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RESIDENTIAL ENERGY DEMAND AND ENERGY EFFICIENCY

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RESIDENTIAL ENERGY DEMAND AND ENERGY EFFICIENCY

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ABSTRACT

The first essay investigates the relatively higher energy efficiency (EE) investment rates in housing units of homeowners versus those of renters. In the empirical analysis, discrete choice models are employed to explore households' EE investment behavior. After testing three groups of implications derived from the initial analysis, the paper suggests that due to the existence of contracting costs, landlords/renters make efficient decisions to invest less in EE than homeowners due to renters' increased mobility and the characteristics of typical EE investments.

The second essay analyzes households' choices of energy efficient dishwashers and the potential influence from those choices on dish washing behavior. An ordered Probit model is developed to investigate households' demand for dish washing services. Two-stage residual inclusion (2SRI) is used to deal with the endogeneity problem, caused by households choosing energy efficient dishwashers because of higher expected usage frequency. Households using energy efficient dish washers compared with households using standing dishwashers display approximately 7.7% more frequent usage behavior.

The final essay examines U.S. residential consumption of four main fuels. Double-log demand models are applied and two-stage residual inclusion is used to address price endogeneity. Besides various elasticity estimates, the paper further explores causes of the rising per capital electricity consumption over time despite the efficiency progress. Historical survey data reveal that households increase electricity consumption by increasing the quantity of electronics and/or purchasing electronics with extra energy-consuming attributes.

DEDICATION

This dissertation is dedicated to my family and many friends. A special feeling of gratitude goes to my father who passed away in 2006 and my mother who trusts me under all circumstances. Neither my father nor my mother got a lot of education, yet they gave me the best education I could ever ask for. They taught me never to give up and also how to love people. My brother, Zhibin, has been a great role model for me and has never left my side. He, together with my sister-in-law and niece, are very special to me. I also dedicate this dissertation to my many friends and church family, who have supported me every step of the way. I will always appreciate their great company and all they have done for me.

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1 Introduction

In the United States, energy efficiency (EE) policies/regulations were first proposed in the late 1970s after the Arab oil embargo to conserve energy. Since then, EE has become an important policy analysis issue among various researchers and policy makers. Benefits from EE are manifold, from the reduced electricity bill to the improved environment. Numerous government policies/regulations have been implemented at the federal and/or state level to promote EE. Immediately after being sworn in as U.S. Energy Secretary, Dr. Ernest Moniz delivered his first remarks at the 2013 Energy Efficiency Global Forum, clearly expressing his determination to make EE a focal point during his tenure.

The economic justification for government interventions is the belief that the actual EE level realized falls short of the social optimal level. The claimed cause for the EE gap is the existence of different market failures/barriers (Hirst & Brown, 1990; Jaffe & Stavins, 1994; Santad & Howarth, 2004; Golove & Eto, 1996; Reddy, 2003; Valentova, 2010; Davis, 2010; Brown, Chandler & Lapsa, 2010; Allcott & Greenstone, 2012). However, there are still heated debates over both the existence and the magnitude of this presumed EE gap among researchers from diverse disciplines, which further raise concerns over the cost effectiveness of current government interventions.

The crux of the engendered debates lies in disentangling market barriers and market failures, both of which can cause the perceived low EE investment rate in some circumstances. There are many barriers to EE investment which affects the energy efficiency level; however, not all of them produce market failures which influence the economic efficiency level. Since energy efficiency itself is not our ultimate goal, we only promote energy efficiency to the extent that increases economic efficiency, which decides the net social welfare or the efficient allocation of resources (Sutherland, 1994). Therefore, removing all market barriers is neither feasible nor desirable, and only the existence of market failures provides a prima facie basis for government intervention.

Market failures identified from literature include distorted energy price (a.k.a. "energy use externality"), imperfect information about EE opportunities, principal-agent problem (a.k.a. "misplaced incentives" or "asymmetric information"), credit constraints (a.k.a. "liquidity constraint" or "capital constraint"), etc. Those market failures are mostly tangled with other market barriers which are not market failures, like consumers' risk management (i.e. uncertainty over future energy price), consumer heterogeneity (i.e. different preference over EE attribute), high transaction cost, etc. It is challenging to separate those two groups of factors, and sometimes, it is even hard to distinguish the effect of one market failure from another since different market failures might be interconnected with each other and reinforce each other.

This dissertation is dedicated to providing some insight into the current discussion over the EE gap. Three papers are developed targeting three closely related questions regarding residential energy efficiency and consumption. The first paper examines the part of the EE gap which was explained in literature as a result of one specific market failure, the incentive problems between landlords and renters. The paper compares the EE investment rates between these two groups of households while controlling for factors that are potential market barriers. The second paper investigates how the EE investment behavior influences the usage behavior. Specifically, the paper explores households' choices of energy efficient dishwashers and their potential impact on dish washing behaviors. The last paper models the per capita demand for four main fuels in the residential sector, especially the rising demand for electricity over time given the technological progress.

2 **Residential Energy Efficiency Investment: Homeowners versus Renters**

2.1 Introduction

Why do households use inefficient appliances or under insulate their living units when investing a reasonable amount for energy efficiency (EE) upgrades would save them money in the long run by reducing utility bills? Although there is little consensus on the answer to this question, misaligned/misplaced/split incentives[1] between parties involved in energy-related investment decision-makings have been persistently pointed out as one main obstacle to residential EE improvements (Hist & Brown, 1990; Jaffe & Stavins, 1994; Brown, 2001; Sullivan, 2009; Valentova, 2010; Maruejols & Young, 2011). Incentive problems typically occur in renter-occupied housing units[2], where landlords can influence the EE levels of the housing units either due to their ownership over some energy-related investments or the existence of utility-included rental contracts.

In a lot of energy literature, split incentives between landlords and renters were believed to cause the lower EE investment rate and consequently higher energy use intensity in renter-occupied housing units (Murtishaw & Sathaye, 2006; IEA, 2007; Gillingham, Harding & Rapson, 2012). According to the Residential Energy Consumption Survey (RECS) conducted by the U.S. Energy Information Administration (EIA) in 2009, approximately 31.49% of housing units in the U.S. were renter-occupied, where the average energy consumption per capita per square foot is nearly 65.88% higher

[1] In some articles, these problems are also described as the Principal-Agent problems or Asymmetric Information Problems.

[2] Some researchers pointed out that incentive problems could also happen between homeowners and home builders. For more information, see Murtishaw & Sathaye (2006).

compared to owner-occupied housing units[3]. Davis (2010) compared appliance ownership patterns between homeowners and renters in the United States. He inferred that if renters and homeowners were equally likely to have EE appliances, more than 9.4 trillion BTUs energy could have been saved every year.

Great saving potentials appear to exist and could be realized just by making rental properties as energy efficient as those of homeowners. If that is the case, then why are rational individuals, landlords and/or renters, not racing forward to reap these benefits? In other words, if misaligned incentives are the sole causes, then why are the two parties involved not trying to remove these barriers and collect the presumed profits? To provide some insights into those problems, this paper will use a subset of 2009 RECS and examine energy-related investment patterns in living units of homeowners versus renters.

The study explains the aforementioned problems from a contracting perspective and justifies a large part of the existing difference in EE investment patterns as a result of high contracting costs. Due to the existence of hidden contracting costs, renters and/or landlords make rational choices to invest less in EE at rental units because of the renter's high mobility and the characteristics of most EE investments. Empirical analyses show that on average, homeowners have a 9.88% higher probability to possess EE appliances, after controlling for their climate, housing and personal characteristics. The magnitudes of those differences change from investment to investment and are generally smaller for portable appliances. To examine the impact from renters' mobility, the paper compares the probabilities to have EE investments between homeowners with long-term tenants.

3 This number is computed from data collected from the 2009 Residential Energy Consumption Survey. Sampling weights are supplied by Energy Information Administration and employed in the calculation.

The results show that the average difference shrinks by 74% and homeowners are only 2.58% more likely to have EE investments compared with long-term tenants.

In literature, most researchers interpret the wide disparity of energy-related investment patterns between owner-occupied and renter-occupied housing units as solid evidence of inefficiencies caused by incentive problems. They used existing differences to make inference for the promising energy savings achievable by solving the problems (Murtishaw & Sathaye, 2006; IEA, 2007; Davis, 2010; Wilkerson, 2012). To check the validity of those methods, this paper also investigates how much of the existing differences can be explained by the incentive problems.

Given that the ownership status over most investments in rental units cannot be identified from the data, the paper will only focus on the incentive problem caused by utility-included rental contracts. By comparing the average probabilities to have EE investments between homeowners with renters who need to pay their energy bills, the study illustrates that most of the differences shown previously between the two groups still exist. The magnitudes of the probability differences do not change much with only a 0.15% drop on average, which implies that utility-included rental contracts do not contribute much to the perceived differences. Among the appliances included in this study, light bulb is specifically mentioned to be installed by households and therefore also free from the incentive problem caused by landlords' ownership over the appliance. This investment is not influenced by any incentive problem. Yet, analyses demonstrate that even the difference for this investment only decrease by 0.14%. To further examine how utility-included rental contracts influence the investment behaviors of landlords and/or renters, the paper provides analyses comparing average probabilities to have EE appliances between renters paying their monthly utility bills and renters with utility bills included in rents. No significant differences are found, except for a minute difference with refrigerators.

Results from this study indicate that incentive problems caused by utility payment arrangements are neither the whole reason nor an important one for the existing differences in EE investment patterns between owner-occupied living units and rental units. Yet various empirical works assume the magnitude of the differences reflect energy savings achievable by addressing these incentive problems. As a result, estimated saving potentials by those works are exaggerated and trying to eliminate the difference by aligning the incentives would fall short of the goal desirable. Additionally, incentive problems have been frequently used as a justification for some energy efficiency policies (IEA, 2007; Doris, Corchran & Vorum, 2009; Convery, 2011; Cluett and Amann, 2013). If the associated saving potentials are exaggerated, then cost benefit analyses for those policies are questionable. Moreover, various existing energy efficiency policies are influencing households' energy-related investment behavior. Some policies directly contribute to the EE gap between living units of homeowners versus renters (as will be explained in part 2.2). Therefore, a more thorough and in-depth understanding of all potential causes for the existing differences is needed to enable accurate cost effectiveness analyses of related government policies.

The rest of the paper is structured as follows. In section 2.2, the paper incorporates both incentive and contracting perspectives to investigate different investment patterns in living units of homeowners versus renters. This section outlines the three groups of implications to be tested based on the initial analyses. Section 2.3 introduces the dataset and econometric models for the study. Section 2.4 compares the probabilities to make EE investments between different groups of households to verify or test some of the implications based on the preliminary analyses. Section 2.5 concludes.

2.2 Misaligned Incentives versus Contracting Costs

2.2.1 Incentive Problems & Government Policies.

2.2.1.1 Two different incentive problems.

Incentive problems occur when landlords are the owners of energy-related investments. In rental housing properties, renters obtain the temporary rights to use the assets through contracts (Handerson & Ioannides, 1983). Therefore, for those energy-related assets, renters are not the ones who decide their energy efficiency (EE) attributes directly but need to pay the incurred energy bills. In this case, landlords represent the interests of renters when making choices concerning some major appliances. Since landlords only need to pay upfront investment costs, they are not motivated to improve the energy efficiency in the housing units to reduce the operation costs borne by renters.

Incentive problems also arise when renters have their utility costs included in their monthly rental payments. Since landlords are responsible for renters' bills, renters are unresponsive to fuel prices and have little/no motivation to make any energy efficiency improvements or to conserve energy, resulting in over-consumption of energy. According to a study by Maruejols and Young (2011), households who were not obligated to pay the heating cost directly consumed more energy for heating. This increased cost was caused by increased thermal comfort and being less sensitive to surrounding or climate conditions when deciding on temperature settings.

The two aforementioned incentive problems are also described as Principle-Agent problems in energy literature, which are market failures, caused by asymmetric information and split incentives between landlords and tenants. There are numerous studies demonstrating the pervasive existence of these two different types of Principal-Agent problems in rental units, and a variety of government interventions have been suggested to tackle those potential market failures (Murtishaw & Sathaye, 2006; Davis, 2010; Maruejols & Young, 2011; Gillingham, Harding & Rapson, 2011).

2.2.1.2 Three Groups of Government Policies.

Various government intervention plans have been proposed because of the inefficiencies claimed to be caused by incentive problems and the alleged energy saving potentials in the residential sector from increased efficiency. Those interventions are supposed to narrow the existing EE gap and promote the overall EE level in the U.S. residential sector. In this section, the paper categorizes existing policies related to the investment patterns of homeowners and/or renters into three big groups, according to the underlying incentive mechanism. A brief summary is provided for each group and whether they will influence the investment behavior of homeowners and renters differently[4].

The first group uses financial incentives to motivate households' EE investment behavior and normally applies to homeowners. Since those policies are only able to

[4] Note: Due to data constraint, the influences from different policies will not be incorporated in the study and treated as exogenous in later estimation.

stimulate the EE investments in owner-occupied housing units, they could also be a potential cause for the EE gap between living units of homeowners and those of renters. Policies in this group include all kinds of subsidies, rebates, grants, loans, tax credits, etc. Take the Residential Energy Efficiency tax credit as an example, this program was first established by the Energy Policy Act in 2005, later on reinstated by the Energy improvement and Extension Act of 2008, and further extended by the American Recovery and Reinvestment Act in 2009 and 2010. The program expired at the end of 2011 and then was renewed again in 2012 by the American Tax Relief Act. According this tax credit, if a household makes EE improvements for the building envelope of existing homes or purchases high-efficient heating, cooling and water-heating equipment in 2011, 2012 or 2013, they are eligible to claim a cumulative maximum amount tax credit as high as $500. However, the program specifically mentions that those efficiency improvements or equipment must serve a dwelling that is owned and used by the taxpayer as primary residence, which excludes the eligibility of renters and landlords (Residential Energy Efficiency Tax Credit, 2013).

The second group of policies tries to increase the EE level by cutting off options that are not energy efficient. This will force landlords to make some EE investments since the non-EE options are no longer available. Thus, those policies have the potential to solve the incentive problem occurring when landlords own some of the investments but do not need to pay the bills. This group includes many types of building codes and appliance standards. In California, the State Building Standard Code (also known as Title 24) includes standards of energy efficiency that all constructions of homes and buildings have to maintain to enhance energy conservation (Macken, 2013). California also implemented new light bulb standards on January 1, 2011 requiring all light bulb manufacturers to meet new efficiency standards. In the new standards, "any former 100-watt light bulb manufactured on or after January 1, 2011 and sold in California will have to use 72 watts or less. The 72-watt replacement bulb will provide the same amount of light (called "lumens") for lower energy cost" (New Light Bulb Standards, 2013). The standard was passed by Congress and became nationally effective on January 1, 2012.

The third group includes policies designed to raise households' awareness of the energy consumption associated with different choices to facilitate their decision-making process. This group provides renters with information concerning the EE level of rental units, thus potentially motivating landlords' EE upgrade activities to attract prospective renters and narrow the EE gap between owner-occupied and renter-occupied housing units. Policies in this group are comprised of different information disclosure strategies, including all kinds of information programs (e.g. rating & labeling programs) and energy use disclosure policies. According to Cluett and Amann (2013), there are approximately 14 jurisdictions with policies in place mandating residential energy use disclosure in the United States. In Chicago, the City Council passed an ordinance on September 11, 2013, requiring landlords to become more transparent and list the energy their buildings/rental units use so they could measure up against their peers.

However, there are potential downsides associated with government interventions. Energy subsidies could crowd out priority public spending and reduce private investments (International Monetary Fund, 2013); mandatory energy efficiency standards would override consumers' preference/choices and undermine their general well-being (Gayer & Viscusi, 2013); and information disclosure might end up useless since there are gaps between information and knowledge, between knowledge and opinion, between opinion and attitude, and also between attitude and behavior (Lutzenhiser, 1993/2008; Abrahamse, Steg, Vlek & Rothengatter, 2005; Barr & Gilg, 2007; Ehrhardt-Martinez & Latitner, 2009). Therefore, without valid evidence or accurate measurement of the claimed problems, the benefits of costly interventions will be questionable.

2.2.2 A Contracting Perspective.

2.2.2.1 Contracting Costs.

Whoever owns the appliance or pays the utility bills would be totally irrelevant to the final investment patterns in rental units in an ideal world consisting of zero contracting costs (or transaction cost in a broad sense). According to Coarse Theorem, landlords and tenants can negotiate effectively and the outcome will always be economically efficient. In real-world economic situations, different obstacles to bargaining prevent efficient Coasian negotiation and various costs will be incurred to make efficient contracts.

From the landlords' perspective, they need to be able to internalize any costs incurred by renters in the rental contract, including both the wear/maintenance costs and the energy costs from using appliances. Monitoring how households treat appliances and appraising the associated wear/maintenance costs is technically difficult and quite expensive. Landlords would by default expect a higher wear/maintenance cost resulting from renters' careless usage behavior. Therefore, unless landlords can reasonably charge tenants this cost, rational landlords are reluctant to invest in the comparatively more expensive EE products for rental units. Evaluating the amount of energy consumed by renters normally can be achieved at a reasonable price. However, for multi-family buildings where several rental apartments share a master meter, this cost can also be prohibitively high. From the renters' perspective, contracting costs arise when they try to verify whether the alleged benefits from existing EE investments in rental units deserve a relatively higher rent. This verification is usually done by checking the old energy bills from the previous occupants or the current status of the living units, which is costly in terms of the time and effort.

Since "Parties are likely to trade off the cost of creating complex contracts against the gain that these contracts create by inducing efficient investment incentives" (Schwartz & Watson, 2001), landlords and renters normally end up adopting simple contract forms which are suboptimal ex post, leaving untapped a lot of energy efficiency investments that have proven positive long term net benefits. Utility-included rental contracts are forms typically adopted in practice. Levinson & Niemann (2004) explained the existence of this apparent inefficiency in from both the demand and the supply sides. The demand-side explanation is that renters value the utility-included arrangements because they are risk-averse, or dislike volatile utility bills, or simply prefer not to face marginal costs during consumption. The supply-side explanation is that landlords value this type of rental contracts due to the high sub-metering costs, economies of scale in master-metered apartment buildings, or because they use it to signal the energy efficiency of the rental units to validate a higher rent.

2.2.2.2 Characteristics of Different EE Investments.

Due to the existence of contracting costs, landlords and renters make their investment decisions independently for the rental units. Each party chooses the most cost effective options after comparing the characteristics of different choices. Therefore, final investment patterns in renter-occupied living units are collaborative efforts from both parties, which will be different from those of homeowners where only one decision maker exists. Three main characteristics of the investments are related, those being upfront cost, operation costs and relocating costs. Those aforementioned characteristics influence investment decisions in living units of homeowners and renters differently due to the uniqueness of those two groups, especially renters' comparatively higher mobility.

For households (homeowners or renters) who are making investment decisions for their living units and responsible for the utility bills, they try to choose the most cost-effective options by comparing the upfront costs and the expected lifetime operation costs between those EE options with other conventional but less-efficient counterparts. Given that most EE investments involve a higher upfront cost and lower operation cost, if they are not easily/cheaply transferable, then households are required to live in the current housing units long enough to recover the extra upfront cost through utility bill savings from increased efficiency. Therefore, there are time concerns for some EE investments to be the most cost-efficient ones. Since homeowners normally live in the same place much longer than renters, they are less confined by time constraints and more likely to make EE investments.

For landlords to make EE investments on behalf of renters, they need to internalize any involved costs into the charged condominium fees. Usually, the upfront cost is transparent to both parties and thus can be incorporated in rent payments. However, there is also operating cost involved. For investments like insulation and window glass, the operating cost is just the maintenance (wear) cost which can be predicted since the cost is independent of households' behavior and caused by the natural depreciation/aging process. In this case, landlords will make the EE investment if EE attributes are valued or if landlords are paying energy bills. For other investments, like energy efficient appliances, operating cost includes the energy cost and the maintenance (wear) cost, both of which can be difficult to monitor. Energy cost for appliances is normally easy to monitor and charge except when multiple living units share one meter, in which case renters involved usually either share the bill by dividing it equally or have their bills included in their rents. Both circumstances will lead to households' opportunistic behavior since individual household's energy use behavior is invisible. In this case, renters are not motivated to make investments that improve energy efficiency. Landlords are only inclined to make the EE investments if they are responsible for the monthly utility bills. Maintenance (wear) cost for EE appliances depend on renters' daily usage behavior and this is utterly impractical to observe or charge, giving rise to renters' reckless usage behavior and discouraging landlords from investing in a more expensive EE appliance.

2.2.2.3 Characteristics of Households.

Households are the ultimate decision makers and their eventual investment behavior determines the resulting patterns. Therefore, to enhance our knowledge of the existing residential EE investment patterns, we also need to understand the underlying determinants of households' EE investment behavior.

In literature, EE investment behavior (also referred as "efficiency behavior" or "purchase behavior") is normally classified as one of two types of energy-related behavior and often studied with the other subcategory, the usage (or "curtailment") behavior (Raaij & Verhallen, 1982; Gardner & Stern, 2002; Attari, Dekay, Davidson & Bruin, 2010; or Zhao, 2013). There are diverse approaches to understanding energy-related behavior of households, resulting in different groups of factors identified to be accountable for the varying behavior patterns from household to household (Moezzi and Lutzenhiser, 2010).

At the macro level, technology development, economic growth, demographic characteristics, institutional factors and cultural development were recognized as the foremost determinants of energy related behavior (Gatersleben & Vlek, 1998). However, those determinants are almost impossible to capture or change in the short run. Current research has been focused on different variables influencing energy-related behavior at the micro level (i.e. individual or household level). For instance household income, energy price, family size, education, number of children, type of dwelling, rural/urban location, etc. are all being analyzed. (Heslop, Moran & Cousineau, 1981; Schipper, Bartlett, Hawk & Vine, 1989; Allen & Janda, 2006; Santin 2011). In this paper, some of those key determinants at the micro level will be incorporated into the modeling for different EE investment behavior (See section 2.3.1.3)[5].

2.2.3 Testable Implications.

Given the analysis above, there are three groups of testable implications for empirical work: 1). Will differences in probabilities to have EE appliances between owner-occupied units and rental units persist after controlling for household characteristics? 2). Will the differences become smaller if we compare living units of homeowners and renters who need to pay their monthly utility bills? How about renters who pay their monthly energy bills and those who have their bills included in rent? 3). Will we get a substantially smaller difference in the probabilities to have the EE appliances between living units of long-term tenants and homeowners? How about long-term renters vs. long-term homeowners, or short-term renters vs. short-term homeowners?

2.3 Data and Econometric Models

2.3.1 Data.

2.3.3.1 Data Source.

[5] It is noteworthy that there are also significant amounts of related works which are not from the field of economics, but instead from energy-related literature or environment & behavior studies. Consequently, some of those factors identified in literature as determinants of energy-related behavior are qualitative in nature and hard to quantify or incorporate into economic models. For example, based on the energy cultures research project in New Zealand from 2009 to 2012, Barton et al. (2013) concluded that norms, material culture and energy practices all contribute to households' energy behavior. In particular, achievement-related values are strongly correlated with households' EE behavior, while family and friends are influential in their behavior change. Clearly, those variables are hard to put figures on. Factors like those that were found to be linked to energy behavior also include attitudes, social networks, personal lifestyle, social recognition, etc. (Staats, Harland & Wilke, 2004; Staats, Harland & Wilke, 2004; Uitdenbogerd, Egmond, Jonkers & Kok, 2007; Druckman & Jackson, 2008; Lawson, Mirosa, Gnoth & Hunter, 2010; Mirosa, Lawson & Gnoth , 2011). For a detailed list of identified determinants from all reviewed studies, refer to Appendix A.

