Three Essays Examining Household Energy Demand and Behavior

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Abstract

This dissertation consists of three essays examining household energy decisions and behavior. The first essay examines the adoption of energy efficient Energy Star home appliances by U.S. households. Program effectiveness requires that consumers be aware of the labeling scheme and also change their purchase decisions based on label information. The first essay examines the factors associated with consumer awareness of the Energy Star label of recently purchased major appliances and the factors associated with the choice of Energy Star labeled appliances. The findings suggest that eliminating identified gaps in Energy Star appliance adoption would result in house electricity cost savings of $164 million per year and associated carbon emission reductions of about 1.1 million metric tons per year. The second essay evaluates household energy security and the effectiveness of the Low-Income Home Energy Assistance Program (LIHEAP), the single largest energy assistance program available to poor households within the United States. Energy security is conceptually akin to the well-known concept of food security. Rasch models and household responses to energy security questions in the 2005 Residential Energy Consumption Survey are used to generate an energy insecurity index that is consistent with those found in the food insecurity literature. Participating in LIHEAP is found to significantly reduce household energy insecurity score in the index. Further, simulations show that the elimination of the energy assistance safety net currently available to households increases the number of energy insecure households by over 16 percent. The third essay develops a five equation demand system to estimate household own-price, cross-price and income elasticities between electricity, natural gas, food at home, food away from home, and non-durable commodity groups. Household cross-price elasticities between energy and food commodities are of particular importance. Energy price shocks reduce food expenditures for low-income households, as indicated by negative cross-price elasticity estimates for food and energy commodities. Additionally, low-income households reduce energy expenditures more than other households, further indicating "heat or eat" behavior. Results from all three essays provide policy makers with helpful information to shape future federal energy programs.

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To my parents,

Dr. Frank S. Murray

Dr. Lynda B. Murray

Thank you for always showing me the value of an education

and encouraging me to reach for my goals.

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Chapter 1

Introduction

Energy economics research gained prominence in the early 1970's due to oil shocks and has grown significantly in volume and scope since its inception. Because the 1970's oil crisis triggered the rapid growth in the field, it should not be surprising that much of the original research focused on ideas like oil supply and demand, modeling oil production, and exploring cost-benefit analysis to alternative fuels. The oil shocks caused politicians and researchers alike to worry about exhaustion of the available fossil fuels and generated many predictions about when it would occur. "Energy security" grew out of this idea, and could be best explained as a nation's reliance on fuel imports to fulfill its energy demand. Significant research has focused on this explicit definition of energy security.

Subsequent research in the 1980's expanded to estimation of electricity demand, pricing, and effects of potential deregulation. Some of the most important microeconometric household choice models were first used in this literature and provided all economists with new econometric methods and solutions for problems associated outside of the energy economics field (Dubin and McFadden 1984). The ability to create methods and models that were effective in analyzing other problems provided further legitimacy to the subfield. Research continued in the 1990's and early 2000's focusing on the effects of carbon emissions and potential methods for reducing total emissions at a national or international level.

More recently, researchers have returned to studying the individual or household unit using household decision models. Instead of modeling policy solutions through national multi-market or computable general equilibrium (CGE) models, individual household decision framework is used to try and understand the effectiveness of many of the programs and policies that have been implemented to try and reduce carbon emissions or improve energy efficiency. This approach allows researchers to identify specific groups that might be driving or stalling emission reductions through either the adoption of modern appliances or changes in energy consumption behavior. Results from this sort of research provides recommendations to policy makers to directly target and improve consumer behavior of identified populations.

Research in energy economics is not the only tangible result from the oil shocks of the late 1970's. The rapid change in the price of fuel prompted the United States government to craft legislation that provided assistance to the poorest households to pay for their heating costs. The Low-Income Home Energy Act, Title XXVI of the 1981 Omnibus Budget Reconciliation Act officially created the Low Income Home Energy Assistance Program (LIHEAP) that provides utility relief to eligible households through state block grants. Monetary awards are given to each state (plus Indian tribes and territories) based on a specific formula. As a block grant, benefits are directly tied to the money available; an eligible household would only receive benefits if it applies to the program and there is money available for disbursement. This is in direct contrast to other entitlement social welfare programs (such as Supplemental Nutrition Assistance Program (SNAP), or Aid to Family with Dependent Children (AFDC)) that guarantee benefits as long as the household is eligible. Since its creation in 1981, annual LIHEAP funding averaged roughly two billion dollars for the first 25 years of its existence. The rapid rise in energy prices over the last few years prompted Congress to increase funding levels to approximately five billion dollars per year for fiscal years 2009-2011. Funding for fiscal year 2012 was reduced by 25 percent to 3.7 billion dollars and future funding for this program is currently a hotly contested topic, with proposed presidential and Congressional budgets further slashing the funding to the program. One of the major problems with all proposals to cut or increase LIHEAP funding, however, is that no program evaluation exists. Until now, the literature is silent on whether those households that receive program benefits have improved energy security.

This dissertation is a collection of three essays that further examine household energy decisions. The first paper examines demographic and residential characteristics that affect household energy efficient appliance awareness and uptake decisions. Higher uptake of energy efficient appliances, called "Energy Star" appliances, could potentially reduce overall U.S. residential energy consumption with only minor adjustments to consumer behavior. In the second paper, energy decisions of the most vulnerable population—those eligible for energy assistance—is analyzed. An energy security index is created and used to explicitly model whether the federal energy assistance program helps energy insecure households. Finally, the third paper continues to focus on energy decisions of low-income households. A complete demand system is modeled to better understand how households, especially low-income ones, substitute between food and energy expenditures. The results can help shape future federal energy assistance programs and policy through a better understanding of household trade-offs. In this way, it is possible to provide more research on the phenomenon that other researchers have coined "heat or eat" (Bhattacharya, DeLeire, Haider and Currie 2003, Frank, Neault, Skalicky, Cook, Wilson, Levenson, Meyers, Heeren, Cutts, Casey, Black and Berkowitz 2006).

The first paper, entitled *"Read the Label! Energy Star Appliance Label Awareness and Uptake Among U.S. Consumers"*, examines the uptake and awareness of households for Energy Star dishwashers, refrigerators, and washing machines. Energy Star labeled appliances use significantly less energy and water compared to conventional appliances, yet provide the same functionality as conventional appliances. Energy Star appliances cost more when purchased, but provide significant savings over their entire life, normally surpassing the initial purchase price premium of the appliance. Dishwashers, refrigerators, and washing machines make up a significant portion of home energy use in the United States and provide a relatively easy method for reducing total carbon emissions by reducing energy consumption without changing consumer behavior.

Consistent parameter estimates of household awareness and choice are obtained using a probit with selection model. Both the selection and outcome equations are probit equations requiring a slightly different full information maximum likelihood estimation compared to the traditional selection model (van de Ven and Van Praag 1981). The paper identifies household demographic and residential characteristics that significantly reduce appliance awareness and uptake for all three appliances. Using the identified gaps, simulations are created to indicate potential energy savings from having consumers behave as if these gaps were bridged. U.S. carbon emissions would be reduced by about 1.1 million metric tons per year under these simulations, equivalent to removing over 216,000 cars off the road annually.

While several papers have written about energy efficient appliances, this paper builds upon those results in several ways. First, prior results used survey data that was not designed to uniquely identify those households who had the choice between energy efficient appliances and conventional appliances. This problem occurs due to the short length of time between creation of the energy efficient appliances and the implementation of the survey (e.g. Mills and Schleich 2009*a*). This paper is the first, to my knowledge, that focuses only on household appliance decisions made after the creation of the Energy Star label. This provides more precision in the results because all households included had the option of selecting an Energy Star appliance when they made their purchase decision. Second, the paper shows how the common renter-owner investment appropriation of benefit decision applies to uptake of energy efficient appliances.

The second paper, entitled *"The Impact of Low Income Home Energy Assistance Program (LIHEAP) Participation on Household Energy Insecurity"* focuses on another research question dealing with household decision making in energy economics. Households that have an income of less than 150 percent of the poverty level or less than 60 percent of the state's median income, whatever is greater, are eligible for LIHEAP benefits. Governmental reports consistently show only a fraction of eligible households participate in the program (Division of Energy Assistance 2009). Evaluating the effectiveness of LIHEAP requires modeling of this household participation decision jointly with estimates of program impact to get unbiased results. Neo-classical utility maximization implies that households join a program if their overall utility is higher when participating compared to not participating. The low participation rate for LIHEAP could mean that there is a "stigma" for these benefits and any model of LIHEAP must include this possibility (Moffitt 1983). As a block grant program, an additional wrinkle is needed for the theoretical model. Eligible households that apply for benefits are not guaranteed benefits, unlike more traditional federal entitlement programs. This paper provides an econometric framework to better understand the linkages between household energy security, participation in LIHEAP, and the program's overall effectiveness.

The best metric for determining whether any energy assistance program works starts from its effect on household energy security. The appendix to this chapter, *"An Application of Dichotomous and Polytomous Rasch Models For Scoring Energy Insecurity"*, creates the the first continuous "energy insecurity" index using Rasch and Item Response Theory (IRT) models. The Rasch model has previously been used in creating a food insecurity index based on questions that have been incorporated into the U.S. Current Population Survey since 1995 (Bickel, Nord, Price, Hamilton and Cook 2000). In the 2005 Residential Energy Consumption Survey, nine questions about energy behavior were asked to all households who were below 150 percent of the federal poverty line. Using these responses, it is possible to generate an index and identify the most energy insecure households. Several different polytomous (multiple response) and dichotomous (binary response) energy insecurity indexes that are produced are then used as dependent variables to evaluate the program effectiveness of LIHEAP. Specifically, the paper addresses the question does participation in LIHEAP reduce household energy insecurity compared to non-participant households.

After accounting for selectivity issues, households that participated in LIHEAP are found to be significantly more energy secure than otherwise similar non-participant households across all energy insecurity indexes. Policy makers must understand that reductions in funding or elimination of LIHEAP will significantly increase the number of energy insecure households within the United States. Some demographic, residential, and locational attributes all significantly affect LIHEAP participation and household energy insecurity scores. Household demographics, however, have more of an effect on household energy insecurity scores than on the participation decision.

Simulations show that eliminating LIHEAP significantly reduces the number of energy secure households, with over 16 percent more households below 150 percent of the poverty line considered energy insecure. Cutting the LIHEAP program will harm both low-income households and utility firms, as an increase in energy insecure low income households will lead to an increase in late, reduced, or no payments to the utility companies. Utilities have strict regulations preventing termination of services during extreme weather, leading to higher losses, lower profits, and higher rates for paying customers. State agencies must also do a better job targeting future benefits to energy insecure households. Better targeting could be achieved through improved questionnaires, home visits, and increased communication between state LIHEAP coordinators, households, and utility companies.

As a block grant, state policy makers have much greater latitude in creating a program that protects energy insecure households for their specific climate, clients, and budget compared to the nationally regulated entitlement programs. Innovative ways for improving household energy security using the LIHEAP benefits are feasible. Programs funded through block grants are much more difficult to study at a national level, but are an important policy tool available to law makers. In an era of government fiscal restraint, block grants may become even more prevalent.

Finally, the third paper entitled *"'Food or Fuel': Calculating Elasticities to Understand 'Heat or Eat' behavior"* further examines the "heat or eat" dilemma faced by low-income households. Low-income households spend almost equal shares of their budget (10-15 percent) on food and energy. Previous research finds low-income households extremely susceptible to energy price shocks and observes these households reducing food expenditures to compensate for higher prices (Bhattacharya, Currie and Haider 2004, Nord and Kantor 2006). None of the research examining the "heat or eat" problem, however, calculate elasticities for these households. Own-price, cross-price, and income elasticities are calculated using a Quadratic Almost Ideal Demand System (QUAIDS) of Banks, Blundell and Lewbel (1997) for five commodities (electricity, natural gas, food at home, food away from home, and "other non-durable" expenditures). This is a refinement that better estimates non-linear Engel curves compared to the original Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980*b*).

Demand system estimation requires a large sample with detailed price and quantity data to generate meaningful elasticity estimates. Analysis in this chapter uses quarterly expenditure data that is pooled for eleven years from the Bureau of Labor Statistics' Consumer Expenditure Survey (CES). The survey includes very specific expenditure categories that encompass 95 percent of all household expenditures. Price data comes from assorted agencies and non-governmental organizations. The ACCRA Cost of Living Index provides prices for food at home, food away from home, and non-durable goods. The Energy Information Administration, the statistical agency of the U.S. Department of Energy, publishes electricity and natural gas prices. Along with expenditure information, the CES also includes demographic information about individual households, making it possible to estimate a complete demand system that includes differences in demographics between consumers. Elasticities for many unique demographic groups are also estimated.

Elasticity estimates demonstrate that all households make trade offs between food and fuel. As a whole, U.S. households consider food and fuel as complements. When the price of energy increases, the quantity demanded of food at home decreases. Low-income households have different elasticity estimates compared to the non-poor. Low income households reduce energy expenditures by more than the price shock itself, indicating an elastic own-price elasticity. On the other hand, households with higher income react to the price shocks with smaller reductions to energy expenditures. The heat or eat effect exists for low income households, but cross-price elasticity estimates are lower than expected. Non-poor households appear to reduce food at home expenditure more due to energy price shocks than low-income households. Already constrained food purchases of low-income households might lead to these lower observed cross price elasticities.

The paper shows that structural differences exist between different demographic groups. Elasticity estimates are statistically different between households headed by Blacks and Whites, Hispanics and non-Hispanics, and poor and non-poor households. Locational differences between households also matter. Southern and non-southern households exhibit different estimates, while differences for rural and non-rural households are not as strong. Results illustrate that policy makers cannot prescribe one approach to help all households, since different regions and demographic groups behave in different manners.

The results demonstrate that energy price shocks have the largest effect on low income household energy expenditures, but also reduce food consumption. Federal assistance programs need to be able to help households alleviate the dual problem of higher energy costs and less food. Currently, food assistance programs like SNAP and energy assistance programs like LIHEAP are independent of each other. Eligible households apply for, and receive, benefits due to need within each category separately. Elasticity estimates for low-income households show that when energy price shocks occur, food and fuel consumption both suffer. Policy makers should adapt current programs to better help households meet dual food and fuel needs given this evidence.

Researchers must examine both household food and energy consumption behavior. However, researchers have often focused on the former while ignoring the latter. Together, all three essays create a theme to promote research that analyzes household energy decisions as rigorously as food decisions. The first essay examines ways to reduce energy consumption while marginally changing consumer behavior and habits. The second essay determines whether current federal safeguards work to protect households vulnerable to energy price shocks. Finally, the third essay analyzes how energy price shocks adjust household expenditures on food and fuel. The three essays constitute a topically relevant, narrowly focused research agenda to shape future energy assistance program policy for households, especially low-income ones.

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Chapter 2

Essay 1: Read the Label! Energy Star Appliance Label Awareness and Uptake Among U.S. Consumers

2.1 Introduction

Introduced in 1992 by U.S. the Environmental Protection Agency (EPA), the "Energy Star" program originally created a labeling system to promote the use of energy efficient computers and monitors for offices. The program grew from this singular task, evolving into a joint venture between the U.S. Department of Energy and the EPA and currently encompasses over 60 different product categories (U.S. Environmental Protection Agency 2008*a*), including major 'white' appliances, refrigerators, dishwashers, and washing machines (clothes washers) that account for 65% of household electricity use (Berry 2009). Augmented utilization of Energy Star appliances can potentially generate substantial energy savings. In fact, it is estimated that if consumers only bought new Energy Star labeled dishwashers, refrigerators, and washing machines, greenhouse gas emissions would decrease by 4.5 billion pounds per year, equivalent to reducing emission levels by 370,000 cars (U.S. Environmental Protection Agency 2008*b*). Yet consumer awareness of labels and purchasing behavior constrain full realization of these potential energy savings.

Energy Star appliance standards are relatively new, only recently has knowledge about the Energy Star label spread to the average consumer. In 1999, only 30% of consumers could identify the Energy Star label (U.S. Environmental Protection Agency 1999). However, initiatives to increase awareness and promote the Energy Star "brand" led to doubling the awareness in only six years, with over 60% of consumers knowing about the labeling program by 2005 (U.S. Environmental Protection Agency 2005). However, awareness of the labeling program is not likely to be evenly distributed across the population. Awareness also does not directly translate into the purchase of Energy Star appliances. Consumers may purchase conventional appliances in lieu of Energy Star appliances for several reasons. All appliances have two costs; a "fixed" cost of initial purchase and a "variable" cost for monthly operating expenses. Energy Star appliances, on average, have a higher fixed cost, but reduced monthly costs in comparison to conventional appliances. If consumers have a high discount rate, future lower monthly costs will not outweigh the higher initial purchase costs. Some consumers may also have strong environmental preferences that lead them to purchase Energy Star products, even if not justified based strictly on cost.

This paper empirically examines the factors associated with consumer awareness of the Energy Star program and determinants of the the choice to purchase Energy Star white appliances (dishwashers, refrigerators, washing machines) using the 2005 Residential Energy Consumption Survey (RECS). The RECS data set is a sample of almost 4,500 U.S. households that is nationally representative after adjusting for sample weights. Using this survey data and a Heckman-type selection model, it is possible to jointly identify factors associated with consumer propensity to buy Energy Star appliances and with their "knowledge" or awareness of the program. Estimation results suggest that household characteristics influence awareness levels more than household propensities to purchase an Energy Star appliance for all three appliances studied, but significant gaps exist in Energy Star appliance adoption that, if eliminated, would generate significant household and social benefits.

