter 6, I estimate discount rates for a hypothetical energy efficiency investment and for a non-energy income, using the same sample.

[4] Most previous work assumes that an increase in the energy efficiency of household equipment will reduce energy demand. Changes in usage behavior that accompany energy investments, however, may have perverse effects on energy saving. The idea that a compensating consumption increase will diminish energy savings is called the "rebound effect." Greening *et al.* (2000) find rebound effects ranging up to 50% of energy saved, suggesting that the anticipated savings may differ significantly from realized savings. Hsueh and Gerner (1993) document this effect for home heating demand in the United States, reporting that that savings estimates following attic or wall insulation may differ by as much as an order of magnitude compared with engineering estimates that assume no consumption change.

D. Conservation and Energy Efficiency Investment

In the U.S., homes count for between 20 and 40% of total energy consumption, and heating represents 41% of this consumption (U.S. EIA, 2010). In general, a change in household energy demand can be achieved through conservation (for example, moderating the temperature in the home) or investment in energy efficiency (repairing or purchasing a more efficient heater). Energy efficiency can be defined as the ratio of useful energy services (*e.g.,* heating or lighting) to the required energy input (Sorrell and Dimitropoulos, 2008). Studies suggest that conservation changes tend to be temporary and small (Barr *et al.*, 2005). In contrast, household investments can significantly and permanently reduce the energy demand in the home (National Academy of Sciences, 2010). In chapters 5 and 6, I study household investments in energy efficiency.

Economic theory dictates that the determinants of household energy consumption (such as dwelling and household characteristics, weather, income and prices) also explain energy investments (Fernandez, 2001). Using 1761 survey responses U.S. households, and a nested logit model with simulations, Cameron (1985) finds that consumer efficiency investment behavior is sensitive to price, especially heating fuel price. She finds that home insulation retrofits are elastic with respect to income, heating fuel price, and government subsidies. More recent evidence from Swiss households likewise suggests that the payback period for the investment, the upfront cost, and the availability of subsidies significantly influence residential energy efficiency investments (Jakob, 2007a).

Alberini, Banfi and Ramseier (2011) find evidence that uncertainty about future energy prices decreases the likelihood of undertaking hypothetical energy efficiency renovations in homes. Metcalf and Rosenthal (1995) find that uncertainty about the cost of equipment may discourage investment: extended policy discussions regarding efficiency incentives signal a lack of political commitment and raise the potential for policy reversal.

Fernandez (2000) and Fernandez (2001) use the Residential Energy Consumption Survey (RECS) and find that housing square footage, income, urban environment, and poor credit all significantly influence household investment in heating and cooling appliances. Those with larger homes are less likely to make investments in either electric space heaters or central air conditioning, and credit constrained households (those with a lower credit score) are more likely to purchase an electric space heater, which has a lower upfront cost but is less efficient, and therefore more expensive to operate in the long-run.

Numerous standards and incentives are currently targeted at energy efficiency in the residential sector.[5] Such programs have met with mixed success. Geller *et al.* (2006) document the success of informational campaigns combined with labeling (*e.g.,* "EnergyStar") and financial incentives in the U.S., and of appliance standards used in Japan. Hassett and Metcalf (1995) use panel data from US taxpayers and find that a 24% increase in investment probability results from a 10% increase in tax incentives amount, but caution that subsidies may comprise a windfall for those households that would have invested anyway. In a separate paper, Hassett and Metcalf (1993) suggest that efficiency standards and taxes have greater effectiveness in altering behavior than subsidies alone. Turning to the effect of building efficiency standards, Jacobsen and Kotchen (2011) show

[5] For a comprehensive listing of state and federal efficiency incentives, see the DSIRE database, www.dsireusa.org

that tighter building standards decreased energy consumption by 4% to 6% in new Florida homes.

The matter of split incentives between renters and owners has received considerable attention. It is typically impractical for renters to take efficient appliances with them when they move, so there is reluctance among renters to invest in energy efficiency. Levinson and Niemann (2004) show that it can be privately optimal for a landlord to pay energy costs in inefficient rental units if the energy-inclusive rental contract exceeds the expected cost of energy. Even among those who pay their own energy bills, renters tend to be less energy-efficient. Using the RECS database, Davis (2010) finds that renters are 5 – 10% less likely to have efficient appliances, even while controlling for house and household characteristics. All else equal, lower efficiency results in higher consumption: Rehdanz (2007) finds that owner-occupied households spend 5 – 15% less on heating fuel than rental homes.

In Chapter 5, I focus on planned tenure in the home and its role in energy efficiency investment. Planned tenure time is often unobserved, so occupant age is sometimes used as proxy for current and planned tenure. However, occupant age may also be correlated with occupancy habits or demand for thermal comfort.[6] Unsurprisingly, the evidence of the effect of age on investment is mixed. Brill *et al.* (1999) document an increased likelihood to make insulation investments if householders are elderly. Poortinga *et al.* (2003) report that elderly Dutch were much less likely to report a willingness to make

[6] Age of the household has also been found to influence energy consumption and expenditures given the existing appliance stock. Meier and Rehdanz (2009) report that elderly British homes spend less on heating, but speculate that this may be due to smaller home size or income constraints rather than decreased demand. Liao and Chang (2002) document increased demand for space heating among the elderly, either due to different preferences for thermal comfort or for increased time within the home, which would suggest an increased likelihood to adopt efficient thermal appliances.

hypothetical efficiency investments or conservation measures than others. Fernandez (2001) reports a negative correlation between age and household investment in electric space heaters and central air conditioners.

For a home or building owner, a critical determinant in the decision to invest is whether energy efficiency investments are capitalized into the value of the home or building. The evidence from the literature is mixed. Eichholtz *et al.* (2010) find that energy savings measures are capitalized into commercial buildings, but do not expand their analysis to include residential space. Laquatra *et al.* (2002) review several studies that show capitalization of varying magnitudes. Yet, absent a certified signal about the efficiency of the home, information asymmetry impedes the extent to which home efficiency is capitalized: a seller possesses information about home attributes and has an incentive to overstate energy efficiency; a potential buyer therefore views stated home efficiency with skepticism. As a result, energy efficiency may only be partly capitalized into the home price. Recent government programs seek to mitigate this information problem with energy performance labeling and reporting.[7] Brounen and Kok (2011) show that such schemes can boost the capitalization of energy efficiency. Their study of Dutch homes finds a statistically significant sales premium for those homes with higher energy performance labels, even while controlling for other home characteristics associated with quality.

Informing questions of durable good investment is an underlying decision about how long the household expects to occupy their home (Hausman, 1979, Jaffe and Stavins, 1994). Existing policies to entice energy efficiency investments are most likely to appeal

[7] The City of Austin, TX, implemented the Energy Conservation Audit and Disclosure (ECAD) Act in June 2009, which requires all homes to receive and disclose the results of an energy audit prior to home sale.

to those who plan to be in the home for the foreseeable future or those who believe investments will be capitalized into home values. Absent regulation or disclosure requirements, homeowners may not expect to reap the full return on efficiency investments, and therefore factor in their planned tenure when making investment decisions: specifically, some homeowners may choose to underinvest in efficiency rather than risk losing money in the undercapitalization of efficiency at the point of home transaction. To capture this effect, I explicitly incorporate planned tenure in my model of investment. To my knowledge, no previous study has focused on the effect of planned tenure on investment in home energy efficiency.

Chapter 3: Residential Energy Demand Estimation Using American Housing Survey [8]

What are the determinants of residential energy consumption in the US, and how is consumption influenced by energy prices, weather, structural characteristics, household attributes, and energy efficiency investments? This is the fundamental question asked by academic and government researchers for the past 50 years. Historically, the paucity of the data has severely constrained the external validity of any conclusions. With few exceptions, the studies published heretofore are geographically specific, time-specific, and rely on cross-sectional data. While such studies undoubtedly inform our understanding of residential energy consumption, they have a short shelf-life. To address these shortcomings, I use a panel dataset spanning 10 years with unprecedented geographic coverage (the AHS data, see chapter 3.A).

For the purpose of forecasting demand and planning for generation, transmission and distribution capacity, and for energy policy purposes, it is important to measure the responsiveness of residential energy demand to the prices of electricity and gas, the two major sources of residential energy in the US. Earlier research has examined household demand for energy and its responsiveness to price, but these analyses (i) used old data (Quigley and Rubinfeld, 1989, Metcalf and Hassett, 1999), (ii) are restricted to limited geographical areas (*e.g.*, Garcia-Cerrutti, 2000; Reiss and Weiss, 2005), so that it is difficult to extrapolate their results to other areas with different climates, stock of housing and electricity suppliers, or (iii) were based on cross-sections or extremely short panels of data (with a maximum of two observations per household) (*e.g.,* Metcalf and Hassett,

[8] Another version of this work appears in Alberini, Gans, and Velez-Lopez (2011)

1999), and did not fully address issues of unobserved heterogeneity and endogeneity. In some cases, responsiveness to price was inferred from supply shocks so severe and geographically circumscribed (*e.g.,* Bushnell and Mansur, 2005; Reiss and White, 2008) as to render them inapplicable for broader areas and more gradual price changes.

For these reasons, in this chapter I wish to ask three research questions. First, what *are* the (nationwide) price elasticities of residential electricity and gas demand? Second, how does such responsiveness depend on equipment and energy choices that are not easily reversed (*e.g.,* using gas or electricity for heating or cooling)? Third, how does household income influence demand and the price elasticities?

A. American Housing Survey Data

To answer these questions, I use a large and comprehensive dataset based upon the American Housing Survey. The American Housing Survey (AHS) is a longitudinal study conducted by the Department of Housing and Urban Development that follows dwellings (not households) nationwide. The AHS contains extensive information about the structural characteristics of the dwelling, renovations and retrofits, home ownership and its financial aspects (mortgages, maintenance costs, etc.), appliances and heating/cooling systems, socio-demographic and economic circumstances of the occupants, and their assessment of the quality of the home and the neighborhood.

The nationwide "national" surveys are done every other year, and are supplemented by additional surveys in selected metro areas (47 different metropolitan areas) in even years. For this work, I focus on national survey AHS data for 1997, 1999, 2001, 2003, 2005, and 2007, which means that homes appear for up to T=6 periods.[9] This sample is augmented with observations from the AHS "metro"[10] surveys, which are conducted in even years in specific areas. The 2002, 2004, and 2007 metro surveys are used. Homes in the metro surveys are surveyed only once, so our sample is a mix of panel data plus multi-year cross-sections.

Earlier studies of energy demand and household investment use cross-sectional data in limited geographic areas (*e.g.,* Dubin and McFadden, 1984, Revelt and Train, 1998), thus limiting the degree to which each household's response to prices and other factors can be observed. Furthermore, with only 10% of households making appliances investments in any given year, a large sample is required to make any inference.[11]

Because of privacy concerns, the AHS discloses the location of the dwelling (i.e. the metro area) only if the area has a population of 100,000 or more. Attention is restricted to dwellings in the 54 cities corresponding to the 50 largest metropolitan areas in the U.S. as of 2008, unless the AHS SMSA identification makes it impossible to unambiguously identify the state in which the dwelling is located. Table 3.1 lists the metro areas included in the data. These locations should ensure considerable variation in climate, age of the stock of housing and construction materials (which may affect efficiency of space heating and cooling), and utility prices.

[9] The 2009 survey-year of the data was not available for this chapter, but is incorporated into Chapter 4, where the maximum number of periods is T=7.

[10] The Nationwide AHS sample returns to the same homes for every survey, and adds some newly constructed homes to keep the sample representative of the housing stock in the U.S.. The metro surveys are conducted on a representative sample of homes in different cities every two years, but in the metro surveys different homes are selected in different waves for the same city, thus do not contribute to the panel.

[11] In my sample, energy investments occur for 3 – 12% of the population, depending on the technology and the year in question.

Table 3.1 Included metropolitan areas selected for the study

Metro Area	
Atlanta-Sandy Springs-Marietta, GA	Minneapolis-St. Paul-Bloomington, MN-WI[3]
Austin-Round Rock, TX	Nashville-Davidson--Murfreesboro--Franklin, TN
Baltimore-Towson, MD	New Orleans-Metairie-Kenner, LA
Birmingham-Hoover, AL	New York-Northern New Jersey-Long Island, NY-NJ-PA[4]
Boston-Cambridge-Quincy, MA-NH	Oklahoma City, OK
Buffalo-Niagara Falls, NY	Orlando-Kissimmee, FL
Charlotte-Gastonia-Concord, NC-SC[1]	Phoenix-Mesa-Scottsdale, AZ
Chicago-Naperville-Joliet, IL-IN-WI[2]	Pittsburgh, PA
Cleveland-Elyria-Mentor, OH	Portland-Vancouver-Beaverton, OR-WA
Columbus, OH	Providence-New Bedford-Fall River, RI-MA[5]
Dallas-Fort Worth-Arlington, TX	Raleigh-Cary, NC
Denver-Aurora, CO	Richmond, VA
Detroit-Warren-Livonia, MI	Riverside-San Bernardino-Ontario, CA
Hartford-West Hartford-East Hartford, CT	Sacramento-Arden-Arcade-Roseville, CA
Houston-Sugar Land-Baytown, TX	Salt Lake City, UT
Indianapolis-Carmel, IN	San Antonio, TX
Jacksonville, FL	San Diego-Carlsbad-San Marcos, CA
Las Vegas-Paradise, NV	San Francisco-Oakland-Fremont, CA
Los Angeles-Long Beach-Santa Ana, CA	San Jose-Sunnyvale-Santa Clara, CA
Miami-Fort Lauderdale-Pompano Beach, FL	Seattle-Tacoma-Bellevue, WA
Milwaukee-Waukesha-West Allis, WI	Tampa-St. Petersburg-Clearwater, FL

Notes: (1) 1=Charlotte; 2=Chicago; 3=Minneapolis-St. Paul; 4=New York, Northern New Jersey; 5=Providence; (2) Excluded cities include: Cincinnati-Middletown, OH-KY-IN; Kansas City, MO-KS; Louisville/Jefferson County, KY-IN; Memphis, TN-MS-AR; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD; St. Louis, MO-IL; Virginia Beach-Norfolk-Newport News, VA-NC; Washington-Arlington-Alexandria, DC-VA-MD-WV

My sample is composed of single-family homes and duplexes in the 50 largest major metropolitan areas in the U.S. with clearly distinguishable jurisdictional boundaries,[12] for a total of 54 cities, 58 statistical metropolitan areas (SMSA), and 27 states.[13] Attention is restricted to single-family homes that are owner-occupied or occupied by a tenant, excluding residences where the heating equipment is shared with other units. The economic agent for my study is the household: I exclude multi-family

[12] Because of the difficulty in identifying utility and state policy data, I excluded metro areas that straddle state lines (*e.g.,* Washington, D.C., Kansas City, or Philadelphia).

[13] Large metropolitan areas can encompass more than one SMSA or city. The New York City metro area, for example, covers both Manhattan, part of Long island, and areas of Northern New Jersey. As a result, the sum total of cities and SMSAs exceeds 50.

dwellings or those with shared energy-using equipment because consumption and incentives to invest will be different in these cases.

Observations were deleted where (i) the home was occupied as a residence for only part of the year, (ii) the utility bills had been imputed using "hot deck" procedures, (iii) the square footage (which should be an important determinant of energy usage) had been imputed using "hot deck" procedures, and/or (iv) large and implausible changes in square footage were observed from one time period to the next.[14] Finally, I exclude from the sample dwellings less than 400 or more than 10,000 square feet (N = 1770), with more than four floors (N = 2001). The resulting sample size is 98,772 observations on 69,169 dwelling units. Table 3.2 displays the distribution of this final sample by city.[15]

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[14] Specifically, observations were excluded if the amount of energy or gas used that changed by more than 500% from one period to the next, while at the same time no renovation in the home and no square foot change was reported. Homes that experienced a change in square footage of more than 1000% from one period to the next, or with a change in square footage of more than 100% without a reported renovation to the home, were also discarded.

[15] For ease of exposition, this table shows only data used in Chapter 4 (e.g. excluding the year 2009 data). The distribution of sample by city did not change significantly.

Table 3.2 Distribution of the sample by city (N=98,772)

City	Nobs	Percent	City	Nobs	Percent
Anaheim	3,618	3.66	Minneapolis	2,112	2.14
Atlanta	3,335	3.38	Monmouth	339	0.34
Austin	193	0.20	Nashville	275	0.28
Baltimore	1,522	1.54	New Orleans	2,387	2.42
Bergen-Passaic	428	0.43	New York	2,585	2.62
Birmingham	343	0.35	Newark	612	0.62
Boston	1,754	1.78	Northern New Jersey	659	0.67
Boulder	91	0.09	Oakland	793	0.80
Buffalo	1,739	1.76	Oklahoma City	2,752	2.79
Charlotte	2,681	2.71	Orlando	434	0.44
Chicago	4,306	4.36	Phoenix	3,665	3.71
Cleveland	3,137	3.18	Pittsburgh	3,313	3.35
Columbus	3,315	3.36	Providence	271	0.27
Dallas	3,488	3.53	Raleigh-Durham	280	0.28
Denver	2,415	2.45	Riverside San Bernardino	3,883	3.93
Detroit	3,467	3.51	Sacramento	2,584	2.62
Ft. Worth	2,992	3.03	Salt Lake	532	0.54
Hartford	2,010	2.03	San Antonio	2,781	2.82
Houston	2,430	2.46	San Diego	2,978	3.02
Indianapolis	2,908	2.94	San Francisco	502	0.51
Jacksonville	357	0.36	San Jose	579	0.59
Jersey City	91	0.09	Santa Rosa	90	0.09
Las Vegas	453	0.46	Seattle	2,706	2.74
Los Angeles	4,870	4.93	Tacoma	224	0.23
Miami	4,115	4.17	Tampa	2,089	2.11
Middlesex County	300	0.30	Tucson	355	0.36
Milwaukee	2,295	2.32	West Palm Beach	339	0.34

Table 3.3 summarizes information about the longitudinal component of the sample, examining the case where the cross-sectional units are the dwellings, and that where the cross-sectional units are dwelling-families (households). There are a total of 69,169 homes and 74,697 households (because families may move into and out of any given home during the study period).

Table 3.3 Distribution by length of the longitudinal component (N=98,772)

Length of the panel	Dwellings		Households	
	N	Percent	N	Percent
1	58,088	58.81	63,916	64.71
2	7,094	7.18	9,616	9.74
3	5,315	5.38	6,126	6.20
4	8,232	8.33	6,236	6.31
5	10,905	11.04	6,740	6.82
6	9,138	9.25	6,138	6.21
Total Unique	69,169		74,697	

A.1 Energy Consumption and Utilities' Rates

The AHS reports the average monthly utilities bills from the previous year, but does not include electricity or gas rates, or the actual energy consumption (in kiloWatt–hours *kWh* for electricity and thousand cubic feet *Mcf* for gas). It is necessary to construct consumption by taking the bills and dividing them by unit price. Unfortunately, the names of the utilities and the rate structure are not identified in the AHS either, so average tariffs were imputed for each dwelling in a number of ways.

For each metropolitan area, the relevant gas and electric utilities were identified (listings appear on the state's public utility commission, and on a variety of on-line city services), and utility-level price information was obtained from the Energy Information Agency (EIA) 861 forms (for electricity) and EIA 176 forms (for gas), which the utilities are required to file every year with the agency. Next, if the area was supplied by a single utility, we computed the average price per kWh (MCF) as the utility's annual revenue from sales to residential customers divided by the kWhs (MCFs) sold to residential customers.[16]

If the area was supplied by more than one utility, the utility average price was calculated in the aforementioned fashion, then three alternative measures of price were constructed. The first is "residential price 1," a weighted average of each utility's average tariff per KWh, where the weights are proportional to the utility's customer base. The second, "residential price 2," is also a weighted average, with weights assigned to represent the utility's dominance of the market.[17] Finally, "residential price 3" is a simple average of the individual utilities' average tariffs.[18] A similar approach was used for gas utilities.

The electricity and gas prices are used in two ways. First, I use them to create the dependent variables in our regressions: Consumption of electricity and gas are obtained as the amount on the bill divided by (nominal) price. Second, (real) prices enter in the right-hand side of the demand equations.

Technically speaking, these average prices are not necessarily equal to the prices faced by the households. The majority of the utilities apply block pricing, but with such a geographically broad sample and such a long study period, it would be unfeasible to obtain the block pricing schemes used by each utility in each period. The only remaining econometric concern is that the price used in the regression is measured with error. This

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[16] The EIA computes state-level electricity prices and gas prices exactly in this fashion—by taking the revenues of all utilities and dividing by all kWhs (or gas) served to residential households.

[17] If a utility dominates the market completely, despite the nominal existence of other utilities, that utility received a weight of ones and the others weights equal to zero. If two utilities were perceived to share the market in the area in a relatively equitable fashion, we assigned weights of 0.5 to each.

[18] Clearly, if there is a single utility, residential price 1, 2 and 3 are all identical.

would make the household demand appear to be more elastic than it truly is. Steps were taken as explained in section [3.D], to account for this.

Descriptive statistics about prices and energy use are displayed table 3.4. Attention is restricted to the "price 1" variables because the others were very close to them.[19] Every home is served by electricity, and, as shown in table 3.4, on average households use about 930 KWh per month. This is in line with nationwide estimates collected by the Department of Energy using a dedicated survey (RECS). Just over three-quarters of the sample (76.6%) use natural gas as well, and almost 88% of such natural-gas connected households use gas heat. In a typical month, gas usage is 7.27 MCF.

Over the study period, the average price of electricity is about 11 cents per kWh (2007$). However, there is evidence of considerable variation across states. The state with the lowest prices is Indiana (about 6.8 cents per kWh on average over the study period) and that with the highest prices is New York, where a kWh averaged almost 18 cents over the study period (2007$). The price of natural gas exhibits similar variability across locales. The average price per MCF is $11.41 (2007$), with Georgia exhibiting the lowest prices ($6.10, 2007$, on average) and Florida the highest ($17.83, 2007$).