Data used in this paper are micro data from the 2009 Residential Energy Consumption Survey (RECS). RECS is a periodic survey administered by U.S. Energy Information Administration (EIA) with a nationally representative sample of housing units. The survey was first conducted in 1978. The latest one, the 13th iteration of the RECS program, was conducted in 2009 and the final version of data was released in January 2013. The 2009 survey used a multi-stage probability design to select samples and included housing units from all 50 States and the District of Columbia. Altogether there were 12,083 households selected to represent the 113.6 million housing units occupied as primary residence in the United States. Information concerning energy characteristics on the housing unit, usage patterns, and household demographics was collected by specially trained interviewers. The dataset also includes consumption and expenditure data obtained from energy suppliers.

2.3.3.2 Dependent variables.

This paper is devoted to the comparison of EE investment patterns in housing units for homeowners and renters. All the dependent variables are discrete, the weighted frequencies for which are listed in table 2.1. In the original data set, there are 12,083 households, including owner (67.31%), renters (31.49%), and occupants who are not paying the rent (1.21%). Since the study is only interested in the choices of owners and renters, the last group is omitted and the final sample size becomes 11,941. In addition, for investments on EE appliances, only households who have at least one corresponding appliance are included. For example, when analyzing the investment behavior on clothes washers, we only include households who have at least one clothes washer at home. The Sampling weights applied are provided by EIA.

As we can see from Table 2.1, the percentages of U.S. households using energy efficient appliances are greater than 50% in most cases. The only exception is for refrigerators and only about 40% of the households have an energy efficient one. In Table 2.2, we compare the percentage of homeowners who have energy efficient appliances in their living units versus that of renters. As expected the results conveyed that homeowners have much higher EE investment rates than renters without controlling for any other exogenous variables. On average, the percentage of households having EE appliances at home is about 22% higher for homeowners than renters. It is also worth mentioning that the differences are inversely related with the mobility of the appliances, from about 11% between the two groups of households for energy efficient light bulbs to approximately 37% for energy star dishwashers.

2.3.3.3 Independent variables.

In section 2.2.2.3, the paper summarized the identified determinants for energy-related behavior in reviewed studies. This paper does not include all of them as control variables, because some are qualitative in nature and cannot be quantified accurately, like people’s attitude towards environment. A detailed description of included independent variables is located in Table 2.3. Summary statistics are not provided since observations are different for different investments. For each investment decision, we only include households who answered the corresponding question clearly, excluding nonresponses or those with “don’t know”. Additionally, each sample only includes those who have at least one corresponding appliance no matter if it is energy efficient or not.

2.3.2 Discrete Choice Models.

This study focuses on households’ EE investment behavior, which is characterized by their choices involving appliances used in the housing units. Although some of choices are not made by households directly, we still assume those choices reflect their utility or preference since they chose the living units as bundles, including assets inside and their EE attributes. Given that consumers’ investment behavior involves decisions among a number of alternatives, discrete choice models are applied in this study. To fit in the discrete choice framework, the choice set must be composed of alternatives that are finite, mutually exclusive, and collectively exhaustive, all of which are satisfied by the investment decisions in this study.

Since investments in this study are associated with two-level choices (yes or no), the binary logit model is employed. Either the household has the EE appliance (recorded as “1”), or the household’s appliance is not EE (coded as “0”). For those binary logit models, we assume households’ preferences can be represented by the random utility function (U), which is deterministic (V) for household but contains elements (ϵ) that are not unobservable to the investigators. For observation i to choose option j, we have

$$U_{ij} = V_{ij} + V_{ij} \tag{2.1}$$

where U_{ij} gives the utility level of i-th observation making the j-th choice, and ϵ_{ij} is assumed to identically, independently and Gumbel distributed. Household i will choose option j over option k if a higher utility is associated with choice j (U_{ij}>U_{ik}). Thus we can write the probability of i-th individual to choose alternative j as

$$P_i(j) = P(U_{ij} > U_{ik}) = P(V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik}) = P(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik}) \qquad (2.2)$$

Since ϵ_{ij} and ϵ_{ik} have Gumbel distributions, the difference ϵ_{ik}-ϵ_{ij} has a logistic distribution (Bierlaire, 1997). Therefore, the probability can also be written as following:

$$P_i(j) = F(V_{ij} - V_{ik}) \qquad (2.3)$$

where F is the cumulative logistic distribution function. For V_{ij}, we assume a linear-in-parameters functional form, $V_{ij} = X_{ij}\beta$, where X_{ij} is a row vector of exogenous variables and β is a column-vector of parameters to be estimated. The likelihood function can be written as:

$$LF = \pi_{i=1}^{n}\{P_i(j)^{Y_i} * [1 - P_i(j)]^{1-Y_i}\} \qquad (2.4)$$

where n is the number of observations. Y_i=1 when agent i chooses option j, and 0 if otherwise. The corresponding Log-likelihood function for the model can be written as:

$$\mathrm{LLF} = \sum_{i=0}^{n}[Y_i * \ln(P_i(j)) + (1 - Y_i) * (1 - \ln(P_i(j)))] \qquad (2.5)$$

which can be maximized to obtain estimates of β or other parameters of interest.

2.4 Three Groups of Tests

Using the binary logit model specified in Section 3, the study will test the three groups of implications listed in section 2.3. Hosmer and Lemeshow Goodness-of-Fit tests together with different Pseudo-R^2s are used to check the fitness of the binary logistic models. Besides the estimation of coefficients β, the primary interest of the paper is to calculate the marginal effects and compare the average probabilities to have different EE appliances between different groups of households.

2.4.1 Implication one: will differences in probabilities to have EE appliances between owner-occupied units and rental units persist after controlling for household characteristics?

To test implication 1, we will use the binary logit model and compare the probabilities to make the EE investments between homeowners and renters, while controlling for their climate, housing and personal characteristics (See Table 2.3). This is accomplished by calculating the marginal effect from variable OWNER for each observation and then calculating the average. Results are summarized in Table 2.4. This test serves as the base case and will be compared with the other tests. Light bulbs, energy star window/wall AC, refrigerator, clothes washer and dish washer are all household appliances which may or may not exist in some housing units, especially renter-occupied housing units. Consequently, the study only includes households that have at least one appliance in the housing unit for the estimation of each corresponding investment.

Table 2.4 summarizes differences in the average probabilities to have EE investments in living units of homeowners versus renters. According to the results, homeowners have higher probabilities to have EE investments except for energy star windows/wall ACs, in which case, probabilities are not significantly different between the two groups of households. Furthermore, the differences are significantly smaller in comparison to those shown in Table 2.2 when we do not control for exogenous variables. Now the probabilities to have EE investments are on average 9.88% higher for homeowners than renters compared with 22% found previously in Table 2.2. This implies that household characteristics may be held accountable for a portion of the differences in the investment patterns in living units of homeowners versus renters.

To further understand how household characteristics influence investment decisions, we refer to the complete results for all five binary logit models in Appendix B for light bulbs, Appendix C for ACs, Appendix D for refrigerators, Appendix E for clothes washers, and Appendix F for dish washers. Although parameter estimates for binary logit models are not marginal effects, the signs of all estimates indicate whether corresponding control variables have positive or negative effects on the dependent variables. According to the results, signs of the influences from most household characteristics change from investment to investment. However, a few are fairly consistent for all investments. For example, age of householders has a significant effect on all investments. The probabilities of having EE appliances increases with householder's age as shown by the positive sign of variable HHAGE for all investments, and then decrease with the age as revealed by the negative sign of variable SAGE (=age*age) for all investments. In addition, energy price has no significant effect on any investment decision while household income has a positive impact on all investments except for light bulbs, where income effect is not significant.

2.4.2 Implication two: will the differences become smaller if we compare living units of homeowners and renters who need to pay their monthly utility bills? How about renters who pay their monthly energy bills and those who have their bills included in rent?

According to the 2009 RECS, among households who gave valid responses, a significant proportion of those surveyed have their energy bills included in rental payments or condominium fee, or paid by relatives, rental or condominium agents, or some other party. For electricity, the percentages of households that don't need to pay fuel consumption directly are: 5.09% for space heating, 4.85% for water heating, 5.04% for cooking, 3.77% for air conditioning, and 6.14% for lighting or other appliances. For natural gas, the percentages of households that don't need to pay the fuel consumption directly are: 10.07% for space heating, 12.10% for water heating, and 10.97 % for cooking. In addition, 2% don't need to pay propane consumption, and 19.8% don't need to pay fuel oil consumption. Most of those households are renters who have their energy bills included in their rents. In particular, 83% households who do not pay the electricity consumption are renters, 86.6% of those who do not pay the natural gas consumption directly are renters, 78.51% of those who do not pay the fuel oil directly are renters, and 78.51% of those who don't pay the propane consumption directly are renters.

To test the first question of implication 2, we select observations exactly as we did previously for testing implication 1, then we restrict the sample for each investment to households who are responsible for monthly energy bills. In table 2.5, the differences in probabilities to have EE appliances between homeowners and renters who need to pay their monthly utility bills are calculated. Comparing these results with the base case for implication 1, the magnitudes of most differences only decline slightly (0.15% on average), which indicates that the presence of utility-included rental contracts is not a main cause of the existing difference in EE investment patterns between owner-occupied and renter-occupied housing units. The most interesting part of the results is derived from investment in EE light bulbs. This investment is specifically mentioned to be made by households and thus not suffering from the incentive problem due to landlords' ownership over them. Since we already restrict the sample to those who pay the monthly utility bills directly, this investment is free from any incentive problem. However, from table 2.5, we notice that homeowners are still 3.21% more likely to have this EE investment.

Addressing the second part of implication 2, we select observations as previously for implication 1, and then we select the sample for each investment by including renters only. Results are summarized in Table 2.6. According to the table, the probabilities to make/have most of the EE investments by renters who need to pay the monthly energy bills directly are not significantly different from those by renters who have their bills included in the rents. The only exception is for refrigerators, where renters who do not pay their energy bills directly on average have a 3.63% higher probability to own an energy efficient one. This can be explained by the fact that a large proportion of refrigerators in rental units are preinstalled by landlords before renters move in. When landlords are responsible for the energy bills, they are motivated to make the energy efficiency investments for renters.

2.4.3 Implication three: will we get a much smaller difference in the probabilities to have the EE appliances between living units of long-term tenants and homeowners?

Renters do not usually reside in the same place as long as homeowners do, and thus are less likely to make EE investments that involve high upfront costs and are costly or impossible to be transferred to new place when they move out. According to the 2009 RECS, about 50.6% of the U.S. homeowners live in their current residence at least 10 years and around 71.62% at least 5 years, while for renters, only 11.18% live in the same place at least 10 years and 24.02% at least 5 years. To test implication 3, we select observations as previously for testing implication 1, and then we restrict our samples to households who moved in before 2000. In other words, only those who lived in the current housing units for at least 10 years are included in the samples.

Table 2.7 summarizes differences in the average probabilities to have EE appliances between homeowners and long-term tenants who lived in the current residence for at least 10 years, after controlling for household characteristics. From the table, we observe that the differences shown previously in test 1 for EE light bulbs and dishwashers are not significant anymore. The magnitudes fall dramatically for the two investments that had significant differences from 17.69% to 5.76% for refrigerator and from 11.57% to 7.13% for clothes washer. Compared with test 1, the EE gap between living units of homeowners and renters shrinks by 74%. On average, homeowners are only 2.58% more likely to have EE appliances.

Regarding changes in all differences compared with test 1, there are two plausible explanations. First, renters are more likely to make EE investments if they can harvest all the potential benefits from increased energy efficiency. This could happen when renters can easily relocate the investments, like light bulbs, which are fairly portable. The scenario could also occur when the life expectancies of the EE investments are short and the renters live in the same place long enough, like dish washers, the average life expectancy for which is less than 10 years. For refrigerators and clothes washers, they both are rather cumbersome in terms of the size and weight, and have long the life expectancies, 13[6] and 10 years respectively (NAHB, 2006). Another plausible explanation is that the landlords are more likely to replace those appliances with energy efficient ones after their usage period due to the mutual trust developed over time between landlords and tenants.

In order to gauge the importance of a households' mobility, the paper includes two additional tests. Those tests compare the probabilities of possessing EE appliances between long-term homeowners versus long-term tenants (Table 2.8) and between short-term homeowners versus short-term tenants (Table 2.9). Results convey small differences in the probabilities associated with long-term homeowners versus long-term tenants, yet there are notable differences between short-term homeowners and short-term tenants. According to Table 2.8, long-term homeowners have an averaged 3.43% higher probability to have all EE appliances. In contrast, Table 2.9 reveals that short-term homeowners are on average 10.15% more likely to have all EE appliances.

2.5 Conclusions

In this paper, energy-related investment patterns in living units of homeowners versus renters are investigated. In energy literature, the existing differences in EE investments between those two types of living units are explained as inefficiencies caused

[6] Here we use the life expectancy for a standard refrigerator. For compact refrigerator, the life expectancy is 9 years.

by two types of incentive problems. These incentive problems have been used in the justification for ratification of various energy policies. Using a different perspective, this study vindicates the differences as households' rational choices due to the existence of contracting costs.

The previous literature only has performed a few quantitative studies. In these studies, the authors normally divide the households into four groups according to the existence of the two types of incentive problems. Then they calculate the potential energy savings by multiplying the number of households in each group affected by the problem and the difference in energy consumption of those groups compared with base case. Some of those aforementioned studies were conducted by agencies who were involved in the government EE programs. However, this study concludes that different efficiency investment patterns between several groups of households are caused by various factors, including household characteristics and attributes of EE investments. In particular, renters' high mobility appears to account for a large part of the resulting difference in EE investments between owner-occupied and renters-occupied housing units. Therefore, quantitative studies that exclude those factors are biased and the estimated energy savings are exaggerated.

3 Choices of Energy Efficient Dishwashers and the Demand for Dishwashing

3.1 Introduction

How much energy can be saved from improved energy efficiency? This appears to be a technical question that is to be answered by engineers. Provided the specific estimate of the percentage efficiency increase, we should be able to approximate the percentage savings achievable. While the logic sounds plausible, this approach is flawed due to behavior changes from consumers or producers in response to perceived technological progress. Specifically, this behavior adjustment in energy consumption can be summarized as increased marginal product of energy causing decreased marginal cost of energy service and therefore driving up the quantity demanded of the service. This direct effect[7], triggered by increased energy efficiency on consumers' usage behavior, causes the realized energy savings to fall short of the expected engineering estimates and can even result in more energy consumption in specialized cases (Brookes, 2000; Saunders, 2000; Alcott, 2008).

The increased utilization of energy services induced by energy efficiency was introduced by William Stanley Jevons in his famous work entitled "*The Coal Question of 1865*" when he observed that more economical use of coal from the invention of more efficient steam engines in Britain did not reduce national coal consumption, but rather led to increased coal demand and ultimately a higher coal consumption level (Jevons, 1865). From this point forward, the effect from energy efficiency on energy service demand has garnered attention from researchers in varied disciplines. Although there is a general consensus on the existence of this effect, the estimated magnitude of the effect from

[7] This direct response has been called "direct rebound effect" in various energy literatures.

empirical works is controversial due to the high diversity in terms of the definitions, methodologies and data sources (Greening, Greene & Difiglio, 2000; Sorrell, Dimitropoulos & Sommerville, 2009; Tuner, 2013). Additionally, a majority of studies were focused on a few energy services – namely personal automotive transport, household heating and cooling. For other energy services, like the usage of household appliances, empirical studies are limited.

In this paper, the author provides empirical estimates of consumers' changes in dish washing behavior from having energy efficient dishwashers. Within the framework of household production theory, the study examines this change by investigating how the choices of energy efficient dishwashers influence households' average dish washing frequencies per week, while controlling for various household characteristics. The 2009 Residential Energy Consumption Survey (RECS) data is employed in the empirical analysis. Since the recorded outcomes for this usage behavior from the survey are discrete and ranked, an Ordered Probit model is applied to analyze the behavior. To confront the endogeneity problem caused by the fact that households might choose to have energy efficient appliances simply because they want to use it more frequently, two-stage residual inclusion[8] (2SRI) is used to make the estimation (Lee, 2007; Terza, Basu & Rathouz, 2008; Cai, Small & Have, 2011). Results show that households with energy efficient dishwashers are 1%-3% more likely to report frequent usage behaviors in the survey compared with those without. This approximates 7.7% more frequent usage or

[8] 2SRI is a special case of the Control Function (CF) approach. For more details on the CF approach, see Heckman & Robb (1985) and Newey, Powell & Vella (1999).

about 0.24 additional dishwashing times per week compared with those using standard dishwashers.

There are two main causes for the lack of research on household appliances. First and foremost, a lot of empirical studies estimate the direct effect from energy efficiency on service utilization with the elasticity of demand for energy consumption of the related service with respect to the energy price (Sorrel, Dimitropoulos, and Sommerville ; 2009). This approximation results from the difficulty associated with measuring energy efficiency or energy service directly and is based on the assumption that households' responses to efficiency increases are identical as the price of energy decreases. However, in the residential sector, households usually only have one energy bill and sub-metering energy use for each appliance is costly and sometimes technically difficult. Consequently, obtaining appropriate data for research on specific appliances becomes challenging and deters research in this subfield. Secondly, modeling energy use behaviors with existing data is not easy either, especially due to an endogeneity problem. Although various two-stage models have been developed to alleviate this problem for linear or nonlinear models, a longstanding, common obstacle for this approach is the lack of appropriate instrumental variables. Finding instruments of good quality is a cumbersome and challenging process. The efficiency of the instruments will directly impact the consistency of the final results.

In this study, the author conducts a selection process by evaluating the first stage Probit model with and without a mixture of potential instrumental variables. Those instrumental variables all correlated with households' choices of energy efficient dishwasher but do not directly influence their weekly dish washing frequencies. By comparing different goodness-of-fit measures from the first stage, the final model chooses a combination of three different instrumental variables. By including those instruments in the first stage model, the Pseudo-R^2s increase by twice on average compared with the base case without any instrument. To deal with the trade-off between the goodness-of-fit of the model and the complexity of the model, the paper also compares the Akaike information criterion (AIC) and Schwarz criterion (SC) for different fist-stage models. Those two criterions give the minimum values for the best model. By including the three chosen instrumental variables, the AIC and SC values both decrease by 18%.

As compared with refrigeration, lighting, or heating, the author expects the demand for dish washing to be more elastic due to the existence of an immediate substitute – hand washing. Therefore, this paper serves as a representative case for home services with close substitutes, the demands for which are more elastic and the author expects more significant behavior changes. Among the few empirical works examining residential appliances, Davis (2008) found that an average household increased clothes washing by 5.6% after receiving the energy efficient clothes washers. This behavior change means the actual energy savings from improved energy efficiency are 5.6% less than engineering calculations. To control the endogeneity problem, David (2008) used data from a field trial in which households received energy efficient clothes washer for free. For residential lighting, the increased usage was estimated to range from 5% to 100% (Roy, 2000; IEA, 2005; Tsao, Saunders, Creighton, Coltrin & Simmons, 2010). Most of the aforementioned studies were not contained in economic literature and did not even consider potential endogeneity problems.

Dishwashers are a unique major household appliance because it is not installed in all households and traditionally installed more frequently in higher income households. Given the increasing living standards in U.S., we would expect a large amount of marginal consumers who would begin to use this service, because the increased energy efficiency means a lower operation cost for using dishwashers. This is also true for most major appliances in developing countries, where there is an excessive amount of potential demand (Orasch & Wirl, 1997; Roy, 2000; Herring & Roy, 2007; Bergh, 2011). Due to the data constraint, increased utilization of this service by those prospective consumers is not examined in the study. Consequently, the computed magnitude of the increased consumption from this paper is more conservative compared with the potential size.

Besides the direct effect investigated in this paper, the entire effect from the efficiency improvement on consumers' energy consumption behavior also includes the indirect effect and the general equilibrium effect [9](Greening & Greene, 1997). Indirect/Secondary effect results from increased real income due to decreased price of the energy service/output. Since consumers have more disposable income, they can consume

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[9] To help understand the mechanisms underlying the (rebound) effect, researchers usually decompose the (rebound) effect into separate parts. The most commonly used typology is from the early work of Greening and Greene (1997). There are also lots of other different typologies for the (rebound) effect. In the later work from Greening, Greene and Difiglio (2000), for example, they distinguished four types of the (rebound) effect: direct, secondary fuel use, market clearing price and quantity adjustments, and transformational effects. Sorrell (2007) simplified the (rebound) effect into two types: direct and indirect, and then categorized the indirect effect into five types in his later work (Sorrell, 2009). There are also studies trying to explain it either in terms of consumption versus production (Schettkat, 2009), or from the short run versus the long run (Small & Van Dender, 2005). Although there is no general agreement on the classification of the (rebound) effect, all of them agree on the part of direct (rebound) effect and thus almost all the empirical work that has been done was trying to measure the direct (rebound) effect, especially in the residential sector.

more of other services/output whose production or usage also involves energy consumption (Greening, Greene & Difiglio, 2000). For example, consumers use the money they saved from using energy efficient appliances to purchase additional electronic goods, which also require energy as an input. The general equilibrium effect, also known as market effect, dynamic effect, structural effect, or economy-wide effect, refers to macro level reactions from both the demand and the supply sides in all markets due to the increased energy efficiency. Neither indirect nor general equilibrium effects are included in this study. Therefore, the effect referred to in this paper is only the direct effect and the whole effect from energy efficiency on energy consumption could be much larger than results presented in this study.

This paper explores the direct effect from using energy efficient dishwashers on the quantity demanded for dish washing service while controlling for factors such as energy price, gross household income, frequencies that hot meals are cooked, whether household members are at home on a typical week day, and additional household characteristics which may also affect the usage frequencies. In the next section, the paper describes the household production theory and makes the initial predictions on consumers' behavior changes from increased energy efficiency. Section 3.3 develops an ordered Probit model for households' dishwasher usage behavior and illustrates how to control the endogeneity problem with 2SRI. Section 3.4 discusses the summary statistics for key variables, the selection of instrumental variables and the final results of the estimation. Implications and conclusions remarks of the research will be contained in Section 3.5 and Section 3.6.

3.2. Household production with Dishwasher

In accordance with the commercial and industrial sectors, energy is considered as an input in the residential sector. Households cannot consume energy or appliances directly. Instead, households are producers who combine energy, appliances, and other inputs together utilizing diverse household production functions to supply different energy services. Those aforementioned services are the final consumption goods appearing in the forms of clean dishes/clothes, light, temperature controlled homes, cooked meals, etc. Unlike the commercial or industrial sector, the producers (households) are also the consumers of the outputs. Those produced energy services satisfy households' desire for the basic amenities and will appear as arguments in their utility functions (Dubin & McFadden, 1984; Quiqley, 1984; Klein, 1988; Davis, 2008).