The paper is organized as follows: Section 2 describes the paper's contributions to the previous literature examining energy-saving consumer behavior within the context of the model specification. Section 3 discusses the RECS 2005 data set and other secondary data used in the paper. Section 4 presents the results. Section 5 discusses simulations that highlight the economic and environmental implications of the results and section 6 concludes with policy implications.

2.2 Study Framework

Inferences about consumer behavior from survey data are often subject to significant bias due to missing or incomplete answers from survey respondents. In the current application, information on the Energy Star labels of appliances is only available for the sub-population of households who are aware if the appliance had an Energy Star label or not. The omission of individuals who are unaware of the Energy Star label of the appliance could cause significant bias because observed and unobserved characteristics of the two groups may be significantly different. Those who are 'aware' and answer the Energy Star questions might be more environmentally conscious or be more energy-aware compared to those who do not answer (or do not know). In this case both the sample selection awareness variable and the purchase outcome variable are discrete and can be modeled with probit equations in the maximum likelihood framework (van de Ven and Van Praag 1981).

Statistical Model

A household's latent propensity to purchase Energy Star appliances can be modeled as

$$y_i^* = \mathbf{X}_i\beta + \varepsilon_{1i}, \tag{2.1}$$

where y_i^* represents the latent measure of household preferences for Energy Star appliances, while $\mathbf{X}_i$ is a 1×K row vector of household characteristics. β represents a K×1 parameter vector and ε_{1i} is the residual. Consumers are observed to purchase Energy Star appliances $y_i = 1$, only if the latent preference is positive.

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \tag{2.2}$$

Similarly, if $y^* \leq 0$ then y_i equals zero and the respondent is observed to not have purchased an Energy Star appliance. However, this choice requires the respondent to be aware of the appliance classification. In the current application many respondents are unable to provide this crucial piece of information. Awareness can be modeled as another latent variable.

$$\kappa_i^* = \mathbf{Z}_i\gamma + \varepsilon_{2i}, \tag{2.3}$$

where κ_i^* is a latent measure of household awareness concerning Energy Star appliances. $\mathbf{Z}_i$ is a 1×J row vector of household characteristics. γ represents a J×1 parameter vector and ε_{2i} is the residual. Consumers who are able to answer "yes" or "no" to owning an Energy Star appliance all indicate they have a positive latent awareness of their appliance classification, while those who did not know would lack this awareness. Formally:

$$\kappa_i = \begin{cases} 1 & \text{if } \kappa_i^* > 0 \\ 0 & \text{if } \kappa_i^* \leq 0 \end{cases} \tag{2.4}$$

Estimating only the sample of respondents who provided an answer on the Energy Star status of the appliance is equivalent to (Heckman 1976, Heckman 1979):

$$E(y_i) = \mathbf{X}_i\beta + E(\varepsilon_{1i}|\mathbf{X}_i, \kappa^* \geq 0) \tag{2.5}$$

Assume $\varepsilon_1 \sim \mathcal{N}(0,1)$, $\varepsilon_2 \sim \mathcal{N}(0,1)$, and let $\rho = \text{corr}(\varepsilon_1, \varepsilon_2)$, then

$$\begin{aligned} E(\varepsilon_{1i}, \kappa^* \geq 0) &= \rho\lambda_i, & (2.6) \\ \text{where } \lambda_i &= \frac{\phi(\mathbf{Z}_i\gamma)}{\Phi(\mathbf{Z}_i\gamma)}. & (2.7) \end{aligned}$$

λ_i is the inverse of the Mills ratio, or the ratio of the normal density function $\phi(\cdot)$ over the cumulative distribution function $\Phi(\cdot)$. If there exists some residual correlation (as hypothesized) between Energy Star appliance classification awareness and propensity to choose an Energy Star appliance then the estimation of equation 2.1 will yield biased results as $E(u_1) \neq 0$.

The traditional Heckman 2-step method removes this bias by including $\hat{\lambda}_i$ in the outcome equation. A more efficient method uses maximum likelihood estimation to jointly model the probability of sample inclusion and the probability of Energy Star purchase as a bivariate normal distribution:

$$\prod_{i=1}^{N_1} F(\mathbf{X}_i\beta, \mathbf{Z}_i\gamma; \rho) \prod_{i=N_1+1}^{N} F(-\mathbf{X}_i\beta, \mathbf{Z}_i\gamma; \rho) \prod_{i=N+1}^{M} F(-\mathbf{Z}_i\gamma), \tag{2.8}$$

where 1 to N_1 observations includes respondents who are aware of the classification of the appliance and affirm ownership of an Energy Star appliance, $N_1 + 1$ to N observations includes respondents who are aware of the classification of the appliance and did not own an Energy Star appliance, and $N + 1$ to M observations included individuals who are not aware of the appliance classification.

Model Specification

For each appliance less than five years old at the time of the survey, respondents were asked if the appliance had an Energy Star label. Respondents that answered this question either positively or negatively are assumed to have awareness of the program, in that they knew what the program label represented and whether or not their appliance had a label. Respondents who did not know or skipped the question are assumed to lack awareness of the Energy Star classification of the appliance. Characteristics of a household, their residence, and their region all possibly influence both label awareness and Energy Star appliance purchase propensity.

Household Characteristics

Respondent age, sex, and marital status are included in both the Energy Star awareness and Energy Star purchase equations. Previous research has found that older respondents know less about new technology, are less likely to adopt new technology, and care less about energy conservation for non-monetary reasons (Linden, Carlsson-Kanyama and Eriksson 2006, Carlsson-Kanyama, Linden and Eriksson 2005, Walsh 1989, Mills and Schleich 2009*a*). Evidence of the impact of gender is mixed. Zarnikau (2003) finds that men are likely to spend more for renewable energy compared to women, but finds no gender difference in willingness to pay for energy efficiency. Similarly, DeFronzo and Warkov (1979) find no evidence that marital status affects household energy consumption.

Indicators for African-American, Asians, and Hispanics are included in the purchase and awareness equations. Poyer, Henderson and Teotia (1997) find that Hispanic and African-American populations spend less on energy compared to other ethnic and racial groups. Lutzenhiser (1997) finds similar lower levels of spending for Asians. Lower spending levels will, ceteris paribus, reduce incentives to learn about Energy Star appliances and also to purchase Energy Star appliances.

Household size is also likely to have a significant impact on both awareness and purchase propensity. Generally, larger households use appliances more frequently and thus use more energy; this would be particularly true for dishwashers and washing machines compared to refrigerators. Higher use levels should increase household awareness of energy saving technology. More frequent use of appliances should also increase purchase propensity for Energy Star appliances, since energy savings will be greater (Mills and Schleich 2009*a*, Walsh 1989).

Household income is also an important variable in both equations. Previous research has consistently shown that more affluent households have a higher propensity to purchase energy-saving technology. Environmental concerns and, thus, awareness also increase with income (Mills and Schleich 2009*b*, Zarnikau 2003, Long 1993, Walsh 1989). Further, households that are poor and near poor (measured as those earning less than 150% of the federal poverty line) need to be considered as a distinct group. Credit constraints are much more likely to be binding for poor and near-poor households, making it less likely they will invest in Energy Star appliances with high upfront costs. Exposure to poverty is also closely associated with low education levels (education level is not collected in the survey). Poor and near poor households may, therefore, be less aware of the Energy Star program due to associated low education levels. Finally, the price per kilowatt hour of electricity is included in both the awareness and purchase propensity equations. Higher electricity prices are expected to create incentives for consumers to learn about Energy Star appliances and increase the likelihood that they actually purchase Energy Star appliances.

Residence Characteristics

One of the most important residential characteristics for both awareness and purchase propensity is whether the respondent owns or rents the residence. Previous studies have shown that renting a residence inhibits the adoption of residential energy saving technologies (e.g. Mills and Schleich 2009*a*, Jaffe and Stavins 1994a). Since most renters in the U.S. inherit the appliances in the residence and then leave them upon moving, there is little incentive for them to actively acquire awareness of Energy Star appliance options. Additionally, renters might know of the general Energy Star program, but not have any incentive to learn the classification of their household appliances. Renters often pay utilities separately from their rent. This reduces incentives for landlords to purchase more costly Energy Star appliances because the long-term energy savings are directly transfered to the renter in the form of reduced monthly utility bills. An additional characteristic that could affect Energy Star awareness concerns the specific case where utility costs are included in rent. Under these circumstances, renters have even less incentive to learn about their appliance classification (Davis 2010).

Another important characteristic is the age of the residences; new houses normally have new appliances. Energy Star ratings for household appliances were introduced in 1997, but diffusion of awareness of the labels took time. The study examines only post-2000 appliances. Households in homes built in that period are likely to have made multiple appliance purchases. Returns to investments in awareness are then spread across multiple appliances, making the household more likely to be aware of the Energy Star label for any individual appliance. Whether a household residing in a recently built home influences their Energy Star purchase propensity is left as an empirical question.

Finally, rural and urban environments may have different impacts on label awareness and appliance purchase propensity compared to suburban environments. Washing machines may be particularly impacted in urban areas as laundry facilities are often readily available compared to rural and suburban areas, making washing machines less of a necessity and more of a luxury good. However, the exact nature of the impact of urban and rural residence on Energy Star program awareness and purchase propensity is also left as an empirical question.

Regional Energy Efficiency Characteristics

Regions may have different energy-saving characteristics or propensities to purchase Energy Star appliances. Two separate model specifications attempt to account for these differences. First, regional differences are controlled for in the awareness equation with indicators for eight of the nine census divisions, with the "East-South Central" division used as the benchmark division. Additionally, the RECS data provides indicators for the four largest states (California, New York, Texas, and Florida). Households in these states were excluded from the Census divisions and included in the model as additional state indicator variables. In the purchase propensity equation, regional differences in energy conservation propensity are controlled for through a regional scorecard of residential energy efficiency.[1] An alternative specification maintains the regional scorecard of residential energy efficiency in the purchase propensity equation, but models regional spillovers in awareness by calculating the share of all other households within each region that are aware of their Energy Star appliance classification. The hypothesis in this case is that an individual household in a region will have greater awareness of the program if aggregate regional awareness is greater.

[1]The scorecard is state specific for California, New York, Texas, and Florida and region specific for the other areas.

2.3 Data

The Residential Energy Consumption Survey (RECS) 2005, a nationally representative survey of almost 4,500 U.S. households, is the primary data set for the analysis. The RECS contains limited information of household demographics, but detailed information on energy consumption obtained through individual interviews. As noted, the American Council for an Energy-Efficient Economy (ACEEE) 2005 "scorecard" of residential energy efficiency is also employed. All 50 states and the District of Columbia received a score and weighted averages are computed to control for possible regional preferences in energy conservation in the purchase propensity equation.[2]

Several deficiencies in the data need to be addressed. First, the data does not contain any information on the price paid for appliances or price differences between Energy Star and non-Energy Star appliances. Second, according to the EIA, there is no set "rule" for determining the head of household (e.g. the primary wage earner or the person who is primarily at home). Instead, if the contacted person indicates that he or she is the head of household, that is taken at face value. Further, as noted, very limited information about the household head is collected. For example, education level is not reported in the survey data.

Since consumer exposure to the Energy Star program is relatively recent, the analysis focuses only on households that report having an appliance less than five years old at the time of the survey. By limiting the sample, only those households that have appliances built after the labeling scheme was implemented are included in the sample.[3] Thus, the sample size for each appliance analyzed differs; 1,116 households for dishwashers, with 1,920 households for refrigerators, and 1,539 households for washing machines. One of the interesting features of the data is that in over forty percent of households these three appliances were less than five

[2]Except for households in California, New York, Texas and Florida, which use state scorecards.

[3]Most previous analysis of energy labels have not been able to focus only on post-labeling scheme appliances; e.g. Mills and Schleich (2009*a*) for German household uptake of 'class-A' appliances.

years old. The refrigerators share was highest at 45 percent, while 43 percent of households had dishwashers and 42 percent of households had washing machines less than five years old. This may show that while lifespans of appliances have often been measured near 15 years, some households may choose to replace appliances for reasons other than failure.

Table 2.1 provides information about the Energy Star awareness for each appliance. Awareness of Energy Star classification is remarkably high for washing machines; almost 83 percent of the sample provided a classification, though awareness was quite high for all appliances. For dishwashers, 78 percent of the sample stated the appliance Energy Star classification, and for refrigerators, 76 percent of households identified the Energy Star classification. The similarities across appliances may stem from the marketing campaigns promoting the Energy Star label.

Among households that were aware of the Energy Star label, 71 percent purchased an Energy Star dishwasher, 67 percent purchased an Energy Star washing machine, and 65 percent purchased an Energy Star refrigerator. While these rates are high, it is worth noting that the rates likely do not represent rates for the general population of purchasers of each appliance, given the heterogeneity between households that are aware of their Energy Star classification and those that are not.

Descriptive statistics for all regressors are included in table 2.1. Even though the sample size differs across appliances, the summary statistics are quite similar and the descriptive statistics are not discussed in detail. Table 5.2 presents the sample percentage represented for each Census division by appliance. ACEEE scorecard values are reported in the last column of table 5.2. California, New York, and the New England regions show markedly higher regional residential energy efficiency scores than other regions.

2.4 Results

Tables 2.3, 2.4, and 2.5 present model parameter estimates for dishwashers, refrigerators, and washing machines, respectively. Looking first at results across appliances, estimates of ρ are significant (p=0.10) for both dishwashers and refrigerators. The result suggests that after conditioning on observed variables any unobserved heterogeneity between those who are aware of the Energy Star label and those who are not may significantly bias Energy Star adoption model parameter estimates if not controlled for in the estimator. The estimate of ρ for washing machines, however, is not significantly different from zero. The remaining results are discussed separately by appliance. Results from the alternative specification for each appliance, which drops regional fixed effects in the awareness equation for a measure of regional household awareness, are presented in the appendix.

Dishwashers

Household demographics play an important role in household awareness of whether it has an Energy Star dishwasher, as a large number of the parameter estimates in the Energy Star awareness equation are significant.[4] Respondent gender is marginally significant (p=0.10), with males being more likely than females to be aware of the appliance label. Respondent age positively affects the awareness equation as well. This result is a bit surprising as Mills and Schleich (2009*a*) and Zarnikau (2003) both find older households to be less willing to adopt energy-efficient technology. However, as noted, the age of the survey respondent may not be completely representative of the age structure of the household and the effect may be non-linear. Marriage positively affects awareness of dishwasher Energy Star classification. Larger households are also more likely to be aware of their dishwasher Energy Star classification,

[4]Significance, unless otherwise noted, refers to parameter estimates different from zero at the p-value = 0.05 in a two-tailed z-test.

which is consistent with previous studies. Ethnicity also matters, with Hispanics being less likely than non-Hispanics to be aware of the dishwasher Energy Star classification.

Some residential characteristics show strong correlations with Energy Star label awareness as well. As expected, households who dwell in recently built houses are more likely to be aware of the Energy Star label of their dishwasher, while households that rent their residence are less likely to be aware. Location attributes do not matter when examining dishwashers. Households that reside within a city or in a rural area are just as likely to know their dishwasher Energy Star classification as those residing in the suburbs. Price per kilowatt hour, a measure of electricity cost, also does not seem to influence label awareness.

Households residing in the West-South Central Census region, and New York (p= 0.10) are more likely to be aware of their Energy Star classification compared to households in the base East-South Central division, suggesting significant regional variation in awareness. In the alternative specification (table 2.9), a measure of the share of other households in the region who are aware of the Energy Star label replaces the regional indicators. The variable is not significant, suggesting regional label awareness levels do not generate significant spillovers in individual label awareness for dishwashers.

When examining the purchase equation, fewer household characteristics are significant than in the awareness equation, with the notable finding being that less affluent households (below 150% of the poverty line) are less likely (p=0.10) to purchase an Energy Star dishwasher even after controlling for income. As expected, renters are less likely to invest in an Energy Star dishwasher than owners.

Household location does not significantly affect the purchase decision; in particular residents living in rural and urban environments are just as likely to purchase an Energy Star dishwasher as those living in suburban areas. But the regional energy efficiency scorecard, a variable omitted from the knowledge equation is statistically significant. The result suggests that regional energy conservation propensities may positively influence Energy Star dishwasher purchases.

Refrigerators

Results for refrigerators are quite similar to results for dishwashers (table 2.4). The gender and age of the respondent are no longer significant for refrigerators, but married respondents are still more likely to be aware of the refrigerator classification compared to single respondents. Larger households are also more likely to be aware of the Energy Star classification. Asians are less likely to be aware of their refrigerator classification than whites, as are Hispanics compared to non-Hispanics. But the parameter estimate for African-Americans is not statistically significant (though the sign is negative).