Since I exploit the longitudinal feature of the data, it is important to check the extent of the variation in prices across and within units. In what follows, the units are the dwellings. I computed the total variation of real electricity prices and of log real electricity prices, and in each case the variation within dwellings accounted for only 4% of the total variation.[20] Gas prices are more variable over time: the "within" dwelling

[19] The correlation coefficients between the "price 1" variables and the others were generally higher than 0.97.

[20] Our measure of variation is the sum of square deviations from the grand mean.

variation accounts for about 14% of total variation in real gas prices, and 15% of the total variation for log real gas prices.

Table 3.4 Prices and monthly consumption of electricity and natural gas

Variable label	Description	Obs	Mean	Std. Dev.	Min	Max
kwh1	monthly electricity usage (KWh)	97344	930.39	654.09	11.06	5697.54
gasuse1	monthly gas usage (MCF)	67154	7.27	5.50	0.23	71.86
residentialprice1_r	price of electricity per kWh (2007 dollars)	98487	0.11	0.03	0.05	0.22
gasprice1_r	price of natural gas per MCF (2007 dollars)	94315	11.42	3.10	3.90	22.89
Log kwh1		97344	6.61	0.70	2.40	8.65
Log gasuse1		67154	1.75	0.68	-1.49	4.27
Log residentialprice1_r		98487	-2.23	0.26	-2.92	-1.49
Log gasprice1_r		94315	2.40	0.26	1.36	33

A.2 Other Determinants of Energy Use

The weather is an important determinant of energy use. Weather data were gathered using the T3 Summaries of the Day from NOAA's National Climatic Data Center and merged with AHS. Each metro area was matched with the T3 monitors in that area, and I retrieved the mean temperatures for each day of the year prior to the date of the survey. I use these mean temperatures to calculate the heating and cooling degree-days (HDDs and CDDs) for each day, which are 65°F minus the average temperature (average temperature minus 65°F), then sum daily HDDs and CDDs over the year prior to the survey.[21] This construction is the same as that used by the US Department of

[21] In the AHS, reported expenditures on energy are annual averages, so it is appropriate to include weather averages for the year prior to the survey.

Energy. The average HDDs and CDDs are 3450 and 1658 degree-days, respectively, with good variation in climate across the entire sample (see Figure 1).

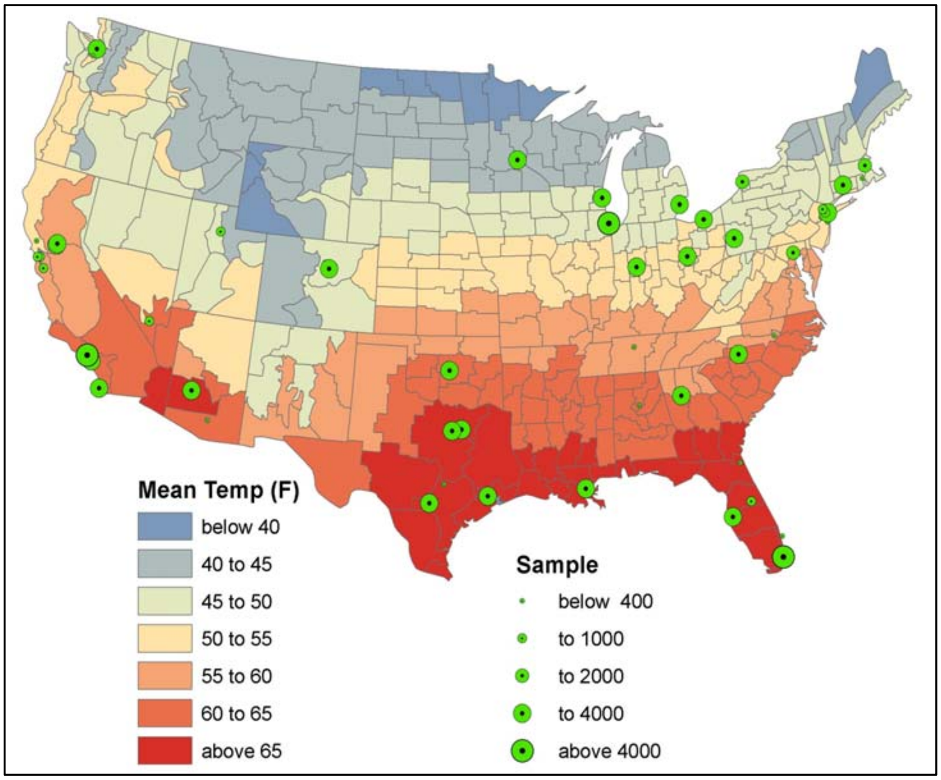

Figure 1: Map of Distribution of AHS Sample

Both energy demand and demand for energy efficiency renovations should depend on the structural characteristics of the dwelling. I have the age and size of the home, number of rooms, and number of floors, which come from the AHS. Descriptive statistics for these variables are displayed in table 3.5. The average size of the home is about 2000 square feet. This figure matches up nicely with the nationwide estimates for single-family homes and homes that are part of a two-unit building from the 1997, 2001, and 2005 RECS.[22]

Table 3.5 House characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Square footage	91254	2073.96	1615.04	99	18083
Basement (dummy)	98772	0.37	0.48	0	1
No. Floors	98772	1.83	0.96	1	21
No. Rooms	98772	6.42	1.86	1	21
Age of the home	98772	38.69	23.27	0	88

Descriptive statistics about heating and cooling equipment, as well as appliances that use energy, are reported in table 3.6. All of this information comes from the AHS. Briefly, in terms of heating, about 67% of the sample has a gas heating system, 26% relies on electricity for heating, and about 5% on heating oil as the main source of heat. Homes with electric heat are located primarily in states with mild or warm climates, such as Arizona (66% of all Arizona homes), Florida (93.80%), Louisiana (43%), Tennessee (59%) and Texas (43.76%), or cheap electricity (*e.g.,* Washington, 29%).

About 84% of the sample has some type of air conditioning, and about 67% has central air conditioning. Window units are used by 20% of the sample, sometimes alongside with central air conditioning. Only 2% of the observations have gas-powered heat pumps.

[22] Note that a value of zero for the age of the house is correct: it means that the home was built in the same year of the survey. (The AHS does add new dwellings to mirror the stock of housing and new constructions. Homes with age 0 account for less than 1% of the sample.)

Turning to appliances, virtually all homes have a fridge, almost 72% a dishwasher, 32% use gas-powered clothes dryers, and a little more than half of the sample has an electric stove.

Table 3.6 Heating and cooling equipment and appliances

Variable	Obs	Mean	Std. Dev.	Min	Max
Gas heat	98772	0.67	0.47	0	1
Electric heat	98772	0.26	0.44	0	1
Heating oil heat	98772	0.05	0.23	0	1
Window A/C units	98772	0.21	0.40	0	1
Number of rooms with A/C	20251	1.78	1.02	1	8
Central A/C	98772	0.67	0.47	0	1
Gas heat pump for A/C	98772	0.03	0.16	0	1
Any type of A/C present	98772	0.84	0.37	0	1
Refrigerator	98772	1.00	0.04	0	1
Dishwasher	98772	0.72	0.45	0	1
Gas powered clothes dryer	98772	0.32	0.47	0	1
Electric stove	98772	0.53	0.50	0	1

In my sample, the average household income is about $88,000 (2007$). There are a small number of households (93, or 0.09%) that report negative income. When these observations are removed, the distribution of household income is essentially unchanged: The new sample average is still $88,000 (2007$).[23] The average household size is 2.8, 31% of the sample has small children, 22% has at least one person aged 65 or older living in this house, and almost 84% owns the home. Summary statistics of household characteristics are shown in table 3.7.

[23] In my regressions, which use log income, I simply recode log income to zero when income is negative.

Table 3.7 Household characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Household income in thou. 2007$	98772	87.92	115.49	-42.33	11473.2
Number of household members	98772	2.81	1.52	1	17
Young child (12 or less) lives in this house (dummy)	98772	0.31	0.46	0	1
Elderly person (65+) lives in this house	98772	0.23	0.42	0	1
Owner (dummy)	98772	0.84	0.37	0	1

B. Estimation Strategy

To answer my research questions, I estimate a model of residential energy demand (see equation 3.1). I assume that consumers have as their energy source both electricity and natural gas, but exclude other fuels.[24] The model posits that the main determinants of energy usage are: price, weather fluctuations and housing characteristics, household income, and number and age of residents. I include all of these determinants in the right hand side of my demand equations.

I estimate both a static and dynamic model. The static model is the specification most prevalent in the literature for reasons described above: namely, panel data was not available. I include it here primarily as a benchmark to these studies. A static model, while operationally expedient and possible to estimate in spite of limited data, is guided by very strong assumptions. The most problematic is that of fixed stock. In essence, a static model assumes that households cannot and do not adjust the structural characteristics of the home or energy-using equipment in response to energy price changes. Nevertheless, in the short-term, this may be an entirely appropriate assumption. The static model estimated here is:

[24] In my sample, 5.8% of customers use other fuels. The analysis is performed with and without these customers. The results did not vary in any meaningful way.

$$\ln\ Q_{it}^{(j)} = \beta_0^{(j)} + \beta_1^{(j)} \ln P_{E,it} + \beta_2^{(j)} \ln P_{G,it} + \boldsymbol{x_{it}\gamma}^{(j)} + \boldsymbol{\tau_t} + \varepsilon_{it}^{(j)} \quad (3.1)$$

where j=E, G for electricity and gas, respectively, i denotes the dwelling, and t denotes the time period. Q is consumption, P denotes price, and the coefficients on the log prices are the short-term own- and cross-price elasticities. Here the price of the substitute energy source is included. For example, if j refers to electricity, then equation 4.1 would explain the consumption of electricity in terms of the explanatory characteristics of the home and use, the electric price P_E, and the natural gas (substitute) price P_G.

Vector **x** is comprised of dwelling and household characteristics thought to influence the consumption of energy, such as weather, size and age of the home, heating and cooling equipment dummies, and appliances. For example, a house heated only with electricity would have a higher electricity demand than an identical home with gas heat. Household characteristics included in **x** are the number and age of occupants, income, the presence of children or elderly persons,[25] and a homeownership dummy. Equation (3.1) includes year effects (the τs), and is easily amended to include dwelling or city-specific effects to account for unobserved heterogeneity.[26] The results from the static model are reported in columns A through G in table 3.8 (table 3.9 for natural gas).

It is of interest to assess how consumption changes if individuals are allowed to adjust their stock of appliances and make energy efficiency and conservation

[25] Earlier literature has examined the effect of age, race and ethnicity on energy demand. Poyer and Williams (1993) find that while the demand is inelastic for all groups, blacks appear to be more sensitive to short-run price variations than Hispanics and whites. Liao and Chang (2002) find that the elderly require more natural gas and fuel oil but less electricity, the demand for space heating increases as the elderly get older, and the demand for energy for heating water decreases with age.

[26] A special case of this situation is when the dwelling-specific effects are suppressed, but the error terms in the demand for electricity and gas equations are correlated within the same dwelling unit in the same period (but uncorrelated in different period and across dwellings). If so, the equations for log $Q^{(E)}$ and log $Q^{(G)}$ are part of a system of seemingly unrelated regression equation. Since the regressors are the same in the equations for log electricity and gas consumption, the most efficient estimation technique (GLS) is simplified to OLS applied separately to each equation.

investments. A partial-adjustment model (Houthakker, 1980) lets individuals adjust their stock of appliances and energy-efficiency investments. This model assumes that the change in log actual demand between any two periods ($t-1$ and t) is only some fraction (λ) of the difference between log actual demand in period $t-1$ and the log of the long-run equilibrium demand in period t, Q_t^*. Formally,

$$\ln Q_t - \ln Q_{t-1} = \lambda(\ln Q_t^* - \ln Q_{t-1}) \tag{3.2}$$

where $0<\lambda<1$. The dwelling subscript, i, and the electricity or gas equation superscript, j, are omitted to avoid clutter. This implies that given an optimum, but unobservable, level of energy consumption, demand only gradually converges towards that optimum level between any two time periods.

Assume that desired energy use (for example, desired electricity consumption) can be expressed as $Q^* = \alpha P_E^{\eta} P_G^{\theta} \exp(\boldsymbol{x\gamma})$, where η and θ are the long-term elasticities with respect to the price of the electricity and that of gas, and $\mathbf{x}$ is the vector of variables influencing demand for energy, including income, climate, characteristics of the stock of housing, income, etc. Inserting this expression into (3.2) yields

$$\ln Q_t - \ln Q_{t-1} = \lambda \ln\alpha + \lambda\eta \ln P_E + \lambda\theta \ln P_G + \lambda\boldsymbol{x}\gamma - \lambda \ln Q_{t-1} \tag{3.3}$$

Re-arranging and appending an econometric error term produces the regression equation:

$$\ln Q_t = \lambda \ln\alpha + \lambda\eta \ln P_E + \lambda\theta \ln P_G + \lambda\boldsymbol{x}\gamma + (1-\lambda) \ln Q_{t-1} + \varepsilon \tag{3.4}$$

Equation (3.4) shows that the short-run elasticities are the regression coefficients on the log prices, whereas the long-run elasticities can be computed by dividing these short-run elasticities (i.e., the coefficients on the log prices) by the estimate of λ. In turn, the latter is easily obtained as 1 minus the coefficient on $\ln Q_{t-1}$.

C. Estimation of the Dynamic Model

I wish to estimate the partial adjustment model (equation 3.4) with fixed, dwelling-specific effects. One concern with this specification is that the lagged dependent variable in the right-hand side may be serially correlated and hence correlated with the error term, which makes the LSDV and GLS estimators biased and inconsistent, since $\left(y_{i,t-1} - \bar{y}_{i,-1}\right)$ is correlated with $(\varepsilon_{it} - \bar{\epsilon}_i)$, where $y_{i,t-1} = \ln Q_{i,t-1}$ and $\bar{y}_{i,-1}$ is the average of the $y_{i,t-1}$ terms for unit i, (see Baltagi, 2001). The bias vanishes as T gets large, but the LSDV estimator remains biased and inconsistent for N large and T small, as is the case here, since I have tens of thousands of homes but the maximum length of the longitudinal component of the sample is 6.[27]

Kiviet (1995) derives an approximation for the bias of the LSDV estimator when the errors are serially uncorrelated and the regressors are strongly exogenous, and proposes an estimator that is derived by subtracting a consistent estimate of this bias from the LSDV estimator. An alternative approach is to first-difference the data, thus swiping out the state-specific effects:

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + \Delta \mathbf{w}_{it} \boldsymbol{\beta} + \Delta \varepsilon_{it} \tag{3.5}$$

where $\mathbf{w}$ denotes all exogenous regressors in the right-hand side of equation (3.4), and to use $y_{i,t-2}$ and $\Delta \mathbf{w}_{it}$ as instruments for $\Delta y_{i,t-1}$ (Anderson and Hsiao, 1982).

Arellano and Bond (1991) point out that the latter approach is inefficient and argue that additional instruments can be obtained by exploiting the orthogonality conditions that exist between the lagged values of y_{it} and the disturbances. The Arellano-

[27] Restricting attention to those dwellings that appeared in more than one round of AHS survey yields an unbalanced panel with T ranging from 2 to 6. A similar argument applies by using dwelling-household effects instead of dwelling effects.

Bond procedure is a generalized method of moments (GMM) estimator that is implemented in two steps. In practice, the Arellano-Bond estimator has been shown to be biased in small samples, and the bias increases with the number of instruments and orthogonality conditions. Moreover, Arellano and Bond (1991) show that the asymptotic approximation of the standard errors of their two-step GMM estimator is biased downwards, and they, as well as Judson and Owen (1999), find that the one-step estimator outperforms the two-step estimator.

Under the additional assumption of quasi-stationarity of y_{it}, $\Delta y_{i,t-1}$ is uncorrelated with ε_{it}, and Blundell and Bond (1998) suggest a "system" GMM estimation where one stacks the model in the levels and in the first differences, imposes the cross-equation restriction that the coefficients entering in the two models be the same, and uses the full set of instruments (corresponding to the full set of orthogonality conditions for both models). Blundell and Bond report that in simulation the "system" GMM estimator is more efficient and stable than the Arellano-Bond procedure. This is the approach I adopt for the partial adjustment model.

D. Mismeasured Prices

In this study the price of energy is measured with an error, because I do not know the exact price(s) faced by the household and impute the average price paid by residential customers in that area. Standard econometric theory shows when a regressor is mismeasured, and the measurement error is classical, the estimated regression coefficient is downward biased (Greene, 2008, page 325-326). Here, the mismeasured price enters in the construction of the dependent variable as well as in the right-hand side of the model as a regressor. Omitting for simplicity all other regressors and the cross price, I estimate the regression equation:

$$\ln \frac{A_{it}}{p_{it}^{*}} = \alpha_i + \beta \ln \frac{p_{it}^{*}}{CPI_{it}} + \varepsilon_{it} \tag{3.6}$$

Where subscript i denotes the dwelling, A is the utility bill at time t, p_{it}^{*} is nominal price, and CPI is the CPI index that converts nominal prices to real prices.[28] In this simplified model, the own-price elasticity is β. Variable p_{it}^{*} is mismeasured. Specifically, I assume that $p^{*} = p \exp(e)$, so $\ln p^{*} = \ln p + e$.

Equation (3.6) can be re-written as

$$\ln A_{it} = \alpha_i + (1+\beta) \ln p_{it}^{*} - \beta \ln CPI_{it} + \varepsilon_{it} = \alpha_i + \beta_1 \ln p_{it}^{*} - \beta_2 \ln CPI_{it} + \varepsilon_{it} \tag{3.7}$$

where $\beta_1 = 1 + \beta$ and $\beta_2 = -\beta$. The elasticity with respect to price is thus the LSDV coefficient on log price, $\hat{\beta}_1$, minus 1.

Is this estimate consistent or biased? Suppose that the measurement error is approximately constant within a dwelling over time. If this is the case, then the measurement error is swiped out by the LSDV procedure, which produces consistent estimates of the slopes in equation (3.1).

Consider now the situation where the measurement error is completely uncorrelated within and between the units in every period. If the measurement error is classical, then it can be shown that

$$plim\ \hat{\beta}_1 = \beta_1 \cdot \frac{Var(\ln p) \cdot Var(\ln CPI) - Cov^2(\ln p, \ln CPI)}{[Var(\ln p) \cdot Var(\ln CPI) - Cov^2(\ln CPI, \ln p) + Var(e) \cdot Var(\ln CPI)]} \tag{3.8}$$

[28] City-level Consumer Price Indices are taken from the Bureau of Labor and Statistics (BLS) at http://www.bls.gov/data/ by selecting "urban consumer series" for all items. Prices are then divided by the ratio of the annual CPI to the year 2007 CPI, to convert to constant 2007 dollars.

where variances and covariances are computed using the deviations from the dwelling means. Clearly, $\hat{\beta}_1$ underestimates the true β_1 (i.e., is biased towards zero), and so, since β is negative and $\beta = \beta_1 - 1$, the price elasticity will be overstated (i.e., the absolute value of the estimated coefficient will be greater than $|\beta|$).[29]

Equation (3.7) also shows that the price elasticity is the negative of the coefficient on *ln CPI*. Unfortunately, this coefficient is estimated consistently using LSDV only if *ln CPI* is uncorrelated with the log price of electricity, or (as shown in expressions (3.9)-(3.10) below), $\beta = -1$. In my case, *ln CPI* is positively correlated with the log price of electricity (correlation coefficient 0.37), and β is likely different from -1, and so the bias induced by the measurement error on price is propagated to the coefficient on *ln CPI*. For large samples,

$$plim\, \hat{\beta}_2 = \beta_2 + \beta_1 \cdot m \; = \; -\beta + (1 + \beta) \cdot m \qquad (3.9)$$

where

$$m = \frac{Var(e) \cdot Cov(\ln CPI, \ln p)}{[Var(\ln p) \cdot Var(\ln CPI) - Cov^2(\ln CPI, \ln p) + Var(e) \cdot Var(\ln CPI)]} \qquad (3.10)$$

Again, in expression (3.10) variances and covariances are based on deviations from the dwelling means. It is difficult to sign the bias, because it depends on the magnitude of the true elasticity. In my case, term *m* in expression (3.10) is clearly positive. Term $(1 + \beta)$ is positive if the true price elasticity is negative but small (i.e., $|\beta| < 1$), in which case $\hat{\beta}_2$ is biased away from zero, and its opposite ($\beta_2 = -\beta$) overstates the true elasticity. If the true elasticity β is large (i.e., greater than 1 in absolute

[29] Note that this is only the case when $|\beta| < 1$. An elasticity greater than one in absolute value leads to an understatement. The elasticities estimated in this chapter are all well below one in absolute terms.

value), then term $(1+\beta)$ is negative, $\hat{\beta}_2$ is biased towards zero and its opposite understates the true elasticity.

How can one get around the mismeasurement problem? One approach is to restrict estimation to areas where mismeasurement is likely to be less severe (*e.g.,* areas with only one utility). Another is to instrument for $\ln p_{it}^{*}$, which I do using state-level electricity and gas prices, or, in alternate runs, lagged electricity prices. The results obtained in this fashion can be compared with those from equation (3.1) directly, and with those from equation (3.7).

E. Results

Results for several specifications of the static model (see equation 3.1) are reported in table 3.8 for log electricity consumption, and in table 3.9 for log gas consumption. All include the prices of gas and electricity, structural characteristics of the home (log square footage, age of the home and age squared, number of floors, number of rooms), household characteristics (log household income, log number of household members, whether children or elderly persons are present), heating system and air conditioner type, appliances, and log CDD and HDD. I also control for whether the dwelling is occupied by its owner.