This paper investigates households' production of dish washing services. Inputs include energy (E), dishwasher (D), and other factors involved (O), while outputs are the clean dishes (Z_1) and can be measured indirectly through dish washing frequencies (DISHUSE). Let f(•) denotes the household production function, P_e the energy price, K the fixed capital cost of the dishwasher , P_o the average price of other inputs, and P_s output price. As producers, households' problem can be summarized as a profit maximization problem:

$$\max_{\{E,O\}} \quad Profit \tag{3.1}$$

$$= \max_{\{E,O\}} \quad \mathrm{P}_s * \mathrm{Z1} - \mathrm{P}_e * \mathrm{E} - \mathrm{P}_o * \mathrm{O} - \mathrm{K} \tag{3.2}$$

$$= \max_{\{E,O\}} \quad \mathrm{P}_s * \mathrm{f(E,O)} - \mathrm{P}_e * \mathrm{E} - \mathrm{P}_o * \mathrm{O} - \mathrm{K} \tag{3.3}$$

First-order conditions for this maximization process with respect to E (equation 3.4) and O (equation 3.5) are:

$$\mathrm{P}_s * \frac{\partial f(E,O)}{\partial E} - P_e = P_s * \mathrm{MP}_e - P_e = 0 \tag{3.4}$$

$$\mathrm{P}_s * \frac{\partial f(E,O)}{\partial O} - P_o = P_s * \mathrm{MP}_o - P_o = 0 \tag{3.5}$$

Where MP represents the marginal product of energy (MP_e) or other inputs (MP_o) with respect to the production function (f(•)).

Rearranging terms, we can re-express the first-order conditions as:

$$P_s = \frac{P_e}{MP_e} = \frac{P_o}{MP_o} \tag{3.6}$$

Compared with standard dishwashers, energy star dishwashers have higher MP_e and MP_o[10](see footnote 10 for explanations for higher MP_o). Therefore, the real price for the service (P_s) is lower compared with the standard dishwashers, holding the energy price and other input prices constant.

As consumers, households maximize utility by choosing their optimal consumption level of the service (Z_1) and all other goods, which are defined as a composite good (Z_2). The composite good (Z_2) is assumed to be a numéraire with price normalized to be one. Prices for dishwashing services are defined as P_s for energy efficient dishwashers and P_s' for standard dishwashers, where $P_s < P_s'$. Given a household income M and liner budget equations, we have the budget constraints for using energy

[10] Other inputs for dishwashers normally include water, time, and dish soap. Besides saving energy, energy star dishwashers are also 20% more water efficient compared with the standard models.

efficient dishwashers (equation 3.7) and for using the standard dishwashers (equation 3.8) as shown below:

$$P_s * Z_1 + Z_2 \leq M \tag{3.7}$$

$$P_s' * Z_1 + Z_2 \leq M \tag{3.8}$$

Denote household's utility function U (•) and two Lagrange multipliers $\boldsymbol{\lambda}$ and $\boldsymbol{\lambda}$'. Now, the households' problem as consumers can be simplified as equation (3.9) for using energy star dishwashers and equation (3.10) for using the standard dishwashers:

$$\max_{\{Z_1,Z_2\}} \quad U(Z_1, Z_2) + \lambda(M - \mathrm{P}_s * \mathrm{Z}_1 - Z_2) \tag{3.9}$$

$$\max_{\{Z_1,Z_2\}} \quad U(Z_1, Z_2) + \lambda'(M - \mathrm{P}_s{}' * \mathrm{Z}_1 - Z_2) \tag{3.10}$$

The paper further assumes that both Z_1 and Z_2 are normal goods and households have strictly convex indifference curves (ICs). Compared with those choosing standard dishwashers, households using energy star dishwashers will increase the consumption of both Z_1 and Z_2. This is caused by households' utility-maximization behavior and the decrease of service prices from P_s' to P_s. Specifically, both the substitution effect and the income effect will move the optimal consumption bundle of rational households with energy star dishwashers towards the direction with a higher level of dish washing services (Z_1). Therefore, we can conclude the analysis in section 3.2 as increased energy efficiency of dishwashers making dish washing service cheaper and therefore driving up consumption of this service. In section 3.3 and 3.4, we will verify this conclusion and show how the demand of this service changes from having energy star dishwashers with empirical data.

3.3 The Econometric Model

3.3.1 Data Source.

The study is based on data from the 2009 Residential Energy Consumption Survey (RECS). This survey is administered by U.S. Energy Information Administration (EIA) with a nationally representative sample of housing units. First conducted in 1978, the 2009 version represents the latest iteration of the RECS program and the final version of the data was released in January 2013. The 2009 survey used a multi-stage probability design to select samples and included housing units from all 50 States and the District of Columbia. Altogether there were 12,083 households that were selected to represent the 113.6 million housing units occupied as primary residence in the United States. Since this paper is investigating households' dishwasher usage behavior, only those with dishwashers are included in the analysis, which accounts for 61.09% of the original sample units. By further excluding those without valid answers[11], the final sample is comprised of 4684 observations.

3.3.2 The Ordered Probit Model.

The utilization of the dish washing service can be approximated by the dishwasher usage behavior. In the survey data, variable "DISHUSE" represents how often households use dishwashers every week. The values for this variable are frequencies ranging from less than once a week, once each week, 2 to 3 times each week, 4 to 6 times a week, to at least once a day. Considering those categorical responses are arranged in a meaningful sequential order, an ordered Probit model is applied to demonstrate households' dishwasher usage behavior. In an ordered Probit model, an

[11] Households refusing to answer or giving an answer "don't know" are not included in the sample.

underlying continuous latent variable "Y*" is assumed to exist reflecting the ordinal choices "Y" made by households. We can interpret Y* as a continuous measure of the usage behavior or the propensity to use the dishwashers. In order to quantify the effects of control variables included in the study, we will describe this measure Y* as a linear function of those factors with an additive error term.

$$Y^* = X_1\beta_1 + \epsilon \tag{3.11}$$

Where X_1 is a vector of covariates that are predictive of the outcome, β_1 is a column-vector of parameters to be estimated and made inference from, and ϵ is a random term which is assumed to be independently, identically, and normally distributed $N(0,\sigma^2)$. Therefore, Y* is also normally distributed.

Furthermore, suppose we have m choices that households choose from to describe how often they use the dishwasher every week, we can assume that there are (m-1) cut-off points C_1, C_2, C_3……C_{m-1} such that we have the following:

$$Y=1 \text{ when } Y^*= X_1\beta_1+\epsilon \leq C_1$$

$$Y=2 \text{ when } C_1<Y^*= X_1\beta_1+\epsilon \leq C_2$$

$$Y=3 \text{ when } C_2<Y^*= X_1\beta_1+\epsilon \leq C_3$$

$$\ldots\ldots\ldots\ldots\ldots\ldots$$

$$Y=m-1 \text{ when } C_{m-2}<Y^*= X_1\beta_1+\epsilon \leq C_{m-1}$$

$$Y=m \text{ when } C_{m-1}<Y^*= X_1\beta_1+\epsilon \tag{3.12}$$

Thus, the probability for the ith observation to make choice j can be written as:

$$P_{ij} = N\left(C_j - X\beta_1\right) - N(C_{j-1} - X\beta_1) \tag{3.13}$$

where N is the cumulative normal distribution function. Accordingly, the likelihood function for the model can be written as:

$$LF = \prod_{i=1}^{n} \prod_{j=1}^{m} {P_{ij}}^{\mathrm{Zij}} \tag{3.14}$$

where n denotes the number of observations, m represents the number of choices, and Z_{ij} is equal to 1 if Y_i* falls within interval j (i.e. ith observation makes choice j), and 0 if otherwise. Taking the logarithms of the likelihood function, we can obtain the log-likelihood function:

$$\mathrm{LLF} = \sum_{i=1}^{n} \sum_{j=1}^{m} z_{ij}\ Iog(P_{ij}) \tag{3.15}$$

It can be shown that this log-likelihood function is globally concave in the parameter vector β_1, and therefore can be easily maximized to yield estimates of β_1 or other parameters interested.

3.3.3 Endogeneity Problem and 2SRI.

All right-hand variables (X_1) included above are exogenous except the dummy variable ESDISHW, which has a value of 1 if households use an energy-star dishwasher and 0 if otherwise (For better reference later, assume X_1=X_2+ESDISHW). Since households might self-select to have energy-star dishwashers because they planned to use them more often, there are potential endogeneity problems. Given the nonlinearity of our model, we use two-stage residual inclusion (2SRI), which extends the linear two-stage least square estimation to nonlinear models to deal with the endogeneity problem.

According to Terza, Basu, and Rathouz (2008), 2SRI generally gives consistent results for both linear and nonlinear models with endogenous treatments.

For the first stage of 2SRI, we add instrumental variables (IVs) to estimate the reduced forms equations. The selection of IVs is included in part 3.4. In the final regression model, three selected instruments (IV) and covariates X_2 are included as control variables. Since values for dependent variable (ESDISHW) are discrete choices (0 or 1), the binary Probit model is applied. In this model, we assume households have identical preferences and the preference is given by the random utility function:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{3.16}$$

where U_{ij} gives the utility level of i-th household making the j-th choice, and the ϵ_{ij} are bivariate normally distributed N(0, Σ). Thus we can write the probability of i-th household making the j-th alternative as:

$$P_i(j) = N(\frac{V_{ij} - V_{ik}}{\sigma}) \tag{3.17}$$

For $V_{ij,}$ we assume a linear-in- parameters functional form, $V_{ij} = X_{ij}\beta_2$, where X_{ij} is a row vector of exogenous variables (i.e. $X_{ij} = IVs_{ij} + X_{2ij}$) and β_2 is a column-vector of parameters to be estimated. Usually, we normalize by setting $\sigma=1$. Let Y_i be 1 if agent i choose alternative j and 0 otherwise. Therefore, we can derive the likelihood function for the model as:

$$LF = \prod_{i=1}^{n} \{P_i(j)^{Y_i} * [1 - P_i(j)]^{1-Y_i}\} \tag{3.18}$$

Taking logarithms, we can obtain the log-likelihood function as

$$LLF = \sum_{i=1}^{n} [Y_i * In(P_i(j)) + (1 - Y_i) * (1 - \ln(P_i(j)))] \quad (3.19)$$

which can be maximized to obtain estimates of β_2.

Given estimates of vector β_2 , the generalized residuals (Gourieroux, Monfort, Renault & Trognon, 1987) for the Probit model can be computed as by:

$$r = ESDISHW * \left(\frac{F(X_{ij}\hat{\beta}_2)}{N(X_{ij}\hat{\beta}_2)}\right) + (1 - ESDISHW) * (\frac{F(X_{ij}\hat{\beta}_2)}{1 - N(X_{ij}\hat{\beta}_2)}) \quad (3.20)$$

where F(•) is the probability density function and N(•) is the cumulative density function for standard normal distribution.

In the second stage of 2SRI, instead of replacing the endogenous variables with their predicted values as in the case of two stage least-squares (2SLS) for linear models or two stage predictor substation (2SPS)[12] for some nonlinear models, the first stage residuals will be included as additional regressors in the second stage regression. Now, we have the following structural equation:

$$y = X_1 * \beta_3 + r * \gamma + w \quad (3.21)$$

where X_1 is a vector of covariates as defined above in the ordered Probit model, r is a vector of generalized residuals,β_3 & γ are column-vectors of parameters to be estimated and made inference from, and w is a random term which is assumed to be independently, identically, and normally distributed N $(0,\sigma^2)$.

3.4 Empirical Results

3.4.1 Descriptive Statistics for Key Variables.

[12] According to Terza, Basu & Rathouz (2008), although both 2SPS and 2SRI are used to address endogeneity in nonlinear models, 2SRI is consistent and 2SPS is not in a generic parametric framework.

Two interesting variables in this study are households' usage behavior (DISHUSE) and their choices of energy efficient dishwashers (ESDISHW). Both are categorical variables and summarized in Table 3.1. According to Table 3.1, among those who own dishwashers at home, 64.94% use the energy star dishwashers and 35.06% use the standard ones. Households' dish washing behavior varies, with 13.64% observations using the dishwashers less than once a week , 13.46% once a week, 33.01% two to three times a week, 18.87% four to six times a week, and 20.99% at least once every day. To have a preliminary view of the relationship between those two variables, we can look at the two-way frequency table (Table 3.2) of those two variables. As shown in Table 3.2, households using energy star dishwashers have higher proportions with more frequent dishwasher usage behavior, compared with those using standard dishwashers. However, without addressing the endogeneity problem or controlling for other exogenous variables, this seemingly high correlation between the two variables is meaningless as either the direction or the size can be determined.

3.4.2 Selection of Instrumental Variables (IVs).

In this paper, the endogeneity problem is caused by households choosing to have an energy efficient dishwasher because they are heavy users or an unforeseen circumstance will cause abnormal usage. To solve this problem with 2SRI, we need instrumental variables, which are correlated with households' choices of energy star dishwashers but won't influence their usage frequencies directly. Since there is only one endogenous variable, we need at least one instrumental variable. Given the data available from the survey, there are four potential candidates that may serve this role.

The first candidate is variable “ESFRIG”. This variable represents whether households have an energy-star refrigerator. There are two ways that this variable can be correlated with households’ choices of energy-star dishwashers. Firstly, households may live in an energy-star certificated home. Data from the 2009 RECS does not include information on whether the household lives in an energy efficient home. However, one typical feature of those homes can be observed. That feature is the whole household contains an energy efficient package, equipped with efficient appliances, including energy-star certificated dishwashers, refrigerators, clothes washers, etc. (Energy Star, n.d.). Therefore the certification of other appliances may be a good indicator. Secondly, households may choose energy-star products simply because they have a higher value in energy efficiency or the energy-star label (Mirosa, Lawson & Gnoth, 2011; Barton, et al, 2013). As a result, they may purchase more than one energy-star appliance. Since refrigerators are the only appliance that all U.S. households own at least one[13] and it does not influence households’ dish washing behavior, variable “ESFRIG” can be a good instrument for the two aforementioned reasons.

Three additional potential instrumental variables are “KOWNRENT”, “OCCUPYRANGE” and “YEARMADE”. “KOWNRENT” represents whether households are homeowners, renters or occupants without a rent payment. “OCUUPYRANGE” denotes the year-range that household moved in. “YEARMADE” stands for the year that the house was built. Those three variables are irrelevant to households’ dish washing behavior but could impact their choices of the dishwashers. In

[13] According to data from the 2009 RECS, approximately 99.8% U.S. households have at least one refrigerator in 2009. For other appliance, the percentages are much lower.

this paper, the main household characteristics are included in the models, controlling for the possible systematic difference between households choosing energy star dishwashers and those with standard dishwashers. However, according to Wang (2014), the probability to make energy efficiency investments is higher for homeowners than renters and for households living in the same place longer, even after controlling for their climate, housing and personal characteristics. Therefore, variable "KOWNRENT" and "OCCUPYRANG" could serve as valid IVs. The variable "YEARMADE" is also considered as a potential candidate given the belief that old homes are more likely to come with the energy inefficiencies inherent in these houses. However, this variable could influence the choices of energy efficient dishwashers in a different direction. The average life expectancy of dishwashers is 9 years. Therefore dishwashers in homes older than 9 years are more likely to get replaced with newer efficient ones.

To provide further justification for suitable IVs, this study also conducts a selection process by comparing the efficiency of different first stage models with and without different IVs. Given that the first stage model is contained in the class of logistic regression models, the study assesses the model fit by using three groups of goodness-of-fit measures (Amemiya, 1981). The first group includes the Likelihood Ratio (R) and Upper Bound of R (U). Those two measures normally have bigger values for more efficient models. The second group includes 7 different Pseudo-R^2s, such as Aldrich-Nelson R^2, Cragg-Uhler 1 R^2, Cragg-Uhler 2 R^2, Estrella R^2, Adjusted Estrella R^2, Mcfadden's LRI R^2 and Mckelvey-Zavonia R^2. Long (1997) recommends the Mckelvey-Zaoina Pseudo-R^2 as the best fit measure for binary and ordinal probit/logit models. Since the first stage model in this paper is a binary probit model, the magnitude of this measure is given more attention to during the selection process. The third group includes the Akaike information criterion (AIC) and Schwarz criterion (SC). Those two criterions will consider the trade-off between the goodness-of-fit of the model and the complexity of the model. They give minimum values for the best model.

The comparison of different first stage models is summarized in Table 3.3. According to the table, "ESFRIG" is the strongest instrument, which increases the efficiency of the first stage model significantly as indicated by all the goodness-of-fit measures. In particular, the Mckelvey-Zaoina Pseudo-R^2 value increases by nearly 1.5 times in size compared with the base case without any IV. Variable "KOWNRENT" and "OCCUPYRANGE" are shown as weak instruments that increase the efficiency of the first stage model to some extent. By including "YEARMADE", there is no significant change in almost all goodness-of-fit measures, suggesting that variable "YEARMADE" may not be a good instrument in this case. By further adding different instruments in the first stage, the best fit is shown to be the combination of "ESFRIG", "KOWNRENT" and "OCCUPYRANGE". By including those three instruments, the Pseudo-R^2 values for the first stage model increase by twice on average compared with the base case, while the AIC and SC values both decrease by 18%.

3.4.3 Empirical Results from 2SRI.

In the first stage, three instrumental variables and twelve other control variables are used to model households' choices of energy efficient dishwashers. Those twelve control variables include the energy price, 2009 gross household income, whether household pays the energy bill, householders' age, number of household members, number of meals cooked every week, whether household members stay home on typical week days, householder's education level, whether householder lives with spouse or partner, householder's race and gender. The energy price is computed by the ratio of total energy cost (in whole cents, 2009) to total site energy usage (in thousand BTU, 2009) for each household.

The main results for the first stage regression are summarized in Table 3.4. From the results, we notice that all instrumental variables are significant and thus are useful for the prediction. In the second stage, explanatory variables include the residual term, ESDISHW, and the twelve control variables. Parameter estimates for the second stage are summarized in Table 3.5. Given all the small P values provided, we can conclude that all variables are useful for the prediction. In particular, the significance of the residual term confirms the existence of endogeneity problem.

In both the first stage and the second stage models, the signs of the parameter estimates indicate whether the corresponding control variables have positive or negative effects on the dependent variables. For the first stage regression, a positive sign means that an increase in the control variable will lead to higher probability to have energy efficient dishwasher, while a negative sign indicates the higher value of the variable is associated with lower probability. Likewise, in the second stage, a positive sign of the parameter implies that greater value of the variable will result in higher probability to use the dishwasher more often, while a negative sign reveal an opposite effect. In this study, we want to know how energy efficiency investment will influence the energy usage behavior. In Table 3.5, we find the point estimate for ESDISHW being 1 (i.e. energy efficient dishwasher) to be “0.126528”. From the positive sign of the parameter estimate, we can conclude households with energy star dishwashers have higher propensities to use dishwashers more frequently, which verifies the initial prediction from the theoretical model.

Besides directions of the effects, we are also interested in the magnitudes of the effects, which can be computed from the parameter estimates. In both the first stage binary Probit model and the second stage ordered Probit model, marginal effects (ME) are nonlinear functions of the parameter estimates and also values of all control variables. Therefore, MEs are not constant across observations. We can either calculate the overall marginal effect for an “average household”[14] or take the average of MEs calculated for each observation. The latter has been adopted for this study. The average marginal effects for key variables are summarized in Table 3.6 for the first stage regression and Table 3.7 for the second stage regression.

From Table 3.6, we notice that the magnitude of the ME is the biggest for ESFRIG among three instrumental variables, further proving this variable being the strongest instrument. In particular, having an energy star refrigerator will increase the probability of owning an energy star dishwasher by 33.42% on average. If we choose homeowners as the base case, the probability to choose energy star dishwasher decreases by 11.18% on average for renters, confirming the conclusion from the paper of Wang (2014). Additionally, the probability increases by 4.04% on average for households

[14] The “average observation” is created with values for all control variables equal to the means of those variables.

occupying the living units without payment of rent compared with homeowners. For instrumental variable OCCUPYRANGE, the positive MEs show the increased probabilities to have energy star dishwasher for each year range when households moved in, compared with the base case when households moved in between 2005 and 2009. The average ME for PRICE is 0.0156, indicating that the probability to have an energy star dishwasher increased by 1.56% for every 1 unit (cent/1000 BTU)15 rise in energy price. The income effect is much smaller, with an average ME of 0.1%. This ME indicates that for 1 unit (1000 dollars) increase in 2009 gross household income16, the probability to have energy star dishwasher only increase by 0.1%.

In this paper, the main interest lies in the effects of having energy efficient dishwashers on the usage behaviors, which are the marginal effects of variable "ESDISHW" and are summarized in Table 3.7. According to results in Table 3.7, compared with households without energy efficient dishwashers, those having energy star dishwashers are 2.38% less likely to use them less than once a week, 1.27% less likely to use them once each week and 0.68% less likely to use them 2 or 3 times a week, but about 1.05% more likely to use them 4 to 6 times each week and about 3.28% more likely to use them more than once a day. Obviously, having energy efficient dishwasher leads to more frequent usage behaviors. The price effect and the income effect are also included in Table 3.7. For a one unit increase in energy price (in cent/1000btu), households are 0.74% more likely to use them less than once a week, 0.39% more likely to use them

[15] According to the 2014 Monthly Energy Review data from EIA, the average retail price of electricity in the residential sector in 2009 is 11.51 cents per kilowatt-hour, which is equal to 3.37 cents per thousand BTUs.

[16] According to the Current Population Survey by U.S. Census Bureau, the median household income in 2009 is approximately 53 thousand in 2012 dollars, which is about 50 thousand in 2009 dollars.

once a week and 0.21% more likely to use them 2-3 times a week, while are 0.33% less likely to use them 4 to 6 times a week and 1.02% less likely to use them more than once a day. To summarize, the higher the energy price, the less likely frequent usage behavior occurs. Income effects are in opposite directions from the price effects and much smaller in magnitudes. For every 1 unit increase in 2009 gross household income (in 1000 dollars), households are 0.04% less likely to use them less than once a week, 0.02% less likely to use them once a week and 0.01% less likely to use them 2-3 times a week, but are 0.02% more likely to use them 4 to 6 times a week and 0.05% more likely to use them more than once a day. Evidently, the higher the gross household income, the more likely frequent usage behavior takes place.

3.5 Implications

Using the empirical results of this study, direct behavior response from choosing an energy star dishwasher is related with a 1%-3% higher probability of households using dishwashers more frequently. Needing a more straightforward understanding of this behavior change, we assign different weights to different usage frequencies. This way, the paper can approximate the usage behavior under two distinct scenarios. Scenario 1: the average usage frequencies for households with energy star dishwashers and those with standard dishwashers, without controlling for any exogenous variables. Scenario 2: the average frequency changes caused by the choices of energy efficient dishwashers, the price effect and income effect on dishwashing behavior, after adjusting the endogeneity problem and controlling varied exogenous variables.

The weights are as follows: 0.5 for using dishwashers less than once a week, 1 for once a week, 2.5 for two to three times a week, 5 for four to six times a week, and 7 for more than seven times a week. Given the probability/percentage of each usage frequency in Table 3.2, the average usage frequency per week can be approximated by summing the weighted probabilities. The results are summarized in Table 3.8 and Table 3.9. According to Table 3.8, households with standard dishwashers use the appliance about 3.119 times per week or 162.118 times per year. Using Table 3.9, the average usage frequency of households using energy star dishwashers is approximately 3.615 times a week or 187.972 times a year. So the difference is about 0.50 extra dishwashing times a week or 25.78 times a year if we do not control for the endogeneity problem or other exogenous variables.

Provided the marginal effects computed in Table 3.7, we can estimate the expected changes in dishwashing behavior from purchasing energy star dishwashers while controlling for exogenous variables discussed in Section 3.4. Those marginal effects are the probability changes associated with each usage frequency category. Therefore, we estimate the expected changes by summing up the weighed probability changes. The results are summarized in Table 3.10. According to Table 3.10, having an energy star dishwasher causes households' to increase dishwasher usage by 0.24 dishwashing times per week or 12.50 times per year, indicating a 7.7% increase compared with standard dishwashers. In order achieve the "energy star" certification, dishwashers are required to be 10% more energy efficient than non-qualified (standard) models (Energy Star, n.d.). Therefore, the behavior change from increased efficiency will offset a large proportion of the predicted engineering savings.