Residential characteristics influence Energy Star label awareness for refrigerators. Unlike dishwashers, respondents living in newly built houses show no significant difference in awareness compared to those living in older homes. Households that rent their residences are again less likely to be aware of their refrigerator Energy Star label. Refrigerators are the only appliance where renters having utilities included in their rent further decreases (p=0.10) awareness. Rural and urban households show no differences in awareness compared to suburban households. Similarly to dishwashers, electricity prices do not seem to affect household awareness of the refrigerator Energy Star label. As noted, refrigerators consume the most energy of any household appliance and cannot be “turned off”. Thus, it is surprising that no relationship between label awareness and energy prices exists.

In terms of the regional diffusion of awareness, households living in the West-North Central (p=0.10) and the Pacific (excluding California) census divisions are less aware of their refrigerator Energy Star label compared to households living in the East-South Central census division. Three of the four large states show significant differences compared to the base region as well. Households from California (p=0.10) are more likely to be aware of their classification, while those from Texas (p=0.10) and Florida are less aware. While the regional fixed effects in awareness show differences, under the alternative specification (table 2.10) no evidence of regional spillovers in awareness is found, as the variable measuring the share of other households in the region who are aware of the Energy Star label is not significant.

The three significant variables affecting household propensities to purchase Energy Star dishwashers all remain significant for refrigerators. Poor and near-poor households are less likely to purchase an Energy Star refrigerator. Renters are less likely to purchase an Energy Star refrigerator compared to those who own their residence. Households living in regions with higher energy conservation scorecards are more likely to own Energy Star refrigerators as well. Additionally, location matters in the purchase decision for refrigerators, with rural households being more likely in rural area (p=0.10) to purchase Energy Star refrigerators. Possible explanations for higher Energy Star purchase propensities in rural areas are lower household discount rates and household expectations that they will reside in their current residence for longer periods.

Washing Machines

Results for washing machines provide the fewest regressors that significantly affect the awareness of the appliance Energy Star label, yet the largest number of significant regressors affecting the purchase decision (table 2.5). Household characteristics continue to have an important impact on label awareness. Neither gender nor age of respondents are significant, but marriage positively affects awareness of the Energy Star classification. Surprisingly, larger households are not more aware of their label classification, even though they would use their washing machine more often. Asian households are less likely to be aware of their washing machine classification compared to whites. Hispanic households are also less likely to be aware of their washing machine classification than non-Hispanic households.

Fewer residence characteristics affect washing machine Energy Star label awareness than for the other two appliances. Similar to the other two appliances, renting a residence makes households less likely to be aware of the washing machine Energy Star label. In contrast to dishwashers and refrigerators, electricity prices positively (p=0.10) affect awareness levels. This positive awareness may be a result of large marketing efforts that note Energy Star washing machines reduce energy costs sufficiently to pay the cost of a dryer.

Regional differences in label awareness for washing machines seem to be minor. No census divisions or states have statistically different levels of awareness compared to the base division. Additionally, the alternative specification (table 2.11) shows higher regional awareness does not significantly affect individual household awareness of washing machine Energy Star labels.

Turning to the purchase propensity equation, two household demographic characteristics influence the purchase decision. As expected, married households—who are likely to use washing machines more intensely—are more likely to purchase an Energy Star labeled washing machine compared to unmarried households. Hispanic households are less likely to purchase an Energy Star washing machine compared to non-Hispanic households. Unlike refrigerators, poor and near poor households are not statistically less likely to purchase more efficient Energy Star washing machines (though the estimate is still negative).

Similar to results for refrigerators and dishwashers, renters are less likely to purchase Energy Star labeled washing machines. Households residing in an urban environment are less likely to purchase an Energy Star washing machine. As previously suggested, this may be due to the close availability of laundry facilities. Higher electricity prices also positively affect purchase decisions of Energy Star washing machines. Similar to results from dishwashers and refrigerators, living in a region with a higher regional energy efficiency score increases the likelihood of purchasing an Energy Star washing machine.

2.5 Marginal Effects and Simulations

Marginal Effects

Table 2.6 shows the average marginal effects of all significant variables in the purchase equation for each appliance. Most of the statistically significant variables seem to have an economically important impact on Energy Star adoption as well. Being married increases the probability of Energy Star washing machine adoption by 11.7 percentage points. Hispanic households show a 14.3 percentage point lower propensity to purchase Energy Star washing machines. Poor and near poor households show a nine percentage point lower propensity to purchase Energy Star dishwashers and refrigerators. Households that rent show large negative effects ranging from 7.7 to 12.9 percentage points on purchase behavior across all three appliances. The regional ACEEE score marginal effect appears small for all three appliances, but as will be seen in the simulations, changes from regions with lower scores to those with higher scores can significantly increase purchase propensity.

Simulations

The estimated marginal effects are used to estimate the impacts of closing observed "gaps" in the adoption of Energy Star appliances. Specifically, we simulate the closure of the "Hispanic" gap, the "renter" gap, the "poverty" gap, and the "ACEEE scorecard" gap. The ACEEE gap is closed by simulating that all households live in the region with the highest score, California. These four simulations are chosen because the marginal effects are large and the gaps are amenable to policy interventions. Carbon reductions, energy savings, and monetary savings associated with increased appliance adoption are also calculated using the technical parameters presented in Sanchez, Browning, Homan and Webber (2008).[5]

Simulations for dishwashers demonstrate that closing all four gaps generate significant electricity savings and environmental benefits. Closing the Hispanic gap yields the smallest gain, which is not surprising since the Hispanic gap is statistically insignificant variable for dishwashers. Policies that forced renters to behave like owners would increase the rate of adoption of Energy Star dishwashers by 1.7 percent. The attendant benefits to households are roughly $6 million in electricity costs and a reduction of roughly 40 thousand metric tons of carbon emissions compared to current conditions. Improving the poor and near poor adoption behavior results in a 1.4 percent increase of Energy Star dishwashers leading to electricity savings of about $5 million and carbon emission reductions of almost 34 thousand metric tons. The largest potential savings comes from bridging the ACEEE scorecard gap between California and the rest of the country, with a potential increase in household purchases of Energy Star dishwashers of almost eight percent. This increased adoption is equivalent to electricity savings of about $26 million and carbon emission reductions of 186 thousand metric tons.

Refrigerator simulations yield similar results. Reducing the Hispanic gap again provides relatively low benefits. However, renters and the poor and near poor present opportunities for significant electricity cost savings, at $11.9 million and $10.6 million respectively. Savings from the simulations equate to reductions in carbon emissions of roughly 81 thousand

[5]Table 5 and 6 from Sanchez et al. were used to estimate potential savings from each appliance. Energy Star refrigerators save households $7.59 (in 2006 dollars) each year in electricity costs. Energy Star dishwashers saves households $11.45 yearly, while an Energy Star washing machine reduces annual electricity expenditures by $12.23 compared to a conventional washing machine. For calculations of carbon emissions, the monetary savings are divided by the mean price per kilowatt hour of electricity for each appliance. The "saved" kilowatt hours are then input into the EPA calculator to calculate carbon emissions. See `http://www.epa.gov/cleanenergy/energy-resources/calculator.html`.

metric tons for renters and roughly 72 thousand metric tons for poor and near poor households. Savings from the 10.4 percent increase in Energy Star refrigerators from the ACEEE scorecard again provides the largest opportunity for electricity savings at over $37 million, translating into 253 thousand metric tons of carbon emission reductions.

Finally, closing adoption gaps for Energy Star washing machines would have the greatest impact of the three appliances. Simulations show that bridging the Hispanic gap would increase aggregate adoption by almost two percent. The reduction of this gap would save consumers over nine million dollars annually. Eliminating the Hispanic adoption gap reduces carbon emissions by over 62 thousand metric tons. While the Hispanic gap offers significant savings, addressing the rental gap generates larger benefits. If renters behave similarly to owners in terms of Energy Star purchase propensity, the adoption rate of Energy Star washing machines would increase by almost three percent. This increase translates into annual savings to households of over $13.5 million a year in electricity costs and reductions in carbon emissions of over 93 thousand metric tons. Increasing poor and near poor households Energy Star washing machine adoption rates to those of other households would not generate significant savings. But simulating all households adopting Energy Star washing machines at the rate of in the highest ACEEE scorecard region again provides large potential benefits. Households could save over $38 million in electricity costs, which would yield a reduction in carbon emissions of almost 267 thousand metric tons.

Table 2.8 summarizes the total monetary and carbon emission savings that are possible from closing the Hispanic, renter, poverty, and ACEEE scorecard gaps in Energy Star adoptions for the three appliances. In addition, the final column of the table presents the estimated "combined" reduction. Policies that reduce all of these gaps would save households over $164 million per year in electricity costs and reduce carbon emissions by over 1.1 million metric tons. The carbon reduction is equivalent to removing over 216,015 cars from the road annually.[6] The simulations show that there are large potential gains from Energy Star adoption, but it is necessary to note that having all households adopt Energy Star appliances might not be the most efficient level of adoption. For instance, it may not be efficient for a simple person with very low washing machine usage to purchase a significantly higher priced Energy Star washing machine. However, the evidence from the simulations and the results seems to show that closing some of the identified gaps can yield social benefits in terms of carbon dioxide reductions as well as individual benefits in terms of energy savings.

2.6 Conclusions

Consumer awareness of the Energy Star label has grown significantly since its initial implementation in 1992. In 1999, only 30% of consumers were aware of the existence of an Energy Star label and generally what it meant (U.S. Environmental Protection Agency 1999). Consumer awareness then doubled by 2005 (U.S. Environmental Protection Agency 2005). More recent research suggests increases have not leveled off, as estimated consumer awareness of Energy Star labeling has exceeded 75% of the population in 2008 (U.S. Environmental Protection Agency 2008*a*). EPA literature implicitly assumes that the increased awareness will cause consumers to shift from non-Energy Star appliances to Energy Star appliances.

Results from the paper, however, seem to indicate a different story. First, while overall awareness of the branding of Energy Star might have increased, certain racial and ethnic groups appear to remain relatively unaware of the Energy Star label; i.e. Asians and Hispanics. Hispanics are also less likely to purchase Energy Star washing machines. This suggests that the EPA may need to adopt different marketing techniques to target information on

[6] According to EPA calculations, one car that gets 21 miles to the gallon and is driven 11,720 miles yearly (both national averages) produces 11,669 pounds of carbon in yearly carbon emissions. See `http://www.epa.gov/climatechange/emissions/ind_calculator2.html` for further information.

the Energy Star classification to these population groups. The EPA already recognizes this issue and has started publishing their Energy Star pamphlets and information sheets in both English and Spanish. Poor and near poor households are also less likely to own Energy Star dishwashers or refrigerators, most likely due to credit constraints or very high discount rates, since extra upfront costs for an Energy Star appliance is very likely to come at the cost of basic necessities such as food, clothing, and shelter.

Several clear and important implications for energy policy can be drawn from the results. For example, rebates on Energy Star appliances developed as part of the American Recovery and Reinvestment Act did not target specific groups, but were instead offered to any household. The rebates were quickly used, but it is still unclear whether the rebates induced marginal consumers to purchase Energy Star household appliances. Future rebates should be targeted to households that are poor or near poor since these households are less likely to purchase an Energy Star appliance and, thus, a rebate would be more likely to influence the energy efficiency purchase decision. While rebates might increase the likelihood of minorities purchasing Energy Star appliances, it is not feasible for the government to target specific racial or ethnic groups for rebates and alternative incentive mechanisms will need to be devised.

The commonly cited owner-renter investment benefit appropriation problem extends to Energy Star appliances. Previous incentives focused primarily on home owners and provided tax credits for owners to replace their old appliances with new Energy Star appliances. One solution to improve adoption of Energy Star appliances by renters is to extend tax credits only to owners of rental properties. In this manner, landlords observe direct benefit from the purchase of Energy Star appliances, regardless of whether the tenet or landlord pays for utilities. Marketing provides another method for increasing Energy Star adoption in rental units. If renters are more aware of the reduced utility bills from Energy Star appliances, rental properties that include Energy Star appliances may become more desirable.

Finally, regions with greater propensities to conserve energy, based on the ACEEE scorecard also show greater propensities to purchase Energy Star labeled appliances, suggesting regional norms do play a significant role in purchase behavior. Thus, efforts to generate 'conservation cultures' may have significant spillovers.

Table 2.1: Summary Statistics for Awareness and Choice of Energy Star Appliances

		Dishwasher		Refrigerator		Washing Machine	
Variable Name	Description	Estimate	Std. Deviation	Estimate	Std. Deviation	Estimate	Std. Deviation
hhsex	Household respondent male = 1	0.437	0.016	0.430	0.012	0.446	0.014
hhage	Age of household respondent	46.745	0.493	46.377	0.418	47.261	0.435
spouse	Household respondent married = 1	0.700	0.015	0.607	0.012	0.686	0.013
nhsldmem	Household size	2.760	0.045	2.754	0.039	2.930	0.042
black	African American household respondent = 1	0.092	0.009	0.133	0.009	0.112	0.009
asian	Asian household respondent = 1	0.022	0.005	0.034	0.004	0.031	0.005
hisp	Hispanic household respondent = 1	0.087	0.009	0.172	0.009	0.137	0.009
tpci	Household per capita income	27252.81	671.79	22002.68	497.04	23626.06	557.85
*poor*150	Household income $\leq$ 150% pov. Line = 1	0.137	0.011	0.290	0.011	0.206	0.011
newhouse	Dwelling built within last 5 years = 1	0.240	0.014	0.162	0.009	0.147	0.010
kownrent	Respondent rents dwelling = 1	0.205	0.013	0.352	0.012	0.208	0.011
included	Utility costs included in rent = 1	0.032	0.005	0.065	0.006	0.016	0.004
urban	Dwelling lies within a city = 1	0.370	0.015	0.455	0.012	0.407	0.014
rural	Dwelling lies in a rural area = 1	0.191	0.012	0.173	0.009	0.214	0.011
ppkw	Price per Kilowatt hour	0.102	0.001	0.107	0.001	0.104	0.001
sval	Regional Scorecard Value	13.725	0.239	14.424	0.198	13.966	0.214
shared	Region share of households Energy Star	0.150	0.001	—	—	—	—
sharer	Region share of households Energy Star	—	—	0.216	0.001	—	—
sharew	Region share of households Energy Star	—	—	—	—	0.196	0.001
aware	Aware of Energy Star appliance type	0.782	0.013	0.761	0.011	0.829	0.010
buy	Own Energy Star appliance type	0.712	0.017	0.649	0.014	0.675	0.014
		N=1116		N=1920		N=1539	

Table 2.2: Percentage of Sample within Each Census Division

Region	Dishwasher	Refrigerator	Washing Machine	ACEEE Scorecard Value
New England	4.84%	5.22%	4.32%	23.00
Mid-Atlantic	5.67%	6.15%	6.86%	18.50
East North Central	14.26%	13.71%	12.85%	9.80
West North Central	8.21%	6.95%	6.84%	7.71
South Atlantic (excluding Florida)	13.61%	13.03%	13.87%	8.69
East South Central	5.18%	5.62%	6.49%	3.38
West South Central (excluding Texas)	3.79%	4.01%	4.27%	4.00
Mountain	8.13%	7.46%	8.32%	10.56
Pacific (excluding California)	4.97%	4.3%	4.67%	17.88
California	10.53%	12.09%	11.46%	30.00
New York	3.35%	6.44%	5.21%	23.00
Texas	9.11%	8.33%	7.48%	17.50
Florida	8.35%	6.69%	7.36%	9.00

Table 2.3: Dishwasher Energy Star Label Awareness and Purchase

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	-0.0472	0.0964	0.1882 †	0.1002
Age of head of household	-0.0009	0.0037	0.0123 **	0.0037
Married	0.1239	0.1282	0.3175 **	0.1145
Household size	0.0302	0.0470	0.1194 **	0.0447
African-American	0.1489	0.1805	-0.0380	0.1767
Asian	0.4138	0.4243	-0.3610	0.3365
Hispanic	-0.1956	0.1774	-0.3337 *	0.1585
Per capita income $ ($\times$ 1000)	-0.0029	0.0033	0.0041	0.0000
Below 150% poverty line	-0.2809 †	0.1683	-0.2158	0.1472
House recently built	-0.1251	0.1097	0.2501 *	0.1200
Rent residence	-0.2428 †	0.1394	-0.3747 **	0.1214
Utilities included in rent dummy variable	—	—	0.0959	0.2336
Urban dummy variable	0.0490	0.1087	-0.0379	0.1071
Rural dummy variable	0.0820	0.1243	0.0406	0.1392
Price per kilowatt hour	0.8965	1.2445	0.7599	1.2448
Regional ACEEE score	0.0185 **	0.0070	—	—
New England	—	—	0.0948	0.2341
Mid-Atlantic (without New York)	—	—	0.1818	0.2659
East North Central	—	—	0.0767	0.2110
West North Central	—	—	-0.0918	0.2195
South Atlantic (without Florida)	—	—	0.1198	0.2070
West South Central (without Texas)	—	—	0.7148 *	0.3400
Mountain	—	—	0.2272	0.2319
Pacific (without California)	—	—	0.2439	0.2305
California	—	—	0.1927	0.2372
New York	—	—	0.6649 †	0.3604
Texas	—	—	-0.0740	0.2345
Florida	—	—	0.0617	0.2569
Constant	0.4596	0.3564	-0.5894	0.3473
ρ: -0.7949†			Number of observations = 1116	
†: Significant at 10% level		*: Significant at 5% level	**: Significant at 1% level	