Table 3.8 Static model (Dependent: log of electricity usage)

	(A)	(B)	(C)	(D) one utility	(E) one utility	(F) electric heat	(G) gas heat
Log elec price	-0.860*** -9.37	-0.667*** -9.69	-0.681*** -8.16	-0.685*** -8.26	-0.692*** -6.82	-0.679** -3.22	-0.825*** -8.12
Log gas price	0.117* 2.02	0.122* 2.45	0.139* 2.36	0.115* 1.97	0.107 1.58	0.126* 2.04	0.102 1.63
Log sq. ft.	0.216*** 11.05	0.0593 1.64	0.0522 1.21	0.0538 1.29	0.0396 0.81	0.226*** 7.12	0.220*** 9.15
Age of Home	0.00553*** 8.38	-0.00477 -1.70	-0.00195 -0.53	-0.00164 -0.48	-0.000416 -0.09	0.00685*** 7.44	0.00517*** 7.39
Age of Home^2	-5.4E-05*** -7.56	4.91E-05 1.69	3.07E-05 0.81	1.54E-05 0.43	4.86E-06 0.1	-6.32E-05*** -5.19	-4.98E-05*** -6.80
Owns the Home	0.0696*** 4.86	-0.0558 -1.69	0.0408 0.7	-0.0803 -1.79	0.0215 0.26	0.0899** 3.33	0.0518** 3.25
No. of Rooms	0.0659*** 14.74	0.0159*** 3.42	0.0103 1.94	0.0202*** 3.39	0.013 1.91	0.0701*** 8.14	0.0626*** 14.07
N. of Floors	-0.0171* -2.07	0.0371 1.34	0.0297 0.85	0.0425 1.29	0.0297 0.71	-0.0524** -3.35	0.00476 0.59
Log Income	0.0225*** 8.83	0.00906* 2.3	0.00677 1.49	0.0107* 2.12	0.00804 1.38	0.0251*** 6.1	0.0208*** 8.08
Young child dummy	0.0963*** 15.06	0.0721*** 4.24	0.0353 1.48	0.0614** 2.82	0.0335 1.09	0.0913*** 11.36	0.0964*** 11.93
Elderly dummy	-0.0390*** -4.20	-0.0204 -0.88	-0.00932 -0.32	-0.0137 -0.49	-0.00911 -0.25	-0.0154 -0.95	-0.0400*** -4.22
Log CDD	0.0727*** 3.58	0.0299 1.07	0.025 0.78	0.0417 1.2	0.0272 0.68	0.141** 3.14	0.0762** 3.33
Log HDD	0.0035 0.07	-0.0123 -0.39	0.00277 0.07	-0.0278 -0.58	-0.0244 -0.42	0.0393 0.63	0.0384 0.54
Gas Heat dummy	-0.0990** -2.79	-0.0152 -0.17	-0.0183 -0.18	-0.00105 -0.01	-0.0704 -0.56		
Electric Heat dummy	0.154*** 4.72	0.106 1.23	0.123 1.2	0.117 1.09	0.0722 0.57		
Heating oil heat dummy	-0.0971* -2.28	0.00475 0.04	0.103 0.64	0.023 0.15	0.0945 0.51		
A/C	0.161*** 8.0	0.0572* 2.21	0.0493 1.61	0.0566 1.71	0.0445 1.15	0.0928* 2.63	0.176*** 8.61
Constant	1.422** 2.72	4.053*** 7.61	3.861*** 6.07	4.000*** 5.64	4.212*** 4.97	1.510* 2.12	1.094 1.49
Effects	City	dwelling	dwelling -family	dwelling	dwelling -family	city	city
R-squared	0.457	0.0557	0.0491	0.0564	0.0481	0.418	0.407
N. of cases	82905	82905	82905	48027	48027	22003	55688
Clustered	City	dwelling	dwelling	dwelling	dwelling	city	city

Notes: (1) T-stats reported;(2) significance level * p<0.05 ** p<0.01 *** p<0.001

Table 3.9 Static model (Dependent: log of gas usage)

	(A)	(B)	(C)	(D) one utility	(E) one utility	(F) electric heat	(G) gas heat
Log elec price	0.150* 2.15	0.0376 0.48	-0.0334 -0.36	0.0763 0.78	0.0192 0.16	0.461 1.49	0.128* 2.12
Log gas price	-0.693*** -6.57	-0.565*** -9.51	-0.577*** -8.21	-0.583*** -8.31	-0.587*** -7.24	-0.634*** -4.52	-0.693*** -6.45
Log sq. ft.	0.189*** 9.88	0.0524 1.26	0.0459 0.89	0.049 1.03	0.0439 0.76	0.120* 2.33	0.201*** 10.25
Age of the home	0.00383*** 5.87	0.0000321 0.01	0.000597 0.15	-0.0000686 -0.02	-0.000542 -0.12	0.00252 1.06	0.00384*** 5.85
Age of the home^2	-9.11 E-06 -1.30	6.84E-06 0.22	1.68E-05 0.42	6.19E-06 0.16	2.01E-05 0.42	-1.07E-05 -0.47	-7.25E-06 -1.05
Owns the Home	0.0322* 2.56	-0.0426 -1.08	-0.00991 -0.14	-0.0331 -0.61	-0.00764 -0.07	0.00436 0.15	0.0412** 3.28
N. of Rooms	0.0549*** 18.61	0.0149** 2.72	0.0125 1.93	0.0171* 2.51	0.014 1.74	0.0695*** 7.37	0.0536*** 17.83
N. of Floors	0.00974 1.18	0.0573 1.75	0.0485 1.09	0.0645 1.72	0.0673 1.32	0.0224 0.62	0.00998 1.3
Log Household Income	0.00357 1.61	0.00285 0.6	0.00298 0.55	0.00446 0.74	0.00313 0.47	0.0095 1.40	0.00497* 2.2
Young child dummy	0.0711*** 12.01	0.0635** 3.05	0.0657* 2.25	0.0658* 2.44	0.0813* 2.18	0.0549*** 3.73	0.0683*** 11.12
Elderly dummy	0.0640*** 7.23	-0.00246 -0.10	0.00278 0.08	-0.00266 -0.08	-0.000376 -0.01	0.0574* 2.53	0.0659*** 7.4
Log CDD	-0.00384 -0.13	-0.0262 -0.85	-0.00987 -0.28	-0.0189 -0.49	0.000143 0	0.105 1.24	0.00162 0.06
Log HDD	0.0991 1.67	0.105* 1.99	0.114 1.93	0.192* 2.2	0.198* 2.15	0.0936 1.15	0.149** 2.83
Gas Heat dummy	0.215*** 4.2	-0.0797 -0.55	-0.089 -0.48	-0.0855 -0.36	-0.108 -0.45		
Electric Heat dummy	0.0211 0.47	-0.225 -1.47	-0.226 -1.15	-0.237 -0.95	-0.229 -0.90		
Heating oil heat dummy	-0.938*** -11.47	-0.730** -2.82	-0.564* -1.99	-0.677 -1.91	-0.506 -1.36		
A/C	-0.0147 -0.94	0.0171 0.62	0.00614 0.18	-0.000232 -0.01	-0.0155 -0.36	-0.0348 -1.09	-0.0154 -1.01
Constant	0.214 0.35	1.931** 2.76	1.587* 1.97	1.334 1.29	1.05 0.95	3.746** 2.79	0.206 0.33
Effects	city	dwelling	dwelling -family	dwelling	dwelling -family	city	city
R-squared	0.438	0.0497	0.0465	0.0556	0.0512	0.25	0.429
N. of cases	59492	59492	59492	34371	34371	5176	53027
std. err. clustering	city	dwelling	dwelling	dwelling	dwelling	city	city

Notes: (1) T-stats reported;(2) significance level * p<0.05 ** p<0.01 *** p<0.001

The runs differ for the type of effects I include to account for unobserved heterogeneity. I choose to report results for fixed city-, dwelling- and dwelling-family specific effects. I include city-specific effects because 1) the coefficients on most regressors are similar to those from a random effects model with dwelling-specific effects (estimated using GLS), 2) it stands to reason that homes and people might share similar unobservable characteristics as other homes and people in the same metro area, 3) I do not lose the observations with T=1, and 4) I am able to assess the impact on consumption of factors that vary widely across locales (*e.g.,* home size, income, etc.) but little within a house over time.

Fixed dwelling effects are a natural candidate, since the AHS follows a dwelling over time, while dwelling-family effects allow for unobservable heterogeneity to depend on the household as well as the home. I prefer fixed effects because Hausman tests indicate that if the unobserved heterogeneity is modeled using random effects, these are correlated with the included regressors, which makes the GLS estimates inconsistent. For good measure, the standard errors are clustered around the city (in specifications with city effects) or dwelling (in specifications with dwelling and dwelling-household effects).

Starting with table 3.8, most of the coefficients are significant and have the expected sign. Importantly, column (A)—the results of a model with city-specific effects—shows that the elasticity of electricity use with respect to the price of electricity is -0.860, and the cross-elasticity with respect to the price of gas is positive and equal to 0.117, indicating that the two are substitutes.[30]

[30] It is useful to compare these figures with their counterparts in an OLS regression that ignores unobserved heterogeneity. The own price elasticity when the city effects are suppressed is -1. Adding state effects (but no city effects) makes it -0.894.

Consumption of electricity increases by 22% for every 10% increase in the square footage of the home, is 16% higher if the home has air conditioning, and about 15% higher if the home is heated using electricity. Dishwashers and electrical stoves increase usage by 8% and 7%, respectively (not displayed in the table). F tests reject the null hypotheses that heating/cooling systems are jointly equal to zero (F statistic = 37.65, p value less than 0.0001) and that the appliances are not associated with electricity consumption (F statistic = 38.05, p value less than 0.0001).

The income elasticity of electricity consumption is only about 2%. One reason for such a low elasticity might be the fact that income is highly correlated with characteristics of the home, such as the size, the number of floors, and the presence of certain appliances. Once I removed these from the specification, income elasticity of electricity usage increased to almost 5%.

Column (B) presents the results of a FE specification where the cross-sectional units are the homes. The own price elasticity is lower (-0.667), as expected, but the cross-price elasticity is slightly stronger. As expected, the coefficients on most other variables are much smaller than their counterparts in the city-specific effects specification, because these variables rarely change within a home over time. In column (C), I present the results of a model with dwelling-household specific effects. They are similar to those in column (B), with slightly stronger own- and cross-price elasticities.

In the gas equation, columns (A)-(C) of table 3.9 show that the own price elasticity ranges from -0.693 (city-specific effects) to -0.565 (dwelling-specific effects). The model with dwelling-household effects produces a price elasticity of -0.577. The cross-price elasticity is positive (0.150) and indicates that gas and electricity are substitutes in the model with city-specific effects (column (A)), but turns insignificant when I use dwelling-specific effects, and negative and insignificant in the model with dwelling-family effects.

The model with city-specific effects indicates that gas usage increases by 19% for every 10 percentage point increase in the square footage of the home, and is about 24% larger in homes with gas heating systems. The impact of these variables is small and statistically insignificant in the variants with dwelling- and dwelling-household effects.[31]

F. Robustness checks

My first order of business is to examine the size of the potential bias due to measurement errors in the prices of electricity and gas. To see if such bias is severe, I began with regressions where the sample is restricted to metro areas served by one utility. I argue that the measurement error due to our price imputation procedure is the smallest. For electricity usage, the results of these runs are reported in columns (D) and (E) of table 3.8 for the models with dwelling-specific effects and dwelling-family effects. Similar models for gas usage are displayed in columns (D) and (E) of table 3.9. Clearly, the own-price elasticities are very close (and slightly higher than) to their counterparts in columns (B) and (C).

Next, focusing on electricity usage for the sake of simplicity, I estimated a regression that is similar to those reported in table 3.8 and includes fixed dwelling-

[31] Including regional price interactions in these specifications reveals some differences in the nature of demand. Adding regional price interactions to specification C in table 3.8 reveals an own price elasticity for electricity demand of -0.55 for the basis (West), with homes in the South having a statistically significant interaction term coefficient of 0.43, equivalent to a much lower price elasticity of -0.12 for the region. For gas, specification 3.9C with added interactions reveals an own price elasticity of gas demand of -0.6, with Midwest homes having a significantly lower elasticity: a coefficient of 0.23 (price elasticity of -0.37). These findings may be explained by the heavy usage of air conditioning in the South and the reliance on gas heating in the upper Midwest.

specific effects, but omits the price of gas. The "within" (LSDV) estimator results in an estimated own price elasticity of -0.6794 (which is very close to the coefficient in (B) in table 3.8, where I do include the price of gas). When I instrument for log electricity price using the log of the state average prices of electricity and gas as the identifying instruments, the coefficient on log price is -.67907.[32] Using log state-level electricity price as the only identifying instrument produces an own price elasticity of electricity demand of -0.6584, while replacing that the first lag of log price of electricity in the metro area yields an elasticity of -0.6108.

Finally, I estimated a model similar to equation (3.7), namely one where the dependent variable is log electricity bill, the right-hand side includes fixed dwelling-specific effects, all other controls, the log of nominal electricity price and the log of the CPI (but no gas price). The coefficient on log nominal electricity price is 0.3223 and that on log CPI is 0.5981. The corresponding estimates of the elasticity with respect to the price of electricity are -0.6777 (= 0.3223 - 1) and -0.5891. Although I argue in section 3.C that these are both likely to overstate the true elasticity, they are within 10-15% of the original estimates and of the IV estimates of the price elasticity, suggesting that the impact of measurement error is modest.

To check if consumption depends on current or recent prices, I also estimated models similar to the ones shown in tables 3.8 and 3.9, but where I further included lagged prices. I found that (i) the coefficients on contemporaneous price were strongly significant and similar to their counterparts in table 3.8 and 3.9, and (ii) the coefficients

[32] I use the xtivreg procedure in STATA, using instruments are in the spirit of Black and Kniesner (2003), who propose using another mismeasured variable (i.e., state-level annual average prices) to clean out the measurement error in the original mismeasured regressor (here, average price in the metro area).

on lagged prices were very small in magnitude and insignificant at the conventional levels. This is unsurprising if I recall that the "previous period" is usually two years prior to the current observations. I would expect people to react to changes in recent billing periods, and billing periods are usually one month (see Reiss and White, 2008).

In columns (F) and (G) of tables 3.8 and 3.9, I report regression results for the subsamples with electric heat and gas heat. I report only the results for the models with city-specific effects for the sake of brevity, but the same qualitative results hold for the models with dwelling- and dwelling-households effects (although the magnitude of the coefficients is slightly smaller). In contrast to earlier literature (Metcalf and Hassett, 1999; Reiss and White, 2005), I find households with electric heating systems are actually *less* responsive to the price of electricity than households that use gas heat. Households with gas heat are slightly *more* sensitive to the price of gas than households that use electric heat.

However, Wald tests of the null that the elasticities are the same across the two groups fail to reject the null. For example, if attention is restricted to the equations in columns (F) and (G) of table 3.8, the Wald statistic of the null of identical own price elasticities is only 1.13 (p-value 0.29).

The Wald statistics are even smaller in runs with fixed dwelling (or dwelling-household) effects. One possible explanation for this is that the sample size is rather uneven across the groups of homes served with electric and gas heat. The number of observations with electric heat is 23,542, but drops to 8,416 when only true "panels" are used. This is only about 8% of the total sample. The resulting increase in variance may help explain the lack of significant differences across the two subsamples.

Finally, I estimated models where I allow the responsiveness to energy prices to vary with the quartile of the income distribution that the household falls in. I find that the responsiveness to prices is a bit higher in the first quartile, and declines monotonically by quartile. For example, the elasticity of electricity consumption with respect to electricity price is -0.681 among households in the first income quartile, -0.673 among those in the second quartile, -0.663 among those in the third, and -0.645 among those in the fourth. An F test of the null that these elasticities are all identical rejects the null at the 1% level or better (F statistic=15.96, p-value less than 0.0001). Though statistically different, these elasticity estimates are close in value.

G. Dynamic Models and Models with Investments

Turning to the partial adjustment model, I report results based on the Blundell-Bond estimation procedure in table 3.10. Column (A) shows that the short-run own price elasticity of electricity consumption is -0.736, and the long-run one is -0.814, while the short-run cross-price elasticity (with respect to gas) is 0.265, and the long-run one is 0.293. For gas consumption, shown in column (C), the short-run own price elasticity is -0.572 and the long-run one is -0.647. The price of electricity is not significant in the gas equations. These equations include controls for the heating and cooling system, and I interpret them to imply adjustment when the current heating and cooling technology is considered irreversible.

Table 3.10 Blundell-Bond estimates of dynamic models

	Log of energy usage - lkWh		Log of energy usage - lMCF	
	(A) dwelling effect	(B) no HVAC	(C) dwelling effect	(D) no HVAC
Lag Consumption	0.0958*** 6.09	0.0939*** 5.83	0.116*** 6.2	0.123*** 6.41
Log electric price	-0.736*** -12.26	-0.743*** -12.29	-0.0716 -0.91	-0.0821 -1.05
Log gas price	0.265*** 5.15	0.283*** 5.56	-0.572*** -9.15	-0.586*** -9.32
Log sq. ft	0.142** 2.64	0.142** 2.65	0.14 1.91	0.137 1.83
Age of the home	-0.00624* -2.04	-0.00699* -2.22	0.00691* 2.22	0.00720* 2.31
Age of the home^2	0.0000497 1.63	0.0000522 1.68	-0.0000353 -1.07	-0.0000365 -1.11
Owns the Home	-0.0261 -0.90	-0.031 -1.06	-0.0168 -0.45	-0.0101 -0.27
N. of Rooms	0.0128*** 3.7	0.0126*** 3.6	0.0162*** 3.72	0.0162*** 3.7
N. of Floors	0.00976 0.45	-0.00316 -0.14	0.149*** 4.98	0.164*** 5.4
Log Hhold Income	0.00935** 3.09	0.00925** 3.05	0.00318 0.93	0.00425 1.23
Young child dummy	0.0725*** 4.89	0.0714*** 4.8	0.0574** 3.01	0.0578** 2.99
Elderly dummy	-0.00728 -0.36	-0.00829 -0.41	0.016 0.69	0.019 0.81
Log CDD	0.0660** 3.01	0.0793*** 3.56	-0.0297 -1.21	-0.0304 -1.22
Log HDD	0.0222 0.95	0.00478 0.21	0.200*** 5.46	0.202*** 5.41
Constant	2.389*** 4.06	2.422*** 4.08	-0.661 -0.91	-0.844 -1.14
N. of cases	24487	24487	17679	17679
Long term elasticity	-0.814	-0.82	-0.6471	-0.6682

Notes: (1) T-stats reported; (2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

In specifications (B) and (D) for electricity and gas, respectively, I exclude heating, cooling, and appliance dummies from the regression and interpret the result to apply when the choice of heating and cooling technology is reversible. It has been argued that durable goods and heating and cooling equipment are variable in the long-run, hence these specifications should allow for greater response with respect to energy prices. In fact, I do find slightly elevated price elasticities, but the differences are minor, on the order of 1% for electricity regressions, and 3% for gas regressions.

H. Conclusions

In their Annual Energy Outlook, the Energy Information Agency historically employed a short-term price elasticity of -0.15 for residential demand for energy. In their 2010 report, they adopt an electric elasticity of -0.30 in anticipation of improved consumer awareness resulting from recent smart grid projects.[33] These projections highlight the drivers of demand for energy while underscoring the growing need for energy efficiency. Earlier reports commissioned by the DOE have summarized the potential role of energy efficiency in the residential sector (*e.g.,* Granade *et al.,* 2009). The price of energy, and various policy options that affect price, are usually considered to be the most direct means to affect energy consumption, promote conservation behavior, and incentivize energy efficiency. Yet investigators have found a very wide range of consumer response to energy price, with estimates ranging from the inelastic to the highly elastic depending on the time frame, location, aggregation level, as well as on the estimation methodology. This makes energy policy design a difficult challenge.

To address these limitations of external validity, I assembled a panel dataset of households in the 50 largest metropolitan areas in the United States, maintaining

[33] The text refers specifically to smart grid projects funded under the American Recovery and Reinvestment Act of 2009 http://www.eia.doe.gov/oiaf/aeo/assumption/residential.html and EIA (2010)

individual household and dwelling characteristics. By controlling for unobserved heterogeneity at the household, dwelling, city, and state levels, I examine the relationship between estimates across different specifications using the same data. By using a panel of recent data, I observe dynamic energy usage behavior while accounting for changes in the household or dwelling.

I find strong household response to energy prices, both in the short and long term, controlling for heating and cooling equipment and home appliances. These results stand in marked contrast to much of the literature on residential energy consumption in the United States, and suggest a more central role for policies which affect energy price than may have been previously appreciated.

Chapter 4: The Role of Planned Tenure in Energy Efficiency Investments

Researchers have proposed many explanations for low levels of observed investment in residential energy efficiency. Planned tenure within the home has not been one of them. Armed with data of unprecedented scope and duration, in this chapter I examine the relationship between staying/moving and residential investment in energy efficiency. I ask three questions: First, what are the determinants of household investment in energy efficiency? Second, what is the relationship between planned tenure in the home and energy efficiency investment? And, third, does the effect of tenure vary by investment type?

My contribution is to provide the first empirical estimate of the effect of planned tenure on residential energy efficiency investment. The analysis is possible because of the unprecedented scope and detail of data on the economic decisions of households. This allows me to study the role of house and household characteristics, weather, and energy price on different types of household investments. I also explore the effect of the age of the householder and their education level on investment decisions, an area where previous literature has found mixed results.

The econometric analysis is complicated for four reasons. First, I assume energy efficiency investments depend on whether the household plans to stay in the home, but the likelihood of staying or moving is not asked of respondents or reported in the AHS. Second, the planned tenure decision is endogenous with the investment decision. Third, there is sample selection: I observe presence or absence of investments at time *t* only if the household is still living in the home at time t. Finally, outcomes and key variables such as investment and moving are binary instead of continuous.

Briefly, I find that many of the determinants of energy efficiency investment in the home are the same as the determinants of the demand for energy: larger and older dwellings use more energy, and are more likely to require replacements of equipment. On the role of planned tenure within the home, I find that energy efficiency investments are 20% less likely for households that will move in the next period, but that moving has no effect on the non-energy related home improvements.

These results suggest that homeowners do not believe that energy efficiency is capitalized into the value of their home. This gives those who are unsure as to whether they will stay in the home for the length of time necessary to payback an energy efficiency investment (5 years or more) a disincentive to invest in energy efficiency. Policies that seek to encourage investment in energy efficient appliances may gain broader appeal by attracting planned movers. To provide an incentive for movers to invest, efficiency must be capitalized into home values, which suggests that energy performance needs to be observable to home buyers. Government-mandated auditing or energy certification may help mitigate this problem.