By using Table 3.7 and including the weight for each frequency range, we also estimate the price effect and income effect, which are summarized in Table 3.11and Table 3.12 respectively. According to Table 3.11, raising the energy price by 1 unit (in cent/1000BTU), households will decrease their usage by 0.0749 dishwashing times a week or 3.895 times a year. According to the 2014 Monthly Energy Review Data from EIA, the 2009 average retail price of electricity in U.S. is approximately 11.51 cents per kilowatt-hour (EIA, u.d.). This is equivalent to 3.37 cents per 1000 BTU, the unit used in this paper. Consequently, 1 unit increase in energy price indicates approximately a 30% rise in the price. According to Table 3.12, for 1 unit increase in the 2009 gross household income (in 1000$), the average dishwashing times increase by 0.004 per week or 0.2077 times a year. According to the Current Population Survey by U.S. Census Bureau, the median household income in 2009 is approximately 53 thousand in 2012 dollars, which is around 50 thousand in 2009 dollars. Therefore, 1 unit increase in 2009 Gross household income implies a 2% increase in the household income.

3.6 Conclusions

In this paper, household production theory is employed to make initial predictions on households' behavior responses to increased energy efficiency. In the empirical analysis, we focus on residential dishwasher usage. An ordered Probit model is developed to estimate a household's demand for dishwashing services and how their demand is influenced by choices of energy efficient dishwashers. Two-stage residual inclusion is applied to solve the endogeniety problem. This issue arises because households may choose to have energy efficient dishwashers because they plan to use them more frequently. Particularly, to find valid instrumental variables for this two stage approach, the paper conducts a selection process by comparing the efficiency of different first stage models.

Using the 2009 U.S. residential household survey data, the study finds evidence consistent with our initial predictions. Households containing energy star dishwashers have a 1% to 3% higher probability of using dishwashers more frequently compared with those containing standard dishwashers. This change indicates a 7.7% higher usage behavior or nearly 12.5 additional dishwashing times per year compared with household s using standard dishwashers. With an estimated 10% energy savings from using an energy star dishwasher, this behavior change will offset a great proportion of the predicted engineering savings.

This paper investigates consumers' behavior alterations after the introduction of new technology that improves the efficiency of resource use. Due to data constraints, this investigation is carried out by comparing dishwasher usage behaviors between households with energy star dishwashers and those without, keeping households' key characteristics constant. A potential improvement could be made by implementing a before-after comparison on the same group of observations. Additionally, as pointed out in Section 3.1, this study only focuses on the direct effect on dishwasher users caused by an increase in energy efficiency. Future research can also explore the indirect effect, general equilibrium effect, or expand the sample by including households without dishwashers.

4 U.S. Residential Energy Consumption: two opposing trends

4.1 Introduction

There are two main opposing trends that affect residential energy demand. One is steady increases in energy-based living standards lured by rising household income, which stimulates households' energy consumption. The other trend is more efficient energy use worldwide boosted by the emerging energy efficiency technologies and enforcing energy efficiency policies, which have been significantly reducing households' energy consumption. These aforementioned trends shape residential energy demand worldwide and result in different patterns in countries. The patterns vary over time during different time periods within a specific country. In the United States, per capita residential energy consumption increased steadily from 1940s to 1960s. From 1970s forward, the energy consumption has remained stagnant (See Figure 4.1).

In this paper, the author focuses on the steady period of residential energy consumption in the United States. Using a panel data set covering 48 contiguous states and ranging from 1970 to 2008, the study models residential demands for "four"[17] different fuels. Fuel prices, per capital income, climate factors, time trend, and cross-state heterogeneity are all controlled. Double-log demand models are applied and two-stage residual inclusion is employed to address the price endogeneity. The results discover positive income effects and negative own price effects. Various cross price elasticities are analyzed and suggest potential substitution or complementary effects between different fuels. Additionally, the paper illustrates that per capita electricity consumption increases

[17] In this paper, three main fuels are investigated, including electricity, natural gas and LPG. The study also aggregate the consumption of wood, fuel oil, kerosene and solar as one category, because only a small proportion of the households use them. Therefore, altogether, demands for "four" fuels will be analyzed.

over time, after controlling for exogenous variables. This result is difficult to explain because of the technological progress and thus more efficient electricity use in the residential sector. In order to explain this curious result, the paper examines multiple household level survey data between 1970s and 2000s. Two potential explanations are provided. First, data demonstrates that even though electricity-consuming products become more efficient over time, households increase their fuel consumption by purchasing additional electronics and appliances at home. Second, besides energy efficiency, households desire different attributes over time. Those attributes usually increase energy consumption and offset the expected savings from increased energy efficiency.

Residential sector is one of the four major sectors[18] that consume energy at the point of end use. Residential energy consumption is considered a driving force behind the underlying energy demand worldwide. According to data from U.S. Energy Information Administration (EIA), 18% of world marketed energy was consumed in the residential sector in 2011, with generally higher ratios in developing countries and lower ratios in developed countries (Dzioubinski & Chipman, 1999; Chow, Kopp & Protney, 2003). Energy use in the residential sector as a proportion of total energy consumption has been growing slowly but steadily in the United States since the late 1940s. Residential energy consumption averaged 19% of total energy consumption from 1949 to 1969, 20% from 1970 to 1990, and reached 21% from 1991 to 2012[19]. Fuels commonly used in the

[18] The U.S. Department of Energy breaks down national energy consumption into four broad sectors: industrial, transportation, residential, and commercial.
[19] Those proportions are calculated from data in the Annual Energy Review of EIA released on February 26, 2014.

residential sector include electricity, natural gas, propane/liquefied petroleum gas (LPG), wood, fuel oil, kerosene and solar. According to the 2009 Residential Energy Consumption Survey (RECS) conducted by EIA, among the 113.6 million homes included in the survey, 100% used electricity, 61% used natural gas, 43% used propane/LPG, 11.5% used wood, 6.7% used fuel oil, 1.5% used kerosene, and only about 1% used solar. Natural gas, petroleum and electricity are the three main fuels consumed in the residential sector. Electricity is the only one with full penetration among U.S. households and becomes the focus of this paper.

Acquiring sound knowledge of residential energy demand and its determinants is of crucial importance for predicting future resource requirements, environmental impacts, and developing energy related policies. Recently, the US residential energy demand literature has focused on state level panel data to analyze the aggregate energy demand or the demand for a single fuel, mainly electricity, using econometric modeling techniques. Alberini and Pilippini (2010) estimate residential electricity demand using panel data for 48 states over the period 1995 to 2007 and apply a dynamic partial adjustment model using the Kiviet corrected LSDV and the Blundell-Bond estimator. Filippini and Hunt (2010) estimate the US residential energy demand and energy efficiency using data for 48 states over the period 1995 to 2006 with a stochastic frontier model. Paul, Myers and Palmer (2009) also use state-level panel data spanning January 1999 through December 2006 to estimate electricity demand by region, season and sector using a partial adjustment model estimated in a fixed-effects OLS framework. Neeland (2009) analyzes US residential electricity demand through an ADF unit root test, Johansen test and a rolling regression with panel data for the period 1970 to 2007. Additional related studies on US residential electricity demand include Dergiades & Tsoulfidis (2008) using a Autoregressive Distributed Lag (ARDL) cointegration technique and Horowitz (2007) using a counterfactual difference in differences estimator to estimate energy efficiency program commitment impacts.

According to a thorough review by Swan and Ugursal (2009), most researchers were modeling energy demand either through a top-down approach based on historical information or a bottom-up approach utilizing historical or detailed input information at household level. In this paper, the author investigates households' demand for different fuels by exploring various residential energy consumption data, including both state level panel data and multiple household level micro time series data. The paper is organized as follows. Section 4.2 models residential energy demands for "four" main fuels. Section 4.3 investigates potential explanations for increasing demand of electricity presented in section 4.2, after controlling for various exogenous variables. The conclusions are contained in Section 4.4.

4.2 Residential Energy Demand by Fuels

4.2.1 Econometric Models.

4.2.1.1 Double-Log Demand Model.

This paper employs the double-log regression to estimate residential demands for different fuels. The functional form can be represented as following:

$$y = x * \beta_1 + w \tag{4.1}$$

where y is the per capital fuel consumption in logarithmic form, x is a vector of explanatory variables most of which are in logarithmic forms, β_1 is a vector of parameters, and w is the error term, which is assumed to be identically, independently and normally distributed.

In this study, dependent variables (y) are the per capita demand for four different fuels, including electricity (ESRCB), natural gas (NGRCB), LPG (PARCB), and other fuels as one category (OFRCB). The same independent variables (x) are employed to make all the estimations. Among the control variables included, fuel prices (P)[20], per capital income (PerY), heating degree days (HDD) and cooling degree days (CDD) are used in their logarithmic forms. Two additional control variables are the time trend (T) and a state dummy (D). Time trend (T) is used to capture the technological progress over time and the state dummy (D) is applied to deal with the cross state heterogeneity.

4.2.1.2 Price Endogeneity and 2SRI.

All independent variables are exogenous except fuels prices (P) due to their simultaneity with consumptions. Given the nonlinearity property of our model, we use two-stage residual inclusion (2SRI), which extends the linear two-stage least square estimation to nonlinear models to deal with the endogeneity problem. According to

20 Price vector P include price of electricity (ESRCD), price of natural gas (NGRCD), price of LPG (PARCD) and the price of other_fuels (OFRCD). Price of other_fuels (OFRCD) is defined as the average price of other fuels used in the residential sector and is calculated as: OTRCD= (TERCV-ESRCV-NGRCV-PARCV)/(TERCB-ESRCB-NGRCB-PARCB), where TERCV is the total energy expenditures in the residential sector, ESRCV is the total electricity expenditure in the residential sector, NGRCV is the total natural gas expenditure in the residential sector, PARCV is the all petroleum products total expenditures in the residential sector, and TERCB is the total energy consumed by the residential sector.

Terza, Basu, and Rathouz (2008), 2SRI generally gives consistent results for both linear and nonlinear models with endogenous regressors.

In the first stage of 2SRI, we add instrumental variables (IV) to estimate the reduced form equations. Four endogenous variables are included, price of electricity (ESRCD), price of natural gas (NGRCD), price of LPG (PARCD) and price of other fuels (OFRCD). Therefore, at least four IVs are needed to address the endogeneity problem. Variables chosen as IVs are either production side variable from the same year or consumption side variables from the previous year. Both types of IVs impact fuel supplies and equilibrium fuel prices but do not influence households' fuel demands.

Ten IVs are included. They are coal production (CLPRB), biomass inputs for the production of fuel ethanol (EMFDB), natural gas marketed production (NGMPB), electricity produced from nuclear power (NUETB), crude oil production (PAPRB), renewable energy production (PEPRB), consumption of electricity from previous year (LAGESRCB), consumption of natural gas from previous year (LAGNGRCB), consumption of LPG from previous year (LAGPARCB), and consumption of other_fuels from previous year (LAGOFRCB). In the first stage regression, independent variables include IVs and control variables from the second stage. The reduced form equation can be displayed as following:

$$P = \alpha * IV + X * \beta_2 + \varepsilon \qquad (4.2)$$

where P is a vector of endogenous prices, α and β_2 are vectors of parameters, IV is a vector of instrumental variables, and ϵ is the random error term. By applying ordinary least squares (OLS) regression method, we can obtain consistent estimates of α and β_2. The residuals (r) can be computed by:

$$r = P - \widehat{\alpha} * IV - \widehat{\beta_2} * x \tag{4.3}$$

In the second stage of 2SRI, first stage residuals will be included as extra regressors in the model. Now the following simple linear demand/structural equation holds:

$$y = x * \beta + r * \gamma + w \tag{4.4}$$

where r is a vector of residuals and γ is a vector of parameters. OLS can be applied to perform the estimation.

4.2.2 Data and Descriptive Statistics.

4.2.2.1 Data Source.

The main interest of this section is to explore the underlying factors influencing U.S. residential demands for different fuels. The estimation is based on panel data, which covers 48 states and ranges from 1970 to 2008. The 48 states included are restricted to the contiguous states (i.e. Alaska and Hawaii are excluded). All energy data are obtained from the US Energy Information Administration database called States Energy Data System. Population and per capital personal income are acquired from the Bureau of Economic Analysis of the US Census Bureau. The Consumer Price Index (CPI-U) is compiled by the Bureau of Labor Statistics and is based upon a 1982-1984 Base of 100. Heating and cooling degree days are obtained from the National Climate Data Center at National Oceanic and Atmospheric Administration (NOAA).

4.2.2.2 Descriptive Statistics.

Descriptive statistics for key variables in the demand equations are summarized in Table 4.1. All prices (i.e. ESRCB, NGRCB, PARCB and OFRCB) and income (PerY) in Table 4.1 are adjusted for inflation and in real 1982-1984 dollars. From the table, we notice that both the standard deviation and the range of per capital electricity consumption (ESRCB) are smaller in size compared with other fuels, indicating a relatively stable consumption. However, the price of electricity (ESRCD) appears to have additional fluctuation, with larger standard deviation and range than other prices. It is also worth mentioning that the mean price of other fuels (OFRCD) is much smaller than prices of electricity, natural gas or LPG. This is caused by the fact that a large proportion of this aggregate category is consumed with no cost. Most variables used in the model are in logarithmic forms. Table 4.2 summarizes the descriptive statistics for key variables in logarithmic forms contained in the demand equation.

Descriptive statistics for instrumental variables are summarized in Table 4.3. This paper recodes IVs that have a value of 0 in some of the states over the entire 1970 to 2008 periods as dummy variables. Those recoded variables are coal production (CLPRB), biomass inputs for the production of fuel ethanol (EMFDB), natural gas marketed production (NGMPB), electricity produced from nuclear power (NUETB) and crude oil production (PAPRB).

4. 2.3 Empirical Results.

4.2.3.1 First Stage Results.

First-stage regressions are employed to model four fuel prices. Parameter estimates are included in Appendix G for electricity price, Appendix H for natural gas price, Appendix I for LPG price, and Appendix J for other-fuels price. Most IVs are significant for all four regressions, indicating strong correlations between those IVs with prices. The fit of the models is supported by the medium to high R-Squares obtained from outputs, with values equal to 0.8390, 0.7835, 0.6480 and 0.5313 respectively.

4.2.3.2 Second Stage Results.

Second-stage regressions estimate per capita demand for electricity, natural gas, LPG and other fuels as one category. Detailed parameter estimates can be found in Appendix K for electricity, Appendix L for natural gas, Appendix M for LPG, and Appendix N for other-fuels. The goodness of fit for those models is validated by the fairly high R-Square values: 0.9502, 0.9754, 0.9352, and 0.9247 respectively. Results from the second stage include four parts: elastricities, time trend, state dummy and residual terms. State dummy demonstrates significant effects in all cases, indicating the existence of cross state heterogeneity. The significance of the residual terms confirms the existence of the price endogeneity. For the elasticities and time trend, more detailed analyses are provided in the following paragraphs.

Table 4.4 summarizes all elasticity terms. Per capita demand of electricity, natural gas and other fuels all have negative own price elasticities. These elasticities represent the percentage decrease in demand for a one percentage increase in their own prices. According to the table, demand for natural gas is relatively elastic with the own price elasticity greater than 1 in absolute value, while demands for electricity and other fuels are rather inelastic with elasticities less than 1. Own price elasticity for LPG is not significant. Income elasticities are all positive, indicating the percentage increase in demand for a one percentage increase in per capita income. Electricity, natural gas and other fuels are necessity goods with income elasticity less than 1, while LPG is shown as a luxury good with income elasticity greater than 1. Elasticities with respect to HDD or CDD are positive in all cases, revealing the percentage increase in demand for a one percentage increase in HDD or CDD. The table also contains all cross price elasticities between different fuels. Cross price elasticities are the percentage change in the per capita demand of a specific fuel for a one percentage increase in the price of another fuel. Usually, a positive cross price elasticity value identifies two fuels as substitutes and a negative value indicates two fuels as complements.

The time trend variable is used to capture the influence from technological progresses on per capita fuel demand after excluding effects from fuel prices, per capita income, CDD, HDD, and state heterogeneity. For natural gas and other fuels, time trend variable does not show any significant effect. For LPG, the time trend has a significant negative effect. This makes sense because LPG, primarily propane, is widely used as a fuel for heating and cooking. Heating and cooking devices are becoming more energy efficient due to technological progress and thus help reduce the consumption of related fuels. However, the time trend variable for electricity consumption has a positive effect. These results appear to contradict our expectations because of rising efficiency in both home electronics and electricity-consuming appliances. Section 4.3 will further investigate this unforeseen result by using the micro level household data.

4.3 Residential Electricity Consumption: two opposing trends

4.3.1 Increased Efficiency.

Electricity is used in innumerable ways in a household, from the refrigerator in the kitchen, the TV in the living room, the water heater in the basement, to the electric lawn mower outdoors. Electricity is the most versatile energy source and the only fuel consumed by every U.S. household. Over time, electricity has been used more and more efficiently at home, empowered by ongoing advances in energy-saving technologies and enforcing energy efficiency policies both at federal and state levels.

The thermal envelopes of U.S. homes are designed and constructed to be more energy conservative. The term 'thermal envelope" refers the outside shell of the building and it prevents the wanted heat transfer between the inside living space and the outside environment. New homes are more likely to have improved insulation, more energy-efficient windows, well-sealed doors, and so on, all of which reduce the energy required to heat or cool the homes. According to data from the 2009 Residential Energy Consumption Survey, around 35% of U.S. households use electricity as the main fuel for space heating and 100% use electricity for air conditioning. Therefore, increased efficiency in residential thermal envelope helps reduce the electricity consumption.

Efficiency programs and policies related to the thermal envelopes include various building codes, constructions codes, building ratings and disclosures, etc. Although most of those programs and policies are not mandatory at the federal level, a lot of states choose to adopt them voluntarily and enforced them at state level. For example, in California, all new homes are required to meet minimum energy efficiency standards contained in Title 24 since 1978. This Title specifies the mandatory measures regarding home insulation, roof, window, thermal mass, etc.

Second, electronics and household appliances consume less electricity than previously produced comparable models because of yearly improvements in energy efficiency. Based on historical data published by the Association of Home Appliance Manufacturers (AHAM), from the year 1981 to 2011, energy efficiency has increased by 46% for room air conditioner, 65% for freezer, 102% for clothes washer, 114% for dishwasher, and 207% for refrigerator (Perry, 2012).

Since the first appliance standard enacted in California in 1974, mandatory standards, labeling programs, and laws have been adopted for residential appliances and equipment at federal levels in the United States. Almost all appliances and equipment used in the residential sector are covered by National Minimum Efficiency Standards in the U.S. by law. These appliances and equipment range from small light bulbs and battery chargers to large refrigerators and pool heaters. Usually states took initiatives first and continued to lead on the adoption of different programs and policies. Then federal responses were elicited and national Acts got passed by congress.

4.3.2 Increased Quantity of Electronics and Appliances.

Even after controlling for income effects, price effects, climate effects, and cross-state heterogeneity, per capita electricity consumption has been increasing despite the increased efficiency of electronics and appliances over time. One plausible explanation may be that households choose to purchase more electronics and appliances.

For common electronics and appliances, like refrigerators and TVs, households are more likely to purchase more than one. Take refrigerators as an example. In the 1980 RECS, 99.7% households in the U.S. reported to own a least one refrigerator. This rate increased only slightly over time and reached 99.82% in the 2009 RECS. However, percentage of households having two or more refrigerators has grown steadily, from only 14% in 1980 to 22.9% in 2009. After purchasing new refrigerators, most households continue using the previous old and less energy efficient models. (World Economic Forum, 2010). According to the 2009 RECS, approximately 76% of the second-most used refrigerators are more than 5 years old and around 49% are more than 10 years old. 86% households keep the secondary refrigerators running all year round.

For electronics and appliances that could not be found in most U.S. homes, ownership rates have increased significantly. In 1980, only 37.2% U.S. households owned a dishwasher. This rate has been increasing over time and reached 59.34% in 2009. Furthermore, many modern electronics or electric appliances did not even exist in the 1970s and have been gradually introduced into the households over time, like iPhone, iPad, espresso machine, etc.

4.3.3 More Energy-Consuming Attributes.

Energy efficiency is just one of the many important attributes households desire. When purchasing energy efficient electronics and appliances, households are tempted to buy newer models with auxiliary energy-consuming attributes, like automatic ice-makers and through-the-door dispensers for refrigerators. According to the U.S. Environmental Protection Agency (EPA), just the two aforementioned attributes consume 14% to 20% extra energy. Comparing data from the 5 most recent RECSs from 1993 to 2009, the proportion of the most-used refrigerators with through-the-door ice and water service has risen over time, from approximately 10.5% in 1993 to roughly 33.5% in 2009. Added attributes, like those for newer models of electronics and appliances, may be another plausible explanation for the increasing electricity consumption after controlling for various exogenous variables. In this paper, we use refrigerators as an example and demonstrate how households' demand for three main energy-related attributes changes over time.

The first attribute investigated in this paper is the refrigerators defrost method. Holding other attributes constant, manual defrost refrigerators use less energy than frost free. By comparing data from the past 11 RECS (see Table 4.5), the paper finds the percentage of the most-used refrigerators that are frost-free has been increasing. In the 1980 survey, 60.2% most-used refrigerators are frost free, while in 2009 survey, the percentage reached 92.4%.

The second attribute included in the study is the refrigerator door arrangement. In table 4.6, the paper summarized door arrangement types for the most-used refrigerator in percentages from 1990 to 2009. The table ordered the types from the most energy-consuming category "3 or more doors" to the least energy-consuming category "half-size". According to the table, over time, higher percentage of households own the more energy consuming types, i.e. "2-doors (side-by-side)" or "3 or more doors".

The third attribute examined is the refrigerator size. Generally speaking, the larger a refrigerator gets, the greater the energy it consumes. In table 4.7, sizes of the most – used refrigerators are summarized in percentages of households from 1993 to 2009. According to the table, a growing proportion of the most-used refrigerators are large (19-22 cubic feet) or very large (23 or more cubic feet).

Furthermore, when households purchase energy efficient refrigerators, they are more inclined to include some extra energy-consuming attributes than when they buy standard ones. This can be another plausible explanation for the increased electricity consumption. The study compares attributes of energy star refrigerators versus attributes of standard refrigerators using data from the 2009 RECS (see Table 4.8). Results indicate that existing energy star refrigerators in the residential sector also appear to be bigger in size, designed with more complex or energy-consuming door arrangements, and more likely to have through-the-door ice and water service.

4.4 Conclusions & Limitations

This paper investigates the U.S. residential energy demand during the fairly stable time period between 1970s and 2000s. Both state level panel data and multiple household level survey data are explored in this research. The study models residential energy demands for four main fuels: 1) electricity, 2) natural gas, 3) LPG, 4) other fuels aggregated into one category.

Findings show positive income effects and negative own price effects. Various cross price elasticites are also provided suggesting the potential substitution or complementary effects between different fuels. Cross-state heterogeneity and the existence of endogeneity problems are verified by the statistically significant results. Time trend variables suggest different consumption patterns for different fuels over time, after controlling for various exogenous variables. For LPG and the aggregated category which combines several less commonly used fuels, the per capita consumptions have not changed significantly over the years. Per capita natural gas consumption has decreased over time, which can be justified by the long standing technological progress causing more efficient use in the residential sector. One unexpected result is identified. This result indicated increasing per capita electricity consumption over time despite significant efficiency improvements over time. To investigate the potential causes for this unusual result, multiple household level survey data is incorporated into the research. Two potential explanations are suggested by the data. First, households increase fuel consumption by purchasing more electronics and electric appliances at home. Second, besides energy efficiency, households desire different attributes. Those added attributes usually increase energy consumption and offset the expected savings from improved energy efficiency.