Table 2.4: Refrigerator Energy Star Label Awareness and Purchase

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	0.0615	0.0761	0.0389	0.0753
Age of head of household	0.0028	0.0027	-0.0010	0.0025
Married	0.0889	0.0966	0.2285 **	0.0864
Household size	0.0416	0.0336	0.0688 *	0.0324
African-American	0.0228	0.1191	-0.0213	0.1202
Asian	0.0935	0.2044	-0.4406 *	0.1766
Hispanic	-0.0724	0.1175	-0.3158 **	0.1086
Per capita income $ ($\times$ 1000)	-0.0002	0.0029	0.0011	0.0000
Below 150% poverty line	-0.2572 *	0.1120	-0.1259	0.1011
House recently built	-0.1088	0.1004	0.0767	0.1041
Rent residence	-0.2474 †	0.1303	-0.5349 **	0.0878
Utilities included in rent dummy variable	—	—	-0.2560 †	0.1404
Urban dummy variable	0.0201	0.0853	0.0589	0.0840
Rural dummy variable	0.1815 †	0.1053	0.0007	0.1114
Price per kilowatt hour	-0.3481	1.2761	2.2614	1.4470
Regional ACEEE score	0.0222 **	0.0059	—	—
New England	—	—	-0.2669	0.1850
Mid-Atlantic (without New York)	—	—	0.1705	0.2126
East North Central	—	—	-0.0687	0.1754
West North Central	—	—	-0.3421 †	0.1768
South Atlantic (without Florida)	—	—	-0.0356	0.1612
West South Central (without Texas)	—	—	0.1633	0.2288
Mountain	—	—	-0.1587	0.1842
Pacific (without California)	—	—	-0.3739 †	0.1973
California	—	—	0.3156 †	0.1906
New York	—	—	0.1245	0.2439
Texas	—	—	-0.3347 †	0.1770
Florida	—	—	-0.4319 *	0.1919
Constant	0.1022	0.2902	0.5662	0.2849
ρ: -0.6283†		Number of observations = 1920		
†: Significant at 10% level		*: Significant at 5% level	**: Significant at 1% level	

Table 2.5: Washing Machine Energy Star Label Awareness and Purchase

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	-0.0850	0.0779	-0.0209	0.0869
Age of head of household	0.0013	0.0028	0.0003	0.0029
Married	0.2975 **	0.0920	0.2938 **	0.1001
Household size	0.0340	0.0324	0.0397	0.0366
African-American	-0.0310	0.1224	-0.0753	0.1483
Asian	-0.1063	0.3214	-0.5594 *	0.2203
Hispanic	-0.3601 **	0.1154	-0.2379 †	0.1330
Per capita income \$ ($\times$ 1000)	0.0045	0.0032	0.0008	0.0034
Below 150% poverty line	-0.0547	0.1077	0.0312	0.1221
House recently built	-0.1363	0.1067	-0.0999	0.1253
Rent residence	-0.3271 **	0.1086	-0.1014	0.1127
Utilities included in rent dummy variable	—	—	0.3503	0.2969
Urban dummy variable	-0.1537 †	0.0877	-0.0773	0.0999
Rural dummy variable	-0.0622	0.1004	-0.0489	0.1236
Price per kilowatt hour	3.4394 *	1.4133	3.4922 †	1.9702
Regional ACEEE score	0.0142 *	0.0061	—	—
New England	—	—	0.2951	0.2531
Mid-Atlantic (without New York)	—	—	0.1381	0.2280
East North Central	—	—	-0.0289	0.1762
West North Central	—	—	-0.1723	0.1860
South Atlantic (without Florida)	—	—	0.2827	0.1790
West South Central (without Texas)	—	—	0.2924	0.2604
Mountain	—	—	-0.0864	0.2050
Pacific (without California)	—	—	0.1393	0.2113
California	—	—	0.0504	0.2203
New York	—	—	0.0931	0.2954
Texas	—	—	-0.0560	0.2929
Florida	—	—	0.1079	0.2525
Constant	-0.5795	0.2577	0.3308	0.3244
ρ: 0.8520		Number of observations = 1539		
†: Significant at 10% level		*: Significant at 5% level	**: Significant at 1% level	

Table 2.6: Marginal Effects of Significant Variables

Primary Specification			
Variable	Dishwasher	Refrigerator	Washing Machine
Married	—	—	0.1173
Hispanic	—	—	-0.1427
Below 150% poverty line	-0.0906	-0.0900	—
Rent residence	-0.0768	-0.0858	-0.1294
Urban dummy variable	—	—	-0.0604
Rural dummy variable	—	0.0596	—
Price per kilowatt hour	—	—	1.3499
Regional ACEEE score	0.0056	0.0075	0.0056

Table 2.7: Simulation of Impacts by Appliance

Dishwasher

Identified "Gap"	Percentage	Monetary Savings (2006 $)	Carbon Emission reductions (tons)
Hispanic	0.57%	$1,884,428.73	13,273
Renter	1.71%	$5,689,580.80	40,076
Below Poverty Line	1.44%	$4,785,613.32	33,709
ACEEE Scorecard	7.93%	$26,431,844.39	186,179
Total:	—	$38,791,467.25	273,237

Refrigerator

Identified "Gap"	Percentage	Monetary Savings (2006 $)	Carbon Emission reductions (tons)
Hispanic	0.43%	$1,559,215.31	10,508
Renter	3.30%	$11,998,059.05	80,858
Below Poverty Line	2.95%	$10,693,421.44	72,066
ACEEE Scorecard	10.36%	$37,605,852.62	253,436
Total:	—	$61,856,548.42	416,868

Washing Machine

Identified "Gap"	Percentage	Monetary Savings (2006 $)	Carbon Emission reductions (tons)
Hispanic	1.94%	$9,156,498.94	63,213
Renter	2.87%	$13,504,720.37	93,232
Below Poverty Line	0.51%	$2,401,090.74	16,576
ACEEE Scorecard	8.20%	$38,621,724.97	266,631
Total:	—	$63,684,035.02	439,652

Table 2.8: Simulation Summary

	Dishwasher	Refrigerator	Washing Machine	Combined
Monetary Savings (2006 $)	$38,791,467.25	$61,856,548.42	$63,684,035.02	$164,332,050.69
Carbon Emission reductions (tons)	273,237	416,868	439,652	1,129,757

Table 2.9: Dishwasher (Alternative Specification)

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	0.0347	0.1403	0.1530	0.1010
Age of head of household	0.0064	0.0075	0.0123 **	0.0036
Married	0.3311 *	0.1337	0.3391 **	0.1218
Household size	0.0984	0.0628	0.1106 **	0.0467
African-American	0.0792	0.2136	-0.0855	0.1634
Asian	0.0265	0.5594	-0.4677	0.2866
Hispanic	-0.3713 *	0.1783	-0.2588	0.1677
Per capita income \$ ($\times$ 1000)	-0.0003	0.0048	0.0040	0.0034
Below 150% poverty line	-0.4581 **	0.1629	-0.2677 †	0.1483
House recently built	0.0128	0.1957	0.2232 †	0.1242
Rent residence	-0.4774 **	0.1286	-0.2897 *	0.1338
Utilities included in rent dummy variable	—	—	-0.1699	0.3712
Urban dummy variable	0.0405	0.1122	-0.0125	0.1068
Rural dummy variable	0.1232	0.1249	0.0636	0.1417
Price per kilowatt hour	1.6360	1.5103	1.6062	1.5119
Regional ACEEE score	0.0179	0.0140	—	—
Regional Share Value	—	—	-1.3975	2.1225
Constant	-0.8237	1.0566	-0.3168	0.4258
ρ: 0.6728		Number of observations = 1116		

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

Table 2.10: Refrigerator (Alternative Specification)

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	0.0712	0.0795	0.0255	0.0746
Age of head of household	0.0029	0.0028	-0.0010	0.0025
Married	0.1355	0.1071	0.2023 *	0.0849
Household size	0.0585	0.0375	0.0729 *	0.0318
African-American	0.0267	0.1249	-0.0215	0.1125
Asian	0.0354	0.2250	-0.4512 *	0.1767
Hispanic	-0.1448	0.1387	-0.3580 **	0.1049
Per capita income \$ ($\times$ 1000)	0.0001	0.0030	0.0014	0.0000
Below 150% poverty line	-0.3072 **	0.1187	-0.1250	0.1009
House recently built	-0.1081	0.1048	0.0140	0.1042
Rent residence	-0.3900 *	0.1724	-0.5388 **	0.0873
Utilities included in rent dummy variable	—	—	-0.2788 *	0.1408
Urban dummy variable	0.0391	0.0899	0.0619	0.0820
Rural dummy variable	0.2065 †	0.1095	0.0192	0.1075
Price per kilowatt hour	-0.0853	1.4010	3.1001 *	1.2238
Regional ACEEE score	0.0259 **	0.0062	—	—
Regional Share Value	—	—	1.5930	1.1447
Constant	-0.1432	0.3963	0.0677	0.3107
ρ: -0.1881		Number of observations = 1920		

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

Table 2.11: Washing Machine (Alternative Specification)

	Purchase		Awareness	
Variable	Estimate	Std. Error	Estimate	Std. Error
Gender of head of household	-0.1002	0.0863	-0.0240	0.0870
Age of head of household	0.0020	0.0030	-0.00002	0.0031
Married	0.2349	0.3027	0.2879 **	0.0962
Household size	0.0286	0.0477	0.0355	0.0377
African-American	-0.0419	0.1342	-0.0236	0.1495
Asian	0.2101	0.6558	-0.5505 **	0.2132
Hispanic	-0.3265	0.2544	-0.2333 †	0.1349
Per capita income \$ ($\times$ 1000)	0.0058 †	0.0031	-0.00002	0.0032
Below 150% poverty line	-0.0630	0.1190	0.0056	0.1195
House recently built	-0.1145	0.1719	-0.1351	0.1225
Rent residence	-0.3681 **	0.1134	-0.0669	0.1350
Utilities included in rent dummy variable	—	—	0.1431	0.8428
Urban dummy variable	-0.1599	0.1139	-0.0703	0.0972
Rural dummy variable	-0.0740	0.1103	-0.0097	0.1223
Price per kilowatt hour	2.6352	3.9590	4.3358 **	1.4729
Regional ACEEE score	0.0166 *	0.0072	—	—
Regional Share Value	—	—	-1.5374	2.1251
Constant	-0.2600	1.3116	0.6507	0.4841
ρ: 0.0637		Number of observations = 1539		

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

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Chapter 3

Essay 2: The Impact of Low Income Home Energy Assistance Program (LIHEAP) Participation on Household Energy Insecurity

3.1 Introduction

An extensive literature in economics has evaluated the efficacy of U.S. public assistance programs. Important information about how programs affect well-being, labor market decisions, and individual program participation have been studied. Researchers have developed advanced econometric methods to account for the self-selection inherent in the voluntary choice of program and labor market participation. Most of the large assistance programs like Aid to Families with Dependent Children (AFDC), the Supplemental Nutritional Assistance Program (SNAP), Women Infant and Children (WIC), and the National School Lunch Program (NSLP) have been evaluated over the last 40 years.

One large federal program, however, has received little rigorous attention in terms of impact.

The Low-Income Home Energy Assistance Program (LIHEAP) is the single largest energy assistance program available to poor households within the United States. LIHEAP benefits assist households in several ways. First, eligible households can receive aid to help pay their utility bills during the critically cold or hot months of the year. Second, LIHEAP provides "crisis" funds to return service to eligible households that have had (or will imminently have) their utility services cut off. Finally, LIHEAP provides eligible households with funds to improve the energy efficiency of their home through weather-stripping, upgrading the home insulation, or replacing inefficient heating systems. The largest component of LIHEAP has traditionally been the heating and cooling payment assistance program, accounting for almost 80 percent of households who receive benefits.

The LIHEAP program has recently come under significant scrutiny from the U.S. Congress and the White House. Both the White House and the House of Representatives have proposed slashing the current funding levels of LIHEAP by approximately half. The major rationale for these cuts has been based on the "lower" energy prices observed during the most recent recession. Recent spikes in energy prices in early 2011, however, cast doubt that energy prices will remain low. A more compelling reason to cut LIHEAP funding would be because the program doesn't work, though no one has put forth this argument. Like most federal programs, LIHEAP has a target group of households to assist: "vulnerable households" and "high burden households". Vulnerable households are low-income households that have young children, elderly, or disabled individuals and high burden households have high energy costs but low-income levels. Little empirical evidence has been generated to determine whether LIHEAP effectively helps these vulnerable and high burden households.

However, measures for determining LIHEAP effectiveness can be generated. If LIHEAP participation improves low-income household energy security, then cuts to its funding could negatively impact the poor. Energy security is similar to the well-known concept of food security that is extensively researched. In many national surveys, households are asked for responses to questions regarding their food consumption actions and behavior. An Item Response Theory (IRT) model has been employed by the USDA to create a positively continuous food security index based on household response. A similar index for energy security can be constructed from questions asked in the 2005 Residential Energy Consumption Survey (RECS). After accounting for selectivity issues, it is then possible to provide policy makers with an unbiased estimate of the impact of LIHEAP benefits on household energy security.

The rest of this paper is organized as follows: Section 3.2 provides more details of LIHEAP and discusses the literature examining LIHEAP and Section 3.3 outlines a theoretical model of LIHEAP participation. Section 3.4 explains how the theoretical model is transformed into an econometric model and Section 3.5 presents the specification of the econometric model. Section 5.2 discusses the data and provides summary statistics of all variables, Section 5.4 provides the results, Section 3.8 examines simulated changes to the program, and finally Section 5.5 presents some conclusions. The appendix provides a full description of the specific IRT model (the Rasch model) used to develop the energy security index.

3.2 Background

In 1981, the United State Congress funded LIHEAP block grants to alleviate energy burdens on low-income households through the Low-Income Home Energy Act, Title XXVI of the 1981 Omnibus Budget Reconciliation Act. As a block grant individual states receive funding from the federal government without specific federal guidelines for allocation. As a non-entitlement program, eligible households are not guaranteed LIHEAP funds. The drastic energy shocks of the late 1970's provoked Congress to protect two distinct groups: low-income households and utility companies. Low-income households are arguably most directly affected by the rapid increase in energy prices, and the rise in utility bills in the early 80's meant that these households faced an increased likelihood of making partial payments or having delinquent utility bills. These actions by low-income households forced utility companies to either terminate service, an unpopular option that could endanger households during extreme temperatures, or continue service while losing revenue. By creating LIHEAP, Congress provided a mechanism for states, utility companies, and low-income households to address these difficulties.

LIHEAP eligible households must meet certain criteria. Specifically, they must have an income of less than 150 percent of the poverty line or less than 60 percent of the state's median income, whatever is greater. States may offer benefits to households that are more generous than these criteria, but they may not make more stringent eligibility requirements. Additionally, households that receive other entitlement benefits such as food stamps, aid to families with dependent children (AFDC), or supplemental security income (SSI) also qualify. Unfortunately, being eligible does not necessarily guarantee the household benefits. Households must apply for LIHEAP benefits and the available funds may not be sufficient to meet the needs of all eligible households. The number of eligible households rose by over 70 percent from 1981 until fiscal year 2007, yet funding increased by only 17.3 percent. Currently, the Administration for Children and Families, a division of the U.S. Department of Health and Human Services, estimates that only 16 percent of eligible households receive heating benefits from LIHEAP. This is a substantial decrease from program inception when 36 percent of eligible households received benefits (Division of Energy Assistance 2009).

Energy needs of low-income households have changed since 1981. LIHEAP funded households have adjusted their heating and cooling habits due to technological changes. Approximately 33 percent of these households used electricity to heat their homes in 2005 compared to only 15 percent in 1981, while use of fuel oil for heating has fallen to roughly eight percent from almost 18 percent in 1981 (Division of Energy Assistance 2009). With over 60 percent of all households using natural gas throughout the time period, it remains the primary source of heat for low-income households. Perhaps most importantly, air conditioning use has drastically increased as a household amenity since LIHEAP first began. Approximately 45 percent of low-income households use central air conditioning in 2005 compared to only 15 percent in 1981 (Division of Energy Assistance 2009).

One reason few economic studies have examined LIHEAP may be its level of funding in conjunction with the complexity of the block grant program. Congress has traditionally allocated between $1.5 billion and $2 billion annually to LIHEAP compared to almost $50 billion for SNAP or $10 billion for the national school lunch program, two heavily researched entitlement programs. LIHEAP funding rose dramatically from 2009 until 2011 to roughly $5 billion per year. The recently passed 2012 budget cuts funding to LIHEAP by roughly 25 percent from its previous budget to $3.7 billion. Interestingly, other programs that have relatively similar funding levels, such as WIC ($6 billion annually over the past two fiscal years), have received extensive coverage in the economic literature (e.g. Arcia, Crouch and Kulka 1990, Carlson and Senauer 2003), and numerous ERS publications. The few economic articles that examine LIHEAP focus on the allocation formula problems derived by Congress instead of discussing the effectiveness of the program in reducing or removing energy insecurity (Kaiser and Pulsipher 2003*a*, Kaiser and Pulsipher 2003*b*). Theisen (1993) examines a single county from Iowa to determine if the additional funds allocated to these low-income households encourages them to use more energy, a potential flaw in the execution of the program. His results show that LIHEAP funding does not cause low-income income households within the county to increase their use of electricity, but none of the analysis examines the energy security of the study households. Additionally, the limited nature of the data prevent a broader analysis at the national level.