A. American Housing Survey Data

Earlier research on household investment was performed with cross-sections or extremely short panels of data (with a maximum of two observations per household as in Dubin and McFadden, 1984), restrictive geographical areas and investment categories (*e.g.,* Revelt and Train, 1998), or on old data. I have assembled a large and comprehensive set of data (based upon the AHS data, Chapter 3) that documents U.S.

household investment behavior from 1997 to 2009.[34] The AHS contains extensive information about the structural characteristics of the dwelling, renovations and retrofits, home ownership and its financial aspects (mortgages, maintenance costs, etc.), appliances and heating/cooling systems, socio-demographic and economic circumstances of the occupants, and their assessment of the quality of the home and the neighborhood.

In this dataset (as compared to chapter 3), I add the 2009 wave of the AHS, but I exclude from my sample those reporting investments necessitated by disasters (*e.g.,* fires, floods, etc.; N = 1841) and homes with nobody over the age of 18 (N = 418). Relative to the sample used in chapter 3, the addition of 2009 data increases the overall sample to 111,825 observations from 90,880 dwellings and 100,337 households. However, for the investment models estimated here, all specifications consider the decision to invest and/or move in the future. Investment variables are constructed from observed household variables in the subsequent period (*t+1*), while independent variables are formed from characteristics observed in this period (*t*). As a consequence, the sample is restricted to households that appear in at least two periods (N = 42,019). Table 4.1 displays the distribution of the sample by survey year, and table 4.2 according to the longitudinal component.

[34] Quigley and Rubinfeld (19892001) used AHS to estimate their hedonic model of residential energy demand, but use only the 1980 survey year.

Table 4.1 Sample observations by survey year

	1997	1999	2001	2002	2003	2004	2005	2007	2009
Total Obs (N)	6,346	8,579	6,554	25,377	8,092	22,978	6,235	10,390	17,274
(cross-section)	220	891	178	24,843	580	21,501	99	4,981	8,709
(panel)	6,126	7,688	6,376	534	7,512	1,477	6,136	5,409	8,565
Heater	284	438	346	1,184	405	1,517	306	653	854
Water heater	483	694	520	2,395	643	2,381	500	995	1,427
Flooring	298	1,542	1,108	4,668	1,455	5,526	1,286	2,226	2,375
Fencing	413	486	428	2,043	489	2,224	429	767	1,103
Heat-related	834	1,233	942	3,821	1,115	4,161	891	1,747	2,202
(single)	186	205	158	474	181	543	162	275	327

Table 4.2 Sample observations by longitudinal component

Length of the Panel	Dwellings	Households	Heater Investments	
	N	N	N	Rate
1	17,448	24,233	611	2.50%
2	12,385	12,559	366	2.90%
3	8,055	6,635	231	3.50%
4	6,534	4,458	164	3.70%
5	4,773	2,889	111	3.80%
6	2,843	1,668	42	2.50%
7	1,161	757	-	
Total (Panel)		53,199		
Unique (Dwelling)		18,906		
Unique (Household)		25,361		

A.1 Investment Variables

Economic theory dictates that investment should be influenced by expected benefits and discount rate (see *e.g.,* Hausman, 1979). I estimate demand curves for different types energy efficiency investments / home renovations. Demand drivers include (i) dwelling characteristics associated with total energy usage, such as square footage, the number of bedrooms and floors, and age of the home; (ii) operating costs (and proxies for cost) of the current stock of energy equipment; (iii) the upfront cost of replacement or renovation, proxied with labor costs for doing home renovation projects; and (iv) a home price index to proxy the state of the local housing market.

The AHS reports home repairs and renovations in 76 distinct categories.[35] For the choice of dependent variable, I choose heater and water heater investments to represent energy efficiency investments in the home. I also check the sensitivity of the results to non-energy "cosmetic" types of investment, such as flooring replacements or kitchen remodels. To distinguish between planned investments and required replacements, in alternative specifications I split the sample into observations with a single investment to proxy a breakage, and those with more than one simultaneous investment, arguing that simultaneous breakages are unlikely.[36] Descriptive statistics for investment types are displayed in table 4.3.

Table 4.3 Classification of investment types

Variable	Obs	Mean	Std. Dev.	Min	Max
Heater Invest	49463	0.03	0.181	0	1
Water heater Invest	49463	0.05	0.227	0	1
Any heater Invest	49463	0.08	0.271	0	1
Kitchen Invest	49463	0.03	0.180	0	1
Flooring Invest	49463	0.11	0.315	0	1
Fencing Invest	49463	0.04	0.203	0	1
Move out	36957	0.20	0.399	0	1
Log Electric Bill	105702	4.41	0.634	0.27	6.43
Log Gas Bill	77743	4.14	0.697	0.98	6.36
Log HDD	106,880	7.87	0.931	4.56	9.05
HPI	106,880	168.71	46.532	100.53	337.80
Wage Rate	106,880	13.52	3.008	5.80	23.66

[35] For each investment, the total cost is recorded, along with a dummy variable indicating whether a household member did 'most of' the work

[36] The AHS does not include explicit questions about what prompted an investment, yet the motivation for a replacement, dictated by an unforeseen breakdown in equipment and a planned replacement or renovation, dictated by the preferences of the household may be starkly different.

A.2 Household Characteristics

Dwelling and household characteristics for the AHS data were reported in chapter 3. The addition of 2009-survey year data does not materially change the distribution of these variables. For comparison, while the average household income is slightly lower in real terms: $87,000 (2009$), the average household size is 2.8, 31% of the sample has small children, and 23% has at least one person aged 65 or older living in this house; nearly identical statistics to those reported in chapter 3.

Incentives to making durable investments in the home are different for owners and renters, and I include a "renter" dummy in the model.[37] I expect the coefficient on this variable to be negative, since the time horizon over which to reap the investment capitalization are typically much shorter, and any capital investments made in the home by renters are forfeited to the owner or the subsequent tenants when the renter moves out.

Household characteristics are also important in explaining tenure and energy efficiency investment decisions. Income, the number and age of occupants, education level, and the number of employed household members are used. In the sample used in chapter 5, 26% of households report that the head of the household graduated from college (19% from high school), and there are an average of 1.3 workers per household. Neighborhood quality is also important in explaining planned tenure. A dummy variable indicating observed crime in the neighborhood (18% of households) and whether the household has a child in the local public school (25%) affect the decision to relocate, but not the decision to invest in energy efficiency directly, and so serve as identifying

[37] In alternative specifications, I include a renter dummy or exclude renters entirely from the sample.

instruments in the tenure model. House and household characteristics of the sample are reported in table 4.4.

Table 4.4 Descriptive statistics of the sample

Variable	Obs	Mean	Std. Dev.	Min	Max
Child under 5	106,880	0.03	0.229	0	6
Child 6 to 13	106,880	0.07	0.352	0	7
No. Children	106,880	0.69	1.075	0	10
No. Adults	106,880	2.04	0.869	1	10
Youngest Age	106,880	32.29	25.269	0	101
Oldest Age	106,880	52.04	15.886	19	101
Elderly	106,880	0.23	0.420	0	1
Log Income	106,880	10.82	1.618	-0.43	15.79
High School	106,880	0.19	0.392	0	1
Some College	106,880	0.31	0.462	0	1
College Grad	106,880	0.26	0.437	0	1
Post College	106,880	0.17	0.375	0	1
Home Rating	106,135	8.06	1.733	1	10
Public School	106,880	0.25	0.431	0	1
No. Workers	106,880	1.28	0.955	0	9

B. Model and Estimation

In this section I present a basic model of investment in energy efficiency renovations and appliances. Policies aimed at residential energy efficiency seek to reduce the structural energy demand in the housing sector by encouraging investment in more efficient appliances and equipment. Each appliance offers a bundle of attributes between which a household must choose: energy efficiency, purchase price, operating and maintenance costs, and aesthetic characteristics. In this section, I focus on the efficiency-cost tradeoff: the decision between upfront purchase price and long-term running costs.

I posit that a household maximizes the utility from an equipment investment subject to their budget constraint. The household derives utility from the service, *S*, provided by the appliance (*e.g.,* refrigeration, washing, or heating), and from consumption of the non-energy composite commodity *X*. Consider a two-period model in which the consumer can invest in efficiency, I, which is a substitute for energy consumption, *E,* in period 2. Formally,

$$\max_{I,X,E}\{U(X_1, S(E_1)) + \delta U(X_2, S(E_2, I))\}$$

$$\text{s.t.} \qquad Y = X_1 + \delta X_2 + p_E(E_1 + \delta E_2) + p_I I \tag{4.1}$$

where for simplicity it is assumed that the price of energy is constant over the two periods. The Lagrangian of the household problem is:

$$\mathfrak{L} = U(X_1, S(E_1)) + \delta U(X_2, S(E_2, I)) + \lambda\{Y - X_1 - \delta X_2 - p_E(E_1 + \delta E_2) - p_I I\} \tag{4.2}$$

I assume a concave utility function and energy usage decreasing in energy efficiency investment, holding E constant. The first order conditions with respect to energy and investment result in a standard tradeoff between present and discounted future consumption, as well as between expenditure on energy and investment:

$$\left[\left({}^{\partial U}/_{\partial S(E_2)}\right)\left({}^{\partial S}/_{\partial E_2}\right)\right] \Big/ \left[\left({}^{\partial U}/_{\partial S(I))}\right)\left({}^{\partial S}/_{\partial I}\right)\right] = {}^{p_E}/_{p_I} \tag{4.3}$$

$$\left({}^{\partial U}/_{\partial S(E_1)}\right)\left({}^{\partial S}/_{\partial E_1}\right) = \delta\left({}^{\partial U}/_{\partial S(E_2)}\right)\left({}^{\partial S}/_{\partial E_2}\right) \tag{4.4}$$

The equality of marginal productivity condition (equation 4.3) ensures that marginal energy savings and investment per unit price are equalized in period 2. The no-arbitrage condition (equation 4.4) indicates that (if the energy price is constant) the household will equalize the marginal utility of energy demand in period 1 and the discounted energy demand in period 2. Essentially, the household trades consumption in period 1 for energy savings in period 2. The optimal demand functions for investment in energy efficiency depend on consumer income, price of energy and investment, and the discount rate:

$$I^* = I^*(p_E, p_I, Y, \delta) \tag{4.5}$$

I make three claims from this simple model. First, the investment in efficiency should be increasing in energy price: the benefits of efficiency grow as potential savings accumulate. Second, investment is decreasing in the rate of intertemporal preference: The more patient the household, the more they are willing to invest in energy efficiency, other things being equal. I proxy the discount factor with planned time horizon within the home, and I explicitly focus on both time horizon and energy price in my econometric specifications.

B.1 Model Selection

I wish to estimate the following model:

$$I_{it}^{(k)} = \boldsymbol{x_{it}\beta^{(k)}} + S_{it+1}\gamma + \varepsilon_{it}^{(k)} \tag{4.6}$$

where $I_{it}^{(k)}$ is a dummy variable for investment type *k* in period *t* by household *i*, and $\boldsymbol{x}$ is a vector of dwelling and household characteristics, energy prices, and weather. S_{it+1} is a dummy denoting whether the household plans to stay at the present home in the next period:

$$S_{it+1} = \boldsymbol{z_{it}\delta} + \eta_{it} \tag{4.7}$$

where $\boldsymbol{z_{it}}$ is a vector of dwelling and household characteristics that influence desire to relocate (*e.g.,* income, presence of children, housing market conditions, the age of the home), duration (the accumulated years within the dwelling at the start of the sample), and neighborhood characteristics that have no direct bearing on investment (*e.g.,* the reported presence of crime, neighborhood school quality and heavy traffic).

The estimation of model 4.6 is complicated for three reasons: (i) the simultaneity of the investment and move decision, (ii) sample selection bias (which can be interpreted as an omitted variable bias due to the missing selection term explaining the presence in the sample), and (iii) both the dependent variable and the selection variable are binary.

I use two alternative strategies to estimate the effect of tenure on the investment decision: (i) a bivariate probit model of the joint decisions for planned tenure and investment (Evans and Schwab, 1995), adjusted by inverse probability weighting to account for attrition (Wooldridge, 2010), or (ii) an attrition-adjusted 2SLS model (Angrist, 2001). My dataset does not contain a variable on planned house tenure, therefore I estimate a model of moving and use the predicted probability of being in the home, $\tilde{S}_{it+1}$, in lieu of S_{it+1} in (3.6). I control for unobserved heterogeneity by using year controls and by clustering standard errors at the household level. These adjustments are discussed in detail below.

B.2 Econometric Issues

The model (eqs 4.6 and 4.7) can be rewritten as:

$$I_{it}^{*} = S(x_{it}\beta + \epsilon_{it}) \tag{4.8}$$

$$I_{it} = 1 \qquad \text{if} \qquad I_{it}^{*} > 0$$

$$I_{it} = 0 \qquad \text{otherwise.}$$

where the tenure decision, *S*, is an indicator function that takes a value of 1 when at time (*t-1*) the household chooses to stay in the home at time *t*, and is otherwise missing. In particular, households make an endogenous selection choice that influences investment: whether to stay in the home. If the household decides to move before the next period (S=0), I do not observe whether they have made an investment in this or any subsequent period. Thus, it is appropriate to condition the investment decision on the decision to stay in the home, and to handle observations differently depending on their spell in the sample.

With panel data, selection out of the sample is typically an absorbing state: all subsequent observations for that unit are lost. This is true of my data: households generally move out for good. An additional challenge is posed by the fact that my dependent variable is binary: commonly, attrition is handled by using a two-stage instrumental variables approach, and possibly differencing the equation to remove unobserved effects (Wooldridge, 2010), but these approaches are undesirable with a binary dependent variable.

In general, a linear panel data model is specified as:

$$y_{it} = x_{it}\beta + \epsilon_{it} \text{ for } i = 1, \cdots, N \text{ and } t = 1, \cdots, T \tag{4.9}$$

Under strict exogeneity, ($E[\epsilon_{it}|\, x_{im}] = 0$, for $m, t = 1, \cdots, T$) serial independence of the errors, and no unobserved heterogeneity, equation 5.9 can be estimated consistently with OLS. Of course, with panel data it is possible to correct for unobserved heterogeneity. If the heterogeneity is time-constant, ($\epsilon_{it} = \alpha_i + \mu_{it}$) and ($E[\mu_{it}|\, x_i, \alpha_i] = 0$), $t = 1, \cdots, T$), it is desirable to use the "within" estimator. However, I have an unbalanced panel, and if attrition is non-random, the idiosyncratic error term is potentially correlated with *x*: ($E[\mu_{it}|\, x_i] \neq 0$) and the estimates are inconsistent.

Heckman's (1978) two-stage instrumental variables approach can be used to address sample selection and attrition (Wooldridge, 2010), yet there is limited application of this approach to data with a longitudinal component and unobserved heterogeneity.[38]

[38] The literature on treatment for selection bias is quite extensive; unfortunately, most applications relate to the cross-sectional case. Recent attention has been devoted to panel data (see, e.g. Semykina and Wooldridge 2010), but studies typically assume continuous dependent variables and/or continuous endogenous regressors, or no attrition. The case of

In the setting of this chapter, the estimation challenge is how to consistently estimate the effect of planned tenure (a binary selection variable) on the likelihood of investment (binary dependent variable) over time.

B.3 Estimation Methodology

In a seminal paper on schooling and self-selection, Evans and Schwab (1995) utilize both a bivariate probit model and 2SLS to estimate a binary treatment effect (Catholic high school enrollment) with a binary outcome (enrolling in college). I follow a similar approach here. In the second stage of my 2SLS approach, I estimate:

$$I_{it}^{(k)} = \boldsymbol{x_{it}}\boldsymbol{\beta}^{(\boldsymbol{k})} + \hat{\boldsymbol{z}}_{\boldsymbol{it}}\boldsymbol{\gamma} + \varepsilon_{it1}^{(k)} \tag{4.10}$$

where $\boldsymbol{\gamma}$ captures the effect of tenure on efficiency investment, and $\hat{\boldsymbol{z}}_{\boldsymbol{it}}$ is predicted from a first stage regression of moving on a vector of instruments. Consistent estimation of $\boldsymbol{\gamma}$ requires that the instruments be correlated with the moving decision, but be exogenous to the investment equation, $Cov\left(\boldsymbol{z_{it}}, \varepsilon_{it1}^{(k)}\right) = 0$, and at least one variable of $\boldsymbol{z_{it}}$ does not appear in $\boldsymbol{x_{it}}$.

Alternatively, assuming that the errors in the investment and selection equation are jointly normally distributed: $(\epsilon, \eta) \sim Normal(0, \Omega)$, where $\Omega = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$, one can estimate a bivariate probit model. The first step is to construct the probability of investment conditional on selection (see Wooldridge, 2010, p. 595):

$$P(I = 1 |\, S = 1, \boldsymbol{z}) = \frac{1}{\Phi(z\delta)} \int_{-z\delta}^{\infty} \Phi\left[(\boldsymbol{x\beta} + \rho\xi)/(1 - \rho^2)^{1/2}\right]\phi(\xi)d\xi \tag{4.11}$$

a binary dependent variable with a binary endogenous regressor and attrition does not appear to have been comprehensively studied.

where $\rho = corr(\epsilon, \eta)$ is the off-diagonal term of the covariance matrix Ω. Estimation is by maximum likelihood. The effect of moving on investment is thus $E[I|S = 1] - E[I|S = 0]$, and is estimated using the predicted probabilities post-estimation: $E[I|\Delta S] = \hat{P}(I|\,S = 1) - \hat{P}(I|\,S = 0)$.

Regardless of the estimation procedure, attrition is a concern. I follow Wooldridge (2010) in adjusting for attrition by using inverse probability weights (IPW), *i.e.* the reciprocals of predicted probabilities from a selection equation. I adjust all specifications with IPW formed from the initial values for each household, an approach used by Contoyannis *et al.* (2004).[39]

B.4 Statistical Tests and Robustness Checks

The appropriate estimation methodology in a model of binary selection is a matter of debate. Angrist (2001) notes that average effects estimated using 2SLS, which do not rely on distributional assumptions, are often similar to estimates from models that impose more assumptions and structure (*e.g.,* IV tobit, bivariate probit). Altonji *et al.* (2005) note the estimated average effect in a bivariate probit model often rests crucially on the nonlinearity rather than the exclusion restriction. Yet binary events may not be well approximated by a linear probability model, resulting in imprecise estimates from the 2SLS, a point made in Carrasco (2001) and elsewhere. In sum, both procedures have merits and disadvantages.

[39] This approach relies on the existence of good instruments to model selection, such that, conditional on those instruments, attrition is exogenous. This is termed the 'selection on observables' condition. In my specifications, I use a vector of initial household characteristics (t=0) related to move propensity, such as income, age, and neighborhood rating, to proxy selection, as reported in table A1. The selection equation is a probit for the biprobit estimation, and an LPM for the 2SLS approach.

I investigate the robustness of the estimated coefficients in several ways. First, by running two distinct models, the LPM-based 2SLS model, and a bivariate probit, I check the sensitivity of the results to the assumptions implicit in either. I also repeat the estimation of the models for different subsamples created according to (i) the number of periods each household appears, (ii) the number of periods each dwelling appears, (iii) for successive 2-year balanced intervals of my data. These results are shown in the appendix B, Table AB.1).

I test for attrition in two ways: by including for each household (i) the number of periods they appear in the sample, and (ii) a dummy variable indicating whether they are present for all periods in the sample. If attrition is not a concern, the coefficients on these additional regressors should be statistically indistinguishable from zero (Contoyannis *et al.*, 2004).

C. Results

C.1 Reduced Form

My model differs from the previous literature on energy efficiency investment, so I first wish to compare my estimates for the determinants of investment with the findings of earlier studies. I estimate a series of models similar to (5.6) but without relocation variables (table 4.5). *Heater* investment is chosen as the dependent variable because it accounts for the largest share of residential energy consumption (41%, EIA 2005), is one of the most common home energy efficiency investments, and is studied frequently in the literature (see *e.g.,* Vaage, 2000, Meier and Rehdanz, 2010, or Liao and Chang, 2002).

Table 4.5 Reduced form results

Dependent	Heater Investments		
Model	**LPM**	**LPM**	**RE**
Sample	**All**	**Homeowners**	**Homeowners**
	(A)	**(B)**	**(C)**
Renter	-0.0270***		
Log Electric Bill			0.00178
Log Gas Bill			0.00608**
Log Electric Price	-0.0076	-0.0093	
Log Gas Price	-0.00255	-0.00143	
Log Income	0.000627	0.000959	0.000773
No. Children	0.00183	0.00211	0.00183
No. Adults	0.0000969	0.000115	-0.000209
Elderly	-0.00265	-0.00277	-0.00364
Youngest Age	0.000107	0.000132*	0.000146
College Grad	0.0116***	0.0150***	0.0146**
Post College	0.0119***	0.0151***	0.0167***
Log HDD	0.00565***	0.00683***	0.00624**
Wage Rate	-0.0000967	-0.000284	-0.00159**
HPI	-0.0000659*	-0.0000728*	-0.0000664
Log Sq. Ft	0.000511	0.000492	0.00066
Home Age 20+	0.0379***	0.0419***	0.0436***
Rooms	0.00283***	0.00315***	0.00332***
A/C Dummy	-0.00288	-0.00494	-0.00642*
Constant	-0.0672**	-0.0903**	-0.0884***
Year Effects	Yes	Yes	Yes
R-squared	0.0208	0.0179	
N. of cases	47258	40023	32092
N. groups			12292

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

All specifications in table 4.5 control for household education level, fuel type, the age of the home, sample year, and the number of adults in the household, and use standard errors clustered around the household.[40] Model (A) demonstrates, as expected,

[40] Here I do not model the fuel choice of the household directly; the investment decision is aggregated across technologies.

that renters are significantly less likely to make investments; all remaining models in table 4.5 exclude renters entirely.