There are two main limitations of this study. One comes from the choice of the demand model. This paper employs the double-log demand function. This functional form imposes the restriction of constant elasticity, which may not be appropriate. According to a meta-analysis by Espey & Espey (2004) on residential electricity demand, price elasticity estimates did not change significant over time but estimates of income elasticity were found to increase over time. The other limitation is caused by the data constraints. In this study, fuel prices, real per capita income, HDD and CDD are included as control variables. Although those variables are key drivers of the demand, other factors, like the house size, the household size, and number or price of appliances, were also shown to have a significant influence on the fuel demand (Neeland, 2009; Inglesi, 2010).

5. Conclusions

The first paper investigates different energy efficiency (EE) investment patterns in housing units of homeowners versus renters. In the empirical analysis, discrete choice models are employed to explore households' EE investment behavior. Results demonstrate that homeowners on average have a 9.88% higher probability to have EE appliances compared with renters, after controlling for climate, housing and personal characteristics. In literature, the existing differences were explained as inefficiencies caused by landlords' ownership over some investments and/or utility-included rental contracts. However, if we compare homeowners with renters who need to pay the monthly utility bills directly, the differences only decrease about 0.15% on average for all investments. Statistical results also reveal that the probabilities to have most EE appliances are not significantly different between renters paying their monthly energy bills and those having their bills paid by landlords due to utility-included rental contracts. Furthermore additional analysis suggests that due to costly contracts, renters' increased mobility coupled with the characteristics of typical EE investments account for most of the perceived probability differences. In particular, the differences shrink around 74% on average if we compare homeowners with long-term tenants living in the current residences for more than 10 years.

The second paper explores households' choices of energy efficient dishwashers and their potential influence on dish washing behaviors. Household production theory is employed to make initial predictions for households' responses to increased energy efficiency. In the empirical analysis, an ordered Probit model is developed to investigate households' demand for dish washing services and how the choices of energy efficient dishwashers influence the quantity demanded for this service. Two-stage residual inclusion (2SRI) addresses the endogeneity problem, caused by households potentially choosing energy efficient dishwashers because of their expected higher usage frequency. With data from the 2009 U.S. residential energy consumption survey, the empirical results verify the predicted behavior alteration. Households with energy efficient dish washers averaged 1%-3% higher probability of using dishwashers more frequently, which is approximately 7.7% more frequent usage or nearly 0.24 additional dishwashing times per week compared with those using standard dishwashers. With an estimated 10% energy savings from using an energy star dishwasher, this behavior change will offset a large proportion of the predicted engineering savings.

The last paper focuses on the stable U.S. residential energy consumption per capita since the 1970s. The paper decomposes energy consumption into four main fuel sources and models the demand for each source. Double-log demand models are applied and two-stage residual inclusion is employed to address the price endogeneity. Estimation is based on panel data, which covers 48 states and spans from 1970 to 2008. Results illustrate positive income effects and negative price effects after controlling for the climate factors and cross-state heterogeneity. Additionally, this study discovers steady per capita consumption of LPG and other fuels over time. Natural gas consumption decreases with time, which can be justified by long standing technological progress and demonstrates more efficient use. In contrast, after controlling for exogenous variables per capita electricity consumption has been increasing with time. This paper investigates multiple household level survey data between 1970 and 2000 to pinpoint the unexpected result of electricity consumption. Two potential explanations are provided. First, although electricity-consuming products get more efficient over time, households increase the fuel consumption by purchasing more electronics and electric appliances. Second, households desire product attributes besides energy efficiency. Those attributes usually add extra energy consumption and offset the expected savings from increased energy efficiency.

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Table 2.1

Weighed frequencies for dependent variables interested

Investment	# of OBS	Percentage with EE appliance	Weighted Percentage	Standard Err of Weighted Percentage
Energy Efficient bulbs	7336	88.55%	88.41%	0.42%
Energy Star Window/Wall AC	1811	63.28%	62.02%	1.40%
Energy Star refrigerator	11924	40.71%	39.66%	0.48%
Energy Star clothes washer	6614	67.09%	66.64%	0.77%
Energy Star dishwasher	4656	64.95%	64.39%	0.81%

Note: * For each investment, only households having the appliance and providing valid answers are included *Sum of Weights: 113616229 *Number of Replicates: 244 *Method: Fay's Balance Repeated Replication

Table 2.2

Percentages of households with EE investments: homeowners versus renters

Energy Efficiency Investments		obs	Percentage with EE Investment
Energy Efficient bulbs installed by household (Sample Size=7336, with 74.14% homeowners and 25.86% renters)	owner	5439	91.01%
	renter	1897	80.92%
Energy Star Wall/Window AC (Sample Size=1811, with 56.71% homeowners and 43.29 % renters)	owner	1027	69.72%
	renter	784	54.85%
Energy Star most-used refrigerator (Sample Size=11924, with 68.17% homeowners and 31.83% renters)	owner	8129	48.17%
	renter	3795	24.72%
Energy Star clothes washer (Sample Size=6614, with 78.32% homeowners and 21.68 % renters)	owner	5180	72.14%
	renter	1434	48.81%
Energy Star dishwasher (Sample Size=4656, with 79.15% homeowners and 20.85% renters)	owner	3685	72.81%
	renter	971	35.12%

Note: Sample changes from investment to investment. For each investment, we only included observations that had at least one corresponding appliance at home and provided valid answers.

Table 2.3

Independent Variables

Categories	Variables	Labels
Ownership Status	OWNER	0 Renters 1 Owners
Payment Arrangements	Pay	0 Households who don't pay the related energy bills 1 Households who pay the related energy bills
Energy Price	Price	Price of the related fuel used
Climate Related Variables	HDD65	Heating Degree days in 2009, base temperature 65F
	CDD65	Cooling Degree days in 2009, base temperature 65F
	HDD30YR	Heating Degree days, 30-year average 1981-2010, base temperature 65F
	CDD30YR	Cooling Degree days in 2009, 30-year average 1981-2010, base temperature 65F
	Climate_Region_Pub	Building American Climate Region (5 categories): 1. verycold/cold; 2.Hot-dry/mixed-dry; 3. Hot-humid; 4. mixed-humid; 5 Marine.
	REGIONC	Census region (4 categories)
Housing Characteristics	TYPEHUQ	1 Mobile Home 2 Single-Family Detached 3 Single-Family Attached 4 Apartment in Building with 2 – 4 Units 5 Apartment in Building with 5+ Units
	METROMICRO	Housing unit in Census Metropolitan Statistical Area Housing unit in Census Micropolitan Statistical Area Housing unit in neither
	UR	Urban Rural
	YEARMADE	Year housing unit was built
	TOTROOMS	Total number of rooms in the housing unit

	TOTSQFT	Total square footage (includes all attached garages, all basements, and finished/heated/cooled attics)
	OCCUPYRANGE	1 Before 1950 2 1950 to 1959 3 1960 to 1969 4 1970 to 1979 5 1980 to 1989 6 1990 to 1999 7 2000 to 2004 8 2005 to 2009
Householder characteristics	HHSEX	1 Female 2 Male
	EMPLOYHH	0 Not employed/retired 1 Employed full-time 2 Employed part-time
	SPOUSE	1 Householder lives with spouse or partner
	SDESCENT	1 Householder is Hispanic or Latino
	Householder_Race	1 White Alone 2=Black or African/American Alone 3=American Indian or Alaska Native Alone, or Asian Alone, or Native Hawaiian or Other Pacific Islander Alone, or Some Other Race Alone, or 2 or More Races Selected
	EDU	0= No schooling completed, Kindergarten to grade 12, or High school diploma or GED 1= Some college no degree, Associate's degree, Bachelor's degree, Master's degree, Professional degree, or Doctorate degree
	NHSLDMEM	Number of household members
	HHAGE	Age of householder
	MONEYPY	2009 gross household income
	ATHOME	1 Household member at home on typical week days

Table 2.4

Results from Test 1: homeowners versus renters after controlling for household characteristics

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	7336	1811	11924	6614	4656
P (Homeowners)- P (Renters)	3.75%*** (SE=0.02%)	Not significantly Different	17.69%*** (SE=0.03%)	11.57%*** (SE=0.03%)	16.40%*** (SE=0.06%)

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01.*

Table 2.5

Results from Test 2.1: homeowners versus renters who need to pay the monthly utility bills

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	7029	-	11292	6469	4549
P(Homeowners)-P(Renters)	3.21%*** (SE=0.02%)	-	17.51%*** (SE=0.03%)	11.70%*** (SE=0.03%)	16.39%*** (SE=0.06%)
Comparison: Test 1	3.75%***	Not significantly different	17.69%	11.57%	16.40%

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01. For Energy Star Window/Wall AC, the number of valid respondents becomes too small for the estimation.*

Table 2.6

Results from Test 2.2: renters who need to pay the monthly utility bills versus renters whose energy costs are included in rents

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	1864	-	3725	1410	954
P(Renters Pay)- P(Landlord Pay)	Not significantly Different	-	-3.63%* (SE=0.02%)	Not significantly Different	Not significantly Different

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01. For Energy Star Window/Wall AC, the number of valid respondents becomes too small for the estimation.*

Table 2.7

Results from Test 3.1: homeowners versus long-term renters after controlling for household characteristics

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	5660	1165	8552	5292	3732
P(Homeowners)-P (Renters)	Not significantly Different	Not significantly Different	5.76%* (SE=0.01%)	7.13%* (SE=0.02%)	Not significantly Different
Comparison: Test 1	3.75%***	Not significantly Different	17.69%***	11.57%***	16.40%***

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01.*

Table 2.8

Results from Test 3.2: long-term homeowners versus long-term renters after controlling for household characteristics

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	2984	707	4535	2431	1582
P (Homeowners)-P (Renters)	Not significantly Different	Not significantly Different	7.04%** (SE=0.01%)	10.13%** (SE=0.06%)	Not significantly Different
Comparison: Test 1	3.75%***	Not significantly Different	17.69%***	11.57%***	16.40%***

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01.*

Table 2.9

Results from Test 3.3: short-term homeowners versus short-term renters after controlling for household characteristics

Investments	EE light bulbs by Households	Energy Star Window/Wall AC	Energy Star Refrigerator	Energy Star clothes washer	Energy Star dish washer
Sample Size	4352	1104	7389	4183	3074
P(Homeowners)-P(Renters)	4.83%*** (SE=0.03%)	Not significantly Different	17.16%*** (SE=0.04%)	11.23%*** (SE=0.03%)	17.55%*** (SE=0.07%)
Comparison: Test 1	3.75%***	Not significantly Different	17.69%***	11.57%***	16.40%***

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01.*

Table 3.1
Frequency Table for ESDISHW & DISHUSE

Variable	Value	Frequency	Percent	Cumulative Frequency	Cumulative Percent
ESDISHW	0: not energy star dishwasher	1642	35.06	1642	35.06
	1: energy star dishwasher	3042	64.94	4684	100
DISHUSE	11: less than once a week	639	13.64	639	13.64
	12: once each week	632	13.49	1271	27.13
	13: two to three times a week	1546	33.01	2817	60.14
	20: four to six times a week	884	18.87	3701	79.01
	30: at least once every day	983	20.99	4684	100

Table 3.2

*Two-way Frequency Table of ESDISHW*DISHUSE*

ESDISHW		DISHUSE					Total
		< once a week	once a week	2-3 times a week	4-6 times a week	> once a day	
0： not energy star dishwasher	Frequency	300	237	546	272	287	1642
	Percent	6.4	5.06	11.66	5.81	6.13	35.06
	Row Pct	18.27	14.43	33.25	16.57	17.48	
	Col Pct	46.95	37.5	35.32	30.77	29.2	
1： energy star dishwasher	Frequency	339	395	1000	612	696	3042
	Percent	7.24	8.43	21.35	13.07	14.86	64.94
	Row Pct	11.14	12.98	32.87	20.12	22.88	
	Col Pct	53.05	62.5	64.68	69.23	70.8	
Total	Frequency	639	632	1546	884	983	4684
	Percent	13.64	13.49	33.01	18.87	20.99	100

Table 3.3

Selection of Instrumental Variables

Goodness-of-Fit Measures	Base Case	Instrumental Variables Used						
	No Instrument	ESFRIG (Energy Star Refrigerator)	KOWNRENT (Homeowner, Renter, or Occupant)	OCCUPYRANGE (Year-Range when household moved in)	YEARMADE (Year House Built)	ESFRIG + KOWNRENT	ESFRIG + KOWNRENT + OCCUPYYRANGE	ESFRIG + KOWNRENT + OCCUPYYRANGE +YEARMADE
Likelihood Ratio (R)	4080000	12200000	5810000	4580000	4080000	12900000	13300000	13300000
Upper Bound of R (U)	55000000	55000000	55000000	55000000	55000000	55000000	55000000	55000000
Aldrich-Nelson	0.0881	0.2243	0.1208	0.0978	0.0881	0.2339	0.2391	0.2392
Cragg-Uhler 1	0.0921	0.2512	0.1284	0.1027	0.0921	0.2631	0.2696	0.2697
Cragg-Uhler 2	0.1265	0.3449	0.1764	0.141	0.1265	0.3613	0.3703	0.3705
Estrella	0.0955	0.279	0.1352	0.107	0.0955	0.2938	0.302	0.3021
Adjusted Estrella	0.0955	0.279	0.1352	0.107	0.0955	0.2938	0.302	0.3021
McFadden's LRI	0.0742	0.2221	0.1055	0.0832	0.0742	0.2344	0.2413	0.2414
	0.1557	0.3966	0.2136	0.1728	0.1558	0.4134	0.4227	0.4228
McKelvey-Zavoina	0.1481	0.3709	0.1969	0.1649	0.1481	0.3854	0.3959	0.3961
AIC	50953450	42813656	49228101	50457507	50951766	42135877	41757208	41752249
Schwarz Criterion	50953932	42814154	49228615	50458098	50952264	42136406	41757846	41752903
N = # of observations, K = # of regressors								

Table 3.4

Parameter Estimates for the First Stage

Parameter	Label	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		0.747942	0.003531	211.80	<.0001
ESFRIG	1: The most used refrigerator is energy-star	1.207367	0.000461	2618.9	<.0001
	0: The most used refrigerator is not energy star (Base case)				
KOWNRENT	1: Rented	-0.403806	0.000656	-615.72	<.0001
	2: Occupied without payment of rent	0.145965	0.002976	-49.04	<.0001
	3: Owned by someone in the household (Base case)				
OCCUPYYRANGE	1: Before 1950	0.548525	0.00613	89.48	<.0001
	2: 1950 to 1959	0.149939	0.002487	60.3	<.0001
	3: 1960 to 1069	0.585318	0.001746	335.29	<.0001
	4: 1970 to 1979	0.247685	0.001116	222.03	<.0001
	5: 1980 to 1989	0.206039	0.000919	224.28	<.0001
	6: 1990 to 1999	0.390768	0.000703	555.59	<.0001
	7: 2000 to 2004	0.197163	0.000636	310.13	<.0001
	8: 2005 to 2009 (Base Case)				
price	Energy price	5.624074	0.019215	292.69	<.0001
HHINCOME	Gross household income 2009	0.004467	0.000007701	580.07	<.0001
PAY	0: Don’t pay the energy bill	0.033917	0.001503	22.56	<.0001
	1: Pay the energy bill (Base Case)				
HHAGE	Householder age	0.00366	0.000019612	186.62	<.0001
NHSLDMEM	Number of Household Members	0.034341	0.000202	170.28	<.0001
NUMMEAL	0:Never cooks (if volunteered)	-0.439239	0.003383	-129.83	<.0001
	1:Three or more times a day	-0.142523	0.001572	-90.67	<.0001
	2:Two times a day	0.007287	0.001365	5.34	<.0001
	3:Once a day	-0.052619	0.001326	-39.68	<.0001
	4:A few times a week	-0.101821	0.00135	-75.44	<.0001

	5:About once a week	-0.323698	0.001754	-184.57	<.0001
	6:Less than once a week (Base Case)				
ATHOME	0: No household stays home on typical week days	-0.073434	0.000524	-140.06	<.0001
	1: Yes. There are households staying home on typical weekdays (Base Case)				
EDUCATION	0: No schooling completed	-0.776434	0.003907	-198.71	<.0001
	1: Kindergarten to grade 12	-0.337016	0.002377	-141.78	<.0001
	2: High school diploma or GED	-0.397397	0.00208	-191.06	<.0001
	3: Some college, no degree	-0.261867	0.002073	-126.33	<.0001
	4: Associate's degree	-0.332572	0.002125	-156.47	<.0001
	5: Bachelor's degree	-0.265154	0.002054	-129.09	<.0001
	6: Master's degree	-0.251832	0.002117	-118.98	<.0001
	7: Professional degree	-0.083004	0.002559	-32.44	<.0001
	8: Doctorate degree (Base Case)				
EMPLOYHH	0: Not employed/retired	-0.083922	0.000843	-99.52	<.0001
	1: Employed full-time	-0.05982	0.000797	-75.04	<.0001
	2: Employed part-time (Base Case)				
SPOUSE	0: No. Householder isn't living with a spouse or partner	0.01261	0.000599	21.07	<.0001
	1: Yes. Householder is living with a spouse or partner (Base Case)				
Householder_Race	1: White Alone	-0.052799	0.001974	-26.75	<.0001
	2: Black or African/American Alone	-0.08042	0.002093	-38.42	<.0001
	3: American Indian or Alaska Native Alone	-0.29119	0.003231	-90.12	<.0001
	4: Asian Alone	-0.449237	0.002349	-191.24	<.0001
	5: Native Hawaiian or Other Pacific Islander Alone	-0.179078	0.004688	-38.2	<.0001
	6: Some Other Race Alone	-0.364557	0.002812	-129.63	<.0001
	7: 2 or More Races Selected (Base Case)				
HHSEX	1: Householder is Female	-0.080055	0.000462	-173.25	<.0001
	2: Householder is Male (Base Case)				

Table 3.5

Parameter Estimates for the Second Stage

Parameter	Label	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		0.592261	0.00251	236.01	<.0001
Residual		-0.007986	0.000499	-16.00	<.0001
ESDISHW	1: Energy Star dishwasher	0.126528	0.000758	166.78	<.0001
	0: Not energy Star dishwasher (Base Case)				
price	Energy price	-0.039416	0.000119	-330.58	<.0001
HHINCOME	Gross household income 2009	0.002102	0.0000058	362.3	<.0001
PAY	0: Don't pay the energy bill	0.412326	0.001082	380.99	<.0001
	1: Pay the energy bill (Base Case)				
HHAGE	Householder age	0.000232	0.0000132	17.66	<.0001
NHSLDMEM	Number of Household Members	0.205863	0.000151	1360.98	<.0001
NUMMEAL	0:Ne ver cooks (if volunteered)	0.245995	0.002745	89.63	<.0001
	1:Three or more times a day	0.67012	0.001174	570.72	<.0001
	2:Two times a day	0.679177	0.001008	673.71	<.0001
	3:Once a day	0.497852	0.000978	509.2	<.0001
	4:A few times a week	0.31831	0.000996	319.5	<.0001
	5:About once a week	0.172902	0.001315	131.53	<.0001
	6:Less than once a week (Base Case)				
ATHOME	0: No household stays home during a typical weekday.	-0.179317	0.000386	-464.85	<.0001
	1: Yes. There are households staying home during typical weekdays (Base Case)				
EDUCATION	0: No schooling completed	-0.42439	0.002868	-147.98	<.0001
	1: Kindergarten to grade 12	-0.25999	0.001647	-157.82	<.0001
	2: High school diploma or GED	-0.127021	0.001385	-91.71	<.0001
	3: Some college, no degree	-0.031513	0.001376	-22.9	<.0001
	4: Associate's degree	0.008835	0.001423	6.21	<.0001
	5: Bachelor's degree	0.023551	0.001361	17.3	<.0001

	6: Master's degree	-0.02712	0.001407	-19.28	<.0001
	7: Professional degree	0.169634	0.001714	98.96	<.0001
	8: Doctorate degree (Base Case)				
EMPLOYHH	0: Not employed/retired	-0.108693	0.000622	-174.86	<.0001
	1: Employed full-time	-0.099214	0.000586	-169.35	<.0001
	2: Employed part-time (Base Case)				
SPOUSE	0: No. Householder isn't living with spouse or partner	-0.289674	0.000442	-655.27	<.0001
	1: Yes. Householder is living with spouse or partner (Base Case)				
Householder_Race	1: White Alone	-0.03854	0.00144	-26.76	<.0001
	2: Black or African/American Alone	-0.390314	0.001528	-255.42	<.0001
	3: American Indian or Alaska Native Alone	-0.002558	0.002417	-1.06	0.2899
	4: Asian Alone	-0.70014	0.001724	-406.18	<.0001
	5: Native Hawaiian or Other Pacific Islander Alone	-0.916469	0.003444	-266.14	<.0001
	6: Some Other Race Alone	-0.010842	0.002062	-5.26	<.0001
	7: 2 or More Races Selected (Base Case)				
HHSEX	1: Householder is Female	0.02477	0.000341	72.66	<.0001
	2: Householder is Male (Base Case)				
_Limit2	Cutoff value 1	0.560413	0.000213	2626.06	<.0001
_Limit3	Cutoff value 2	1.544346	0.000292	5291.99	<.0001
_Limit4	Cutoff value 3	2.159709	0.000329	6555.16	<.0001

Table 3.6

Average MEs for Key Variables in the First Stage Regression

Key Variables		Marginal Effects	
Variable	Label	Mean	Std Error
ESFRIG	1: Energy Star Refrigerator	0.334192***	0.0017266
	0: Standard Refrigerator (Base Case)		
KOWNRENT	1: Renters	-0.11177***	0.000577466
	2: Occupants without payments	-0.04040***	0.000208738
	3: Homeowners (Base Case)		
OCCUPYYRANGE	1: Moved in before 1950	0.151828***	0.000784422
	2: 1950 to 1959	0.041502***	0.000214422
	3: 1960 to 1069	0.162012***	0.000837039
	4: 1970 to 1979	0.068558***	0.000354204
	5: 1980 to 1989	0.05703***	0.000294647
	6: 1990 to 1999	0.108162***	0.000558821
	7: 2000 to 2004	0.054573***	0.000281954
	8: 2005 to 2009 (Base Case)		
PRICE	Energy Price (In cent/1000BTU)	0.0155671***	0.000080428
HHINCOME	2009 Gross Household Income (In 1000$)	0.001236***	0.000006388

Note: Sample Size=4684; All estimates are significant at a significant level of 1% (***).

Table 3.7

Average MEs for Key Variables in the Second Stage Regression

Control Variables		Average Marginal Effects on the Probabilities for different Dishwasher Usage Behavior				
Variable	Label	< once a week	Once each week	2 - 3 times a week	4 - 6 times a week	> once each day
ESDISHW	Energy Star Dishwasher	-0.0237722*** (0.000188653)	-0.0127270*** (0.000077003)	-0.0067986*** (0.000245882)	0.0104966*** (0.000118708)	0.0328012*** (0.000186537)
PRICE	Energy Price (In cent/1000BTU)	0.0074054*** (0.000058768)	0.0039647*** (0.000023996)	0.0021179*** (0.000076596)	-0.0032699*** (0.000036979)	-0.0102181*** (0.000058109)
HHINCOME	2009 Gross Household Income (in 1000$)	-0.000394820*** (0.000003133)	-0.000211377*** (0.000001279)	-0.000112914*** (0.00000408)	0.000174332*** (0.0000019716)	0.000544778*** (0.000003098)

Note: Sample Size=4684; Standard errors are in the parentheses; All estimates are significant at a significant level of 1% (***).