While little research has evaluated the efficacy of LIHEAP, program evaluation of other governmental aid programs is substantial. Significant literature has tried to determine whether the USDA SNAP (formerly called the food stamp program) improves food security. In this literature, there seems to be conflicting evidence depending upon which survey researchers use. For example, Gundersen and Oliveira (2001) find no statistically significant effect in reducing food insufficiency when food insufficiency and receipt of food stamps are jointly modeled. If these two equations are estimated separately, ignoring the important linkages between household food sufficiency and food stamp participation, the results are counterintuitive and show that receipt of food stamps worsens food insufficiency. Conversely, Jensen (2002) uses a similar specification with different data and observes statistically significant positive correlation between food insecurity and SNAP participation.

Alternatively, two recent articles use an instrumental variable approach to provide evidence that food security improves through participation in SNAP (Yen, Andews, Chen and Eastwood 2008, Mykerezi and Mills 2010). Both of these articles use the USDA food insecurity index derived from the Rasch model. Yen et al. (2008) note that in comparison to previous studies, their results might hold due to the unique data set where food insecurity is on average lower among SNAP participants than non-participants. Mykerezi and Mills (2010) find that SNAP participation improves mean household scores on the food security scale by at least 19 percent after controlling for program selection. Any program evaluation of LIHEAP needs to address program self-selection to the econometric model specification. Self-selection concerns are likely to be further heightened by low participation rates among eligible households. General awareness of LIHEAP seems to be low with roughly half of the eligible households unaware of the program (Higgins and Lutzenhiser 1995).

3.3 Theoretical Model

Like other federal assistance programs, households make the decision to participate in LIHEAP if household utility is greater from participation than non-participation. Households are assumed to have monotonic, strictly quasi-concave utility functions. It is not guaranteed that participation will increase household utility due to potential program disutility

(Moffitt 1983). Consumers could face disutility in the form of the shame of needing public assistance (commonly referred to as "welfare stigma") or through administrative transaction costs to obtain the benefits. As an example, eligible households in West Virginia have a four day window to apply for LIHEAP benefits in early December. The rigid time lines and paperwork might reduce household utility more than the additional monetary benefits improve it. Disutility from LIHEAP participation involves a fixed component, ϕ, associated with program participation regardless of monetary outlays. Households additionally discount the benefits from LIHEAP compared to earned income, creating a variable component, γ, that affects the household differently depending upon the level of LIHEAP benefits. A very basic utility function can be modeled from these assumptions, yielding

$$U(Y + \gamma A * B) - \phi A, \tag{3.1}$$

where Y represents non-LIHEAP income, A is a binary variable indicating program participation, B are the program benefits and ϕ and γ are used as previously defined. Households are expected to discount LIHEAP benefits at some level between $0 < \gamma < 1$ and fixed disutility is expected to be greater than zero ($\phi > 0$).

Discounting arises because households have a preference for the type of income ($\gamma \neq 1$). Households prefer labor income to income received from social welfare programs (Moffitt 1983). Since money received from LIHEAP can only be used to supplement paying utility bills or improve weatherization of the residence, households discount its income relative to other income. Generally, a household would prefer to have an increased budget without restrictions.

There are two unique features of LIHEAP for any theoretical model. First, LIHEAP benefits are approved through a block grant, which is much different than an entitlement program since money is not guaranteed. Under an entitlement program, if a household applies for benefits and meets the eligibility requirements, then the household receives the benefits. Under LIHEAP, a household can apply for benefits, meet the eligibility requirements, but not receive benefits due to funding constraints. The model must, therefore, account for this uncertainty involved in receiving the benefits; this is different than most models presented in program participation literature.

There is an important related difference in household LIHEAP benefit awards. In the past, state LIHEAP coordinators have been able to ensure eligible households that apply have almost always received benefits through forecasting. From direct correspondence with state coordinators, there were almost no instances of eligible households applying for benefits, but not receiving any due to insufficient LIHEAP funds. The coordinators forecast the number of eligible households that are likely to apply for benefits during the fiscal year and have an estimate of LIHEAP funding provided by the federal government. Using these two pieces of information, the household benefit levels are then calculated. In this way, the LIHEAP coordinators ensure that almost all households will receive some level of benefits unless there is an extremely large spike in participation.[1] However, all of the coordinators stressed that the amount of the award is often very small relative to energy costs incurred by the households. Many coordinators also worried that reduced LIHEAP funding will prevent them from employing this method in the future, increasing the likelihood of eligible households applying without receiving benefits.

By trying to ensure that all eligible households receive some benefits, household benefit levels are directly tied to aggregate demand for LIHEAP within each state. Higher demand for LIHEAP benefits within a state will reduce the award each household will receive. Additionally, household benefits are directly tied to state allocation of LIHEAP benefits.

[1]Individual states have different ways to deal with unexpected high participation levels. Methods vary between reducing benefit amounts for households that apply later in the cycle, early closure of the application window, or trying to reallocate funds between different programs to make up possible shortages in funding.

Households would observe higher benefit levels in states that receive more funds and have lower participation levels.

These complexities in awarding household benefits, however, can be treated as exogenous to the household participation decision for several reasons. First, the low participation levels observed within each state make it highly unlikely that low-income households would spend time, energy, and resources learning about various LIHEAP benefits in other states, or the participation decisions of other households. Second, even though household participation affects the awards to each household, low-income households effectively ignore this information when making their participation decision as their impact on awards is negligible.

Prior models ignore these complexities and simply require the condition that once defined in utility space, a household will participate so long as

$$U(Y + \gamma B) - U(Y) > \phi \tag{3.2}$$

which means that households receive more utility from participating in LIHEAP even with the fixed disutility and discounted benefits than they could receive from working alone. This equation does not adequately model the LIHEAP participation decision, however. Instead, a household has to have some specific expectations about their chance to receive these benefits. Under this sort of of model, we would observe:

$$U(Y + \gamma(pB)) - U(Y) > \phi \tag{3.3}$$

where $0 < p < 1$ denotes the probability. In equation 5.5, benefits from participation are further reduced due to uncertainty. If we fix $\gamma = \bar{\gamma}$, it is obvious that $U(Y + \bar{\gamma}B) > U(Y + \bar{\gamma}(pB))$, meaning that households prefer entitlement programs where the benefits are certain.

It is also possible to derive the indirect utility function from this sort of model. By assuming that Y^* and B^* optimize household utility, it is possible to obtain

$$V[A,Y] = U(Y^* + \gamma(pB^*)A) - \phi A, \tag{3.4}$$

which can then lead to a household participation decision of

$$A^* = V[1, Y + \gamma pB] - V[0, Y] \tag{3.5}$$

Under this condition, the only time a household would choose to participate in LIHEAP is if $A^* > 0$.

$$A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{if } A_i^* \leq 0 \end{cases} \tag{3.6}$$

3.4 Econometric Model

Homeowners can potentially apply for benefits yet not receive any, but state agencies have methods in place to try to prevent this occurrence. Each state estimates the expected number of households that will apply and qualify for LIHEAP benefits. Using this projection and estimated funding from the federal block grant, the agencies then estimate benefit levels. In this way, the state agencies attempt to provide smaller benefit levels for all households that are expected to apply. States that have rolling admission determine a critical level of funds that when reached, requires them to stop taking LIHEAP applications. From personal correspondence with state LIHEAP agencies, almost no eligible household who applied for benefits was denied assistance in 2005 due to lack of block grant funds. While it is possible for this to occur in the future, it seems that state agencies have methods in place to try to prevent this from happening. Simulations reducing the number of LIHEAP participants can provide information to policy makers regarding any negative spillovers from reduced likelihood of receipt of benefits.

Data restrictions prevent the estimation of the full structural model outlined in section 3.3. Household benefits from LIHEAP are unobserved, but understanding the structural model ensures that the reduced form equations include variables that are likely to influence stigma and benefit levels. The reduced form model uses a two equation treatment effects model that includes an endogenous binary variable. Energy insecurity and participation in LIHEAP can be affected by observed and unobserved attributes within a household, implying that participation in LIHEAP might be endogenous. The system of equations is defined as

$$A^* = X_1'\alpha_1 + \varepsilon_1 \tag{3.7}$$

$$y^* = \gamma_1 A + X_1'\beta_1 + \varepsilon_2 \tag{3.8}$$

where A^* indicates the latent propensity for participation in the LIHEAP program, A indicates the observed (binary) participation decision within the data, y^* denotes the latent continuous household energy insecurity score and X_1 is a vector of independent household variables affecting both the latent LIHEAP participation decision and the latent household energy insecurity score. Additionally, $\alpha_1, \gamma_1, \beta_1$ are regression parameter vectors, while $\varepsilon_1, \varepsilon_2$ represent the error terms which are assumed to be distributed bivariate normal, with a correlation of ρ, and the variance of ε_1 normalized to one. The system of equations is identified through its nonlinearity.

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \rho\sigma_2 \\ \rho\sigma_2 & \sigma_2^2 \end{bmatrix}\right] \tag{3.9}$$

The outcome variables in equations 5.8 and 5.9 are not completely observed. Observed energy security scores are obtained from Rasch modeling, which provide a continuous positive variable censored at zero.[2] Households answering affirmatively to at least one of the nine survey questions indicate positive levels of energy insecurity, while households who failed to answer any question affirmatively have energy insecurity scores of zero. Alternative energy insecurity indexes will be used to test the robustness of the results. The unobservable latent dependent variables are estimated through observable dependent variables as

$$y_i = \max\{0, y_i^*\} \tag{3.10}$$

Similarly, household LIHEAP participation decisions are observed through a binary indicator of participation.

$$A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{if } A_i^* \leq 0 \end{cases} \tag{3.11}$$

The econometric model is estimated through full information maximum likelihood (FIML). The FIML equation uses the bivariate normality assumption and requires four parts for estimation: outcomes where both dependent variables are zero ($y = 0,\ A = 0$), outcomes where one of the two dependent variables is zero [($y = 0,\ A = 1$) or ($y > 0,\ A = 0$)], and outcomes where both dependent variables are non-zero ($y > 0,\ A = 1$). The derivation of each portion of the FIML is listed below.

For the two portions of the FIML where $y = 0$, the derivation is relatively simple since it deals with bivariate normal probabilities resulting in two bivariate normal distributions, denoted as $\Phi_2(\cdot)$.

[2] See `refapp:A` for full derivation of the dependent variable.

$$\begin{aligned}\text{Prob}[y=0,A=0] &= \text{Prob}\left[\frac{\varepsilon_2}{\sigma_2}\leq\frac{-X_1\beta}{\sigma_2},\varepsilon_1\leq-(X_1'\alpha_1)|\rho\right]\\ &= \Phi_2\left(-(X_1'\alpha_1),-\frac{X_1\beta}{\sigma_2},\rho\right) \qquad (3.12)\end{aligned}$$

and

$$\begin{aligned}\text{Prob}[y=0,A=1] &= \text{Prob}\left[\frac{\varepsilon_2}{\sigma_2}\leq\frac{-X_1\beta-\gamma}{\sigma_2},\varepsilon_1>-(X_1'\alpha_1)|\rho\right]\\ &= \text{Prob}\left[\frac{\varepsilon_2}{\sigma_2}\leq\frac{-X_1\beta-\gamma}{\sigma_2},\varepsilon_1<(X_1'\alpha_1)|-\rho\right]\\ &= \Phi_2\left((X_1'\alpha_1),\frac{-(X_1\beta+\gamma)}{\sigma_2},-\rho\right) \qquad (3.13)\end{aligned}$$

For the other two cases ($y>0$), the interaction between the two equations is a bit more complex. Two mixed distributions, $f(y,A=0)$ and $f(y,A=1)$ are derived below.[3]

$$\begin{aligned}f(y,A=0) &= f(\varepsilon_2,\varepsilon_1\leq-(X_1'\alpha_1))\\ &= \int_{-\infty}^{-(X_1'\alpha_1)} f(\varepsilon_2,\varepsilon_1)d\varepsilon_1\\ &= \int_{-\infty}^{-(X_1'\alpha_1)} f(\varepsilon_2)f(\varepsilon_1|\varepsilon_2)d\varepsilon_1\\ &= f(\varepsilon_2)\int_{-\infty}^{-(X_1'\alpha_1)} f(\varepsilon_1|\varepsilon_2)d\varepsilon_1\\ &= \frac{1}{\sigma_2}\phi\left(\frac{\varepsilon_2}{\sigma_2}\right)\int_{-\infty}^{-(X_1'\alpha_1)}\frac{1}{\sqrt{1-\rho^2}}\phi\left(\frac{\varepsilon_1-(\rho/\sigma_2)\varepsilon_2}{\sqrt{1-\rho^2}}\right)d\varepsilon_2\\ &= \frac{1}{\sigma_2}\phi\left(\frac{y-X_1'\beta_1}{\sigma_2}\right)\int_{-\infty}^{-(X_1'\alpha_1)}\frac{1}{\sqrt{1-\rho^2}}\phi\left(\frac{\varepsilon_1-(\rho/\sigma_2)(y-X_1'\beta_1)}{\sqrt{1-\rho^2}}\right)d\varepsilon_2\\ &= \frac{1}{\sigma_2}\phi\left(\frac{y-X_1'\beta_1}{\sigma_2}\right)\Phi\left(\frac{-(X_1'\alpha_1)-(\rho/\sigma_2)(y-X_1'\beta_1)}{\sqrt{1-\rho^2}}\right) \qquad (3.14)\end{aligned}$$

[3]These derivations are drawn from (Greene 2007, E32.42-E32.43), but there appears to be an omission of γ in ϕ, the normal pdf, for the mixed distribution $f(y,A=1)$.

Similarly,

$$\begin{aligned}
f(y, A=1) &= f(\varepsilon_2, \varepsilon_1 < (X_1'\alpha_1)) \\
&= \int_{-\infty}^{(X_1'\alpha_1)} f(\varepsilon_2, \varepsilon_1) d\varepsilon_1 \\
&= \int_{-\infty}^{(X_1'\alpha_1)} f(\varepsilon_2) f(\varepsilon_1|\varepsilon_2) d\varepsilon_1 \\
&= f(\varepsilon_2) \int_{-\infty}^{(X_1'\alpha_1)} f(\varepsilon_1|\varepsilon_2) d\varepsilon_1 \\
&= \frac{1}{\sigma_2}\phi\left(\frac{\varepsilon_2}{\sigma_2}\right) \int_{-\infty}^{(X_1'\alpha_1)} \frac{1}{\sqrt{1-\rho^2}}\phi\left(\frac{\varepsilon_1 + (\rho/\sigma_2)\varepsilon_2}{\sqrt{1-\rho^2}}\right) d\varepsilon_2 \\
&= \frac{1}{\sigma_2}\phi\left(\frac{y - X_1'\beta_1 - \gamma_1}{\sigma_2}\right) \int_{-\infty}^{(X_1'\alpha_1)} \frac{1}{\sqrt{1-\rho^2}}\phi\left(\frac{\varepsilon_1 + (\rho/\sigma_2)(y - X_1'\beta_1 - \gamma_1)}{\sqrt{1-\rho^2}}\right) d\varepsilon_2 \\
&= \frac{1}{\sigma_2}\phi\left(\frac{y - X_1'\beta_1 - \gamma_1}{\sigma_2}\right) \Phi\left(\frac{(X_1'\alpha_1) + (\rho/\sigma_2)(y - X_1'\beta_1 - \gamma_1)}{\sqrt{1-\rho^2}}\right) \qquad (3.15)
\end{aligned}$$

Combining the four terms, we now have derived the likelihood function for this econometric model.

$$\begin{aligned}
\mathcal{L} = &\prod_{y=0,A=0} \Phi_2\left(-(X_1'\alpha_1), -\frac{X_1\beta}{\sigma_2}, \rho\right) \prod_{y=0,A=1} \Phi_2\left((X_1'\alpha_1), -\frac{(X_1\beta + \gamma)}{\sigma_2}, -\rho\right) \times \\
&\prod_{y>0,A=0} \frac{1}{\sigma_2}\phi\left(\frac{y - X_1'\beta_1}{\sigma_2}\right) \Phi\left(\frac{-(X_1'\alpha_1) - (\rho/\sigma_2)(y - X_1'\beta_1)}{\sqrt{1-\rho^2}}\right) \times \qquad (3.16) \\
&\prod_{y>0,A=1} \frac{1}{\sigma_2}\phi\left(\frac{y - X_1'\beta_1 - \gamma_1}{\sigma_2}\right) \Phi\left(\frac{(X_1'\alpha_1) + (\rho/\sigma_2)(y - X_1'\beta_1 - \gamma_1)}{\sqrt{1-\rho^2}}\right)
\end{aligned}$$

3.5 Model Specification

Descriptions and expected effects on the the energy insecurity (EI) and LIHEAP participation (LP) equations are discussed below, grouped by household demographic characteristics, residential characteristics, and regional characteristics. Expected impacts of many of the household characteristics included in the two equation are based on food security literature, since no program evaluation has been conducted on LIHEAP.