The results of table 4.5 mirror earlier findings on household energy efficiency investment: investments are more likely in older, larger homes, or bigger, richer households. In particular, the age of the home is significant in every specification. This result suggests that new heater investments are 5 percentage points more likely in homes built 20 or more years earlier, other things equal. The size of the home (log square feet, number of rooms) is also positively associated with investment. *Elderly*, a dummy variable indicating that a household member is over 65 years old, is insignificant for all specifications. *Youngest Age,* a variable reporting the age of the youngest member of the household, has a positive (and significant in column B) coefficient, suggesting young families are slightly more likely to invest. Those with more modest demands for heat (such as older residents, those with fewer children, or those that live in more moderate climates) are less likely to invest in a heater.[41]

Education is positively associated with heater investment. The coefficient on the dummy variable associated with the head of the household being a college graduate (*College Grad*) or having an advanced degree (*Post College*) are both highly significant with large positive coefficients, suggesting that educated households are more than 10 percentage points more likely to invest in heating than households whose members did not attend college. On comparing columns (B) and (C) in table 4.5, I conclude that

[41] The presence of an air conditioner is negatively associated with heater investment. This may be due to households reporting heat pumps, devices that both heat and cool, as air conditioners. I am unable to explore this further, as the AHS data does not individually identify heat pumps as a separate class of devices in the data.

average monthly electricity and gas expenditures are a better predictor of heater investments than energy prices.[42]

C.2 The Tenure Decision

What is the effect of planned tenure on investment? In table 4.6, I present the results of a series of 2SLS regressions of heater investment on house and household specific characteristics, instrumenting for the decision to move. The results of the first stage (equation 4.7) instrumenting equation are reported in column (C). Table 4.7 (model A) presents the results of a bivariate probit model jointly estimating heating investment and relocation (the planned tenure model estimates appear in column (B) of table 4.7). All investment specifications include age of the home, heating type, ages of the household members, and number of children.[43]

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[42] Model (6c) gives identical estimates for all coefficients when estimated by OLS instead of GLS: nearly all variation comes from between rather than within households.

[43] While the 2SLS employs a Linear Probability Model (table 7), the bivariate probit assumes that the latent variables are normally distributed (table 8). Thus, the coefficients of the bivariate probit model are not directly comparable to the 2SLS estimates, but do reflect their statistical significance.

Table 4.6 2SLS heater investments

Dependent	Heater	Heater	Move
Model	**IV 2SLS**	**IV 2SLS**	**LPM**
	(A)	**(B)**	**(C)**
Move Out	-0.223*	-0.217*	
Log Electric Bill	0.00300	0.00274	0.00073
Log Gas Bill	0.00617*	0.00649*	-0.00606
Log Income	0.000432	0.000440	-0.00182
No. Children	0.00257	0.00272	0.00478
No. Adults	-0.00300	-0.00276	-0.0111***
Elderly	-0.00603	-0.00600	-0.0164*
Youngest Age	0.000209	0.000214	0.00296
No. Workers	0.00195	0.00227	0.00012
College Grad	0.0176**	0.0175**	-0.00366
Post College	0.0194**	0.0190**	-0.00947
Log HDD	0.0102***	0.0103***	0.00122
Wage Rate	-0.00251***	-0.00237**	-0.00044
HPI	-0.0000905	-0.0000912	-0.00003
Log Sq. Ft.	0.00235	0.00237	0.0133***
Home Age 20+	0.0541***	0.0528***	0.0299**
No. Rooms	0.00342**	0.00336**	-0.00189
No. Floors	-0.00502*	-0.00531*	-0.0077**
A/C Dummy	-0.00974*	-0.00932*	-0.00082
All Periods	0.0393	0.0381	0.244***
Household Panel	-0.0212	-0.0203	-0.127***
Gone Next		0.0334*	0.00184
Child 6 to 13			0.00482
Oldest Age			0.00102
Home Rating			-0.00573***
Crime Dummy			0.00743
Public School			-0.00668
Constant	-0.0196	-0.0255	0.528***
R-squared			0.2888
N. of cases	23762	23645	23645
Weights	No	Yes	Yes

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

Table 4.7 Bivariate probit heater investments

Dependent	Heater	Move
Model	Bivariate Probit	
	(A)	(B)
Move Out	-5.814***	
Log Electric Bill	0.0287	
Log Gas Bill	0.0722*	
Log Income	0.00877	-0.0225***
No. Children	0.0222	-0.00188
No. Adults	-0.0195	-0.0884***
Elderly	-0.0599	
Youngest Age	0.00148	-0.000426
No. Workers	0.0149	-0.0357*
College Grad	0.194**	
Post College	0.211**	
Log HDD	0.111***	
Wage Rate	-0.0227**	
HPI	-0.000807	-0.00149***
Log Sq. Ft.	0.00274	
Home Age 20+	0.694***	
No. Rooms	0.0325***	
No. Floors	-0.0444*	
A/C Dummy	-0.0889*	
Household Panel	-0.00519	
All Periods	0.00404	
Gone Next	0.344**	
Child 6 to 13		0.0528
Oldest Age		-0.00814***
Home Rating		-0.0404***
Crime Dummy		0.00533
Public School		-0.142***
Constant	-3.508***	0.484***
rho	0.041	-
N. of cases	23645	-
Weights	Yes	-

Notes: significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

Focusing on specifications (A) and (B) in table 4.6, the predicted probability of moving in the next period, *Move Out*, has a negative coefficient implying a 20% effect. This suggests that households planning to move in the next period *are* less likely to invest in the home, which has important policy implications. The other coefficients in specifications (A) and (B) are similar to those in table 4.5.

The first stage regression, predicting the likelihood of moving in the subsequent period, is reported in Model (C) in table 4.6. Although income is positively correlated with investment, it is negatively correlated with moving in general. Likewise, the presence of children in the household increases the likelihood of investing, but decreases the likelihood of moving. The likelihood of moving is negatively related to the number of adults in the home and the presence of elderly. The age of the home has significantly positive impacts on the probability of moving, but also on the probability of investing, while the size of the home (square feet, number of floors) positively impacts moving but has no direct effect on investment.

Other instruments are significant predictors of the moving decision: the higher the home rating, the less likely the probability of moving. Interestingly, neither the existence of school-aged children in the home, *Child 6 to 13,* nor the attendance of children in the local school significantly affects the move probability. Model (B) in table 4.7, the bivariate estimate for the probability of moving, reflects the correlations noted here, but the level of significance differs because the included variables and the estimation technique are different. Importantly, it confirms that the effect of moving on investment is negative and significant.

C.3 Other Investment Types

In table 4.8, I examine the effect of planned tenure on other types of investments, such as *Water Heater* (column A), *Any heater* – an aggregate of both heater and water heater investments (B), any *Any Heat (single)* – a dummy that takes a value of one if a heater is the only investment made (C), kitchen renovation (D), and replacement of interior flooring or carpeting (E), or exterior fencing (column F).

Table 4.8 Energy and non-energy investments

Dependent	Water Heater	Any Heater	Any Heat (single)	Kitchen	Flooring	Fencing
Model	**IV 2SLS**					
	(A)	**(B)**	**(C)**	**(D)**	**(E)**	**(F)**
Move Out	-0.196**	-0.234**	-0.0775*	0.0486	0.108	0.0967
Log Electric Bill	0.00194	0.00283	0.00345	-0.00177	0.00111	-0.00299
Log Gas Bill	0.00751	0.0122*	0.000193	0.00345	0.0048	0.00287
Log Income	0.00116	0.00162	0.000638	0.00303**	0.00503**	0.00154
No. Children	0.00243	0.00409	0.000841	0.00187	0.0043	-0.00059
No. Adults	-0.00645	-0.00606	-0.00251	0.00369	0.00825	0.000773
Elderly	-0.00479	-0.011	0.000863	-0.00426	-0.0118	-0.0130*
Youngest Age	-0.000174	0.00006	0.000127	-0.000246*	-0.000615**	-0.000297*
No. Workers	0.00581*	0.00635*	0.00132	0.00157	0.0113**	0.0014
College Grad	0.00764	0.0257**	0.000539	0.00665	0.00886	0.0250***
Post College	0.00791	0.0294**	-0.00146	0.0150*	0.0014	0.0222**
Log HDD	-0.00663	-0.0202	0.00234	-0.0164	-0.0105	0.0144
Log Sq. Ft.	-0.000057	0.000264	-0.000878	0.000327	-0.00322	-0.000426
Wage Rate	-0.00303	-0.00216	-0.00107	0.0000412	-0.00630*	-0.00506**
HPI	-0.0000362	-0.0000844	-0.0000689	0.0000638	-0.000367**	0.000029
Home Age 20+	0.0601***	0.0988***	0.0140***	0.0522***	0.0736***	0.0434***
No. Rooms	0.000493	0.00389*	-0.00147	0.00128	0.00557**	0.00415***
No. Floors	-0.000219	-0.00472	-0.00161	-0.00145	-0.00537	-0.00197
Constant	0.101	0.0268	-0.0604	0.0141	0.259	-0.118
R-squared	0.0148	0.033	.	.	.	.
N. of cases	22263	22263	22263	22263	22263	22263

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

In column (A) of table 4.8, water heater renovation is regressed against the vector of house and household characteristics, including the same controls as in table 4.6. The age of the home is significant with a positive coefficient, while the number of workers in the home, *No. Workers*, has a positive effect, significant at the 5% level. Older homes are more likely to require a new water heater, and the cost of installation is a deterrent to investment. The other coefficients in model (table 5.4, column A) generally have the same sign as in table 4.6. The effect of planned tenure on water heater investment is negative and implies a 20% decrease in the likelihood of investment. This estimate is significant at the 1% level.

Model (4.8B) displays the results of the 2SLS regression for *Any Heater* investment. Again, the coefficients are similar to those found in table 4.6 and (4.8A), with the expenditures on natural gas, education level, home age, number of workers, and number of rooms all having positive and significant coefficients. The coefficient on *Move Out* is again very strong: a predicted probability of moving in the next period is seen to decrease the probability of investment by nearly 23%, significant at the 1% level.

Model (4.8C) considers only single renovations, which may be indicative of a breakdown (and a necessary replacement) rather than a planned investment. As might be expected with a sudden event, and replacement of broken equipment, none of the household characteristics are significant. The significant covariates simply reflect the probability of a breakdown: The home age variable, which proxies the age of the equipment, is positively associated with a single heater replacement, but the effect is smaller than in previous models. The *No. Rooms* coefficient takes the opposite sign of specification (4.8A) and (4.8B), and a smaller magnitude.

Interestingly, the coefficient on planned tenure, *Move Out*, is negatively associated with replacement: those predicted to move in the next period are nearly 10 percentage points less likely to replace a heater than those who are not. This result suggests that the construction of the dependent variable may not perfectly distinguish breakages from planned investments.

Models (4.8D), (4.8E), and (4.8F) show the results of the kitchen, flooring, and fencing investments, respectively. The drivers of investment here are similar to those discussed above, with several exceptions that underscore the differing nature of these "functional" investments as compared with energy efficiency investments. First, income is positively and significantly associated with flooring and kitchen investments, and its coefficient is several times larger than the estimates in previous regressions. Second, the presence of elderly and very young children reduces the likelihood of these investments. Notably, for all "cosmetic" specifications, the coefficients on move are positive, although not significant. This suggests that homeowners may expect to reap the additional value of such an investment upon home sale, and therefore, a planned move does not decrease (and may even increase) the likelihood of such an investment.

The central question of this chapter is the relationship between tenure and energy efficiency investment. As discussed in section 3, the estimation of an endogenous binary selection variable in a binary model is not econometrically straightforward. Table 4.9 reports the effect of moving on *Any Heater* investments using different estimation methodologies: Model (4.9A) displays the results of an unweighted IV 2SLS approach, (4.9B) includes inverse probability weights to control for attrition, and (4.9C) presents the results of a bivariate probit estimation of any heater investment and a planned move. The marginal effect of moving, evaluated at the means of all variables, is presented with bootstrapped standard errors. While the addition of IPW does not substantially change the estimate for the effect of moving, the marginal effect evaluated at the mean is a 21% decrease in investment likelihood versus 23% for the 2SLS approach. The slight difference in these estimates may be explained by departure from distributional assumptions in the bivariate probit model, or due the poor approximation of binary process with the 2SLS. Despite differences in the magnitude of the effects, these findings are in line with Evans and Schwab (1995) and Altonji *et al.* (2005). Both approaches agree in that homeowners refrain from making efficiency investments if they plan on moving.

Table 4.9 Model comparison

Dependent	Any Heater (Heater or Water Heater Investments)		
Model	**LPM**	**LPM**	**Bivariate Probit**
Methodology	2SLS	2SLS	MLE
Year Dummies	Yes	Yes	Yes
Inv Prob Weights	No	Yes	Yes
	(A)	(B)	(C)
Move Out	-0.235**	-0.234**	-6.737***
SE	(0.082)	(0.079)	(0.164)
marginal effect			-0.215***
bootstrapped SE	-	-	(0.0155)
observations	23863	23863	23722

Notes: (standard errors in parentheses) significance level * p<0.05 ** p<0.01 *** p<0.001

C.4 Robustness Checks

The variables included to test for attrition, the number of periods they appear in the sample (*Household Panel*) and a dummy variable indicating whether they are present in all periods (*All Periods*) are not significant when included (models 4.6A, 4.6B, 4.7A), suggesting that attrition does not greatly impact the estimates in my models. The similarity of the coefficient of interest (*Move Out*) from the different models (Table 4.9) is further evidence of the robustness of the results.

To further check robustness, I investigate *Any Heater* investments (model 4.8C) using various samples: (i) according to the number of periods each household appears,

(ii) according to the number of periods each dwelling appears, (iii) for successive 2-year balanced intervals of my data. These results show little variation between models. 17 out of 19 specifications result in negative coefficients on *Move Out* (the two positive coefficients are not significant), and the results are robust to inclusion of the attrition test variables. Selected models are shown in appendix B (Table AB.1). Finally, I estimate 2SLS models for alternate dependent variables. The results are consistent with Table 9: the effect of moving is negative on energy–related investments. Although none of the coefficients are significant, the magnitude is greater for energy-related investments that are not directly observable, such as roof renovation, than for non-energy related ones (Table AB.2).

D. Conclusions

Residential energy efficiency investments are regarded as key to unlocking low-carbon economic growth and improved air quality in the U.S (IPCC, 2007, Granade *et al.,* 2009). If homeowners can be persuaded to install more efficient heating/cooling equipment and electrical appliances, the reduction in energy usage will last for decades. Existing policies promoting residential energy efficiency mail fail to account for the relationship between planned tenure and investment. I have used comprehensive data on U.S. households from 1997-2009 and an IV approach, and I find that planned moving out of a home decreases the likelihood of investing in heating equipment by 20%. In contrast, planned moving has no or a positive effect on investments that are unrelated to energy efficiency but may enhance the value of the home aesthetically, such as flooring, fencing or kitchen investments.

Where energy usage is concerned, the relationship between potential homebuyers and home sellers suffers from information asymmetry: the seller has an incentive to overstate the (unobserved) energy efficiency. Lacking proof, efficiency claims by the seller are disregarded, and the energy efficiency of the home is not captured in the sales price. Accordingly, homeowners that plan on selling their home before they have reaped the benefits of an energy efficiency investment will resist paying the efficiency premium. This ongoing underinvestment in energy efficiency results in a low-efficiency building stock.

The information asymmetry has other important policy implications. In the U.S., approximately 14% of homeowners move within a two-year period, and approximately 10% of all homes will replace their heaters in that window. This is equivalent to a population of 1,050,000 homeowners that will move and will also need to replace their heaters.[44]

The efficiency rating of heaters can vary by up to 30% or more. Comparing just the top of the efficiency distribution, the difference between the 'mid-efficiency' and the 'high-efficiency' heater is approximately 10 Annual Fuel Utilization Efficiency (AFUE). At the average heat consumption (40MBtu per year[45]), over a heater lifetime of 20 years, the resulting difference in energy usage for a single household is 80 MBTU, or 4.25 metric tons CO_2 if burning natural gas.[46] Scaling to the entire population of moving households, and adjusting by the reduction of 20% in the likelihood of efficiency

[44] Assuming a heater lifetime of 20 years.

[45] EIA latest available, http://www.eia.gov/consumption/residential/data/2005/c&e/spaceheating/pdf/tablesh8.pdf

[46] Using the EIA conversion rate of 117.1 lbs. CO2 per MMBtu of natural gas

investment, there are approximately 900,000 metric tons of CO_2 emitted annually in the U.S. as a result of this market failure.[47]

The information failure in the market for energy efficiency highlights an important opportunity for governmental involvement. Certain policy measures are already in place: subsidies for efficient equipment enhance adoption by artificially lowering the cost of equipment, and appliance standards increase the minimum efficiency of available equipment. A rental market in efficient equipment[48] could also boost efficiency, but high transaction costs temper that opportunity. A more direct policy solution would be to solve the information problem: require standardized energy performance data or certification as part of home sales and rental transactions, and improve energy efficiency of the residential sector.

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[47] Moving percentages, average HDD taken from the AHS sample; 65.9% of the 114,596,927 occupied housing units in the U.S. are owner-occupied (Census, 2010): 75.5 Million homes. (http://factfinder2.census.gov); Heater statistics relate to furnaces and boilers ratings listed at: http://www.energysavers.gov/your_home/space_heating_cooling/index.cfm/mytopic=12530. AFUE is a measure of operational efficiency applied to furnaces and boilers according to ASHRAE standard 103.

[48] Energy performance contracts, common to institutional settings such as hospitals, schools, and government buildings, allow an energy service company "ESCO" to install and maintain highly efficient equipment in exchange for a share of the resulting energy efficiency cost savings. Due to the large fixed costs involved in such efforts, extending the model to the residential sector would be difficult.

Chapter 5: Discount Rates and Investment

As the previous chapters have shown, household energy consumption and investment are influenced by price and planned tenure within the home. There is also evidence that people may think about energy and the cost of energy consumption differently from other types of economic activities (Allcott, 2010).

The energy-efficiency "paradox" has been interpreted to imply higher discount rates for energy efficiency than for other types of technology. Researchers have suggested a host of behavior differences and market failures that may explain such behavior (Howarth and Sanstad, 1995). Yet, little research has examined the central question of whether consumers *directly* value energy and non-energy expenditures/savings differently: transaction costs and information asymmetry make it difficult to recover true rates of time preference from purchase behavior alone. The individual rate of time preference is one of the fundamental determinants of consumer investment behavior, and differential discounting between energy and non-energy investments poses an enormous challenge to energy efficiency policy. The extent that this discounting behavior can be quantified and understood will inform our understanding of energy efficiency investment in general, and will be useful to improve policy design.

Previous literature on personal discount rates suggests a wide variation in estimates depending on the setting. Earlier studies on appliance discounting, for example, exhibit remarkable variation: Hausman (1979) finds discount rates from 5% to 89%, Gately (1980) between 45% and 300%, and Ruderman *et al.* (1986), 17% to 243%. Clearly, cross-study comparison of discount rates is difficult due to the differing samples and assumptions.[49] Context also matters a great deal. Using a single sample, Thaler (1981) reports individual discount rates for money from 1% to 345%, and reports higher discount rates for smaller amounts of money, or for shorter lengths of time. Discount rate also varies according to personal characteristics such as income (Train, 1985), age, and gender (Curtis, 2002).

Even the very concept of a single personal discount rate, implying a rate of time preference that remains constant over time, is questionable. Time-inconsistent discounting has been observed in many settings (Frederick et al., 2002). Hyperbolic discounting (*e.g.,* Coller and Williams, 1999; Harrison *et al.,* 2002) is increasingly used in the literature as a more realistic approximation to the individual choice.

I designed and conducted a survey of Maryland households specifically to fill some of the gaps implicit in my other sources of data and to allow me to observe choice under well-specified, but hypothetical conditions. I use these data to estimate individual discount rates. My contribution is to provide direct estimates of the discount rate for energy and non-energy contexts from the same sample, and to understand how household and dwelling characteristics, including energy consumption, influence individual discounting and the differences between energy and non-energy discount rates. I study homeowners in the state of Maryland, and I ask three research questions: (1) what is the discount rate that homeowners apply to future energy savings? (2) what are the most important individual characteristics in explaining rate of time preference? and, (3) do homeowners discount energy savings differently than money? I focus on *internal* discount rate comparisons: in other words, I document and characterize the difference

[49] Train (1985) made this point in his review of energy-related discounting.

between energy and non-energy discount rates within the same sample, and over comparable time scales (a money-versus-money tradeoff with a horizon of 10 years, and appliances with a lifetime of 10 to 17 years).

A. Maryland Energy Survey Data

The source of data for this chapter is a survey of homeowners in Southern Maryland.[50] The survey was conducted in the fall of 2011 to examine the energy investment and consumption behavior of homeowners. The survey data are combined with data on the structural characteristics of the home (taken from a state database of all properties in Maryland maintained for tax purposes), as well as demographic data at the tract and block group level (from the U.S. Census).

A.1 Survey Design

The sample I wish to survey is comprised of 10,000 single-family homes and townhomes (attached homes) from three counties in Southern Maryland: St. Mary's, Charles, and Calvert.[51] As I explain below, this "desired" sample is a combination of stratified and choice-based samples. The stratified sample was drawn from the universe of older homes in those counties. Accordingly, the stratified sample contained (i) homes built between 1940-1990, and (ii) homes built between 1990-2000. The survey questionnaire elicits extensive information about recent energy efficiency renovations an activities, so I augmented each of these two samples with: (iii) households that applied

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[50] This geographic region was chosen because the homes are within the service territory of the local electric monopoly, hence all electricity rates and tariffs are constant across individuals.

[51] The survey is targeted at those who own the home and pay their own energy bills, those that rent or have utility-included housing arrangements have markedly different incentives to invest in energy efficiency; I restrict attention to those that live on the premises full-time and pay their own electricity bills from the survey.

for a residential building permits with their county of residence between January 2007 and June 2011 (see data appendix C), and (iv) households that received energy efficiency incentives (such as efficient light bulbs, rebates for efficient equipment, and audits) from the local utility in early 2011, and (v) homes containing those that had moved within the past 12 months. I argue that (iii), (iv), and (v) are more likely to have recent experience or interest in energy efficiency renovations, and for these reasons, are choice-based samples.