Table 3.8

Dishwashing Frequencies with Standard Dishwashers

Usage Frequency	Weights	Households without Energy-Star Dishwasher			
		Percentage/ Probabilities	Weights*Probabilities	Expected Weekly Usage Frequency	Expected Yearly Usage Frequency
Less than once a week	0.5	18.27%	0.09135	3.119	162.188
Once each week	1	14.43%	0.1443		
2 or 3 times a week	2.5	33.25%	0.83125		
4 to 6 times a week	5	16.57%	0.8285		
At least once each day	7	17.48%	1.2236		

Note: Assume 52 weeks a year.

Table 3.9

Dishwashing Frequencies with Energy Star Dishwashers

Usage Frequency	Weights	Households without Energy-Star Dishwasher			
		Percentage/ Probabilities	Weights*Probabilities	Expected Weekly Usage Frequency	Expected Yearly Usage Frequency
Less than once a week	0.5	11.14%	0.0557	3.61485	187.9722
Once each week	1	12.98%	0.1298		
2 or 3 times a week	2.5	32.87%	0.82175		
4 to 6 times a week	5	20.12%	1.006		
At least once each day	7	22.88%	1.6016		

Note: Assume 52 weeks a year.

Table 3.10

Changes in Dishwashing Frequencies by Choosing Energy Star Dishwashers

Usage Frequency	Weights	Changes Due to Increased Efficiency			
		Changes in Percentage/ Probabilities	Weights* Changes in Probabilities	Expected Change in Weekly Usage Frequency	Expected Change in annual Usage Frequency
Less than once a week	0.5	-2.38%	-0.011883	0.24041	12.50141
Once each week	1	-1.27%	-0.012723		
2 or 3 times a week	2.5	-0.68%	-0.016991		
4 to 6 times a week	5	1.05%	0.05247		
At least once each day	7	3.28%	0.22954		

Note: Assume 52 weeks a year.

Table 3.11

Changes in Dishwashing Frequencies for 1 cent/1000BTU increase in Energy Price

Usage Frequency	Weights	Price Effect			
		Changes in Percentage/ Probabilities	Weights* Changes in Probabilities	Expected Change in Weekly Usage Frequency	Expected Change in annual Usage Frequency
Less than once a week	0.5	0.74%	0.00370259	-0.07491075	-3.895359
Once each week	1	0.40%	0.00396446		
2 or 3 times a week	2.5	0.21%	0.00529435		
4 to 6 times a week	5	-0.32%	-0.0163488		
At least once each day	7	-1.02%	-0.0752335		

Note: Assume 52 weeks a year.

Table 3.12

Changes in Dishwashing Frequencies for 1000$ increase in Household Income

Usage Frequency	Weights	Income Effect			
		Changes in Percentage/ Probabilities	Weights* Changes in Probabilities	Expected Change in Weekly Usage Frequency	Expected Change in annual Usage Frequency
Less than once a week	0.5	-0.04%	-0.0002	0.003994	0.207701
Once each week	1	-0.02%	-0.00021		
2 or 3 times a week	2.5	-0.01%	-0.00028		
4 to 6 times a week	5	0.02%	0.000872		
At least once each day	7	0.05%	0.003814		
Note: Assume 52 weeks a year					

Table 4.1

Descriptive Statistics for Key Variables

Variable	Obs	Mean	Std Dev	Minimum	Maximum	Description
ESRCB	1872	13.07146	4.266088	4.760386	24.11803	Million Btu
NGRCB	1872	18.53084	10.00656	0.463558	65.67316	Million Btu
PARCB	1872	9.338514	10.26056	0.209419	58.86025	Million Btu
OFRCB	1872	32.55617	9.101561	13.1953	57.71003	Million Btu
ESRCD	1872	16.89494	4.611282	6.596667	32.21263	Dollars per Million Btu
NGRCD	1872	4.625226	1.43034	1.693896	10.35804	Dollars per Million Btu
PARCD	1872	6.969624	2.13952	2.21257	17.80444	Dollars per Million Btu
OFRCD	1872	0.096995	0.077676	0.003389	0.620284	Dollars per Million Btu
PerY	1872	13863.74	3161.73	6773.20	26829.59	Dollars
CDD	1872	1087.52	777.999	80	3875	Base: 65F
HDD	1872	5238.85	2046.75	400	10745	Base: 65F

Table 4.2

Descriptive Statistics for Log (Key Variables)

Variable	Obs	Mean	Std Dev	Minimum	Maximum
LESRCB	1872	2.514691	0.339909	1.560329	3.18296
LNGRCB	1872	2.700042	0.803249	-0.76882	4.18469
LPARCB	1872	1.697295	1.082739	-1.56342	4.075166
LOFRCB	1872	3.442224	0.289933	2.579861	4.055431
LESRCD	1872	2.789624	0.275641	1.886565	3.472359
LNGRCD	1872	1.482182	0.320103	0.527031	2.337763
LPARCD	1872	1.897392	0.295137	0.794155	2.879448
LOFRCD	1872	-2.61433	0.778105	-5.68738	-0.47758
LPerY	1872	9.511804	0.224169	8.820728	10.19726
LPop	1872	14.99728	0.99532	12.71828	17.41502
LCDD	1872	6.732036	0.749116	4.382027	8.262301
LHDD	1872	8.4590868	0.5128356	5.9914645	9.2821958

Table 4.3

Descriptive Statistics for Instrumental Variables

Variable	Obs	Mean	Std Dev	Minimum	Maximum	Description
CLPRB	1872	0.516026	0.499877	0	1	Dummy Variable
EMFDB	1872	0.264957	0.441428	0	1	Dummy Variable
NGMPB	1872	0.636218	0.481216	0	1	Dummy Variable
NUETB	1872	0.586539	0.492586	0	1	Dummy Variable
PAPRB	1872	0.623932	0.484527	0	1	Dummy Variable
REPRB	1872	1.19E+08	1.68E+08	865000	1.16E+09	Billion Btu
LAGESRCB	1872	63202670	64012937	1715963	4.33E+08	Billion Btu
LAGNGRCB	1872	1.01E+08	1.27E+08	505239	6.7E+08	Billion Btu
LAGPARCB	1872	36787519	52934875	345619.1	4.04E+08	Billion Btu
LAGOFRCB	1872	1.57E+08	1.52E+08	5325331	9.59E+08	Billion Btu

Table 4.4

Demand Elasticities for Four Fuels

	Electricity	Natural Gas	LPG	Other-Fuels
Electricity Price	-0.31837*** (0.04316)	0.04722 (0.07164)	-1.91311*** (0.1568)	-0.14819*** (0.04524)
Natural Gas Price	0.46261*** (0.02728)	-1.08626*** (0.04528)	-0.10837 (0.09912)	0.47435*** (0.0286)
LPG Price	-0.09917*** (0.02491)	0.38978*** (0.04135)	-0.04828 (0.0905)	-0.05584** (0.02611)
Other-Fuels Price	-0.03602*** (0.00639)	0.0666*** (0.0106)	0.15183*** (0.02321)	-0.02971*** (0.0067)
Per Capita Income	0.22674*** (0.03941)	0.46192*** (0.06541)	1.47013*** (0.14316)	0.14718*** (0.04131)
Cooling Degree Days	0.00663 (0.011)	0.03591** (0.01826)	0.13485*** (0.03997)	0.00279 (0.01153)
Heating Degree Days	0.14339*** (0.02567)	0.70141*** (0.04261)	0.65994*** (0.09325)	0.14109*** (0.02691)

*Note: Significant levels: *denotes 0.1; **=0.05; ***=0.01. Standard Errors are included in the brackets.*

Table 4.5

Defrost Method of Most-Used Refrigerators from 1980 to 2009 in Percentages

Year	Defrost Method	
	Frost-Free	Manual
1980	60.56%	39.44%
1981	62.94%	37.06%
1982	62.99%	37.01%
1984	62.59%	37.41%
1987	67.43%	32.57%
1990	79.56%	20.44%
1993	84.77%	15.23%
1997	86.89%	13.11%
2001	90.73%	9.27%
2005	92.78%	7.22%
2009	92.76%	7.24%

Data Source: Residential Energy Consumption Survey in 1980, 1981, 1982, 1984, 1987, 1990, 1993, 1997, 2001, 2005 and 2009 conducted by Energy Information Administration.

Table 4.6

Door Arrangement of Most-Used Refrigerators from 1990 to 2009 in Percentages

Type	Year					
	1990	1993	1997	2001	2005	2009
3 or More Doors	0.00%	0.00%	0.00%	0.00%	0.00%	0.80%
2-Doors (side-by-side)	16.73%	17.13%	20.44%	25.37%	29.81%	34.34%
2-Doors (top and bottom)	67.23%	73.85%	68.14%	68.35%	58.36%	55.40%
Regular (single door)	14.73%	8.22%	10.72%	5.34%	10.93%	8.30%
Half-Size/Other	1.30%	0.80%	0.70%	0.94%	0.90%	1.16%

Data Source: Residential Energy Consumption Survey in 1990, 1993, 1997, 2001, 2005 and 2009 conducted by Energy Information Administration.

Table 4.7

Size of the Most-Used Refrigerator from 1993 to 2009 in Percentages

	Year				
Size	1993	1997	2001	2005	2009
Very Small (Less than 11 cf)	1.30%	0.90%	0.56%	0.63%	0.79%
Small (11-14cf)	9.22%	7.62%	5.34%	4.86%	3.70%
Medium (15-18cf)	54.41%	45.09%	48.88%	48.42%	45.64%
Large (19-22 cf)	31.06%	44.89%	40.26%	38.43%	42.29%
Very Large (23 or More cf)	4.01%	1.50%	4.96%	7.65%	7.58%

Data Source: Residential Energy Consumption Survey in 1993, 1997, 2001, 2005 and 2009 conducted by Energy Information Administration.

Table 4.8

Attributes of Most-Used Refrigerators in 2009 in Percentages: Energy-Star versus Standard

		Standard	Energy-Star
Door Arrangements	Half-size or compact	1.21	0.47
	Full-size with one door	9.16	5.34
	Full-size with two doors, freezer above the refrigerator	61.36	33.52
	Full-size with two doors, freezer below the refrigerator	3.89	12.44
	Full-size with two doors, freezer next to the refrigerator	23.88	45.96
	Full-size with three or more doors	0.23	1.83
	Other kind	0.27	0.43
Size	Very Small (Less than 11 cf)	1.21	0.47
	Small (11-14cf)	4.39	2.3
	Medium (15-18cf)	55.42	33.3
	Large (19-22 cf)	35.02	51.17
	Very Large (23 or More cf)	3.96	12.74
Ice or Water	No such Service	77.83	49.69
	Through-the-Door Ice or Water	22.17	50.31

Data Source: 2009 *Residential Energy Consumption Survey conducted by Energy Information Administration.*

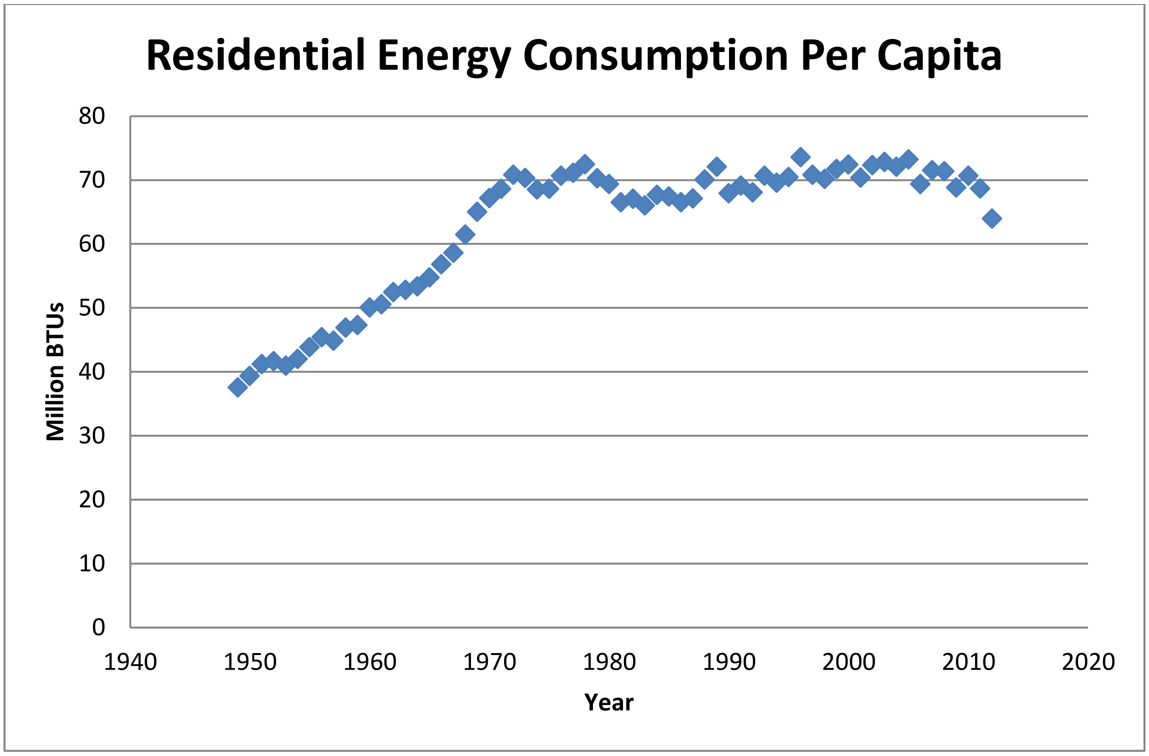

Figure 4.1 U.S. Residential Energy Consumption per Capita 1949-2012

(Data Source: U.S. Energy Information Administration, January 2014 Monthly Energy Review and U.S. Census, Current Population Survey)

APPENDICES

Appendix A

Identified Determinants of Energy-related behavior

Sources	**Related Project or Data Sources**	**Behavior**	**Identified Determinants of Energy-Related Behavior**
Barton, Blackwell, Carrington, Ford, Lawson & Stephenson (2013)	The Energy Cultures research project (2009-2012).	Residential energy-related behavior with respect to space heating and hot water heating	Value of protecting the environment; achievement values such as being competent, intelligent, efficient; family and friends; tradespeople and design professionals
Mirosa, Lawson & Gnoth (2011)	Interviews of residents in three communities in New Zealand	Residential Energy-related behavior	Achievement values such as capability and intelligence
Santin (2011)	Household Survey carried out by the OTB Research Institute (2008)	Residential Energy-related behavior in relation to heating	Household characteristic, lifestyle, background, motivation, values and attitude
Lawson, Mirosa, Gnoth & Hunter (2010)	Interviews of residents in three communities in New Zealand	Residential Energy-related behavior	Capability, respect for tradition, protecting the environment, intelligence, being helpful, and social recognition
Druckman & Jackson (2008)	UK household energy consumption and the associated carbon dioxide emissions at national level, small geographical areas and household level for 2004-5	Residential Energy-related behavior	Income levels, type of dwelling, tenure, household composition and rural/urban location
Uitdenbogerd, Egmond, Jonkers & Kok (2007)	Based on a review study of all relevant literature in the field of energy conservation and consumer behavior commissioned by Dutch Ministry of Housing	Energy-Related behavior	Personal determinants with internal determinants (e.g. Knowledge, attitudes, values and skills to perform the behavior) and demographical determinants (e.g. sex, age, education, income, number of children and household type); External or contextual determinants (e.g. whether people have social support and whether they have access to financial resources and services, price measures, and regulatory measures).
Allen & Janda (2006)	Pilot Study of Real Time Feedback in Oberlin Homes (2006)	Residential Energy-related behavior	Income
Staats, Harland & Wilke (2004)	Based on a -year longitudinal study on Eco Team Program (ETP) participants	Proenvironmental behavior	Intention and Habit
Schipper, Bartlett, Hawk & Vine (1989)		Energy-related behavior in general	Life-styles, price, and income
Heslop, Moran & Cousineau (1981)	Data obtained by mailed questionaire and availabe electricity record of Canadian consumers for 1973-1978 in the midsize southwetern Ontario city of Guelph.	Direct residential electricity use behavior	Household characteristics, family size and price consciousness
Seligman, Kriss, Darley, Fazlo, Beck & Pryor (1979)	Based on two surveys done in New Jersey	Residential summer electric use behavior	Homeowners' attitude toward energy use, especially attitudes about their comfort

Appendix B

Binary logit model for choice of energy star light bulbs

Parameter		Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		5.035553	3.733258	1.35	0.1774
OWNER	0	-0.392435	0.119686	-3.28	0.001
TOTSQFT		-0.00007714	0.000043045	-1.79	0.0731
PRICE		-3.879156	2.837935	-1.37	0.1717
EDU	0	-0.266485	0.086454	-3.08	0.0021
HHINCOME		-0.001037	0.001433	-0.72	0.4695
REGIONC	1	0.203875	0.190413	1.07	0.2843
REGIONC	2	0.184413	0.172814	1.07	0.2859
REGIONC	4	0.509463	0.198663	2.56	0.0103
TYPEHUQ	1	0.123578	0.240707	0.51	0.6077
TYPEHUQ	3	0.15201	0.16329	0.93	0.3519
TYPEHUQ	4	-0.125925	0.167294	-0.75	0.4516
TYPEHUQ	5	-0.111339	0.154388	-0.72	0.4708
HDD65		-0.000144	0.000154	-0.94	0.3492
CDD65		-0.000185	0.000199	-0.93	0.3526
HDD30YR		0.000232	0.000162	1.44	0.1508
CDD30YR		0.00012	0.000216	0.55	0.5806
Climate_Region_Pub	2	-0.077264	0.260328	-0.3	0.7666
Climate_Region_Pub	3	0.109003	0.287567	0.38	0.7046
Climate_Region_Pub	4	0.611319	0.169959	3.6	0.0003
Climate_Region_Pub	5	0.159392	0.275119	0.58	0.5623
METROMICRO	MICRO	-0.049505	0.146736	-0.34	0.7358
METROMICRO	NONE	0.027182	0.203125	0.13	0.8935
UR	R	-0.072964	0.114424	-0.64	0.5237
YEARMADE		-0.002142	0.00187	-1.15	0.252
OCCUPYYRANGE	1	17.891019	4217.501476	0	0.9966
OCCUPYYRANGE	2	0.391773	0.404618	0.97	0.3329
OCCUPYYRANGE	3	0.281371	0.278854	1.01	0.313

OCCUPYYRANGE	4	0.486843	0.217696	2.24	0.0253
OCCUPYYRANGE	5	0.246055	0.16726	1.47	0.1413
OCCUPYYRANGE	6	0.436538	0.121958	3.58	0.0003
OCCUPYYRANGE	7	0.288547	0.112375	2.57	0.0102
WALLTYPE	1	-0.142043	0.112393	-1.26	0.2063
WALLTYPE	2	0.097868	0.125555	0.78	0.4357
WALLTYPE	4	0.222502	0.159388	1.4	0.1627
WALLTYPE	5	-0.181322	0.312402	-0.58	0.5616
WALLTYPE	6	0.158674	0.421727	0.38	0.7067
WALLTYPE	7	0.66256	0.208864	3.17	0.0015
WALLTYPE	8	19.90387	0.000354	56177.4	<.0001
WALLTYPE	9	0.500252	0.751176	0.67	0.5054
ROOFTYPE	1	0.27935	0.233037	1.2	0.2306
ROOFTYPE	2	-0.358761	0.152386	-2.35	0.0186
ROOFTYPE	3	0.35043	0.218076	1.61	0.1081
ROOFTYPE	4	-0.192644	0.318116	-0.61	0.5448
ROOFTYPE	6	0.239762	0.121008	1.98	0.0475
ROOFTYPE	7	-0.365482	0.296257	-1.23	0.2173
ROOFTYPE	8	0.321019	0.47745	0.67	0.5014
TOTROOMS		0.113479	0.030764	3.69	0.0002
HHSEX	2	-0.138829	0.078837	-1.76	0.0782
EMPLOYHH	0	-0.007108	0.108229	-0.07	0.9476
EMPLOYHH	2	0.045588	0.13092	0.35	0.7277
SPOUSE	0	-0.121119	0.093055	-1.3	0.1931
SDESCENT	1	-0.175109	0.114684	-1.53	0.1268
RACE	2	-0.264863	0.121108	-2.19	0.0287
RACE	3	-0.135867	0.134492	-1.01	0.3124
NHSLDMEM		-0.073446	0.031909	-2.3	0.0214
HHAGE		0.036605	0.013929	2.63	0.0086
SAGE		-0.000388	0.000137	-2.84	0.0046
ATHOME	0	-0.170272	0.088535	-1.92	0.0545

Appendix C

Binary logit model for choice of energy star window/wall AC

Parameter		Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		0.787674	4.922684	0.16	0.8729
OWNER	0	-0.107676	0.15371	-0.7	0.4836
TOTSQFT		0.000093457	0.000072994	1.28	0.2004
PRICE		1.269056	3.370153	0.38	0.7065
EDU	0	-0.114383	0.117446	-0.97	0.3301
HHINCOME		0.004327	0.002116	2.04	0.0409
REGIONC	2	-0.863105	0.177471	-4.86	<.0001
REGIONC	3	-0.461602	0.234757	-1.97	0.0493
REGIONC	4	-1.152285	0.288509	-3.99	<.0001
TYPEHUQ	1	-0.018281	0.267397	-0.07	0.9455
TYPEHUQ	3	0.288359	0.224287	1.29	0.1986
TYPEHUQ	4	-0.10442	0.204532	-0.51	0.6097
TYPEHUQ	5	-0.05988	0.219832	-0.27	0.7853
HDD65		0.00014	0.000213	0.66	0.5096
CDD65		-0.000422	0.000376	-1.12	0.2618
HDD30YR		-0.000136	0.000221	-0.62	0.5374
CDD30YR		0.000412	0.000389	1.06	0.2893
Climate_Region_Pub	2	1.005637	0.414484	2.43	0.0153
Climate_Region_Pub	3	-0.029347	0.428009	-0.07	0.9453
Climate_Region_Pub	4	-0.181004	0.189318	-0.96	0.339
Climate_Region_Pub	5	0.161903	0.398607	0.41	0.6846
METROMICRO	MICRO	0.071763	0.199238	0.36	0.7187
METROMICRO	NONE	0.135885	0.238539	0.57	0.5689
UR	R	0.401879	0.172509	2.33	0.0198
YEARMADE		-0.00129	0.002459	-0.52	0.5998
OCCUPYYRANGE	1	-0.009318	0.828237	-0.01	0.991
OCCUPYYRANGE	2	0.505891	0.459401	1.1	0.2708
OCCUPYYRANGE	3	0.225193	0.395403	0.57	0.569