Household demographics are expected to affect both defined LP and EI. Both equations include indicators for African-American households and Hispanic households. Studies have shown that these groups of households often have different behavior with respect to assistance programs and different exposure to food insecurity than white households. Gundersen and Oliveira (2001) finds that black households are more likely to participate in SNAP compared to a white household, but find no statistically significant difference in participation between Hispanic and non-Hispanic households. Conversely, Hispanic households are found to have lower probabilities of being food insecure by Yen et al. (2008), while Mykerezi and Mills (2010) find Hispanic households more likely to participate in SNAP. Higgins and Lutzenhiser (1995) estimated LIHEAP participation and observed no statistically significant difference in participation due to race or ethnicity. An indicator variable for other races is also included in the LP and EI equations.

Household composition also affect LP and EI. Household size is included in both equations. Households that have larger families are expected to have higher energy needs. These larger households are likely to have higher LP since the fixed disutility associated with applications can be distributed over more family members. Two dummy variables are created for households that have young children (less than six years of age) and for households that have elderly family members (greater than 65). One of the specific goals of LIHEAP is to target vulnerable populations, which include these two demographic groups. Households within both groups are expected to have higher energy costs since they are more likely to be at home during the day (Theisen 1993). Similarly, any household that has someone at home during the day incur higher energy costs since they cannot adjust temperatures during the day, likely increasing LP and leading to higher household EI. An indicator denoting these households is included in both equations. In many other social programs, households headed by single women are more likely to participate, as they are disproportionately likely to meet poverty based eligibility criteria (Huffman and Jensen 2008, Moffitt 1992). Similar behavior is expected in this program: households headed by single women will have higher LP and higher measures of EI. An indicator variable for households headed by a single man is also included, and it is left as an empirical question as to the effects on LP and EI. The comparison group for both variables is married households.

Household income is included in both equations and LP and EI are expected to decrease as income rises. Two additional dummy variables that affect income are included in both equations as well. Entitlement benefits from the U.S. government provide additional direct income through cash benefits such as AFDC or SSI. Non-cash entitlement benefits, such as food stamps, augment household income and reduce household food expenditures. Both of these variables are expected to have a positive effect on LP. Previous research on welfare programs (including LIHEAP) has shown that there is a "bundling" of these packages (e.g. Frank et al. 2006, Higgins and Lutzenhiser 1995, Keane and Moffitt 1998) in that if a household participates in one program, they are much more likely to participate in another welfare program. The effects on EI are less clear. Participation in other programs could potentially improve the household EI by providing them with more resources, or participation in the program could indicate higher levels of need, resulting in higher EI.

Employment and other program participation decisions are assumed to be exogenous. This assumption is consistent with previous research evaluating a specific program's effect on food insecurity (e.g. Gundersen and Oliveira 2001, Devaney and Moffitt 1991). Future research can potentially relax this assumption and examine how treating these other decisions as endogenous affect LIHEAP participation impacts on EI.

Renters are expected to have lower levels of LP compared to owners. In particular, incentives for households to apply for any of the weatherization benefits, a component of LIHEAP, are expected to be lower since any improvements renters have done to the house stay upon moving. Previous qualitative research asserts that renters should have higher EI since they have no input into the type of appliances, insulation, or overall condition of the house (Hernandez and Bird 2010), but it is left as an empirical question whether renters have higher or lower EI compared to owners.

Residential characteristics also play an important role for evaluating program effectiveness. Two types of residences are compared relative to single family dwellings: apartments and mobile homes. Households residing in mobile homes are expected to have higher levels of EI due to the limited insulation associated with these types of dwellings. One of the common, well-advertised methods to improve energy efficiency in mobile homes is through improved insulation, which might increase LP as well. Households living in apartment complexes have unique challenges compared to households living in single family homes. Specifically, these households have less available options on improving energy efficiency within their unit. It is not very common to allow tenants to make large structural improvements, such as replacing windows or improving insulation in either apartments or condominiums. Instead, such upgrades are normally undertaken at the "building" level at specified times. Restriction on energy investments may make households live in more energy inefficient dwellings, increasing LP and EI.

Other residential characteristics are important as well. Larger residences have larger energy costs compared to smaller residences. Households living in larger residences are then expected to have higher levels of EI, ceteris paribus. It is left as an empirical question whether LP increases or decreases due to residence size. Air conditioning substantially increases utility bills during the summer months. It is expected that residences with air conditioning available will have higher energy bills compared to those without it. The additional costs of cooling a house are expected to increase LP and EI. Personal perception of how well a house is built can also impact both LP and EI. A dummy variable is created from household responses to two important residential energy efficiency traits: its insulation levels and its draftiness. Households who indicate that their residence has poor or no insulation and indicate almost always having a strong draft within the residence show low levels of satisfaction in their housing quality. Household EI is expected to be higher for these households since the conditions make it much harder to maintain a comfortable temperature within the residence. It is left as an empirical question whether these households have higher or lower LP. Each household's price per kilowatt hour for electricity should affect both LP and EI. Higher prices would mean that households have a larger danger of not being able to pay their bills and be more likely to seek assistance. The year a residence was constructed could also affect household EI levels. The idea of energy efficient housing did not arise until the oil crises of the 1970's. A dummy variable is included only in the EI equation indicating whether the house was built prior to 1970.

Finally, regional and location differences may play an important role in both LP and EI. Regional differences generate differential energy expenditures (Baxter 1998) and households that live in extreme climates are expected to have higher EI levels. The base region chosen for the model is the Mountain Census division. This division consists of states spanning from Arizona to Montana and contains areas that have varying climates.[4] The regional fixed effects are included in both equations and households living in the midwest and northeast are expected to have higher LP due to the favorable funding allocated to those regions compared to the households residing in the south and west.[5] Ambient temperature is also important to household LP and EI. Two variables are included in both equations measuring variations in household temperature between locations. These variables identify total "degree-days"

[4]RECS data masks state level identifiers for each observation. Thirteen unique regional indicators are created from the nine Census division and indicators of the four largest states (California, Florida, New York, and Texas).

[5]Under the alternative specification, regional fixed effects are omitted from the LP equation and the exclusion restriction is used to directly measure the regional differences.

that a household faces a temperature where they would need to expend energy to heat or cool their dwelling (at a 65 degree base). Households with higher heat or cool degree days are expected to have higher levels of EI, since they have harsher climates that require more energy to maintain a comfortable temperature within their residence. The harsher climates could also induce higher levels of household LP. Previous research has found that rural households are more likely to participate in LIHEAP (Higgins and Lutzenhiser 1995), but research on food insecurity finds no difference in levels of security for rural households (Mykerezi and Mills 2010, Yen et al. 2008). Therefore, rural households potentially have higher levels of LP, but unchanged levels of EI compared to suburban households. It is an empirical question whether urban households have higher levels of LP and EI compared to suburban households.

The primary equation of interest concerns whether participation in LIHEAP affects the energy security of households. The endogeneity of participation requires jointly estimating the participation equation with the outcome equation. Identification is obtained through the non-linear form of the model, though it is preferred to have unique variables that affect the selection equation and not rely solely on the non-linearity. Unfortunately, no variable that meets the exclusion criteria of only affect a household's decision to participate in LIHEAP without affecting their energy insecurity levels currently is available. An alternative specification includes an arguably weak exclusion restriction to test the robustness of the primary model.

When relying on nonlinearity for identification, it is important to test the validity of the bivariate normality assumption. If this assumption is wrong, the FIML estimation will provide invalid results. Pagan and Vella (1989) provide a methodology to test this normality assumption through a RESET test. The original, squared, and cubed predicted values from the LIHEAP participation equation are weighted by the inverse Mills ratio and included in the energy insecurity equation. The null hypothesis of the test assumes that these additional terms are correctly excluded from the original model. An F-test for each energy insecurity index fails to reject the null hypothesis. When the test fails to be rejected, it is plausible to assume normality and use this assumption to identify the model.

Since LIHEAP is a block grant, each state is awarded a percentage of federal LIHEAP funds based off of rules created in the early 1980s, though each state is guaranteed a minimum LIHEAP endowment by law (Kaiser and Pulsipher 2003*a*). When a state has excess funds at the end of the year, it is able to apply those funds to the next year, though not all states had surplus funds. This allows the construction of a variable that measures the percentage of each census division that had surplus funds from fiscal year 2004.[6][7] Participation is expected to be higher in regions that have surplus funds since the likely LIHEAP assistance would be higher and admission criteria more lenient.

3.6 Data

The 2005 Residential Energy Consumption Survey (RECS), a nationally representative survey of almost 4,500 U.S. households, is the primary data set used in the analysis. The RECS contains limited information of household demographics, but detailed information on energy consumption obtained through individual interviews. Additionally, all information on energy consumption is verified since respondents sign release forms to allow the Energy Information Administration (EIA) to collect the information directly from respondent utility companies. Unfortunately, no information regarding education levels is collected in the survey.[8]

[6]An additional variable examining whether states that had surplus funds at the end of Fiscal Year 2005 that they applied to the 2006 budget was also examined which found similar results.

[7]Results using several other alternative exclusion restrictions are consistent with the surplus fund instrument results.

[8]Information from the 2007 LIHEAP Notebook, published by the Department of Heath and Human Services Administration for Children and Families is used to augment the RECS data in the alternative

All households that earn income below 150 percent of the poverty line are eligible for LIHEAP. Within the survey, households who were eligible for LIHEAP (determined prior to the interview) were asked nine questions trying to evaluate their energy security levels. This reduced the sample size to only these households, but it was then further reduced to exclude those households who did not own or rent their residence, or pay for utilities. This left 986 households within the sample for analysis. Out of this sample, 273 households, or approximately 28 percent of the sample, reported receiving LIHEAP benefits.

The appendix details the creation of the energy security index using the Rasch and Item Response Theory models. Dichotomous and polytomous index are generated to provide energy security estimates for all households within the sample. Households who answered negatively to all questions have an EI score of zero, while those who answered at least one question affirmatively have positive EI scores. These indexes are the dependent variable of the EI equation and several variants will be estimated to compare the robustness of the results. Out of the 986 households, 282 have an EI score of 0.

Table 4.1 provides summary statistics for all variables included in the two model equations. Several variables need to be highlighted. Roughly 25 percent households within the sample include either a young child or elderly individual, yet surprising, 65 percent of households have someone stay at home during the day. Within the sample, over 55 percent of households surveyed are headed by a single adult, with the majority being single females. Only 44 percent of households within the sample are renters. The traditional costs of homeownership, including a down payment and closing costs, would seem to increase the percentage of low-income households that are renters, yet this is not the case in this sample. It is striking that over 75 percent of households within the sample have air conditioning in their household. Air

specification. The state level data reported by the notebook is aggregated into a weighted average of all states within each Census division due to 2005 RECS data constraints, except for households in California, New York, Texas and Florida, which use state level data.

conditioning now seems to be a standard item in a residence compared to a luxury item when LIHEAP began. A majority (52 percent) of the sample live in dwellings built before 1970, a time when residential efficiency improvements were not considered. Further discussion of the heating and cooling degree day variables is warranted. A formula uses the daily high and low temperatures for each household location, dividing this total by two. The difference between the base of 65 degrees and the average daily temperature provides the daily heat degrees. For cooling degrees, the calculation is reversed. The daily totals are then summed into an annual measure for each household, generating the mean heat and cool degree day values of 4256.99 and 1505.75, respectively. Finally, it is important to observe that almost 30 percent of households within the sample participate in LIHEAP.

Table 4.2 examines the differences between regions and provides total percentages of the sample within each region. The second column shows the percentage of the sample within each division that participates in LIHEAP. It is not surprising that more households participate in the northeastern United States, but a very small percentage within Florida and the West-South Central (excluding Texas) Census divisions participate. The next column of the table describe information about excess LIHEAP funds. The variable is aggregated from the percentage of states within each region that had excess funds from previous years that could be applied to fiscal year (FY) 2005.[9]

3.7 Results

Results are discussed by the type of energy insecurity index used as a dependent variable in the model. The results are consistent between different indexes and all significant variables maintain the same effect. Results from a dichotomous Rasch index and the partial credit model will be discussed in detail. Due to their similarities, discussion of two alternative Item

[9] Regions that carried over surplus block grant funds from FY 05 to FY 06 had similar values.

Response Theory indexes are discussed in Appendix B and focus on differences from the Rasch results. All indexes show a statistically significant positive correlation ($\rho > 0$) exhibited between the EI and LP equations, meaning that omission of the participation equation would positively bias the results. Most importantly, all indexes show that participating in LIHEAP significantly reduces the household energy insecurity score.

Dichotomous Rasch Results

A dichotomous index examines household behavior when households have only the choice of "yes" or "no" responses to the survey. The results from the specification is quite strong and shows that demographics affect household EI scores more than the LP decision. In terms of program evaluation, it appears that LIHEAP does help reduce EI scores, since households that receive benefits from LIHEAP have lower EI scores compared to non-participants after controlling for observed and unobserved heterogeneity.

There are several interesting results from both the LP and the EI equations (Table 4.3). First, ethnicity and race do not appear to significantly affect the LP decision of households. Neither Hispanic nor Black households had significantly different participation in LIHEAP than Whites. Household size does not significantly affect LP suggesting that household disutility is not shared or reduced for larger families. One of the most interesting results from the LP equation is the lack of statistically significant differences in participation for households including a vulnerable member (young children or the elderly). This is quite surprising since both of these groups are targeted by LIHEAP and encouraged to apply for benefits. The evidence suggests the program can do a better job improving participation for households that include these vulnerable target populations.

As expected, households headed by a single female are more likely to participate in LIHEAP, but households headed by a single male are less likely ($p = 10\%$) to apply for benefits. There are several potential reasons for the difference. First, the "welfare stigma" may be much greater for households headed by single men. This might cause them to try to get by without any external assistance. Alternatively, this group might not be as aware of benefits since they are generally not targeted for federal assistance programs like households headed by single females. Higher income significantly reduces LP, while households who receive other federal cash or non-cash entitlement benefits like AFDC or food stamps both have significantly higher LP, which is consistent with previous research (Higgins and Lutzenhiser 1995).

Residential characteristics play less of a role in the the LP equation. Renters are just as likely as owners to apply for LIHEAP benefits. Households living in apartments or mobile homes are just as likely as those households living in single family homes to participate in LIHEAP, as well. The size of the residence does not affect the participation decision, even though larger residences require more energy to heat and cool. Surprisingly, air conditioning does not affect LP, even though air conditioning drastically increases electricity bills during the summer. The exact question on the survey, however, just asks about the existence of air conditioning in the household, but does not ask whether the household uses it. This could be one potential reason that air conditioning is not significant. The price per kilowatt hour of electricity paid by a household did not statistically change LP. Finally, those who had a very poor opinion of the quality of their house were significantly more likely to participate in LIHEAP.

Location also seems to significantly affect LP. Households living in a rural environment are less likely to apply for LIHEAP benefits compared to those living in the suburbs, which is different than results found in previous research (Higgins and Lutzenhiser 1995). One potential reason for the difference could be the increased use of the Internet to apply for benefits. Results from the previous research focus on data from 1987 and 1990, well before the widespread adoption of online applications. It has been shown, however, that rural Internet availability is much lower than that found in a suburban area (Mills and Whitacre 2003) and this lack of availability might reduce rural participation. Additionally, those households living in a urban environment have significantly reduced LP compared to suburban households. Urban households have easy access to Internet, so the reasoning used for lower LP in rural households cannot be applied. Instead, urban households might be unsure whether they are eligible for all LIHEAP benefits. Urban households might misconstrue the potential weatherization and furnace replacement benefits as something only eligible to those living in single family homes that are not as common in an urban environment. Households that face colder climates (indicated by higher heating degree days) are more likely to participate in LIHEAP, though there is no significant effect observed for cooling degree days. Households residing in the West-South Central (excluding Texas) census division ($p = 10\%$) and the Pacific (excluding California) census division are less likely to participate compared to households residing in the Mountain census division.

Household demographics significantly affect EI more than household LP decisions. Households headed by a Black have significantly higher EI scores compared to households headed by a White, though there is no statistical difference between Hispanic and non-Hispanic households. Households with larger families have significantly higher EI scores as well. This result is expected since larger families require more energy to maintain a home. One surprising result is that households that have a child less than six years of age have a significantly lower ($p = 10\%$) EI score compared to those who do not have a young child. Similarly, households that include an elderly individual greater than 65 also have a significantly lower EI score compared to those without. Both of these groups are considered vulnerable populations by the Administration for Children and Families. One potential explanation for this result is that households with a vulnerable member place a higher emphasis on meeting the energy needs (and therefore having a lower EI score) compared to those households without a vulnerable individual. Having an individual stay at home during the day does not significantly change the household EI score. Similar to the LP equation, households headed by a single female have a statistically higher EI score compared to married households and households headed by a single male have a significantly ($p = 10\%$) lower EI score.

Households with higher income levels have significantly lower EI scores. This is consistent with the idea that as income increases, energy needs become a smaller share of the household budget, reducing household behavior that would indicate high levels of EI. Surprisingly, households that participate in other federal entitlement assistance programs (both cash and non-cash) have statistically higher EI scores compared to those who do not. Unfortunately, it is still not possible to explain the causality of this phenomenon. It is possible (and reasonable to assume) that those with the highest levels of EI participate in these programs and would be worse off without them. However, it is a legitimate argument that these programs instead make households more energy insecure by changing the household income structure.