I mailed letters to 10,000 households asking them to participate in a web-based survey. Of these, 44 were returned as undeliverable. Out of the 9,956 successful deliveries, I was able to get a total of 1,143 completed questionnaires (6 of which were conducted by phone), for a response rate of 11.4%. A detailed breakdown of survey respondents by wave and target is included in table 5.1.

Table 5.1 Breakdown of respondents and targets by group

Group		Charles	Calvert	St. Marys	Total
Recent Movers	mail	655	276	273	1253
	response	38	21	24	83
Incentives Group	mail	483	255	428	1216
	response	83	51	78	223
Homes 1940-1990	mail	1638	617	1057	3493
	response	163	81	111	372
Homes 1990-2000	mail	1715	893	956	3770
	response	150	101	85	352
Building Permits	mail	385	178	357	920
	response	49	33	47	129
Wave 1	mail	2372	887	1544	5000
	response	284	135	213	641
Wave 2	mail	2197	1207	1349	5000
	response	199	152	132	502
Total	mail	4569	2094	2893	10,000
	response	483	287	345	1,143

As mentioned, the survey was web-based. Simple instructions on locating and taking the survey were printed on the survey invitation. The survey questionnaire itself was programmed with *SurveyMonkey*, a professional survey website, and was hosted at *www.energyumd.org*, a domain name acquired specifically for the survey. A contact email address, phone number, and another web address linking to a survey fact page were included to provide support if necessary.[52] Twenty-four phone calls were received while the survey was in the field. These calls were from individuals requiring assistance in locating or completing the survey, or from those who did not have access to a computer but were still interested in participating.[53] Detailed survey materials are included in appendix C.

I anticipated that the survey questionnaire could be completed in approximately 30 minutes without requiring past electricity bills or other information. Indeed, the median completion time was 21 minutes. I note here that my unit of observation is the household: I do not identify whether the survey respondent is the head of the household, or a spouse or co-habitator. The following instruction is included early in the survey to encourage participation on the part of the bill-payer or head-of-household:

In this section of the questionnaire we would like to ask you some questions about the utilities in your home.

If you are not familiar with your household's utility bills, please get some assistance from a person who pays these bills or is familiar with them.

[52] The website, energy.arec.umd.edu , contained basic information about the goal of the survey, contact information for the principle investigators, and links to University administration and human subjects office. A phone number on the recruitment letter and the support website connected to a mobile phone that I carried for the duration of the survey. A support email address likewise forwarded to me.

[53] Six individuals were given phone surveys, one individual was turned away because a written questionnaire was not available and he lacked a computer and sufficient phone resources to cover a 30-minute cell phone call.

There were two separate ‘waves’ of the survey, each composed of 5,000 potential respondents. For each of these 2 waves, an initial invitation letter to participate in the survey was sent, followed by a reminder letter between two and four weeks later. The invitation letter for the first wave was mailed September 16, 2011; the second wave invitation was mailed November 16, 2011. For the first wave only, a second reminder letter was mailed. Enticements were offered to participants of the survey. In wave 1, participants were offered the chance to opt-in to a prize drawing to win one of sixteen $100 gift cards. In wave 2, I offered four $100 gift cards, four $200 gift cards, and one $400 gift card. A table containing the mailing dates and enticement amounts is shown below (table 5.2).

Table 5.2: Sequence of Mailings and Enticements for Survey

	Wave 1	**Wave 2**
Mailing Date		
Invitation	9/16/11	11/16/11
Reminder	10/18/11	11/30/11
Second Reminder	11/2/11	-
Enticements		
$100	16	4
$200	0	4
$400	0	1
Overall Response (%)	12.82	10.07

Data on structural characteristics of the homes in the sample were taken from a state property database. The database includes geo-referenced data for Maryland properties and is maintained by the Maryland State Department of Planning for tax purposes. From the property database, structural characteristics of the home were gathered, including year built, square footage, number of floors, and type of home and construction quality. I merged each dwelling with information about the housing stock and population demographics at the 2000 U.S. Census tract level (which is the most recent at this level of detail). This provides summary neighborhood characteristics, such as income, education, ethnicity, and property structures and values.

The final dataset, matched to structural and census data, contains over 500 variables. For the 10,000 homeowners that were invited to participate in the survey, I have data on the characteristics of their dwellings plus neighborhood characteristics at the Census tract/block group level. I have survey responses, included detailed demographics, for 1,143 households. Descriptive statistics are reported in table 5.4.

A.2 Structure of the Questionnaire

The survey questionnaire is composed of 5 distinct sections. The questionnaire begins by collecting information on the respondent's home and neighborhood (with some neighborhood-related questions serving as "warm-up" questions), and the average cost of heating and cooling the home. The second section of the questionnaire leads the respondent through a battery of questions about recent and future heating, cooling, insulation, and appliance renovations.[54] These questions are designed with skip logic to allow, for example, a respondent with no air conditioning to skip past that section. The third section poses a series of hypothetical questions about appliance replacement, rate of time-preference for money, and risk attitudes. The fourth section focuses on respondent monitoring of electric consumption. The final section elicits demographic information, such as number of occupants and household income.

This chapter focuses on the analysis of two choice experiments under perfect certainty: Choice Experiment 1 asks respondents to choose between hypothetical energy-

[54] Energy-using equipment renovations were grouped into these four categories in the questionnaire.

using appliances, while Choice Experiment 2 asks respondents to choose between a lump-sum and annual payouts. I describe these choice experiments below.

A.3 Choice Experiment 1 (Energy)

Respondents are asked to imagine replacing a generic home appliance, and given a choice between two alternatives:

Imagine that an essential home appliance (for example, refrigerator or washing machine) suddenly broke and needed replacement.

You have narrowed down your options to Appliance A and Appliance B, which are identical to each other and to the Appliance you must replace in every way, except for the differences listed in the table below.

The alternatives vary in three dimensions: Purchase price, energy savings, and lifetime (**Figure** 2): Respondents are randomly assigned to one of 16 choice pairs for question one. The choice is forced (respondents can choose only A or B).

	Appliance A	Appliance B
Final purchase price	$500	$300
Energy Savings per year	$40	$25
Lifetime	10 years	5 years

Figure 2: Screen 1 of choice Experiment 1

Screen 2 of the choice experiment reveals a second choice task in which the respondents are assigned randomly to a separate set of 16 choice pairs (see Table 2):

Suppose instead that you were choosing between the two appliances listed below.

Again, Appliance C and Appliance D would be <u>identical</u> to each other and to the appliance you need to replace, <u>except</u> for the differences listed.

Again, respondents are forced to choose between the two choices, C or D, without being given a status quo or indifference alternative. Approximately 6 % (~ 1/16) of the sample was assigned to each choice pair.

Many choice experiments offer respondents the choice of a status quo. I omitted this alternative for 3 reasons: First, I do not observe the household's status quo. It would be impractical, without collecting additional detail on the specific appliances in the home, to construct a plausible alternative to the choices that were offered, and I judged this to be imprudent given the length of the questionnaire. Secondly, given the limited budget available to design and implement the survey, I wanted to achieve a sufficiently large sample size to estimate the model. As it was not practical to construct a reasonable status quo option, allowing respondents not to choose between hypothetical alternatives (a 'do nothing' status quo option) would risk imperiling the sample size available to estimate a choice model. Finally, I wanted respondents to focus on the choice attributes, not on whether they would make the choice.

Validity of hypothetical choice experiments often depends crucially on the suitability of the assumptions and context. One area where experiments are often criticized is in the effects of framing (intentional or not). Here, respondents are instructed to imagine that an *essential* appliance has broken, and needs replacement. Two examples are provided: a refrigerator and a washing machine. Data on household appliances indicates that these are essential: According to the 2009 American Housing Survey data, 93.4% of U.S. households own a washing machine and 99.8% own a refrigerator. (For the state of Maryland, the percentages are 93.8% and 99.8%, respectively.) In addition, washing machines and refrigerators are appliances that are relatively easy to replace. While a range or stove may also be an essential appliance for most households, replacing it may involve a costly and invasive kitchen modification (for example, counters and cabinets may have to be reconfigured). To avoid conflating the process of replacement with the actual purchase decision, the simpler appliances were displayed.

A second potential issue is with the price and performance of the appliances. An informal survey of appliance retailers found washing machine options ranging from $250 to $1499, and refrigerator options from $200 to over $3000.[55] Data on the appliance prices are not standardized, but these anecdotal numbers compare favorably with the choice pairs offered (Table 5.6). The questionnaire also instructed respondents to assume that the new appliance is identical in all respects to the old one, except for purchase price, lifetime, and savings on energy costs (the choice attributes).

[55] I consulted Best Buy, Home Depot, and Sears, three large appliance retailers in the U.S.

Table 5.3 Choice pairs offered in Experiment 1

	Appliance "A"			Appliance "B"					
Version	Cost	Annual Savings	Lifetime	Cost	Annual Savings	Lifetime	δ*	N	%
1	800	100	13	500	200	8	-0.11	52	4.94
2	1000	100	13	1000	200	8	-0.07	74	7.03
3	800	25	10	1000	40	13	0.04	67	6.36
4	300	40	10	1500	200	17	0.12	72	6.84
5	1000	200	5	1000	40	17	-0.06	67	6.36
6	1500	200	13	500	100	8	0.08	73	6.93
7	500	200	5	300	25	13	0.86	73	6.93
8	300	200	8	1000	100	13	-0.14	69	6.55
9	500	40	10	300	25	5	0.05	57	5.41
10	500	40	5	300	25	5	-0.34	70	6.65
11	1000	200	5	1500	100	10	-0.11	57	5.41
12	500	40	17	300	40	5	0.08	70	6.65
13	500	100	13	300	100	5	0.16	62	5.89
14	1500	200	13	500	40	13	0.13	63	5.98
15	800	40	5	500	25	17	0.43	60	5.70
16	800	200	17	300	25	5	0.36	67	6.36
							Total	1053	
1	300	100	17	500	200	10	-0.02	65	6.17
2	300	25	10	300	40	5	0.1	64	6.08
3	800	200	5	300	40	13	0.08	67	6.36
4	500	40	17	800	100	13	0.17	59	5.6
5	1500	100	10	500	40	5	-0.04	65	6.17
6	800	200	8	300	100	17	0.14	52	4.94
7	1500	100	17	1000	200	10	-0.08	65	6.17
8	500	25	8	800	200	17	0.58	63	5.98
9	1500	100	17	1000	100	8	0.05	56	5.32
10	500	200	5	300	100	10	0.2	64	6.08
11	1000	40	17	800	40	5	0.08	67	6.36
12	1500	200	5	800	100	5	-0.13	83	7.88
13	1500	25	8	800	25	5	-0.34	62	5.89
14	800	25	13	1500	40	10	0.01	79	7.5
15	1500	200	5	1500	100	10	0	67	6.36
16	300	25	10	1500	100	5	-0.03	75	7.12
							Total	1053	

δ* is the discount rate of indifference between Appliance A and Appliance B

A.4 Choice Experiment 2 (money-versus-money)

The second choice experiment focuses on the pure time-money tradeoff. Respondents are given a choice between a lump-sum payment now, and a series of annual payments of randomly assigned amount *X*:

Now imagine that you just won the lottery. The prize is $1000. You have a choice:
- receive $1000 today
- receive 10 annual payments of $X each year

Where "$X" in the questionnaire is a dollar value ranging from $95 to $173 (implying discount rates from -0.01 to 0.11 assuming constant exponential discounting). Respondents are given the choice to take $1000 today, annual payments for 10 years, or indifference: "either – no preference." I assigned respondents at random to one of 7 variants (approximately 14%). The choice and response frequencies, along with indifference discount rates, are given in table 5.4.

Table 5.4 Choice pairs offered in Experiment 2, with indifference discount rate

Lump Sum	Annual Payment	Lifetime	δ*	N	%
1000	95	10	-0.01	131	12.45
1000	100	10	0	146	13.88
1000	105	10	0.01	149	14.16
1000	114	10	0.02	163	15.49
1000	123	10	0.04	154	14.64
1000	148	10	0.08	143	13.59
1000	173	10	0.11	166	15.78
			Total	1052	

δ* is the discount rate of indifference between Annual Payments and Lump Sum

The questionnaire is deliberately structured to mitigate some of the concerns raised in reference to the previous literature on discount rates. Differences in samples limit comparisons (Train 1985), and for this reason I examine the same subjects' responses to the two choice questions above. The influence of household characteristics on the time preference for money will thus be constant across choice questions. The size of the investment, and the length of time over which savings accrue have a large effect on discounting (Thaler, 1981). Here, the annual savings and income between the energy (from $25 to $200) and non-energy settings (from $95 to $173), and the lifetime of over which the savings are realized (from 5 to 17 years, and 10 years, respectively), are very similar.

One area where the two experiments differ is the context (energy-savings from appliances versus generic money). Another difference is that the energy choice experiment requires an up-front investment of money, whereas the income choice experiment does not. I argue that by requiring the respondent to choose an (hypothetical) investment, and generalizing the choice to a generic "essential" appliance, the context allows the respondent to focus purely on the time-money tradeoff in the energy setting, and facilitates an apples-to-apples comparison with choice experiment 2.

Finally, energy efficiency investments are often characterized as highly uncertain, which some argue is the basis for why they are chosen less often than other classes of investments (Greene, 2011). By providing consumers with perfect information on energy savings for a hypothetical appliance, I estimate the direct discount rate for future savings on energy bills.[56] This allows direct comparison to the pure rate of time preference estimated from the money-versus-money choice experiment.

[56] Explicit treatment of uncertainty is handled in another choice task in the survey. Analysis of these data is a subject for future research.

A.5 Characteristics of the Sample

Although efforts were made to survey homeowners based upon exogenous characteristics (*e.g.,* the age of their home), and enticements were offered to increase participation in the survey, external validity and representativeness are always concerns in survey work. My sample is less racially diverse (more White, less Black, Hispanic or Asian), lower income, and with a larger family size than the average Maryland household (table 5.5). Consequently, there may be differences in rate of time preference between my sample and the population at large. Other concerns relate to selection into the survey. A survey respondent with 30 minutes of free time, internet access, and the motivation to complete the questionnaire may differ in important ways from the average American electricity consumer.[57]

Table 5.5 Respondent Comparison to State of MD Population (US Census)

Variable	MD (2010)	Mean	Std. Dev.	Min	Max
White (%)	58.2	76.4	13.37	28	94
Black (%)	29.4	18.7	11.93	3	61
Hispanic (%)	8.2	2.0	1.39	0	6
Asian (%)	5.5	1.6	1.12	0	4
< 6 years old (%)	6.3	6.8	1.44	4	13
> 64 years old (%)	12.3	8.5	3.39	0	20
Household (N Persons)	2.62	2.9	0.20	2.5	3.82
Rent (Median)	698	812.1	182.68	468	1232
< Poverty Line (%)	8.6	5.0	2.88	0	18
Income (Median)	70,647	65050.5	11490.92	37040	99246

[57] In particular, those without access to the internet, and those disinclined to take a 30 minute survey (and unmoved by a chance to win a $100 prize), will largely be missing from a survey following that follows this approach. Non-response bias is a concern in any survey, and, to some extent, the professional survey samples often used for marketing and research purposes suffer from the same criticisms about representativeness.

Table 5.6 Descriptive statistics for survey sample

	Obs	Mean	Std. Dev.	Min	Max
High Income	1038	0.383	0.486	0	1
Low Income	1038	0.114	0.318	0	1
Child	1036	0.408	0.492	0	1
Elderly	1036	0.106	0.308	0	1
High School	1038	0.209	0.407	0	1
Grad School	1143	0.239	0.427	0	1
Small House	1143	0.143	0.350	0	1
Big House	1143	0.197	0.398	0	1
Moved < 5yrs	1143	0.191	0.393	0	1
Going to Move	1143	0.160	0.367	0	1
No Programmable Thermostat	1092	0.193	0.395	0	1
Price Increase	1143	0.532	0.499	0	1
Price Decrease	1143	0.018	0.133	0	1
Home Age 30+	1143	0.327	0.469	0	1
High Winter Bill	1143	0.100	0.300	0	1
Low Winter Bill	1143	0.187	0.390	0	1
High Summer Bill	1143	0.068	0.252	0	1
Low Summer Bill	1143	0.179	0.383	0	1
Low ID # (check)	1143	0.500	0.500	0	1
High Winter bill (no elect)	1086	0.257	0.437	0	1

A series of dummy variables was created to explore the dependence of discount rate on household characteristics (table 5.6). *High Income* and *Low Income* signify a household income above $120,000 per year (38% of the sample), or below $50,000 per year (11% of the sample), respectively. The dummy variables *Child* and *Elderly* signify whether there is a dependent child (40% of the sample) or an adult over 65 years of age in the household (11% of the sample). Education level is represented by a dummy variable indicating whether the maximum education attainment was at the high school level or below (*High School,* 20% of the sample), or whether they achieved a post-graduate degree (*Grad School,* 24% of the sample).[58] The size of the dwelling is captured with the variables *Big house* and *Small house*, indicating a square footage of above 2500 (20% of the sample) or below 1200 sq. feet (14% of the sample).

As discussed in Chapter 4, tenure is important to energy consumption and investment decisions; I create a dummy variable for those that have moved within the past 5 years (19% of the sample), or who report that they will definitely move in the next 5 years (16% of the sample). Although most of the survey respondents indicate that they have a programmable thermostat in their home (or that they do not know whether they do), I create the dummy variable *no_ptstat* for those that report not having one (19% of the sample). As one of the most simple and cost-effective energy changes you can make to your home, the absence of a programmable thermostat may indicate neglect of energy efficiency in general, or inability to implement even simple energy efficiency measure.

Price expectations are captured in two dummies, *Price Increase* and *Price Decrease*, which take a value of 1 when the respondent reports that they expect an electricity price increase (decrease) in the coming year, and zero otherwise (53% and 1.8% of the sample, respectively). The age of the home is positively correlated with the need for energy investment, and therefore, possibly inversely correlated to discount rate for energy. Homes built before 1980, *Home Age 30+*, account for 32% of the sample. In the survey, respondents were asked to report the average amount of their winter and summer electricity bills. *Low Winter Bill* and *Low Summer Bill* indicates a bill of less than $100 (19% and 18% of the sample, respectively), and *High* (*Winter* or *Summer*) *Bill*

[58] This refers to education level of the *respondent*. I treat the respondent as the head of the household, but this is not a critical assumption. Questions about intra-household relationships were excised to limit the length of the survey; As discussed in Chapter 3, I encourage somebody who is familiar with the energy usage of the home (*e.g.,* a bill-payer or head of household) to assist or complete the questionnaire directly.

indicates a bill of more than $400 (10% and 7% of the sample, respectively). *High Winter Bill (non-elec)* indicates a reported non-electric heating bill of more than $1000 for the entire winter (5% of the sample). Finally, as a robustness check, *Low ID* indicates that the respondent has an (randomly assigned) ID number in the lower half of the distribution. This dummy variable has no relation to any meaningful observable characteristic of the respondent, and is thus statistically insignificant by design.

After completing Choice Experiment 1 in the survey questionnaire, respondents were asked to use a Likert-type scale to rate the importance of each of the appliance attributes (price, appliance lifetime, and annual energy savings) in shaping their decision. Options ranged from 1 "Not important at all" to 5 "Very important" (See Appendix C, Figure 3). Using these ratings, variables were created to classify the relative importance of the attributes to the respondent. For example, *Pricemost* (20.5%) is a dummy variable which takes a value of 1 if price has the highest rating, and 0 otherwise. *Lifemost* (13.6%) and *Savemost* (7.3%) were constructed in a similar fashion. Likewise, dummy variables were created to indicate that one of the attributes was "not at important at all" to the decision (a rating of 1): *Pricenot* (0.1%), *Lifenot* (0.7%) and *Savenot* (0.8%) (Table 5.5).

At the close of the questionnaire, respondents are asked to rate, again using a Likert-type scale, their level of agreement of several statements about energy and energy efficiency (1 for "Strongly disagree" to 5 for "Strongly agree", Figure 4 in Appendix C). Dummy variables were created to indicate that the respondent strongly agrees or disagrees with each of the following statements (Table 5.7):

- *"*I view energy efficiency as a money saving investment." Strongly disagree: *EE Invest (no)* (1.1%), strongly agree: *EE Invest (yes)* (54.6%)
- *"*I regularly look for ways to save on my energy usage" –strongly disagree: *EE Save (no)* (1.3%), strongly agree: *EE Save (yes)* (34.8%)
- "The resale value of an energy-efficient home is higher." – strongly disagree: *EE Resale (no)* (1.7%), strongly agree: *EE Resale (yes)* (29.9%)

Table 5.7 Descriptive statistics for rating variables

	Obs	Mean	Std. Dev.	Min	Max
Price most important	1038	0.205	0.404	0	1
Lifetime most important	1038	0.136	0.343	0	1
Savings most important	1038	0.073	0.261	0	1
Price not important	1049	0.010	0.097	0	1
Savings not important	1048	0.007	0.081	0	1
Lifetime not important	1043	0.008	0.087	0	1
EE Invest (yes)	1042	0.546	0.498	0	1
EE Invest (no)	1040	0.011	0.102	0	1
EE Save (yes)	1044	0.348	0.476	0	1
EE Save (no)	1044	0.013	0.115	0	1
EE Resale (yes)	1041	0.299	0.458	0	1
EE Resale (no)	1041	0.017	0.130	0	1

B. Model and Estimation

The focus of this research centers on the estimation of consumer rate of time preference rates. Using the responses to the hypothetical choice questions, I estimate a model of an energy efficiency investment in the home (section B.1), and a pure money-time tradeoff (B.2).