OCCUPYYRANGE	4	0.314087	0.271907	1.16	0.248
OCCUPYYRANGE	5	0.227042	0.225628	1.01	0.3143
OCCUPYYRANGE	6	-0.007497	0.164417	-0.05	0.9636
OCCUPYYRANGE	7	-0.024301	0.155418	-0.16	0.8758
WALLTYPE	1	-0.088934	0.164815	-0.54	0.5895
WALLTYPE	2	-0.004621	0.155387	-0.03	0.9763
WALLTYPE	4	0.395412	0.259576	1.52	0.1277
WALLTYPE	5	0.054277	0.361911	0.15	0.8808
WALLTYPE	6	-0.390189	0.49765	-0.78	0.433
WALLTYPE	7	-0.176002	0.349875	-0.5	0.6149
WALLTYPE	9	-1.37264	0.8202	-1.67	0.0942
ROOFTYPE	1	-0.309953	0.778491	-0.4	0.6905
ROOFTYPE	2	-0.084652	0.225117	-0.38	0.7069
ROOFTYPE	3	-0.208913	0.233898	-0.89	0.3718
ROOFTYPE	4	-0.342083	0.423762	-0.81	0.4195
ROOFTYPE	6	0.035207	0.152466	0.23	0.8174
ROOFTYPE	7	1.265528	1.082079	1.17	0.2422
ROOFTYPE	8	0.079878	0.430648	0.19	0.8529
TOTROOMS		0.035725	0.043381	0.82	0.4102
HHSEX	2	0.189646	0.109252	1.74	0.0826
EMPLOYHH	0	0.127992	0.143112	0.89	0.3711
EMPLOYHH	2	0.010015	0.175063	0.06	0.9544
SPOUSE	0	-0.180235	0.121383	-1.48	0.1376
SDESCENT	1	-0.129565	0.155201	-0.83	0.4038
RACE	2	0.312293	0.163237	1.91	0.0557
RACE	3	-0.192352	0.184215	-1.04	0.2964
NHSLDMEM		-0.009508	0.042241	-0.23	0.8219
HHAGE		0.082029	0.019629	4.18	<.0001
SAGE		-0.000758	0.000197	-3.85	0.0001
ATHOME	0	0.050599	0.123153	0.41	0.6812

Appendix D

Binary logit model for choice of energy star refrigerator

Parameter		Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		-9.24354	1.905231	-4.85	<.0001
OWNER	0	-0.820566	0.066552	-12.33	<.0001
TOTSQFT		0.000032966	0.000021068	1.56	0.1176
price		0.494653	1.835137	0.27	0.7875
EDU	0	0.041192	0.045797	0.9	0.3684
HHINCOME		0.003459	0.000727	4.76	<.0001
REGIONC	1	0.48708	0.094	5.18	<.0001
REGIONC	2	0.113608	0.082624	1.37	0.1691
REGIONC	4	0.074737	0.101556	0.74	0.4618
TYPEHUQ	1	-0.545826	0.11751	-4.64	<.0001
TYPEHUQ	3	-0.051861	0.082247	-0.63	0.5283
TYPEHUQ	4	-0.150392	0.097137	-1.55	0.1216
TYPEHUQ	5	-0.184646	0.08776	-2.1	0.0354
HDD65		0.000227	0.000077463	2.93	0.0034
CDD65		0.000253	0.000116	2.19	0.0283
HDD30YR		-0.00033	0.000081416	-4.05	<.0001
CDD30YR		-0.00036	0.000124	-2.9	0.0037
Climate_Region_Pub	2	0.305575	0.135223	2.26	0.0238
Climate_Region_Pub	3	0.014217	0.144854	0.1	0.9218
Climate_Region_Pub	4	-0.094789	0.079044	-1.2	0.2304
Climate_Region_Pub	5	0.021151	0.138343	0.15	0.8785
METROMICRO	MICRO	-0.001053	0.072673	-0.01	0.9884
METROMICRO	NONE	-0.050523	0.096082	-0.53	0.599
UR	R	0.160853	0.057036	2.82	0.0048
YEARMADE		0.003885	0.00095	4.09	<.0001
OCCUPYYRANGE	1	-0.000268	0.321357	0	0.9993
OCCUPYYRANGE	2	-0.171709	0.186388	-0.92	0.3569
OCCUPYYRANGE	3	-0.122976	0.134041	-0.92	0.3589

OCCUPYYRANGE	4	-0.133975	0.096959	-1.38	0.167
OCCUPYYRANGE	5	-0.215106	0.082154	-2.62	0.0088
OCCUPYYRANGE	6	-0.362128	0.061145	-5.92	<.0001
OCCUPYYRANGE	7	-0.103381	0.058394	-1.77	0.0767
WALLTYPE	1	0.145756	0.058629	2.49	0.0129
WALLTYPE	2	-0.044057	0.060164	-0.73	0.464
WALLTYPE	4	0.002489	0.083695	0.03	0.9763
WALLTYPE	5	-0.027318	0.159754	-0.17	0.8642
WALLTYPE	6	0.44998	0.207975	2.16	0.0305
WALLTYPE	7	0.100319	0.110816	0.91	0.3653
WALLTYPE	8	1.110831	0.796427	1.39	0.1631
WALLTYPE	9	-0.908413	0.360251	-2.52	0.0117
ROOFTYPE	1	-0.189352	0.117758	-1.61	0.1078
ROOFTYPE	2	-0.149575	0.087795	-1.7	0.0884
ROOFTYPE	3	0.048267	0.101128	0.48	0.6332
ROOFTYPE	4	-0.046112	0.184789	-0.25	0.8029
ROOFTYPE	6	-0.024315	0.056122	-0.43	0.6648
ROOFTYPE	7	-0.132067	0.17819	-0.74	0.4586
ROOFTYPE	8	0.189451	0.199646	0.95	0.3427
TOTROOMS		0.060659	0.014837	4.09	<.0001
HHSEX	2	0.002473	0.041107	0.06	0.952
EMPLOYHH	0	-0.015516	0.055761	-0.28	0.7808
EMPLOYHH	2	-0.088066	0.068447	-1.29	0.1982
SPOUSE	0	-0.168114	0.04922	-3.42	0.0006
SDESCENT	1	0.045739	0.06589	0.69	0.4876
RACE	2	0.256775	0.065373	3.93	<.0001
RACE	3	-0.158537	0.076132	-2.08	0.0373
NHSLDMEM		0.037651	0.017016	2.21	0.0269
HHAGE		0.061128	0.007958	7.68	<.0001
SAGE		-0.00063	0.000077279	-8.16	<.0001
ATHOME	0	-0.037762	0.046396	-0.81	0.4157

Appendix E

Binary logit model for choice of energy star clothes washer

Parameter		Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		-0.803709	2.69013	-0.3	0.7651
OWNER	0	-0.579678	0.08411	-6.89	<.0001
TOTSQFT		0.000080505	0.000031178	2.58	0.0098
price		3.909566	2.786659	1.4	0.1606
EDU	0	-0.051007	0.063642	-0.8	0.4229
HHINCOME		0.002826	0.001023	2.76	0.0057
REGIONC	1	0.311969	0.136549	2.28	0.0223
REGIONC	2	0.074704	0.111652	0.67	0.5034
REGIONC	4	-0.169904	0.136427	-1.25	0.213
TYPEHUQ	1	-0.298892	0.150428	-1.99	0.0469
TYPEHUQ	3	0.128867	0.113188	1.14	0.2549
TYPEHUQ	4	0.189578	0.137771	1.38	0.1688
TYPEHUQ	5	-0.002673	0.126651	-0.02	0.9832
HDD65		0.000104	0.000113	0.92	0.3575
CDD65		0.000168	0.00015	1.12	0.2622
HDD30YR		-0.000199	0.000118	-1.69	0.0914
CDD30YR		-0.000276	0.000161	-1.72	0.0853
Climate_Region_Pub	2	-0.200785	0.186418	-1.08	0.2814
Climate_Region_Pub	3	-0.44081	0.200377	-2.2	0.0278
Climate_Region_Pub	4	-0.371814	0.116832	-3.18	0.0015
Climate_Region_Pub	5	-0.044664	0.19036	-0.23	0.8145
METROMICRO	MICRO	-0.007389	0.099671	-0.07	0.9409
METROMICRO	NONE	-0.163305	0.128752	-1.27	0.2047
UR	R	0.208323	0.077717	2.68	0.0074
YEARMADE		-0.000034641	0.001342	-0.03	0.9794
OCCUPYYRANGE	1	-0.570394	0.476917	-1.2	0.2317
OCCUPYYRANGE	2	0.453118	0.296942	1.53	0.127
OCCUPYYRANGE	3	0.142849	0.200281	0.71	0.4757

OCCUPYYRANGE	4	0.043564	0.139123	0.31	0.7542
OCCUPYYRANGE	5	0.030286	0.116044	0.26	0.7941
OCCUPYYRANGE	6	0.344114	0.08774	3.92	<.0001
OCCUPYYRANGE	7	0.095446	0.079497	1.2	0.2299
WALLTYPE	1	0.061204	0.082454	0.74	0.4579
WALLTYPE	2	-0.14033	0.083458	-1.68	0.0927
WALLTYPE	4	0.084128	0.115795	0.73	0.4675
WALLTYPE	5	0.032754	0.215176	0.15	0.879
WALLTYPE	6	0.199905	0.32672	0.61	0.5406
WALLTYPE	7	0.220473	0.155597	1.42	0.1565
WALLTYPE	8	19.344852	8613.059215	0	0.9982
WALLTYPE	9	-0.748417	0.440643	-1.7	0.0894
ROOFTYPE	1	-0.030771	0.15509	-0.2	0.8427
ROOFTYPE	2	-0.17954	0.116985	-1.53	0.1249
ROOFTYPE	3	-0.048249	0.136464	-0.35	0.7237
ROOFTYPE	4	-0.223863	0.255492	-0.88	0.3809
ROOFTYPE	6	0.14074	0.079822	1.76	0.0779
ROOFTYPE	7	0.407439	0.263628	1.55	0.1222
ROOFTYPE	8	0.073001	0.282264	0.26	0.7959
TOTROOMS		0.04885	0.021481	2.27	0.023
HHSEX	2	-0.038868	0.057928	-0.67	0.5022
EMPLOYHH	0	-0.107358	0.077044	-1.39	0.1635
EMPLOYHH	2	0.142128	0.09825	1.45	0.148
SPOUSE	0	-0.231515	0.067711	-3.42	0.0006
SDESCENT	1	-0.07959	0.089126	-0.89	0.3719
RACE	2	0.067005	0.093498	0.72	0.4736
RACE	3	-0.250857	0.105161	-2.39	0.0171
NHSLDMEM		0.021916	0.023042	0.95	0.3415
HHAGE		0.068342	0.011037	6.19	<.0001
SAGE		-0.000644	0.000109	-5.9	<.0001
ATHOME	0	-0.034805	0.064949	-0.54	0.592

Appendix F

Binary logit model for choice of energy star dishes washer

Parameter		Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept		-3.625463	3.383987	-1.07	0.284
OWNER	0	-0.860815	0.111162	-7.74	<.0001
TOTSQFT		0.000049606	0.000034807	1.43	0.1541
price		4.900801	3.37064	1.45	0.146
EDU	0	-0.111565	0.081397	-1.37	0.1705
HHINCOME		0.005031	0.001191	4.23	<.0001
REGIONC	1	0.63525	0.164994	3.85	0.0001
REGIONC	2	0.250334	0.139121	1.8	0.072
REGIONC	4	0.195296	0.17723	1.1	0.2705
TYPEHUQ	1	-0.368476	0.223231	-1.65	0.0988
TYPEHUQ	3	0.237541	0.135629	1.75	0.0799
TYPEHUQ	4	-0.01487	0.188426	-0.08	0.9371
TYPEHUQ	5	-0.214065	0.146935	-1.46	0.1452
HDD65		0.00042	0.000133	3.17	0.0015
CDD65		0.000587	0.000201	2.92	0.0035
HDD30YR		-0.00042	0.000138	-3.05	0.0023
CDD30YR		-0.000537	0.000216	-2.49	0.0129
Climate_Region_Pub	2	0.306121	0.231888	1.32	0.1868
Climate_Region_Pub	3	0.104222	0.245999	0.42	0.6718
Climate_Region_Pub	4	0.019957	0.138559	0.14	0.8855
Climate_Region_Pub	5	0.298241	0.229331	1.3	0.1934
METROMICRO	MICRO	-0.003832	0.134319	-0.03	0.9772
METROMICRO	NONE	-0.130029	0.180375	-0.72	0.471
UR	R	0.368645	0.096646	3.81	0.0001
YEARMADE		0.000631	0.00169	0.37	0.709
OCCUPYYRANGE	1	1.151005	1.13299	1.02	0.3097
OCCUPYYRANGE	2	0.419924	0.393032	1.07	0.2853
OCCUPYYRANGE	3	0.807315	0.283877	2.84	0.0045

OCCUPYYRANGE	4	0.110138	0.179042	0.62	0.5385
OCCUPYYRANGE	5	0.181199	0.143766	1.26	0.2075
OCCUPYYRANGE	6	0.324769	0.109394	2.97	0.003
OCCUPYYRANGE	7	0.21886	0.095991	2.28	0.0226
WALLTYPE	1	0.237698	0.097971	2.43	0.0153
WALLTYPE	2	0.209797	0.103642	2.02	0.0429
WALLTYPE	4	-0.082825	0.141559	-0.59	0.5585
WALLTYPE	5	0.222689	0.289605	0.77	0.4419
WALLTYPE	6	0.457454	0.371105	1.23	0.2177
WALLTYPE	7	0.155312	0.183868	0.84	0.3983
WALLTYPE	9	-0.982627	0.544496	-1.8	0.0711
ROOFTYPE	1	0.276352	0.205414	1.35	0.1785
ROOFTYPE	2	-0.245019	0.161782	-1.51	0.1299
ROOFTYPE	3	0.200252	0.202375	0.99	0.3224
ROOFTYPE	4	0.315057	0.35097	0.9	0.3694
ROOFTYPE	6	0.146652	0.097962	1.5	0.1344
ROOFTYPE	7	0.411468	0.309416	1.33	0.1836
ROOFTYPE	8	0.128319	0.395159	0.32	0.7454
TOTROOMS		0.076233	0.025539	2.98	0.0028
HHSEX	2	0.094485	0.070582	1.34	0.1807
EMPLOYHH	0	0.007611	0.097238	0.08	0.9376
EMPLOYHH	2	0.134005	0.120275	1.11	0.2652
SPOUSE	0	-0.037907	0.088432	-0.43	0.6682
SDESCENT	1	-0.119215	0.12751	-0.93	0.3498
RACE	2	0.12402	0.125196	0.99	0.3219
RACE	3	-0.420849	0.13306	-3.16	0.0016
NHSLDMEM		0.009288	0.030807	0.3	0.7631
HHAGE		0.057526	0.013837	4.16	<.0001
SAGE		-0.000538	0.000138	-3.91	<.0001
ATHOME	0	-0.064971	0.078544	-0.83	0.4081

Appendix G

First Stage Results for Electricity Price

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-14.8759	10.98063	-1.35	0.1757
CLPRB	0.45539	0.32083	1.42	0.156
EMFDB	0.33689	0.15934	2.11	0.0346
NGMPB	2.05461	0.33527	6.13	<.0001
NUETB	0.35469	0.18049	1.97	0.0495
PAPRB	2.61595	1.37579	1.9	0.0574
REPRB	4.47E-09	1.33E-09	3.36	0.0008
LAGESRCB	-7.19E-08	1.21E-08	-5.94	<.0001
LAGNGRCB	-3.15E-09	2.84E-09	-1.11	0.2677
LAGPARCB	-5.10E-09	2.49E-09	-2.05	0.0407
LAGOFRCB	3.41E-08	5.57E-09	6.11	<.0001
LNGRCD	1.90068	0.28541	6.66	<.0001
LPARCD	1.27172	0.24532	5.18	<.0001
LOFRCD	0.70154	0.09554	7.34	<.0001
LPerY	0.93135	0.95982	0.97	0.332
LCDD	0.4062	0.26862	1.51	0.1307
LHDD	1.4047	0.62193	2.26	0.024
T	-0.19819	0.01702	-11.65	<.0001
Nstate_1	-0.43325	0.96917	-0.45	0.6549
Nstate_2	3.13531	0.85764	3.66	0.0003
Nstate_3	4.81542	1.03945	4.63	<.0001
Nstate_4	2.8626	2.11047	1.36	0.1751
Nstate_5	2.56606	0.52023	4.93	<.0001
Nstate_6	13.12646	1.5825	8.29	<.0001
Nstate_7	12.05249	1.57017	7.68	<.0001
Nstate_8	3.46804	1.71503	2.02	0.0433
Nstate_9	5.7756	1.73917	3.32	0.0009

Nstate_10	8.27249	1.5516	5.33	<.0001
Nstate_11	1.33758	1.53232	0.87	0.3828
Nstate_12	5.68848	1.54123	3.69	0.0002
Nstate_13	1.09158	0.75495	1.45	0.1484
Nstate_14	3.60839	0.68518	5.27	<.0001
Nstate_15	-1.02402	0.71298	-1.44	0.1511
Nstate_16	2.93245	1.14406	2.56	0.0105
Nstate_17	13.30879	1.63424	8.14	<.0001
Nstate_18	5.9612	1.53477	3.88	0.0001
Nstate_19	11.44349	1.5348	7.46	<.0001
Nstate_20	3.94887	1.24728	3.17	0.0016
Nstate_21	6.3666	1.58858	4.01	<.0001
Nstate_22	2.85482	0.78442	3.64	0.0003
Nstate_23	2.03875	1.01343	2.01	0.0444
Nstate_24	-0.86048	0.48471	-1.78	0.076
Nstate_25	6.36748	1.68275	3.78	0.0002
Nstate_26	0.76336	0.47706	1.6	0.1097
Nstate_27	0.86345	0.68273	1.26	0.2061
Nstate_28	13.91645	1.51931	9.16	<.0001
Nstate_29	15.16948	1.69747	8.94	<.0001
Nstate_30	5.52899	0.62898	8.79	<.0001
Nstate_31	2.65606	0.83966	3.16	0.0016
Nstate_32	10.32994	1.61445	6.4	<.0001
Nstate_33	3.21399	1.30371	2.47	0.0138
Nstate_34	2.50419	0.8035	3.12	0.0019
Nstate_35	-1.33169	1.59656	-0.83	0.4043
Nstate_36	4.72366	1.16994	4.04	<.0001
Nstate_37	14.23475	1.53231	9.29	<.0001
Nstate_38	6.72466	1.7115	3.93	<.0001
Nstate_39	2.80913	0.61485	4.57	<.0001
Nstate_40	-3.10883	0.78738	-3.95	<.0001

Nstate_41	3.23894	1.38681	2.34	0.0196
Nstate_42	2.33475	0.55697	4.19	<.0001
Nstate_43	1.18113	0.73272	1.61	0.1071
Nstate_44	10.57512	1.52322	6.94	<.0001
Nstate_45	-4.67006	1.9208	-2.43	0.0151
Nstate_46	6.33691	1.60663	3.94	<.0001
Nstate_47	0.47741	0.6238	0.77	0.4442

Appendix H

First Stage Results for Natural Gas Price

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	9.50252	3.94721	2.41	0.0162
CLPRB	-0.11684	0.1154	-1.01	0.3114
EMFDB	0.16201	0.057	2.84	0.0045
NGMPB	-0.28208	0.12194	-2.31	0.0208
NUETB	0.24106	0.06435	3.75	0.0002
PAPRB	-0.13564	0.4953	-0.27	0.7842
REPRB	1.74E-10	4.80E-10	0.36	0.717
LAGESRCB	-2.46E-09	4.36E-09	-0.56	0.5737
LAGNGRCB	-6.15E-09	1.00E-09	-6.13	<.0001
LAGPARCB	1.32E-10	8.99E-10	0.15	0.8831
LAGOFRCB	2.24E-09	2.01E-09	1.11	0.2652
LESRCD	0.69272	0.14093	4.92	<.0001
LPARCD	2.3434	0.07407	31.64	<.0001
LOFRCD	0.01459	0.03515	0.42	0.6782
LPerY	-0.94799	0.34492	-2.75	0.006
LCDD	0.05836	0.09673	0.6	0.5464
LHDD	-0.44478	0.22407	-1.99	0.0473
T	0.04817	0.00624	7.72	<.0001
Nstate_1	0.26004	0.34805	0.75	0.4551
Nstate_2	-0.69429	0.30965	-2.24	0.0251
Nstate_3	-0.1748	0.37597	-0.46	0.642
Nstate_4	1.4668	0.75569	1.94	0.0524
Nstate_5	0.46382	0.1877	2.47	0.0136
Nstate_6	2.62574	0.5768	4.55	<.0001
Nstate_7	0.99705	0.57283	1.74	0.0819
Nstate_8	-0.02087	0.61713	-0.03	0.973
Nstate_9	-0.13521	0.62738	-0.22	0.8294

Nstate_10	0.19399	0.56252	0.34	0.7302
Nstate_11	0.36426	0.55103	0.66	0.5087
Nstate_12	2.57137	0.54892	4.68	<.0001
Nstate_13	1.03342	0.26898	3.84	0.0001
Nstate_14	0.17546	0.24803	0.71	0.4794
Nstate_15	-0.02448	0.25651	-0.1	0.924
Nstate_16	-0.7513	0.41231	-1.82	0.0686
Nstate_17	2.46025	0.59568	4.13	<.0001
Nstate_18	1.58885	0.55238	2.88	0.0041
Nstate_19	1.87161	0.56013	3.34	0.0009
Nstate_20	1.70643	0.44577	3.83	0.0001
Nstate_21	0.39499	0.57381	0.69	0.4913
Nstate_22	0.74134	0.28154	2.63	0.0085
Nstate_23	-0.9143	0.365	-2.5	0.0123
Nstate_24	0.15958	0.17431	0.92	0.3601
Nstate_25	0.30619	0.60788	0.5	0.6145
Nstate_26	0.49583	0.17135	2.89	0.0039
Nstate_27	0.11111	0.24558	0.45	0.651
Nstate_28	1.59756	0.55732	2.87	0.0042
Nstate_29	1.77044	0.61967	2.86	0.0043
Nstate_30	-0.50389	0.23139	-2.18	0.0296
Nstate_31	0.16858	0.30238	0.56	0.5773
Nstate_32	3.30523	0.57863	5.71	<.0001
Nstate_33	2.1181	0.46402	4.56	<.0001
Nstate_34	-0.04401	0.28944	-0.15	0.8792
Nstate_35	1.41115	0.57302	2.46	0.0139
Nstate_36	2.37819	0.41683	5.71	<.0001
Nstate_37	1.96223	0.56159	3.49	0.0005
Nstate_38	0.06747	0.61843	0.11	0.9131
Nstate_39	0.3462	0.22255	1.56	0.12
Nstate_40	-0.35979	0.28489	-1.26	0.2068

Nstate_41	-0.05376	0.49805	-0.11	0.9141
Nstate_42	-0.12315	0.20114	-0.61	0.5405
Nstate_43	1.42685	0.26057	5.48	<.0001
Nstate_44	1.01205	0.55534	1.82	0.0686
Nstate_45	0.53865	0.69258	0.78	0.4368
Nstate_46	0.84176	0.58006	1.45	0.1469
Nstate_47	0.66448	0.22291	2.98	0.0029