Residential characteristics do not play a major role in affecting household EI. Renters do not have EI scores that are different than owners. Those households that live in apartment complexes, however, have a significantly lower EI score than those who live in a single family home. One possible explanation is the lower household upkeep costs associated with living in an apartment complex compared to a single family home. The fact that these households do not have to actively maintain the structural elements of the dwelling might make them feel more energy secure. Those households residing in mobile homes have no statistically different levels of EI compared to households living in single family homes. Neither air conditioning nor electricity costs significant affect the household EI score, but households that indicated having a low quality residence had statistically higher EI scores compared to those who did not. Households living in residences built prior to 1970 have significantly ($p = 10\%$) higher EI scores compared to those who live in newer homes.

The location of the household also significantly affects their EI score. Households living in both a rural environment and an urban environment ($p = 10\%$) have significantly lower EI scores compared suburban households. This statistical difference in EI scores based on residential location is different than that observed in previous food security literature (Mykerezi and Mills 2010, Yen et al. 2008). One potential explanation for the difference is the fact that rural households may expect to live in their residence for longer periods of time, making household energy improvements less costly. These improvements would provide rural households with more efficient housing which would improve their EI scores relative to suburban households. It is somewhat surprising that urban households have lower EI scores compared to suburban households. One potential reason for their lower EI scores could be the combination of several differences between urban and suburban residences. For example, on average, urban residences are smaller and more likely to be in an apartment. These differences likely make urban households more energy secure compared to suburban ones. Finally, households that have higher annual heating degree days have significantly higher EI scores though annual cooling degree days does not affect the EI score.

Significant regional differences exist between households living in various Census divisions compared to the Mountain Census division (the base division). Households living in the Mid-Atlantic division (excluding New York) have significantly lower EI scores compared to those living in the Mountain division. Additionally, those households living in the South Atlantic (omitting Florida) and the East-South Central divisions also have significantly lower EI scores compared to the Mountain division. Interestingly, these two divisions comprise a good portion of the southern United States (all states east and south of Kentucky except for Florida). No households residing in the largest four states or other Census divisions show any significant differences in EI scores.

Partial Credit Model

The partial credit model is a polytomous index that allow households to respond with several different answers on the survey questions instead of the simple binary “yes” or “no” observed in a dichotomous model. The partial credit model (PCM) is one of the most generalized Rasch models available and nests the dichotomous Rasch model when more restrictive assumptions are imposed. Results are consistent between this general index and the dichotomous one. It continues to show that participation in LIHEAP significantly reduces the household EI score. Discussion of results from the PCM index will focus on the major similarities and differences between the two models.

Like the dichotomous Rasch energy insecurity index, household demographic and residential characteristics do not seem to dramatically affect LP (Table 4.4). Neither race, ethnicity, nor household size significantly affect LP, which is consistent with other research conducted on LIHEAP (Higgins and Lutzenhiser 1995). It is surprising that race significantly affects participation in SNAP, an entitlement program, but plays no role in LP. Households including vulnerable populations continue to show no difference in LP. PCM index results continue to show that the structure of the head of household significantly affects LP. The results continue to show higher income reduces LP and the existence of a "bundling" of services as described in previous literature (Keane and Moffitt 1998, Higgins and Lutzenhiser 1995). Households who receive cash or non-cash entitlement benefits are both significantly more likely to apply for LIHEAP benefits than households that do not have these benefits. Residential characteristics still do not significantly affect LP using the PCM energy insecurity index. There continues to be no difference observed in LP between renters and owners, type of residence, having air conditioning, or the cost of electricity. Households that reside in residences that are deemed very low quality continue to be more likely to participate in LIHEAP.

Location still matters for LP under the PCM specification. Households residing in a rural or urban environment are still less likely to participate in LIHEAP compared to suburban households and heating degree days continues to affect participation as well. Households living in locations with cooler temperatures continue to have higher participation. Households living in areas that have warmer temperatures, requiring higher cooling cost, however, show no difference in participation. Finally, households living in the West-South Central (excluding Texas) ($p = 10\%$) and Pacific (excluding California) census divisions show significantly lower levels of participation than households in the Mountain division.

Very few differences exist between household and residential characteristics that significantly affect EI scores under the PCM index compared to the dichotomous Rasch model. Households headed by a Black have significantly higher EI scores compared to households headed by a White. Larger households, households headed by a single female, and those receiving cash or non-cash federal entitlement benefits all significantly increase EI scores. Households that include a young child ($p = 10\%$), include an elderly member, have higher income, or are headed by a single male ($p = 10\%$) have lower household EI scores. Only two residential characteristics significantly impact household EI under the PCM index. Households living in apartment complexes continue to have lower scores than households living in single family homes and households dwelling in residences of poor quality continue to have higher EI scores. Under PCM EI index, households residing in buildings constructed prior to 1970 no longer significantly affects household EI scores.

Finally, location and regional differences still affect households under the PCM EI index in a manner consistent to the results observed under the dichotomous Rasch index. Households residing in a rural environment have significantly ($p = 10\%$) lower EI scores compared to households living in suburbia. Households living in an urban environment, however, no longer have significantly different EI scores. Cooler climate conditions continues to affect household EI scores as higher annual heating days significantly increase household EI scores. Finally, divisional differences exist between households in the PCM index that are similar to the dichotomous results. The same three Census divisions have significantly different EI scores compared to the base division. Households residing in the Mid-Atlantic (excluding New York), the South Atlantic (excluding Florida), and the East-South Central still have significantly lower EI scores compared to those households living in the Mountain division.

Alternative Specifications

An alternative specification helps ensure the results are robust. This specification uses an exclusion restriction to explore the robustness of the results to the identification strategy employed. The share of states having excess LIHEAP funds that they can apply to increase benefits the following year is used to augment identification by inclusion in the LP equation. The results from all four indexes are quite similar to those without the variable. The results are discussed generally below, with the full results presented in tables 4.6 and 4.7. When there are differences in results between the indexes, it is specifically indicated.

The alternative specification continues to show that households receiving LIHEAP benefits are less energy insecure across all indexes. Nascent research into household energy insecurity can be greatly improved by future surveys including additional questions that uniquely influence LIHEAP participation and energy insecurity. Household social networks about LIHEAP participation would be a useful instrument. After controlling for other factors, a household that knows more LIHEAP participants is more likely to participate in the program without directly affecting their EI. A survey question that asks households the number of friends or relatives (if any) who are participating in LIHEAP would provide this information.

Results from the LP equation closely follow those observed in the primary specification. Generally, household demographics fail to affect household LP. One slight difference between the primary specification is that larger families are now more likely ($p = 10\%$) to participate in LIHEAP. The exclusion restriction under this specification is insignificant across indexes. Several alternative specifications not discussed included different exclusion restrictions. The results from these specifications were very similar, but no exclusion restriction ever significantly affected household LP.

Demographic, residential, and locational attributes that significantly affected household EI scores maintain their significance under this alternative specification. In particular, households receiving LIHEAP benefits continue to have improved EI compared to non-participants. Other significant characteristics all maintain the same type of effect on household EI observed within the primary specification. One minor difference across the two specifications involves the regional effects. Under the alternative specification, regional fixed effects are no longer included in the LP equation. Therefore, the significant regional differences discussed in the primary specification are not observed under this alternative specification.

3.8 Simulations

Given the current fiscal constraints on federally funded assistance programs, it is important to further understand the overall effect of the results. While many variables are statistically significant, it is just as important to determine the economic significance. This section creates simulations that examine the impact on household energy insecurity of eliminating or modifying the LIHEAP program. Simulations can also show how increasing LIHEAP participation of targeted groups affects energy security levels. Overall, simulations show that removing the energy assistance safety net that is available to households today significantly worsens household energy security.

Using the Administration for Children and Families (ACF) guidelines, it is possible to create cutoff scores to identify energy insecure households. Any household that scored below the value in table 4.8 is energy secure. Each index has a slightly different cutoff, but under this criterion, almost 70 percent of the sample can be considered energy secure. It is important to note that our sample only examines those households below 150 percent of the poverty line.

Given the current federal fiscal environment, it not unreasonable to assume that the LIHEAP funding could be eliminated in the near future. Simulations reveal that this would result in a significant reduction in the number of energy secure households (simulation 1, table 4.9). Both indexes considered under the simulation show that removal of LIHEAP funding results in large reductions in energy security among household below 150 percent of the poverty line. Removal of the LIHEAP benefits has the lowest effect on household energy security under the dichotomous Rasch index, a 16 percent reduction.[10]

There is also merit to see how more funding affects household energy security. More funding for LIHEAP should change the classification of some households currently classified as energy insecure and fewer households should be considered energy insecure. The second simulation (simulation 2, table 4.9) assumes that LIHEAP funding increases and more households can be assisted. Every household considered energy insecure now receive LIHEAP funds besides those households currently receiving benefits. Under this simulation, almost twice as many households are assisted compared to the original sample. The additional funding leads to roughly 10 percent more energy secure households. The benefits might not justify the higher costs associated with this type of simulation due to the number of households assisted.

One method to reduce the costs while still increasing LIHEAP participation is through better targeting of energy insecure households. State LIHEAP agencies could improve targeting and only award benefits to those that are energy insecure. Under this simulation, energy secure households that receive LIHEAP benefits no longer receive those benefits. Instead, LIHEAP benefits are only awarded to energy insecure households. More households are helped compared to the original sample, yet costs are less compared to the second simulation. A larger share of the population is considered energy secure (simulation 3, table 4.9). More households surpass the energy secure threshold, but the impact is relatively small. The largest increase in energy secure households is observed under the PCM index

[10]An alternative classification of energy secure households confirm similar results. Energy secure households fall between 5 and 10 percent depending on the index under this alternative definition of energy security.

at approximately seven percent, while the dichotomous Rasch index increase is only three percent. Improved targeting and higher LIHEAP funding both result in more energy secure households.

Increased funding to any federal assistance program seems unlikely in the current fiscal environment. It is possible to simulate keeping the current funding levels constant, but allow state agencies to award benefits to the most energy insecure households first until benefits are exhausted. The results from the simulation are quite startling (simulation 4, table 4.9). Results show that awarding LIHEAP benefits only to those households who are most energy insecure in effect reduces the number of energy secure households by approximately 14 percent across indexes. LIHEAP benefits are not large enough to improve severely energy insecure households well-being sufficiently to make them energy secure. Instead, it appears that these benefits help marginal households switch between being energy secure and insecure. Further research should explore the linkages between LIHEAP and the well-being of the most energy insecure households.

A final simulation looks at how changes in LIHEAP participation affects the number of energy secure households (table 3.9). Both urban and rural households have low participation rates for LIHEAP. Participation in LIHEAP among urban households increases by roughly five percent when the gap in participation is eliminated between urban households and suburban households. Rural households increase participation by approximately nine percent across all indexes. These increases in participation, however, do not translate into meaningful gains in the energy secure population. There is almost no change in the number of energy secure households by improving urban participation. The overall effect is slightly negative for three of the four indexes, while the one positive result is almost zero. Increased participation by rural households also does not generate a large positive effect, though the effect is positive for all indexes. Overall, there are probably more efficient ways for policy makers to increase the number of energy secure households compared to increasing the participation of rural and urban households.

3.9 Conclusions

LIHEAP, the largest federal energy assistance program has existed for over 30 years, yet its impacts have received little scholarly analysis. One of the major difficulties in examining the program is the inherent problem of dealing with a block grant that varies benefits and specific eligibility criteria between states. The few articles that have looked at the program are silent about its effects on energy security. The best metric for determining whether any energy assistance program works starts from its effect on household energy security. The USDA has funded significant research linking SNAP benefits to food security levels, but there is nothing comparable for LIHEAP. This paper provides an econometric framework to better understand the linkages between household energy security, participation in LIHEAP, and the program's overall effectiveness.

Results indicate that few demographic variables affect household participation. Ethnic and racial characteristics do not affect participation within the program. Households headed by single females are more likely to participate and traditionally are targeted for assistance, though state agencies could try and increase participation of the other types of households through increased awareness. Results continue to show households bundle assistance benefits; the likelihood of LIHEAP participation increases when a household receives cash or non-cash entitlement benefits. Policy makers should try and increase awareness of LIHEAP to energy insecure households who are not currently participating in any other federal assistance program. As a block grant, state policy makers have much greater latitude in creating a program that protects energy insecure households for their specific climate, clients, and budget compared to the nationally regulated entitlement programs. Innovative ways for improving household energy security using the LIHEAP benefits are feasible. Policy makers must also attempt to increase participation among rural and urban households. Urban households may think that LIHEAP benefits are only available to single family home owners and be unaware that they are eligible for LIHEAP benefits. Increasing awareness about LIHEAP eligibility through informational pamphlets is a relatively low cost method to try and improve urban participation. Helping rural households may be a bit more complicated. Rural households may suffer low participation due to the predominant use of on-line applications and limited high speed Internet access. By improving rural infrastructure, an increase in rural LIHEAP participation is a likely byproduct.

In comparison to the household participation decision, many more characteristics affected household energy insecurity scores. Most importantly, households that participated in LIHEAP were significantly more energy secure than otherwise similar non-participant households across all energy insecurity indexes. Under a block grant program, increasing the budget would allow more households to receive benefits and also increase the amount of the household award. At a minimum, policy makers should continue to fund LIHEAP at the FY 2010 budgetary level of approximately 5 billion dollars. If possible, additional funds from ineffective programs could further increase LIHEAP funding.

The ACF considers households that have young children or elderly individuals vulnerable, but results indicate that these households are more energy secure than households without either subgroup. Future research should examine the concessions households make when they include young children or the elderly, since households may sacrifice other basic goods or services to maintain higher energy security levels for these groups.

The large increase in energy insecurity associated with low quality housing provides policy makers with another opportunity to improve low-income housing. Providing tax credits to improve insulation and windows for low-income housing would increase energy security as well. Unlike previous tax credits that only benefited home owners, policy makers could allow landlords to earn a tax credit when they improve low-income rental units.

Simulations show that eliminating LIHEAP significantly reduces the number of households that meet the ACF energy secure threshold with over 16 percent more households below 150 percent of the poverty line considered energy insecure after elimination. Cutting the LIHEAP program will harm both low-income households and utility firms. More energy insecure low income households leads to an increase in late, reduced, or no payments to the utility companies. Utilities have strict regulations preventing termination of services during extreme weather, leading to higher losses, lower profits, and higher rates for paying customers. Policy makers can avoid this downward spiral by supporting LIHEAP funding. Simulations also show that expanding LIHEAP funding to reach a larger number of households improves household security. A cost-benefit trade off exists that must be further analyzed. Larger gains are observed when more households are helped, but large increases to program funding is unlikely. Finally, LIHEAP benefits seem to help the marginally energy insecure households more than the severely energy insecure. When funding levels are held constant and benefits only given to the most energy insecure households, the number of households classified as energy insecure rose drastically. This implies that LIHEAP benefits alone cannot make the most energy insecure households secure. Policy makers must generate additional assistance programs that target these households to improve their security status. State agencies must also do a better job targeting future benefits to these households. Better targeting could be achieved through improved questionnaires, home visits, and increased communication between utility companies.

Additional research analyzing the federal energy assistance program is needed. As better data becomes available, a more refined analysis can be conducted on state LIHEAP grant allocations and their effectiveness in improving energy security. Programs funded through block grants are much more difficult to study at a national level, but are an important policy tool available to law makers. In an era of government fiscal restraint, block grants may become even more prevalent. Tools for future research in block grant programs are needed. In the LIHEAP case, state level data is essential.