B.1 Discounting Future Energy Savings

I assume that the responses to the choice questions are driven by the consumer's indirect utility: $U_{ij} = V_{ij} + \epsilon_{ij}$ where V_{ij} is the utility for individual i for choice j, which is a function of the attributes of the alternative, and ϵ_{ij} is the error term. The consumer will select the alternative *j* that maximizes utility. The probability of selecting a particular choice is:

$$Prob_{ik} = Prob\left(V_{ik} + \epsilon_{ik} > V_{ij} + \epsilon_{ij}\ ,\quad \forall\, j \neq k\right) \tag{5.1}$$

If the error term is independent and identically distributed as Type 1 Extreme value, with a scale of 1, the probability of selecting choice *k* becomes:

$$Prob(k) = {exp(V_{ik})}\Big/{\sum_j \exp(V_{ij})} \tag{5.2}$$

Assuming that the survey responses to the hypothetical choice questions follow the random utility model, and that purchase price (capital cost), C, and appliance savings (operating cost), Σ, are additively separable, I write the indirect utility equation as:

$$V_j = \beta_1 C_j + \ \beta_2 \Sigma_j \tag{5.3}$$

where β_1 and β_2 are the marginal utilities of money. I assume constant exponential discounting.[59] The discounted flow of savings from the hypothetical appliance is:

$$\Sigma = \left[1 - e^{-\delta T}\right] {S}/{\delta} \tag{5.4}$$

I estimate the following model to identify the discount rates for energy savings (5.5):

$$V_j = \beta_1 C_j + \beta_2 \ {S_j}\Big/{\delta_E} \left(1 - e^{-\delta_E T_j}\right) \ \ ,\ \ j = A, B \tag{5.5}$$

To identify my model, I need to place additional restrictions on the parameters. The coefficient on project cost, $-\beta_1$, and the coefficient on discounted present value of

[59] Recent evidence indicates consumers having non-constant discount rates, particularly in contexts with very short-term contexts (*e.g.,* tomorrow versus one year from now, Frederick *et al.*, 2002). Appliance lifetimes are sufficiently long (10-20 years) to mute that effect. In the money-versus-money context, this issue is more of a concern, but I argue that the familiar lottery context ('upfront vs. annual payments') and sufficiently large payout ($1000) are enough to approximate a constant time rate of preference for money.

energy savings, β_2 can be interpreted as the marginal utility of money. Assuming that consumers assign the same marginal utility to costs as they do to savings, then the coefficients on purchase price and discounted savings should be equal (with opposite signs). To estimate the discount rate of energy savings, I impose the restriction $\beta_2 = -\beta_1$.

To investigate the effect of individual characteristics on discount rate, I amend the discount rate to make it a function of household characteristics. For example, I estimate a model where: $\delta_i = \delta_0 + \delta_1 \cdot D_i$, where D_i represents high or low income, education, age, electricity usage, or tenure in the home.

B.2 Discounting Future Income

In the money-versus-money experiment (Choice Experiment 2), the respondent is assumed to have utility only over income, and that the choice responses follow the random utility model. The indirect utility is: $V_j = \beta_1 S_j + \epsilon_j$, where S is equal either to \$1000 for the lump-sum payment, or the present value of future payments for the disbursement option.

Recall that one of the choice alternatives for Choice Experiment 2 is "no preference" between the lump-sum payout and annual payments. Approximately 5% of the sample (55 respondents) chose this option, indicating indifference between the two options.

For each lump sum – payout pair, I first calculate the discount rate for which the two are equivalent (the indifference discount rate, δ_i^*) by setting equation 5.4 equal to the \$1000 lump sum and solving. Assuming that individual discount rate is normally distributed: $\delta_i \sim N(\delta, \sigma^2)$, I write the probability that the respondent chooses the lump sum over the annual payouts:

$$\Pr(lump\ sum) = Pr(\delta_i > \delta_i^*) = Pr(\delta + \varepsilon_i > \delta_i^*) =$$

$$Pr\left(\frac{\varepsilon_i}{\sigma} > \frac{\delta_i^* - \delta_i}{\sigma}\right) = \Phi\left(\frac{\delta_i - \delta_i^*}{\sigma}\right) = \Phi(\alpha + \beta\delta_i^*) \qquad (5.8)$$

where $\alpha = {}^{\delta}/_{\sigma}$ and $\beta = {}^{-1}/_{\sigma}$. Similarly, the probability of choosing annual payouts over the lump sum is:

$$\Pr(payouts) = Pr(\delta_i < \delta_i^*) = \Phi(-\alpha - \beta\delta_i^*) \qquad (5.9)$$

Indifference implies that the respondent's personal δ_i is approximately equal to δ_i^* and that this person's contribution to the likelihood is the normal density evaluated at: $\frac{1}{\sigma}\varphi(\alpha + \beta\delta_i^*)$.

The log likelihood function is:

$$\log L = \sum_{i\epsilon\ SL} log\,\Phi(\alpha + \beta\delta_i^*) + \sum_{i\epsilon\ SP} log\,[1 - \Phi(\alpha + \beta\delta_i^*)] + \sum_{i\epsilon\ SI} log\,\frac{1}{\sigma}\varphi(\alpha + \beta\delta_i^*)$$

where *SL*, *SP*, and *SI* indicate lump sum, annual payments, and indifference, respectively. I estimate this model using Maximum Likelihood Estimation. I also include discount rate interactions, as in section B.1. The results are reported in table 5. 13 – table 5.15.

C. Results

C.1 Comparison of Discount Rates

The first research task was to estimate individual discount rates for energy savings and for money. Table 5.8 reports discount rates calculated for energy savings and for money. In column (A), I estimate the discount rate for energy savings. It is approximately 0.025 (p-value 0.05). In column (B), I report the discount rate for money from the lottery question, approximately 0.08 (p-value < 0.001). These discount rates are individually statistically significant, and I soundly reject the hypothesis that the rates are equal (t-statistic of 186).[60]

Table 5.8 Discount rate estimates

	(A)	(B)
Model	**Energy**	**Money**
Conditions	B1 = -B2	(none)
Beta1	-0.00149*** (0.000121)	
Beta 2	0.00149*** (0.000151)	
Beta 3		0.131*** (0.0071)
Delta (energy savings)	0.0246* (0.0125)	
Delta (income)		0.0829*** (0.0062)
Log-likelihood	-1255.527	-313.255
N Obs	2092	1052

Notes: (1) standard errors in parenthesis;
(2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

While the estimate of the discount rate for money (0.08) is in line with the estimates in other studies, the estimate for the discount rate for energy savings is lower than those reported in previous studies (see Train, 1985). My findings, however, are consistent with Train's point that discount rates in the energy context are lower when based on hypothetical choices. Moreover, whereas the energy efficiency paradox posits that consumers apply a higher discount rate to energy savings than to money, I find the opposite: the estimate for the energy savings discount rate is *lower* than the discount rate for money. This is a striking result. In a recent working paper, Alberini, Banfi, and

[60] To alleviate concern that the difference is discounting is driven by formulaic assumptions, I re-estimate the models using alternative discount formulations. I find that although the rates themselves vary, but the difference between them is robust these alternative models.

Remseier (2011) estimate similar discount rates for energy savings using a choice experiment for hypothetical renovations in Swiss households. They reason that such a low discount rate for energy savings may be attributable to the absence of uncertainty or the abstract context of the hypothetical choice question. Yet both of these circumstances apply to the choice experiment for income, suggesting that the idea that consumers discount energy savings at a greater rate than money should be viewed with caution.

C.2 Interaction of Discount Rate with Sample Characteristics – Energy Savings

To understand how rate of time preference for energy savings varies with household characteristics, I interact discount rate with selected variables in table 5.9 – table 5.12. I include both single interactions (i.e. $\delta = \delta_0 + \delta_1 D_1$) and specifications with multiple interactions ($\delta = \delta_0 + \delta_1 D_1 + \delta_2 D_2 + \delta_3 D_3 + \cdots$).

Income is often thought to be an important determinant of rate of time preference (*e.g.,* Hausman, 1979, Curtis, 2002). I find that income level significantly determines discount rate for energy savings, in the direction expected. Lower income households have a higher discount rate for energy savings than the rest of the sample. For rich households, the effect is the opposite. The effects are similar, although not statistically significant, for the discount rates estimated in the money-versus-money choice.

Education plays a limited role in discounting, with education level inversely correlated to discount rate. The effect is only significant in the money-versus-money setting: those with a high school education have an increased discount rate, whereas highly educated households (with a graduate degree) discount less.

Table 5.9 Discount (Energy) Interactions with Household Characteristics

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Beta1	-0.0015*** (0.00011)	-0.0015*** (0.00012)	-0.0015*** (0.00011)	-0.0015*** (0.00011)	-0.0015*** (0.00012)	-0.0015*** (0.00011)	-0.0015*** (0.00012)
Beta2	0.0015*** (0.00011)	0.0015*** (0.00025)	0.0015*** (0.00017)	0.0015*** (0.00018)	0.0015*** (0.0002)	0.0015*** (0.00016)	0.0015*** (0.00015)
Delta (energy)	0.0161* (0.00754)	0.0354 (0.0278)	0.0232 (0.0145)	0.0227 (0.0181)	0.0287 (0.02)	0.0222 (0.0144)	0.0221 (0.0128)
Low Income	0.0544* (0.024)						0.0528* (0.0244)
High Income		-0.0328* (0.0156)					
Elderly			-0.00816 (0.0208)				-0.0115 (0.0206)
Child				-0.00048 (0.0128)			
Grad School					-0.0221 (0.0143)		-0.0168 (0.0136)
High School						0.00173 (0.0163)	
Log-likelihood	-1217.759	-1218.025	-1221.28	-1221.352	-1220.088	-1221.347	-1216.815
LR test	400.84	400.308	393.797	393.654	396.183	393.663	402.727
N Obs	2046	2046	2046	2046	2046	2046	2046

Notes: (1) standard errors in parenthesis; (2) significance level * p<0.05 ** p<0.01 *** p<0.001

Recent movers are also seen to have a lower discount rate for energy than the sample at large (the effect is not statistically significant on income). This may be because certain recent movers make renovations and appliance purchases as part of their relocation, and are thus more patient with appliance-related savings than those who have not engaged in such efforts.

Table 5.10 Discount (Energy) - Interactions with choice characteristics

	(A)	(B)	(C)	(D)	(E)	(F)
Beta1	-0.00153*** (0.000113)	-0.00152*** (0.000115)	-0.00152*** (0.000115)	-0.00154*** (0.000115)	-0.00152*** (0.000114)	-0.00155*** (0.000124)
Beta2	0.00153*** (0.000162)	0.00152*** (0.000189)	0.00152*** (0.000183)	0.00154*** (0.000177)	0.00152*** (0.000181)	0.00155*** (0.000151)
Delta (energy)	0.0152 (0.0141)	0.0251 (0.0181)	0.0244 (0.0169)	0.0302 (0.0166)	0.0249 (0.0168)	0.0289* (0.0139)
Incentives Group	0.033* (0.0164)					0.0291 (0.0168)
Yes rebate		-0.0106 (0.0146)				
No rebate			-0.0126 (0.0171)			-0.013 (0.0164)
Recent Mover				-0.0437** (0.0155)		-0.0404** (0.0151)
Going to Move					-0.0133 (0.0158)	-0.0199 (0.0152)
Log-likelihood	-1219.076	-1221.085	-1221.085	-1217.648	-1221.008	-1215.125
LR test	398.206	394.188	394.189	401.062	394.343	406.109
N Obs	2046	2046	2046	2046	2046	2046

Notes: (1) standard errors in parenthesis); (2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

Expectations of electricity price changes influence the discount rate in a surprising way. Those reporting that they expect electricity prices to increase in the next year have a significantly higher discount rate than those that do not. This suggests that something other than simple energy savings is driving the discounting behavior of these individuals. The price rise group may not be representative of the entire sample, as the converse of the relationship does not hold: those reporting that they expect the electricity price to decrease do not exhibit a lower discount rate than the sample.

Table 5.11 Discount (Energy) - Interactions with bills and price expectations

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
Beta1	-0.0015*** (0.00011)	-0.0015*** (0.00012)	-0.0015*** (0.00011)	-0.0015*** (0.00011)	-0.0014*** (0.0001)	-0.0015*** (0.00011)	-0.0015*** (0.00012)
Beta2	0.00152*** (0.000172)	0.00153*** (0.000189)	0.00153*** (0.000173)	0.00154*** (0.000163)	0.00143*** (0.0001)	0.00152*** (0.000165	0.00153*** (0.000151)
Delta (energy)	0.0236 (0.0152)	0.0273 (0.0178)	0.026 (0.0156)	0.0152 (0.0136)	- -	0.0213 (0.0141)	0.0274* (0.013)
Low Summer Bill	-0.0208 (0.026)						
High Summer Bill		-0.0346* (0.0175)					-0.0146 (0.018)
High Winter Bill			-0.026 (0.0184)				-0.028 (0.0179)
Low Winter Bill				0.0704* (0.0283)			
Price Increase					0.0218* (0.00918)		
Price Decrease						0.0511 (0.0548)	0.0437 (0.0536)
Log-likelihood	-1221.063	-1219.47	-1220.315	-1216.293	-1222.933	-1220.7	-1218.643
LR test	394.232	397.419	395.729	403.773	390.492	394.959	399.072
N Obs	2046	2046	2046	2046	2046	2046	2046

Notes: (1) standard errors in parenthesis; (2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

Interestingly, the self-reported average electricity bill seems to be important in explaining discounting. A high winter or summer bill for electricity seems to be negatively correlated with discount rate. A higher bill might indicate a greater appetite for efficiency improvements, and this would tend to lower the discount rate compared to the sample at large, but the mechanism would not apply to the money-versus-money discount rate.

Efficiency attitudes did not play an important role in discounting for energy savings. None of the dummy variables created to account for attitudes towards energy efficiency are significant in explaining the discount rate for energy savings, and the signs of the coefficients are not consistent or intuitive (Appendix, Table AC.1).

In contrast, attribute rankings from Choice Experiment 1 have a significant influence on the discount rate for energy savings. Respondents that ranked price as the most important attribute in their decision had a significantly higher discount rate than the sample, and those that rated price as "not important at all" (*Pricenot* = 1) had a significantly lower discount rate. The role of the appliance lifetime was the reverse: those indicating that lifetime was the most important had a lower discount rate (those indicating the lifetime was not important at all had a much higher, but statistically insignificant discount rate). In this way, appliance price and lifetime play a similar role to income and education in the rate of time preference: those concerned more limited resources tend to be more concerned about upfront costs than operating costs (high discount rate), whereas those with higher income place greater value on durability (lower discount rate).

Meanwhile, the role of potential appliance savings was less clear. Those indicating that savings were the most important attribute tended to have a higher (though not significantly so) discount rate, while those that indicated savings was not important at all had a much lower discount rate than the average respondent. Because the categories are not mutually exclusive, it is difficult to say with certainty what distinguishes those that do not value energy savings from other groups; it could be that durability is the only attribute that concerns them, and they are willing to pay any premium for it, or it could be that the range of energy savings offered in the Choice Experiment were all of sufficient improvement that the choices were made based entirely upon the other attributes. This will be a topic for future research.

Table 5.12 Discount (Energy) - Interactions with energy investment attitudes

	(A)	(B)	(C)	(D)	(E)	(F)
Beta1	-0.00157*** (0.000118)	-0.00193*** (8.90E-05)	-0.00152*** (0.000124)	-0.00153*** (0.000115)	-0.00191*** (0.000113)	-0.00156*** (0.000126)
Beta2	0.00157*** (0.000192)	0.00193*** (4.07E-05)	0.00152*** (0.000153)	0.00153*** (0.000174)	0.00191*** (0.000113)	0.00156*** (0.000154)
Delta (energy)	0.0356* (0.0182)	- -	0.0236* (0.0124)	0.0242 (0.0152)	- -	0.0229 (0.0121)
Lifetime most important	-0.0953*** (0.0163)				-0.052*** (0.0109)	
Price most important		0.315** (0.101)			0.32** (0.0984)	
Savings most important					0.0224 (0.0178)	
Savings not important			-0.175** (0.0615)			-0.141* (0.0647)
Price not important				-0.107** (0.0347)		-0.11** (0.0337)
Lifetime not important						0.384 (0.452)
Log-likelihood	-1184.565	-1123.119	-1197.916	-1198.693	-1118.572	-1195.531
LR test	420.095	542.986	393.393	391.839	563.171	409.253
N Obs	2012	2012	2012	2012	2020	2020

Notes: (1) standard errors in parentheses; (2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

C.3 Interaction of Discount Rate with Sample Characteristics – Money

Turning to the discount rate for money (Choice Experiment 2), I find that the household characteristic interactions, while generally insignificant, are intuitive (table 5.13 and 5.14). Lower income households apply a greater discount rate to money, while higher income households apply a lower rate. The education level of the household works in much the same fashion, as lower education leads to higher discounting and vice versa. In column (A) of table 5.13, high school education significantly increases the discount rate for money.

Table 5.13 Discount (Money) - Interactions with household characteristics

	(A)	(B)	(C)
Intercept	0.1303*** (0.0093)	0.1319*** (0.008)	0.1341*** (0.0087)
Delta (money)	0.0841*** (0.0065)	0.0823*** (0.0062)	0.0838*** (0.0064)
Low ID	-0.0057 (0.0082)		
High Income	0.0019 (0.0086)		-0.0029 (0.0084)
High School	0.0235* (0.0114)		
Graduate School		-0.0162 (0.0089)	
Elderly		-0.0044 (0.0132)	
Price Decrease		-0.0106 (0.0283)	
No programmable thermostat		0.0202 (0.0109)	
Incentives Group			0.0027 (0.0106)
Recent mover			-0.0068 (0.0102)
Log-Likelihood	-310.198	-305.919	-312.429
BIC	655.122	653.496	659.583
N Obs	1038	1036	1038

Notes: (1) standard errors in parentheses;
(2) significance level * p<0.05 ** p<0.01 *** p<0.001

Further regressions yield a significant relationship with *Pricemost*, the variable that indicates that the price of the hypothetical appliance was the most important factor in the investment decision (table 5.14). The interaction works in the same way as low income or low education: a household that is concerned most about price is likely to be credit constrained, and thus will be impatient when evaluating long time-horizon investments. The discount rate is more than one-third higher, on average, than the rest of the sample.

Table 5.14 Discount (Money) - Interactions with choice characteristics

	(A)	(B)
Intercept	0.1232*** (0.0088)	0.1319*** (0.0075)
Delta (money)	0.0824*** (0.0063)	0.0835*** (0.0064)
Going to move	0.0045 (0.0108)	
Child	0.0057 (0.0083)	
Price most important	0.032** (0.012)	
Life most important	-0.0041 (0.0116)	
Savings most important	-0.0095 (0.0148)	
Low Income		-0.0076 (0.0125)
New Mover Group		0.0117 (0.0162)
Log-Likelihood	-296.351	-312.303
BIC	641.175	652.387
N Obs	1017	1038

Notes: (1) standard errors in parenthesis;
(2) significance level * $p<0.05$ ** $p<0.01$ *** $p<0.001$

D. Conclusions

Differential discounting of energy and non-energy investments is at the heart of the debate over the energy-efficiency paradox. There are a host of market failures and behavioral reasons why consumer investment behavior might differ between energy and non-energy settings (Howarth and Sanstad, 1995). The empirical literature on energy rate of time preference reports a wide range of individual discount rates (Train, 1985). Yet direct comparisons between energy and non-energy discounting are rare. If consumers truly favor non-energy investments over energy investments, estimates of direct discounting for comparable investments should reflect this.

In this essay, I ask three research questions: (1) at what level to consumers discount future energy savings, (2) do consumers discount energy savings differently from income, and (3) is the discounting difference explained by house and household characteristics? Using data from two choice experiments and a sample of homeowners in Maryland, I estimate a discount rate for energy savings of 0.02, and a discount rate for money of 0.08. I find these estimates to be statistically distinguishable from zero and standard levels of significance, and to be significantly different from each other, for the difference to be robust to various specifications. Suggestively, in contrast to the energy efficiency 'paradox' literature, I estimate that the discount rate for energy is not only different, but lower than the discount rate for money.

In terms of characteristics that explain discount rates, I find evidence that income and education are significant in explaining discount rates, and the relationship is intuitive: higher income, more educated households tend to have lower discount rates. I find that self-reported sensitivity to the price, lifetime, or savings in the evaluation of the hypothetical investment explained time rate of preference in a consistent and intuitive way: those reporting the highest sensitivity to price displayed a higher discount rate, while those to whom lifetime was most important, or to whom savings was not important, displayed a lower discount rate.

Recent movers were seen to display a lower discount rate, suggesting that they may be more likely to invest in efficient durable goods, given an expectation that they will not move again soon. I find further that the estimates of discount rates are robust to membership in one of the choice-based subgroups that comprise my sample, suggesting that systematic bias does not influence my results. Clearly, this is an exciting area for future research.

Chapter 6: Conclusions

Good stewardship of the planet's natural resources is the central challenge of our age. The world's (predominantly fossil-fueled) energy consumption, and the attendant environmental and geopolitical consequences, frame this challenge amongst a host of competing interests, policy initiatives, and consumer behaviors.

A large and growing fraction of all energy usage occurs in homes. According to recent figures, Americans spend, on average, \$1800 annually on energy (5% of the median household income). Despite its economic importance, it has been difficult for analysts to identify *which* price consumers are responding to (Ito, 2010, Borenstein, 2009). In a variety of settings, consumers have been shown to forgo profitable energy efficiency investment, or to be influenced by consumption feedback (Allcott, 2010; Gans *et al.*, 2011). Possible explanations for this behavior include information asymmetry, split incentives, and the difficulty of monitoring energy consumption.

Over the last few decades, many government policies have been targeted at residential energy usage, but evidence about the effectiveness of these measures is limited. Undoubtedly, a greater understanding of residential energy consumption and investment behavior would improve government policy. In this dissertation, I analyzed three key aspects of residential energy behavior.