Appendix I

First Stage Results for LPG Price

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-9.74508	7.52679	-1.29	0.1956
CLPRB	0.54698	0.22001	2.49	0.013
EMFDB	-0.73804	0.10774	-6.85	<.0001
NGMPB	-0.50403	0.23277	-2.17	0.0305
NUETB	-0.7357	0.12346	-5.96	<.0001
PAPRB	0.80264	0.9439	0.85	0.3952
REPRB	7.36E-10	9.14E-10	0.8	0.421
LAGESRCB	7.00E-08	8.29E-09	8.44	<.0001
LAGNGRCB	7.38E-09	1.94E-09	3.81	0.0001
LAGPARCB	5.66E-10	1.71E-09	0.33	0.7413
LAGOFRCB	-2.64E-08	3.83E-09	-6.91	<.0001
LESRCD	0.8012	0.2703	2.96	0.0031
LNGRCD	4.48236	0.16528	27.12	<.0001
LOFRCD	0.96958	0.06423	15.1	<.0001
LPerY	0.45567	0.65829	0.69	0.4889
LCDD	-0.08324	0.1845	-0.45	0.6519
LHDD	0.72927	0.42688	1.71	0.0877
t	0.02195	0.01218	1.8	0.0717
Nstate_1	0.67877	0.66448	1.02	0.3072
Nstate_2	1.46222	0.58931	2.48	0.0132
Nstate_3	2.16412	0.71572	3.02	0.0025
Nstate_4	-1.86485	1.44667	-1.29	0.1975
Nstate_5	-0.75436	0.3585	-2.1	0.0355
Nstate_6	-3.25326	1.10242	-2.95	0.0032
Nstate_7	-1.44701	1.0937	-1.32	0.186
Nstate_8	2.38001	1.17689	2.02	0.0433
Nstate_9	0.77037	1.196	0.64	0.5196

Nstate_10	-0.97475	1.07286	-0.91	0.3637
Nstate_11	0.06889	1.05098	0.07	0.9477
Nstate_12	-3.99387	1.05409	-3.79	0.0002
Nstate_13	-1.76741	0.51688	-3.42	0.0006
Nstate_14	0.36763	0.47316	0.78	0.4373
Nstate_15	-0.10077	0.4896	-0.21	0.8369
Nstate_16	2.68698	0.78349	3.43	0.0006
Nstate_17	-3.76948	1.13819	-3.31	0.0009
Nstate_18	-1.54466	1.05664	-1.46	0.144
Nstate_19	-3.53258	1.06808	-3.31	0.001
Nstate_20	-2.36102	0.85452	-2.76	0.0058
Nstate_21	-0.55682	1.0945	-0.51	0.611
Nstate_22	-1.50809	0.53868	-2.8	0.0052
Nstate_23	2.37064	0.69347	3.42	0.0006
Nstate_24	-0.25843	0.33264	-0.78	0.4373
Nstate_25	-1.00442	1.15972	-0.87	0.3866
Nstate_26	-0.98801	0.32675	-3.02	0.0025
Nstate_27	0.95314	0.46821	2.04	0.0419
Nstate_28	-3.13455	1.06294	-2.95	0.0032
Nstate_29	-2.63517	1.18439	-2.22	0.0262
Nstate_30	0.67769	0.44077	1.54	0.1243
Nstate_31	0.93852	0.57742	1.63	0.1043
Nstate_32	-5.37389	1.10869	-4.85	<.0001
Nstate_33	-3.53781	0.89107	-3.97	<.0001
Nstate_34	-0.07201	0.55254	-0.13	0.8963
Nstate_35	-1.44354	1.09541	-1.32	0.1877
Nstate_36	-4.61975	0.79877	-5.78	<.0001
Nstate_37	-3.2881	1.07264	-3.07	0.0022
Nstate_38	0.33163	1.1793	0.28	0.7786
Nstate_39	-0.38641	0.42466	-0.91	0.363
Nstate_40	1.13567	0.5423	2.09	0.0364

Nstate_41	-1.05403	0.95214	-1.11	0.2684
Nstate_42	-0.72007	0.38353	-1.88	0.0606
Nstate_43	-2.17048	0.50071	-4.33	<.0001
Nstate_44	-2.0304	1.05918	-1.92	0.0554
Nstate_45	-0.98143	1.32135	-0.74	0.4577
Nstate_46	-1.42549	1.1069	-1.29	0.198
Nstate_47	-1.35127	0.42722	-3.16	0.0016

Appendix J

First Stage Results for Other-Fuels Price

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1.37769	0.31529	4.37	<.0001
CLPRB	-0.0104	0.00918	-1.13	0.2577
EMFDB	0.00275	0.00457	0.6	0.5467
NGMPB	0.00932	0.00975	0.96	0.3396
NUETB	0.00428	0.0052	0.82	0.4107
PAPRB	-0.06422	0.03954	-1.62	0.1045
REPRB	-8.96E-11	3.82E-11	-2.34	0.0192
LAGESRCB	-4.30E-09	3.26E-10	-13.2	<.0001
LAGNGRCB	7.39E-11	8.16E-11	0.91	0.3651
LAGPARCB	8.43E-11	7.18E-11	1.17	0.2405
LAGOFRCB	1.92E-09	1.52E-10	12.63	<.0001
LESRCD	0.0336	0.01111	3.02	0.0025
LNGRCD	-0.00344	0.00828	-0.42	0.6778
LPARCD	0.08959	0.00678	13.22	<.0001
LPerY	-0.14679	0.02741	-5.35	<.0001
LCDD	0.00549	0.00773	0.71	0.4775
LHDD	-0.01089	0.0179	-0.61	0.5431
t	0.00073651	0.00050972	1.44	0.1487
Nstate_1	-0.13165	0.02776	-4.74	<.0001
Nstate_2	-0.13096	0.02456	-5.33	<.0001
Nstate_3	-0.15765	0.02982	-5.29	<.0001
Nstate_4	-0.1626	0.06064	-2.68	0.0074
Nstate_5	-0.03219	0.01503	-2.14	0.0324
Nstate_6	-0.05415	0.0462	-1.17	0.2413
Nstate_7	-0.10032	0.04569	-2.2	0.0282
Nstate_8	-0.22588	0.04903	-4.61	<.0001
Nstate_9	-0.18951	0.04997	-3.79	0.0002

Nstate_10	-0.11038	0.04485	-2.46	0.014
Nstate_11	-0.09006	0.04395	-2.05	0.0406
Nstate_12	-0.11404	0.04432	-2.57	0.0102
Nstate_13	-0.09531	0.02164	-4.4	<.0001
Nstate_14	-0.10408	0.01955	-5.32	<.0001
Nstate_15	-0.0804	0.02049	-3.92	<.0001
Nstate_16	-0.1748	0.03267	-5.35	<.0001
Nstate_17	-0.05521	0.04771	-1.16	0.2474
Nstate_18	-0.11438	0.04419	-2.59	0.0097
Nstate_19	0.01023	0.04481	0.23	0.8195
Nstate_20	-0.11487	0.03583	-3.21	0.0014
Nstate_21	-0.11945	0.04572	-2.61	0.0091
Nstate_22	-0.11567	0.02251	-5.14	<.0001
Nstate_23	-0.16254	0.02894	-5.62	<.0001
Nstate_24	-0.03266	0.01388	-2.35	0.0187
Nstate_25	-0.16587	0.04845	-3.42	0.0006
Nstate_26	-0.02235	0.01366	-1.64	0.102
Nstate_27	-0.09641	0.01929	-5	<.0001
Nstate_28	-0.01914	0.04456	-0.43	0.6676
Nstate_29	-0.14731	0.04947	-2.98	0.0029
Nstate_30	-0.07035	0.01838	-3.83	0.0001
Nstate_31	-0.09112	0.02405	-3.79	0.0002
Nstate_32	-0.09796	0.0467	-2.1	0.0361
Nstate_33	-0.12024	0.03746	-3.21	0.0014
Nstate_34	-0.11654	0.02301	-5.06	<.0001
Nstate_35	-0.06208	0.04589	-1.35	0.1763
Nstate_36	-0.07735	0.03373	-2.29	0.022
Nstate_37	-0.04214	0.04494	-0.94	0.3485
Nstate_38	-0.17096	0.04924	-3.47	0.0005
Nstate_39	-0.0845	0.01749	-4.83	<.0001
Nstate_40	-0.12184	0.02269	-5.37	<.0001

Nstate_41	-0.19463	0.03976	-4.89	<.0001
Nstate_42	-0.02085	0.01607	-1.3	0.1947
Nstate_43	-0.05183	0.02106	-2.46	0.0139
Nstate_44	-0.0049	0.04435	-0.11	0.912
Nstate_45	-0.02532	0.05536	-0.46	0.6474
Nstate_46	-0.09523	0.04626	-2.06	0.0397
Nstate_47	-0.04166	0.01792	-2.33	0.0202

Appendix K

Second Stage Results for Per Capita Electricity Demand

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.72419	0.44387	-1.63	0.103
LESRCD	-0.31837	0.04316	-7.38	<.0001
LNGRCD	0.46261	0.02728	16.96	<.0001
LPARCD	-0.09917	0.02491	-3.98	<.0001
LOFRCD	-0.03602	0.00639	-5.64	<.0001
LPerY	0.22674	0.03941	5.75	<.0001
LCDD	0.00663	0.011	0.6	0.5467
LHDD	0.14339	0.02567	5.59	<.0001
T	0.00391	0.00085948	4.55	<.0001
Nstate_1	0.38556	0.03674	10.49	<.0001
Nstate_2	0.39044	0.03576	10.92	<.0001
Nstate_3	0.23691	0.04573	5.18	<.0001
Nstate_4	-0.26154	0.03864	-6.77	<.0001
Nstate_5	-0.2015	0.01969	-10.23	<.0001
Nstate_6	-0.32959	0.03545	-9.3	<.0001
Nstate_7	-0.00785	0.03143	-0.25	0.8029
Nstate_8	0.49373	0.06909	7.15	<.0001
Nstate_9	0.25611	0.03539	7.24	<.0001
Nstate_10	0.04975	0.02432	2.05	0.041
Nstate_11	0.23478	0.02352	9.98	<.0001
Nstate_12	-0.16059	0.02701	-5.94	<.0001
Nstate_13	0.11902	0.02277	5.23	<.0001
Nstate_14	0.09219	0.02844	3.24	0.0012
Nstate_15	0.2611	0.02717	9.61	<.0001
Nstate_16	0.46699	0.04785	9.76	<.0001
Nstate_17	-0.49944	0.03272	-15.27	<.0001

Nstate_18	-0.09084	0.02908	-3.12	0.0018
Nstate_19	-0.28742	0.02983	-9.64	<.0001
Nstate_20	-0.21112	0.02196	-9.62	<.0001
Nstate_21	-0.12049	0.02055	-5.86	<.0001
Nstate_22	0.13565	0.02616	5.19	<.0001
Nstate_23	0.45684	0.04093	11.16	<.0001
Nstate_24	0.0698	0.01907	3.66	0.0003
Nstate_25	0.28423	0.0321	8.86	<.0001
Nstate_26	0.1726	0.02024	8.53	<.0001
Nstate_27	0.11737	0.02298	5.11	<.0001
Nstate_28	-0.25873	0.03111	-8.32	<.0001
Nstate_29	-0.37457	0.03476	-10.77	<.0001
Nstate_30	-0.26483	0.0298	-8.89	<.0001
Nstate_31	0.20365	0.03153	6.46	<.0001
Nstate_32	-0.57885	0.03517	-16.46	<.0001
Nstate_33	0.00733	0.02386	0.31	0.7587
Nstate_34	0.37642	0.03268	11.52	<.0001
Nstate_35	0.20168	0.02719	7.42	<.0001
Nstate_36	-0.14004	0.02673	-5.24	<.0001
Nstate_37	-0.51934	0.03207	-16.19	<.0001
Nstate_38	0.34927	0.03713	9.41	<.0001
Nstate_39	0.09365	0.02299	4.07	<.0001
Nstate_40	0.52032	0.0292	17.82	<.0001
Nstate_41	0.38605	0.04575	8.44	<.0001
Nstate_42	-0.23758	0.0223	-10.65	<.0001
Nstate_43	0.11152	0.02834	3.94	<.0001
Nstate_44	-0.13658	0.02582	-5.29	<.0001
Nstate_45	0.25297	0.02918	8.67	<.0001
Nstate_46	-0.14931	0.02136	-6.99	<.0001
Nstate_47	0.15899	0.02441	6.51	<.0001

RE	-0.00219	0.0026	-0.84	0.4011
RP	-0.00883	0.00357	-2.47	0.0136
RO	-0.15199	0.04949	-3.07	0.0022
RN	-0.07355	0.00582	-12.65	<.0001

Appendix L

Second Stage Results for Per Capita Natural Gas Demand

Variable	Parameter	Standard	t Value	Pr > |t|
	Estimate	Error		
Intercept	-7.05202	0.73675	-9.57	<.0001
LESRCD	0.04722	0.07164	0.66	0.5099
LNGRCD	-1.08626	0.04528	-23.99	<.0001
LPARCD	0.38978	0.04135	9.43	<.0001
LOFRCD	0.0666	0.0106	6.28	<.0001
LPerY	0.46192	0.06541	7.06	<.0001
LCDD	0.03591	0.01826	1.97	0.0494
LHDD	0.70141	0.04261	16.46	<.0001
t	0.00144	0.00143	1.01	0.3144
Nstate_1	0.36464	0.06098	5.98	<.0001
Nstate_2	0.3361	0.05935	5.66	<.0001
Nstate_3	0.18796	0.0759	2.48	0.0134
Nstate_4	0.44195	0.06414	6.89	<.0001
Nstate_5	0.16872	0.03269	5.16	<.0001
Nstate_6	-0.03317	0.05884	-0.56	0.573
Nstate_7	0.02267	0.05216	0.43	0.6639
Nstate_8	-0.67644	0.11468	-5.9	<.0001
Nstate_9	0.50278	0.05874	8.56	<.0001
Nstate_10	0.35737	0.04037	8.85	<.0001
Nstate_11	-0.35956	0.03903	-9.21	<.0001
Nstate_12	0.68962	0.04484	15.38	<.0001
Nstate_13	0.458	0.0378	12.12	<.0001
Nstate_14	0.57804	0.04721	12.25	<.0001
Nstate_15	0.13516	0.0451	3	0.0028
Nstate_16	0.67232	0.07942	8.47	<.0001
Nstate_17	0.30564	0.0543	5.63	<.0001
Nstate_18	0.25383	0.04827	5.26	<.0001

Nstate_19	-2.99914	0.04951	-60.58	<.0001
Nstate_20	0.5546	0.03644	15.22	<.0001
Nstate_21	0.09448	0.0341	2.77	0.0057
Nstate_22	0.48156	0.04342	11.09	<.0001
Nstate_23	0.14029	0.06794	2.07	0.0391
Nstate_24	0.06467	0.03166	2.04	0.0412
Nstate_25	-0.39015	0.05327	-7.32	<.0001
Nstate_26	-0.39496	0.03359	-11.76	<.0001
Nstate_27	0.35532	0.03815	9.31	<.0001
Nstate_28	-1.02533	0.05164	-19.86	<.0001
Nstate_29	0.51525	0.0577	8.93	<.0001
Nstate_30	0.22985	0.04946	4.65	<.0001
Nstate_31	0.19514	0.05234	3.73	0.0002
Nstate_32	0.33969	0.05837	5.82	<.0001
Nstate_33	0.6371	0.03961	16.08	<.0001
Nstate_34	0.52165	0.05423	9.62	<.0001
Nstate_35	-0.22806	0.04513	-5.05	<.0001
Nstate_36	0.42284	0.04437	9.53	<.0001
Nstate_37	0.3504	0.05323	6.58	<.0001
Nstate_38	-0.10698	0.06162	-1.74	0.0827
Nstate_39	-0.16596	0.03817	-4.35	<.0001
Nstate_40	-0.24933	0.04847	-5.14	<.0001
Nstate_41	0.47433	0.07593	6.25	<.0001
Nstate_42	0.33805	0.03701	9.13	<.0001
Nstate_43	-0.09182	0.04704	-1.95	0.0511
Nstate_44	-1.55075	0.04286	-36.18	<.0001
Nstate_45	-0.39678	0.04844	-8.19	<.0001
Nstate_46	0.28766	0.03546	8.11	<.0001
Nstate_47	0.43069	0.04052	10.63	<.0001
RE	0.01765	0.00432	4.08	<.0001
RP	-0.00511	0.00593	-0.86	0.3896

RO	-0.49211	0.08214	-5.99	<.0001
RN	0.15654	0.00965	16.22	<.0001

Appendix M

Second Stage Results for Per Capita LPG Demand

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-12.42746	1.61257	-7.71	<.0001
LESRCD	-1.91311	0.1568	-12.2	<.0001
LNGRCD	-0.10837	0.09912	-1.09	0.2744
LPARCD	-0.04828	0.0905	-0.53	0.5937
LOFRCD	0.15183	0.02321	6.54	<.0001
LPerY	1.47013	0.14316	10.27	<.0001
LCDD	0.13485	0.03997	3.37	0.0008
LHDD	0.65994	0.09325	7.08	<.0001
t	-0.06298	0.00312	-20.17	<.0001
Nstate_1	0.42236	0.13348	3.16	0.0016
Nstate_2	0.96885	0.12991	7.46	<.0001
Nstate_3	-0.10132	0.16613	-0.61	0.542
Nstate_4	-0.69521	0.14039	-4.95	<.0001
Nstate_5	-0.30514	0.07154	-4.27	<.0001
Nstate_6	2.49379	0.12878	19.36	<.0001
Nstate_7	2.17969	0.11417	19.09	<.0001
Nstate_8	0.7361	0.25101	2.93	0.0034
Nstate_9	0.19876	0.12858	1.55	0.1223
Nstate_10	1.2009	0.08836	13.59	<.0001
Nstate_11	-0.12218	0.08544	-1.43	0.1529
Nstate_12	0.20957	0.09814	2.14	0.0329
Nstate_13	0.75348	0.08273	9.11	<.0001
Nstate_14	0.39539	0.10332	3.83	0.0001
Nstate_15	0.32608	0.09871	3.3	0.001
Nstate_16	-0.14454	0.17382	-0.83	0.4058
Nstate_17	2.52933	0.11886	21.28	<.0001
Nstate_18	1.22693	0.10564	11.61	<.0001

Nstate_19	3.2537	0.10837	30.03	<.0001
Nstate_20	1.03528	0.07977	12.98	<.0001
Nstate_21	0.88162	0.07464	11.81	<.0001
Nstate_22	0.62873	0.09504	6.62	<.0001
Nstate_23	0.98813	0.1487	6.65	<.0001
Nstate_24	0.4275	0.06929	6.17	<.0001
Nstate_25	1.60843	0.1166	13.79	<.0001
Nstate_26	1.21239	0.07352	16.49	<.0001
Nstate_27	0.32206	0.08349	3.86	0.0001
Nstate_28	2.94705	0.11303	26.07	<.0001
Nstate_29	2.04567	0.1263	16.2	<.0001
Nstate_30	0.86849	0.10826	8.02	<.0001
Nstate_31	-0.13482	0.11455	-1.18	0.2394
Nstate_32	2.2311	0.12777	17.46	<.0001
Nstate_33	0.68924	0.0867	7.95	<.0001
Nstate_34	0.28828	0.11871	2.43	0.0153
Nstate_35	-0.13979	0.09878	-1.42	0.1572
Nstate_36	1.85425	0.09712	19.09	<.0001
Nstate_37	2.82457	0.11651	24.24	<.0001
Nstate_38	1.14896	0.13488	8.52	<.0001
Nstate_39	1.39671	0.08354	16.72	<.0001
Nstate_40	-0.27897	0.10608	-2.63	0.0086
Nstate_41	0.22175	0.1662	1.33	0.1823
Nstate_42	-0.80972	0.08101	-10	<.0001
Nstate_43	1.24177	0.10296	12.06	<.0001
Nstate_44	2.92376	0.09381	31.17	<.0001
Nstate_45	-0.51222	0.10603	-4.83	<.0001
Nstate_46	1.25647	0.07761	16.19	<.0001
Nstate_47	0.34284	0.08869	3.87	0.0001
RE	0.09043	0.00946	9.56	<.0001
RP	0.03736	0.01299	2.88	0.0041

RO	-0.207	0.17978	-1.15	0.2497
RN	0.05092	0.02113	2.41	0.016

Appendix N

Second Stage Results for Per Capita Demand of Other-Fuels

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.58862	0.46531	1.27	0.206
LESRCD	-0.14819	0.04524	-3.28	0.0011
LNGRCD	0.47435	0.0286	16.59	<.0001
LPARCD	-0.05584	0.02611	-2.14	0.0326
LOFRCD	-0.02971	0.0067	-4.44	<.0001
LPerY	0.14718	0.04131	3.56	0.0004
LCDD	0.00279	0.01153	0.24	0.8091
LHDD	0.14109	0.02691	5.24	<.0001
t	0.0003667	0.00090099	0.41	0.6841
Nstate_1	0.30625	0.03851	7.95	<.0001
Nstate_2	0.27827	0.03749	7.42	<.0001
Nstate_3	0.11405	0.04794	2.38	0.0175
Nstate_4	-0.35176	0.04051	-8.68	<.0001
Nstate_5	-0.27136	0.02064	-13.14	<.0001
Nstate_6	-0.41223	0.03716	-11.09	<.0001
Nstate_7	-0.11209	0.03294	-3.4	0.0007
Nstate_8	0.37406	0.07243	5.16	<.0001
Nstate_9	0.16596	0.0371	4.47	<.0001
Nstate_10	-0.13762	0.0255	-5.4	<.0001
Nstate_11	0.22671	0.02465	9.2	<.0001
Nstate_12	-0.24857	0.02832	-8.78	<.0001
Nstate_13	0.06388	0.02387	2.68	0.0075
Nstate_14	0.01218	0.02981	0.41	0.683
Nstate_15	0.24542	0.02848	8.62	<.0001
Nstate_16	0.33008	0.05016	6.58	<.0001
Nstate_17	-0.57088	0.0343	-16.65	<.0001
Nstate_18	-0.16707	0.03048	-5.48	<.0001

Nstate_19	-0.31348	0.03127	-10.03	<.0001
Nstate_20	-0.26346	0.02302	-11.45	<.0001
Nstate_21	-0.15481	0.02154	-7.19	<.0001
Nstate_22	0.08008	0.02742	2.92	0.0035
Nstate_23	0.37705	0.04291	8.79	<.0001
Nstate_24	0.05354	0.01999	2.68	0.0075
Nstate_25	0.20322	0.03365	6.04	<.0001
Nstate_26	0.06336	0.02121	2.99	0.0029
Nstate_27	0.05293	0.02409	2.2	0.0281
Nstate_28	-0.32686	0.03261	-10.02	<.0001
Nstate_29	-0.4908	0.03644	-13.47	<.0001
Nstate_30	-0.30305	0.03124	-9.7	<.0001
Nstate_31	0.1319	0.03305	3.99	<.0001
Nstate_32	-0.64353	0.03687	-17.46	<.0001
Nstate_33	-0.07233	0.02502	-2.89	0.0039
Nstate_34	0.27416	0.03425	8	<.0001
Nstate_35	0.18723	0.0285	6.57	<.0001
Nstate_36	-0.20582	0.02802	-7.34	<.0001
Nstate_37	-0.59928	0.03362	-17.83	<.0001
Nstate_38	0.25381	0.03892	6.52	<.0001
Nstate_39	0.01235	0.02411	0.51	0.6084
Nstate_40	0.48275	0.03061	15.77	<.0001
Nstate_41	0.24283	0.04796	5.06	<.0001
Nstate_42	-0.28291	0.02338	-12.1	<.0001
Nstate_43	0.05165	0.02971	1.74	0.0823
Nstate_44	-0.17336	0.02707	-6.4	<.0001
Nstate_45	0.25776	0.03059	8.42	<.0001
Nstate_46	-0.17886	0.0224	-7.99	<.0001
Nstate_47	0.12455	0.02559	4.87	<.0001
RE	-0.01129	0.00273	-4.14	<.0001
RP	-0.01421	0.00375	-3.79	0.0002

RO	0.11748	0.05188	2.26	0.0237
RN	-0.08325	0.0061	-13.66	<.0001