First, in Chapter 3, I estimated a residential demand function for electricity and natural gas on a nationwide panel of U.S. homes. I merged recent longitudinal household data drawn from the American Housing Survey from 1997 to 2007, with weather data and information about energy prices and the utilities serving each area covered by the sample. My regressions explain energy consumption well. Electricity and gas demand depend on home and household characteristics, such as size and age of the home and level of income of the family. Importantly, however, my models (a static and partial adjustment model) allow me to identify both short-term and long-term price elasticities of demand, which are much higher than previously appreciated. These results suggest that residential consumers *are* price responsive, even in the short-term, and that price-based policies can be an effective tool to promote energy conservation and investment in energy efficiency.

In Chapter 4, I specifically focus on residential investment in energy efficiency renovations and improvements. Again using a panel of U.S. homes based upon the American Housing Survey, and with the addition of the year 2009 data, I estimate a series of demand functions for energy appliances. Significantly, because the AHS follows homes, not households, and because I have a relatively long panel length (up to 9 periods), I can identify a model that explains energy efficiency investments with a decision to move or stay within the house. I specifically focus on heating systems, since these are durable, long-lived goods that are generally replaced with new (and more efficient) ones. I find the first empirical evidence of split incentives between movers and stayers, and estimate that households that move within 2 years are 20% less likely to invest in heater renovations or replacements. Strikingly, there is no statistically significant relationship between moving or staying and other classes of investment, such as kitchen renovations or yard repairs, suggesting that homeowners do not believe that energy efficiency is capitalized into the value of the home.

This has very important policy implications: Requiring disclosure about the energy efficiency of a home during the sales transaction may alleviate this disincentive.

Indeed, recent evidence (Brounen and Kok, 2011; Eichholtz *et al.,* 2010) suggests that signals about the energy efficiency of a building tend to raise it selling price. For the U.S., calculations show that eliminating the information asymmetry between the buyer and the seller may reduce emissions of CO_2 by 900,000 metric tons or more annually.

In any potential investment, consumers weigh the costs and benefits of a purchase. For investments that offer an efficiency improvement on the status quo, consumers must value the efficiency premium, i.e., the additional upfront cost that translates into reduced operating costs later. Earlier research suggested that residential consumers mispriced this efficiency by applying higher discount rates to potential energy savings than they did to other investment types. In Chapter 5, I use data from an original survey of households to examine how consumers value future savings from energy bills *vis-à-vis* money paid now. I gather original survey data from homeowners in Maryland and directly estimate the rate of time preference from choice experiments in two settings: a hypothetical energy efficiency investment, and a money now-versus-later scenario. I find that consumers apply a *lower* discount rate to energy savings than to money. Other factors thought to influence discount rate (Train, 1985), such as income and education, are seen to have an effect. This result suggests that market failures, rather than consumer values, may be responsible for a low rate of residential energy efficiency investment.

These findings are a contribution to the understanding of residential energy consumption and investment behavior, and underscore the potential for intelligent policy to influence behavior and achieve energy efficiency goals.

Appendices

Appendix A: Notes for American Housing Survey Data

Note on price Estimation

Both our estimate of price and the consumer estimate include taxes paid by consumers. In the AHS survey, consumers are asked to report the average monthly amount paid for electricity, natural gas, and other fuels. This value captures the after-tax amount. Calculations for energy prices based upon the Energy Information Agency forms 861 and 176 estimate a city-level price for energy: dividing total retail revenues (which includes tax) by delivered service (total electricity or natural gas).

Note on square foot imputation

The square footage of the home is an important driver of energy consumption in the home. In the AHS data, square footage estimates are derived from the variable *unitsf*, the respondent's estimate of the living area (climate-controlled, finished) of their home. If one is not given, the interviewer is asked to make an estimate of the home size. If that is not possible, the square footage is imputed subsequently based upon comparable homes (these 'hot-decked' observations are not included in our analysis, see below). Nevertheless, there is wide variation in the housing size estimates recorded in *unitsf*, even accounting for self-reported renovations and home additions, which influence the size of the home. For this reason, additional steps were taken to normalize the value of housing square footage.

First, the square footage of the home was compared to a variable denoting whether renovations or improvements to the home had resulted in a change of square footage (SFCHG). If this dummy variable was zero (no change in square footage), but the estimate of square footage was blank, we re-entered the previous value for square footage. Likewise, if no subsequent change in square footage is reported, the previous value is entered. Observations that are missing an estimate of square footage, and report a qualifying renovation in the first year in which square footage is changed, are given a missing value for square footage.

Note on unit type

Several classes of units exist within the AHS data: mobile homes, apartments or condos in multi-dwelling buildings, attached homes, and detached or semi-detached homes. Our study focuses on single-family detached or semi-detached dwellings. Using the 'TYPE" variable, we select living quarters corresponding to answer 1, which is "house, apartment, or flat". This step excludes mobile homes, hotels and temporary dwellings. We also use the variable "NUNIT" and select only living quarters that reflect "one-unit building, detached from any other building", or "one unit building, attached to one or more buildings". These constraints explicitly exclude the remaining answers (3: "building with two or more apartments", and 4: "manufactured (mobile) home"). Finally, we select on the variable "NUNITS" which is the number of units in the building. For reasons spelled above, we select only observations with a value of "1".

Note on price Estimation

Both our estimate of price and the consumer estimate include taxes paid by consumers. In particular, consumers are asked to report the average monthly amount paid for electricity, natural gas, and other fuels. This value captures the after-tax amount. The estimates for prices obtained from the Energy Information Agency forms 861 and 176 calculate a city-level price for energy by dividing total retail revenues (which includes tax), divided by delivered service (electricity or natural gas). These price estimates don't capture specific utility rate-plan differences, but they are not systematically biased by a tax exclusion. The difference in prices is reported in the graphic below.

Note on square foot imputation

The square footage of the home is an important driver of energy consumption in the home. In the AHS data, square footage estimates are derived from the variable *unitsf*, which records the estimate of finished living space given by the respondent, (or if one is not given, the interviewer is asked to make an estimate). If an estimate is not available, the square footage is imputed subsequently based upon comparable homes (these 'hot-decked' observations are not included in our analysis, see below). Nevertheless, there is wide variation in the housing size estimates recorded in *unitsf*, even accounting for self-reported renovations and home additions which influence the size of the home. For this reason, additional steps were taken to normalize the value of housing square footage.

In particular, the square footage of the home was compared to a variable denoting whether renovations or improvements to the home had resulted in a change of square footage (SFCHG). If this dummy variable was zero (no change in square footage), but the estimate of square footage was blank, we re-entered the previous value for square footage. This was conducted year-by-year throughout the sample, resulting in 2327 additional square footage observations (7518 remain missing).

Note on unit type

Several classes of units exist within the AHS data: mobile homes, apartments or condos in multi-dwelling buildings, attached homes, and detached or semi-detached homes. Our study focuses on single-family detached or semi-detached dwellings. For this reason, the 'TYPE" variable is used to select out some of the other categories. In particular, the question asks: 'Are your living quarters in a…?' and we select values only corresponding to answer 1, which is "house, apartment, or flat". This step excludes mobile homes, hotels and temporary dwellings. We also select using the variable "NUNIT" which asks "these living quarters in a" and we keep observations with answers reflecting either: "one-unit building, detached from any other building", or "one unit building, attached to one or more buildings". This selection explicitly excludes the remaining answers (3: "building with two or more apartments", and 4: "manufactured (mobile) home"). Finally, we select on the variable "NUNITS" which is the number of units in the building. For reasons spelled above, we select only observations with a value of "1".

Note on dropping observations

1. To prepare the sample for estimation, any 'hot-decked' observations for the variables used in the regressions were discarded. 'Hot decking' consists of imputing missing observation values based upon comparable individuals.

2. Observations that self-described as a timeshare, or unsuitable for year-round habitation, were dropped.

3. Observations that experienced a change in the amount of energy or gas used varied by more than 500% in any successive period, when there was no reported renovation in the home and the square footage had not changed.

4. Homes that experienced a 10-fold change in square footage in any successive period, or with a change in square footage of more than 100% without a reported renovation to the home, were discarded.

5. Homes with a reported square footage in excess of 10,000 sq. ft. or less than 400 sq. ft. (roughly the bottom and top 5% of the distribution) were dropped.

This procedure resulted in a reduction of observations from 120,333 to 98,772.

Appendix B: Additional Robustness Regressions from Chapter 4

Table AB.1 Any heater investments on different samples

Dependent	any heat investment (heater or water heater)						
Periods	97-01 (A)	7-Mar (B)	97-99 (C)	7-May (D)	2 periods (E)	6 periods (F)	All (G)
movenext	-0.152	-0.275*	-0.242*	-0.654**	-0.229	-0.564	-0.167
lamte_r	-0.00142	0.0128	-0.00523	0.0144	0.00633	0.0153	0.00271
lamtg_r	0.0149**	0.000894	0.0142*	-0.00442	0.0119	-0.00287	0.0109*
lzinc2_r	0.00259	0.00291	0.00234	-0.00047	-0.000856	-0.000086	0.00265
dep_child	0.0046	0.00473	-0.00149	0.00433	0.00899	-0.0136	0.00422
zadult	-0.00182	-0.0119	-0.00142	-0.0236*	0.00327	-0.0114	-0.00384
elderly	-0.0168	-0.00552	-0.0270*	0.00518	-0.03	-0.0131	-0.0102
youngest	0.00019	0.0000383	0.0000625	-0.000376	0.000705*	0.00000568	0.000116
nworkers	0.00609	0.00574	0.00361	0.00609	0.0124	0.00445	0.00609
collegegrad	0.0217	0.0272	0.0272	0.0295	0.0382	0.0239	0.0235**
postgrad	0.0227	0.0318*	0.0176	0.0289	0.0216	0.0159	0.0265**
lhdd	0.0132*	0.0154	0.0102	0.0363**	0.00617	0.00999	0.0102*
labor_wage_r	-0.00313*	-0.00477**	-0.00245	-0.00760**	-0.00767**	-0.00271	-0.00421***
hpi	-0.000141	-0.00016	-0.000000777	-0.000098	-0.0000526	-0.000164	-0.000158*
lsqft	0.00233	-0.0025	0.00299	-0.00353	0.00438	0.00374	0.000654
hage20plus	0.0868***	0.100***	0.0775***	0.0923***	0.101***	0.126***	0.0961***
rooms	0.00485*	0.0042	0.00612*	0.00259	0.00456	0.00885*	0.00465**
floors	-0.00924*	-0.00654	-0.00863	-0.0149	0.00129	-0.00802	-0.00657*
allP							0.00368
T_willid							-0.00126
Constant	-0.129	-0.0797	-0.0995	-0.121	-0.177	-0.185	-0.0852
R-squared	0.0345	0.015	0.022	.	0.0631	0.00695	0.0376
N. of cases	12698	9978	8804	6299	4662	3371	23645

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

Table AB.2 Additional investment classes

Dependent	A/C	Driveway	Recreate	Door	Roof	Plumbing
Model	IV 2SLS					
	(A)	(B)	(C)	(D)	(E)	(F)
Move Out	-0.0831	-0.00202	-0.0272	-0.00538	-0.128	-0.00136
Log Electric Bill	0.0123***	0.00258	0.00354*	-0.0132**	-0.00692	0.000853
Log Gas Bill	-0.00236	-0.00648*	-0.00167	0.00627	-0.000381	0.00249
Log Income	0.00167	0.00280**	0.000631	0.00139	-0.00234	0.00154
No. Children	-0.000846	-0.0014	0.00275**	0.00622*	-0.0023	0.00606*
No. Adults	-0.00291	0.000141	-0.00158	-0.000643	0.003	0.00162
Elderly	-0.00233	-0.00698	-0.00322	-0.0149*	0.00411	-0.0132*
Youngest Age	-0.00000166	-0.0000984	-0.0000950*	-0.000465**	-0.0000708	-0.000337*
No. Workers	0.00286	0.0011	-0.000278	0.0106***	0.00341	0.00236
College Grad	0.0103	0.0142*	0.00105	0.00163	-0.00135	0.0231**
Post College	0.0126	0.0133*	0.00274	0.0116	0.00277	0.0217*
Log HDD	-0.00691*	0.0124***	-0.00127	0.0146**	-0.00114	-0.00444
Log Sq. Ft	0.00101	0.00366***	0.000971**	-0.00145	-0.00202	0.00149
Wage Rate	-0.00548***	0.00109	-0.000807*	-0.00269*	-0.00231*	-0.00174
HPI	-0.000142**	0.0000439	0.0000347	-0.0000126	-0.000195**	-0.0000656
Home Age 20+	0.0364***	0.0270***	-0.0015	0.0956***	0.0783***	0.0781***
No. Rooms	0.00182	0.00193*	0.00148**	0.00134	-0.00101	0.00406**
No. Floors	0.000737	0.000569	-0.00265**	-0.00463	0.00527	-0.00631*
Constant	0.0676	-0.157***	0.0197	0.00883	0.176**	0.00905
R-squared	0.0301	0.00685	0.0078	0.0202	0.0476	0.0145
N. of cases	23645	23645	23645	23645	23645	23645

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

Appendix C: Supplementary Materials for Chapter 5

C.1 Notes for Maryland Survey Data

Selecting Building Permits

Building permits are public record, and were obtained from the county permit offices St. Marys, Charles, and Calvert counties. After compiling the records, all commercial property applications were removed, along with permits that indicated new construction. Attention was focused on homeowners performing renovations to their home.

Property Data

The dwelling age, number of floors, square footage, lot acreage, and classification and condition are gathered from a property database that includes structural characteristics of the home and is maintained by the Maryland Department of Planning for tax assessment and policy purposes. The database provides property map, parcel information, address, detailed housing unit characteristics (with residential improvements), and any recent sales or transfers within the past year.[61]

Recent Mover Data

[61] More detailed information can be found on the Department of Planning website, http://planning.maryland.gov/home.shtml

Data on the names and addresses of recent movers was obtained from a data services company, Acxiom. The data are gathered from mail forwarding forms processed by the US Postal Service.[62]

C.2 Text of Survey Mailings

Text of the survey recruitment letter

Below is the text of the first wave survey recruitment letter. The enticement language in the second wave recruitment letter was changed to reflect the new prize distribution, but was otherwise the same. The letter was printed on University letterhead and signed by professors Alberini and Towe. The user ID and password were randomly assigned to each individual for use as login credentials for the survey website.

[62] More detailed information can be found on the Acxiom website, http://www.acxiom.com/

Dear Maryland Resident,

The University of Maryland is conducting an on-line survey to study neighborhoods, homes, and energy usage in Maryland. We are requesting your participation in this survey because you represent your household and other Maryland households similar to yours.

The information that you provide through the survey questionnaire is important, and will help guide state and federal policy decisions. In addition, by filling out the questionnaire you will help University of Maryland graduate students with their dissertation research and undergraduate students with hands-on training in data analysis.

Please be assured that your answers to the survey questions are completely confidential. The survey is being conducted for research purposes, and we will not disclose your identity to anyone, nor link your responses to your name. Participation is voluntary and you can stop at any time.

Being a survey respondent is easy and takes only twenty minutes. As a token of our appreciation for completing the questionnaire, you will be entered in a raffle to win a prepaid card worth $100, which you can use at the store of your choice, or on-line. We are giving away a total of sixteen (16) $100 cards. If you wish to participate in the survey but not in the raffle, you will be given the option to decline the raffle at the end of the questionnaire.

You are eligible to participate in the survey if:

- You are the person listed on this letter, or live at the address printed above, and
- You have access to the internet for 20-30 minutes to take the survey.

How to take the survey:

Please go the following **website:** http://www.energyumd.org
Enter your **user ID: XXXXX**
and your **password: YYYYY**

Other information about the survey, including details on data privacy procedures, and information on the raffle drawing are at http://energy.arec.umd.edu Questions? Please call Will Gans at 301 592-7780 or send an e-mail to energy@arec.umd.edu.

We really appreciate your help with this survey.

Text of the survey recruitment follow-up letter

Below is the text of the first wave survey recruitment follow-up letter. Again, the second wave enticement language differed, but the letter was otherwise the same, and the letter was printed on University letterhead and signed by professors Alberini and Towe.

Dear Maryland Resident,

A few weeks ago you received an invitation from the University of Maryland to participate in an on-line survey to study neighborhoods, homes, and energy usage in Maryland. We are requesting your participation in this survey because you represent your household and other Maryland households similar to yours.

If you have already completed the questionnaire, we would like to thank you. At this time, there is no need for you to do anything else. We will contact you within a month's time if you are one of the 16 raffle winners.

If you have not filled out the questionnaire yet, we would like to ask you to do so at your earliest convenience.

Being a survey respondent is easy and takes only twenty minutes. As a token of our appreciation for completing the questionnaire, you will be entered in a raffle to win a prepaid card worth $100, which you can use at the store of your choice, or on-line. We are giving away a total of sixteen (16) $100 cards. If you wish to participate in the survey but not in the raffle, you will be given the option to decline the raffle at the end of the questionnaire.

You are eligible to participate in the survey if:

- You are the person listed on this letter, or live at the address printed above, and
- You have access to the internet for 20-30 minutes to take the survey.

How to take the survey:

Please go the following **website:** http://www.energyumd.org
Enter your **user ID: XXXXX**
and your **password: YYYYY**

Other information about the survey, including details on data privacy procedures, and information on the raffle drawing are at http://energy.arec.umd.edu Questions? Please call Will Gans at 301 592-7780 or send an e-mail to energy@arec.umd.edu.

We really appreciate your help with this survey.

C.3 Information on Support Website

As discussed in Chapter 5, a survey support website (energy.arec.umd.edu) was established. Below are several screenshots displaying the information that was included on the website. The home page is displayed in Figure 3, The Privacy page in Figure 4, and the Research Goals page in Figure 5.

Figure 3: Screen Shot of Support Home Page

Figure 4: Screen Shot of Privacy Page

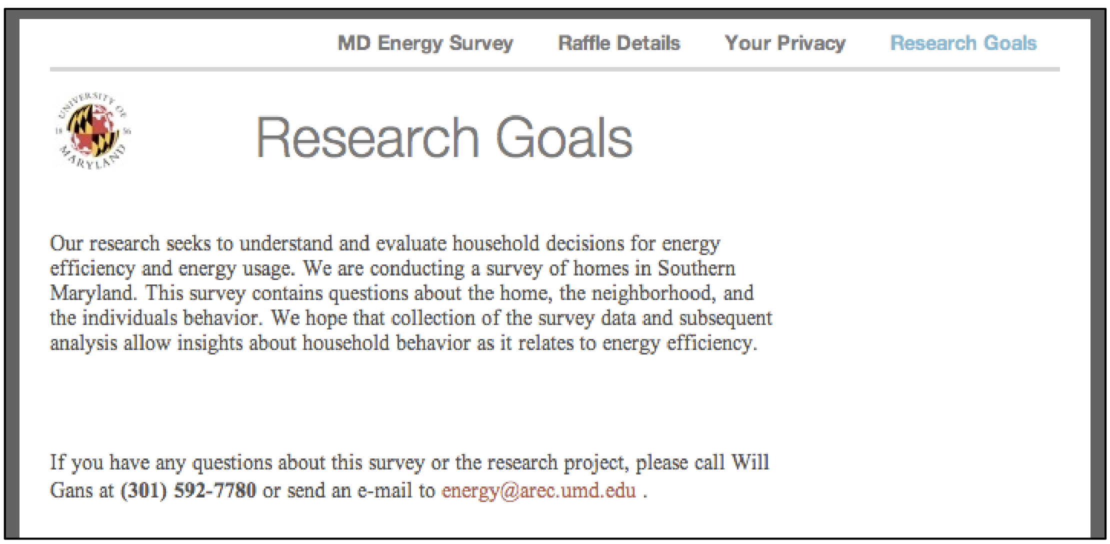

Figure 5: Screen Shot of Research Goals

C.4 Additional Figures from Questionnaire

98. Different people choose different answers for the questions you just saw on the previous screens.

Please rate the importance of each factor in your decision from 1 to 5, where 1 = "Not Important At All" and 5 = "Very Important."

	(1) Not important at all	(2)	(3)	(4)	(5) Very important
Final Purchase Price	○	○	○	○	○
Energy Savings per year	○	○	○	○	○
Lifetime	○	○	○	○	○

Other (please specify)

Figure 6: Attribute Ratings after Choice Experiment 1

116. How strongly do you agree or disagree with each of the following statements?

Please rate each statement on a scale from 1 to 5, where 1 = "strongly disagree" and 5 = "strongly agree."

	(1) Strongly Disagree	(2)	(3)	(4)	(5) Strongly Agree
I make a point to turn off the lights when I leave the room.	○	○	○	○	○
The house is kept very cool during the summer.	○	○	○	○	○
I view energy efficiency as a money saving investment.	○	○	○	○	○
There is usually somebody home during the weekdays.	○	○	○	○	○
I am very aware of the energy usage in the home.	○	○	○	○	○
I regularly look for ways to save on my energy usage.	○	○	○	○	○
The resale value of an energy-efficient home is higher.	○	○	○	○	○
The economic recession has motivated me to conserve on home energy usage.	○	○	○	○	○

Figure 7: Energy Investment Attitudes

C.5 Additional Robustness Checks from Discount Rate Analysis

Table AC.2 Interactions with energy efficiency attitudes

	(A)	(B)	(C)	(D)	(E)
Beta1	-0.00154***	-0.00154***	-0.00153***	-0.00154***	-0.00153***
	0.000115	0.000115	0.000115	0.00012	0.000117
Beta2	0.00154***	0.00154***	0.00153***	0.00154***	0.00153***
	0.000167	0.000173	0.000171	0.000251	0.000208
Delta (energy)	0.0219	0.0233	0.0228	0.0301	0.0211
	0.0142	0.015	0.0147	0.0286	0.0205
EE Invest (no)	0.0466				
	0.0674				
EE Save (no)		-0.0303			
		0.0368			
EE Resale (no)			-0.0171		
			0.0452		
EE Invest (yes)				-0.0143	
				0.0139	
EE Save (yes)					0.00425
					0.0133
Log-likelihood	-1205.221	-1205.29	-1205.507	-1204.928	-1205.521
LR test	392.645	392.508	392.073	393.232	392.045
N Obs	2022	2022	2022	2022	2022

Notes: significance level * p<0.05 ** p<0.01 *** p<0.001

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