Table 3.1: Descriptive Statistics

Variable Description	Mean	Std. Deviation
Black head of household	0.21	0.41
Hispanic head of household	0.22	0.42
Non-white, Non-Black head of household	0.21	0.40
Number of household members	2.95	1.80
House includes a child less than 6 years old	0.26	0.44
House includes an elderly individual greater than 65	0.25	0.44
Household has someone at home during the day	0.65	0.48
Single-female head of household	0.42	0.49
Single-male head of household	0.13	0.34
Household Income ($)	14884.63	7980.84
Receipt of cash benefits	0.22	0.41
Receipt of non-cash benefits	0.30	0.46
Household rents dwelling	0.44	0.50
Household resides in an apartment complex	0.23	0.42
Household resides in a mobile home	0.12	0.33
Total Square footage of household	1686.16	1143.72
House has air conditioning	0.78	0.41
Price per kilowatt hour for electricity	0.10	0.03
Quality of house dummy variable	0.15	0.36
Dwelling is built prior to 1970	0.52	0.50
Household resides in a rural environment	0.23	0.42
Household resides in an urban environment	0.49	0.50
Annual heating degree days	4185.40	2096.09
Annual cooling degree days	1551.76	931.11
Percentage of region that had surplus funds in FY 04	0.72	0.32
Receipt of LIHEAP Assistance	0.28	0.45
Dichotomous Rasch Energy Insecurity Index	2.83	2.21
Partial Credit Model Energy Insecurity Index	2.61	1.99
Two Parameter Logistic (2PL) Energy Insecurity Index	1.10	0.88
Generalized Partial Credit Model Energy Insecurity Index	1.12	0.88

Table 3.2: Percentage of Sample within Each Census Division

Region	Sample %	Participate %	Regional % Carryover Funds
New England	6.19	10.99	83.33
Mid-Atlantic (excluding New York)	8.52	11.72	100
East-North Central	13.79	17.22	60.00
West-North Central	7.61	10.62	71.43
South Atlantic (excluding Florida)	13.18	12.45	100
East-South Central	10.75	7.69	75.00
West-South Central (excluding Texas)	3.85	0.73	33.33
Mountain	8.11	9.89	75.00
Pacific (excluding California)	5.27	4.03	100
California	8.52	6.23	0.00
Florida	3.96	0.73	100
New York	3.65	5.13	100
Texas	6.59	2.56	0.00

Table 3.3: Results using the Dichotomous Rasch Energy Insecurity Index

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits	—	—	-3.6536**	0.333
Black head of household	0.0739	0.125	1.1776**	0.303
Hispanic Head of household	-0.0225	0.146	0.1909	0.335
Non-White, Non-Black head of household	0.0450	0.140	-0.3120	0.318
Number of household members	0.0553	0.038	0.3902**	0.090
Household includes a child less than 6 years old	-0.0282	0.127	-0.5721†	0.294
House includes an elderly individual greater than 65	0.1688	0.124	-0.7236*	0.296
Household has someone at home during the day	-0.0136	0.101	-0.1734	0.241
Single-female head of household	0.2552*	0.111	0.7619**	0.265
Single-male head of household	-0.2956†	0.162	-0.6796†	0.370
Household Income (×1000)	-0.0210*	0.007	-0.0534**	0.018
Receipt of cash benefits	0.5698 **	0.118	1.2476**	0.296
Receipt of non-cash benefits	0.8544**	0.116	2.0662**	0.292
Household rents dwelling	0.0149	0.121	0.3886	0.284
Household resides in an apartment complex	-0.1574	0.138	-0.9156**	0.328
Household resides in a mobile home	-0.2585	0.170	-0.1959	0.384
Total square footage of dwelling	2.26 $\times e^{-5}$	4.91 $\times e^{-5}$	-5.50$\times e^{-5}$	1.15 $\times e^{-4}$
Household has air conditioning	0.1728	0.124	0.4673	0.301
Price per kilowatt hour for electricity	-3.5627	2.312	-6.4712	5.586
Quality of house dummy variable	0.4029**	0.127	1.9160**	0.305
Dwelling built prior to 1970	—	—	0.3321†	0.179
Household resides in a rural environment	-0.4005**	0.135	-0.5750†	0.323
Household resides in an urban environment	-0.2203*	0.109	-0.4850†	0.259
Annual cooling degree days	-2.04 $\times e^{-5}$	1.40 $\times e^{-4}$	7.52 $\times e^{-5}$	3.15 $\times e^{-4}$
Annual heating degree days	1.61* $\times e^{-4}$	6.98 $\times e^{-5}$	3.38* $\times e^{-5}$	1.66$\times e^{-4}$
New England	0.2665	0.280	0.0259	0.673
Mid Atlantic (excluding New York)	-0.2208	0.238	-1.4146*	0.570
East-North Central	-0.3091	0.222	-0.7737	0.527
West-North Central	-0.1889	0.246	-0.3955	0.573
South Atlantic (excluding Florida)	-0.1182	0.232	-1.1000*	0.532
East-South Central	-0.3808	0.249	-2.3489**	0.574
West-South Central (excluding Texas)	-0.7411†	0.444	-0.4859	0.720
Pacific (excluding California)	-0.5803*	0.276	-1.0296	0.636
New York	-0.0797	0.344	-0.6210	0.805
California	0.1040	0.340	-0.3721	0.805
Texas	-0.2471	0.308	-0.2472	0.655
Florida	-0.2130	0.396	-0.3461	0.786
Constant	-1.2095	0.627	1.6434	1.488
ρ: 0.8906**			Log likelihood = -2291.10	

†: Significant at 10% level   *: Significant at 5% level   **: Significant at 1% level

Table 3.4: Results using the Polytomous Partial Credit Model Energy Insecurity Index

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits	—	—	-3.2167**	0.304
Black head of household	0.0780	0.126	0.9159**	0.275
Hispanic Head of household	-0.0113	0.148	0.0947	0.303
Non-White, Non-Black head of household	0.0214	0.141	-0.2810	0.288
Number of household members	0.0557	0.038	0.3359**	0.082
Household includes a child less than 6 years old	-0.0419	0.128	-0.4580†	0.267
House includes an elderly individual greater than 65	0.1735	0.124	-0.6070*	0.268
Household has someone at home during the day	-0.0061	0.102	-0.1672	0.218
Single-female head of household	0.2645*	0.112	0.6869**	0.240
Single-male head of household	-0.3236*	0.165	-0.6249†	0.335
Household Income ($\times$1000)	-0.0205**	0.008	-0.0518**	0.016
Receipt of cash benefits	0.5711**	0.118	1.1586**	0.268
Receipt of non-cash benefits	0.8608**	0.117	1.8477**	0.265
Household rents dwelling	0.0237	0.122	0.3357	0.257
Household resides in an apartment complex	-0.1574	0.139	-0.8373*	0.297
Household resides in a mobile home	-0.2726	0.170	-0.1325	0.348
Total square footage of dwelling	$1.65 \times e^{-5}$	$4.94 \times e^{-5}$	$-3.25 \times e^{-5}$	$1.04 \times e^{-4}$
Household has air conditioning	0.1765	0.125	0.4111	0.272
Price per kilowatt hour for electricity	-3.5425	2.319	-5.3529	5.054
Quality of house dummy variable	0.4003**	0.127	1.6380**	0.276
Dwelling built prior to 1970	—	—	0.1818	0.165
Household resides in a rural environment	-0.3850**	0.136	-0.4919†	0.293
Household resides in an urban environment	-0.2169*	0.110	-0.3399	0.235
Annual cooling degree days	$-3.18 \times e^{-5}$	$1.41 \times e^{-4}$	$1.13 \times e^{-4}$	$2.85 \times e^{-4}$
Annual heating degree days	$1.62^{*} \times e^{-4}$	$7.01 \times e^{-5}$	$3.26^{*} \times e^{-4}$	$1.51 \times e^{-4}$
New England	0.2313	0.282	0.0384	0.610
Mid Atlantic (excluding New York)	-0.2220	0.241	-1.1972*	0.516
East-North Central	-0.3110	0.225	-0.7540	0.478
West-North Central	-0.1888	0.249	-0.2558	0.519
South Atlantic (excluding Florida)	-0.1364	0.234	-0.9457*	0.482
East-South Central	-0.3667	0.252	-2.0580**	0.520
West-South Central (excluding Texas)	-0.7823†	0.433	-0.2883	0.652
Pacific (excluding California)	-0.5805*	0.278	-0.9199	0.576
New York	-0.0632	0.344	-0.4313	0.728
California	0.1051	0.343	-0.1763	0.729
Texas	-0.2286	0.311	-0.1855	0.593
Florida	-0.3203	0.411	-0.0903	0.710
Constant	-1.2126	0.633	1.3909	1.347
ρ: .8760**			Log likelihood = -2233.89	

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

Table 3.5: Dichotomous Rasch Energy Insecurity Index (Alt. Specification)

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits	—	—	-3.7240**	0.321
Black head of household	0.0718	0.120	1.1801**	0.303
Hispanic Head of household	0.0129	0.139	0.2531	0.334
Non-White, Non-Black head of household	0.0151	0.137	-0.3097	0.321
Number of household members	0.0630†	0.037	0.3997**	0.091
Household includes a child less than 6 years old	-0.0485	0.124	-0.6263*	0.297
House includes an elderly individual greater than 65	0.1565	0.121	-0.7331*	0.299
Household has someone at home during the day	-0.0148	0.099	-0.1487	0.243
Single-female head of household	0.2718*	0.109	0.8137**	0.267
Single-male head of household	-0.2863†	0.158	-0.6686†	0.373
Household Income (×1000)	-0.0198**	0.007	-0.0517**	0.018
Receipt of cash benefits	0.5714**	0.115	1.2494**	0.297
Receipt of non-cash benefits	0.8387**	0.113	2.0977**	0.293
Household rents dwelling	-0.0253	0.117	0.3572	0.285
Household resides in an apartment complex	-0.1067	0.133	-0.8481**	0.328
Household resides in a mobile home	-0.2192	0.164	-0.1226	0.386
Total square footage of dwelling	$3.09 \times e^{-5}$	$4.76 \times e^{-5}$	$-3.87 \times e^{-5}$	$1.15 \times e^{-4}$
Household has air conditioning	0.1412	0.116	0.4099	0.297
Price per kilowatt hour for electricity	-0.5642	1.699	-1.5588	4.989
Quality of house dummy variable	0.3871**	0.124	1.9359**	0.307
Dwelling built prior to 1970	—	—	0.3350†	0.179
Household resides in a rural environment	-0.3844**	0.128	-0.5713†	0.321
Household resides in an urban environment	-0.1999†	0.106	-0.4669†	0.260
Annual cooling degree days	$-8.03 \times e^{-5}$	$8.89 \times e^{-5}$	$-9.33 \times e^{-6}$	$2.76 \times e^{-5}$
Annual heating degree days	$1.53^{**} \times e^{-4}$	$3.99 \times e^{-5}$	$3.27^{*} \times e^{-4}$	$1.41 \times e^{-4}$
New England	—	—	-0.4900	0.501
Mid Atlantic (excluding New York)	—	—	-1.1419**	0.434
East-North Central	—	—	-0.2778	0.399
West-North Central	—	—	-0.1496	0.437
South Atlantic (excluding Florida)	—	—	-1.0247*	0.420
East-South Central	—	—	-1.7939**	0.443
West-South Central (excluding Texas)	—	—	0.2974	0.603
Pacific (excluding California)	—	—	-0.2122	0.484
New York	—	—	-0.6343	0.609
California	—	—	-0.4829	0.642
Texas	—	—	0.0128	0.534
Florida	—	—	0.0254	0.670
Percentage of region that had surplus funds in FY 04	-0.1104	0.172	—	—
Constant	-1.5078	0.375	0.9989	1.292
ρ:0.8957**			Log likelihood = -2299.654	

†: Significant at 10% level   *: Significant at 5% level   **: Significant at 1% level

Table 3.6: Polytomous Partial Credit Model Energy Insecurity Index (Alt. Specification)

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits	—	—	-3.3041**	0.293
Black head of household	0.0786	0.121	0.9177**	0.275
Hispanic Head of household	0.0290	0.141	0.1469	0.303
Non-White, Non-Black head of household	-0.0067	0.138	-0.2766	0.291
Number of household members	0.0635†	0.038	0.3446**	0.083
Household includes a child less than 6 years old	-0.0611	0.125	-0.5040†	0.269
House includes an elderly individual greater than 65	0.1616	0.121	-0.6145*	0.271
Household has someone at home during the day	-0.0078	0.099	-0.1473	0.220
Single-female head of household	0.2816*	0.109	0.7347**	0.242
Single-male head of household	-0.3119†	0.161	-0.6182†	0.338
Household Income ($\times$1000)	-0.0192**	0.007	-0.0506**	0.016
Receipt of cash benefits	0.5785**	0.116	1.1724**	0.270
Receipt of non-cash benefits	0.8402**	0.113	1.8804**	0.266
Household rents dwelling	-0.0089	0.119	0.3124	0.259
Household resides in an apartment complex	-0.1100	0.134	-0.7897**	0.298
Household resides in a mobile home	-0.2411	0.165	-0.0800	0.350
Total square footage of dwelling	$2.51 \times e^{-5}$	$4.78 \times e^{-5}$	$-1.91 \times e^{-5}$	$1.04 \times e^{-4}$
Household has air conditioning	0.1424	0.117	0.3612	0.269
Price per kilowatt hour for electricity	-0.6425	1.711	-1.1106	4.541
Quality of house dummy variable	0.3812**	0.124	1.6593**	0.279
Dwelling built prior to 1970	—	—	0.1797	0.165
Household resides in a rural environment	-0.3651**	0.129	-0.4912†	0.291
Household resides in an urban environment	-0.1961†	0.107	-0.3230	0.236
Annual cooling degree days	$-9.73 \times e^{-5}$	$8.94 \times e^{-5}$	$2.59 \times e^{-5}$	$2.53 \times e^{-4}$
Annual heating degree days	$1.52^{*} \times e^{-4}$	$4.02 \times e^{-5}$	$3.12^{*} \times e^{-4}$	$1.29 \times e^{-4}$
New England	—	—	-0.3667	0.461
Mid Atlantic (excluding New York)	—	—	-0.9501*	0.400
East-North Central	—	—	-0.3304	0.369
West-North Central	—	—	-0.0508	0.403
South Atlantic (excluding Florida)	—	—	-0.8554*	0.385
East-South Central	—	—	-1.6021**	0.408
West-South Central (excluding Texas)	—	—	0.4230	0.552
Pacific (excluding California)	—	—	-0.1919	0.446
New York	—	—	-0.4629	0.558
California	—	—	-0.3126	0.590
Texas	—	—	0.0172	0.490
Florida	—	—	0.3010	0.616
Percentage of region that had surplus funds in FY 04	-0.0845	0.174	—	—
Constant	-1.5155	0.380	0.8812	1.182
ρ: 0.8840**			Log likelihood = -2242.13	

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

Table 3.7: Energy Secure Threshold

Index	Secure Cut-off	# Secure	% Secure
Dichotomous Rasch	≤ 4.34	752	76.68
Partial Credit	≤ 3.63	672	68.15

Table 3.8: Simulations: Adjusting LIHEAP funding

	Simulation 1		Simulation 2		Simulation 3		Simulation 4	
Index	% change	# HH Helped	% change	# HH Helped	% change	# HH Helped	% change	# HH Helped
Dichotomous Rasch	-16.47	0	9.74	497	3.25	371	-13.82	273
Partial Credit	-18.39	0	12.59	530	7.05	428	-14.48	273

Table 3.9: Simulation: Adjusting Rural and Urban Household Participation

	Urban		Rural	
Index	% Change LP	% Change ES	% Change LP	% Change ES
Dichotomous Rasch	5.73	-0.36	9.44	0.48
Partial Credit Model (PCM)	5.58	0.13	9.02	1.13

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Chapter 4

Essay 2A: An Application of Dichotomous and Polytomous Rasch Models For Scoring Energy Insecurity

4.1 Introduction

Energy insecurity is often viewed as the level of reliance on external sources of energy, such as foreign oil. This definition ignores the important microeconomic role energy can play in household security. A large body of household security literature has focused on food, but households can be "energy insecure" as well as food insecure. The idea behind energy security concerns an individual's or household's ability to secure clean energy (electricity, gas, fuel) needed to cook food, stay warm in cold weather, and stay cool in hot weather. In terms of household budgets, energy security is just as important as food security since most low income households within the U.S. spend approximately equal shares, roughly 10-15 percent, of their income on food and energy expenditures (Higgins and Lutzenhiser 1995).

It is impossible to discuss the concept of household energy insecurity without some sort of common metric to compare households, though currently, none exists. Some recent work has attempted to categorize household energy insecurity into ordinal groups, but the reasoning for the grouping is arbitrary (Colton 2003, Cook, Frank, Casey, Rose-Jacobs, Black, Chilton, deCuba, Appugliese, Coleman, Heeren, Berkowitz and Cutts 2008). An index that provides a continuum of household energy insecurity ratings would be preferred, but has yet to be developed. This paper creates several different household energy insecurity indexes using Rasch models. Rasch models are designed to measure an unobservable, or latent, trait and provide information on both the difficulty of items and energy insecurity levels of respondents. Using Rasch models and questions from the 2005 Residential Energy Consumption Survey (RECS) that is distributed by the Energy Information Administration (EIA), it is possible to evaluate how well the questions measure energy insecurity and to provide a continuum of household energy insecurity scores that can be used for future analysis of household energy security status.

The remainder of the paper is structured as follows: Section 4.2 discusses previous household energy insecurity scoring in light of the more developed food insecurity literature. Section 5.2 discusses the data used for the analysis and provides some summary statistics. Section 4.4 explicitly defines the Rasch models used to generate the continuous household energy insecurity indexes and Section 5.4 provides the results from the models. Section 4.6 further examines the relationship between household characteristics and generated indexes and Section 5.5 concludes.

4.2 History

The idea of a household energy insecurity index has stemmed mainly from widespread adoption of the household food insecurity index developed by the United States Department of

Agriculture (USDA) for empirical analysis. In 1992, governmental agencies began to frame a survey that would attempt to measure levels of hunger and food insecurity within the United States. The first measurable product came in 1995 when the U.S. Census Bureau added the "Food Security Supplement" to the Current Population Survey (CPS). The questions focused on learning about household eating habits and behavior of households when faced with financial difficulties, specifically how families behaved when facing uncertainty about food access and the methods they used to adjust food consumption in the face of limited access. Households with children were asked several additional questions that examined how they dealt with potential food shortfalls involving children.

The data collected from this survey was used by the Food and Nutrition Service of the USDA to publish a report analyzing overall food insecurity within the United States. One of the key results from this data was the creation of a food insecurity scale that could relate different levels of household food insecurity on one continuum. This allowed the government (and future researchers) to directly compare household food insecurity levels. This powerful measure provided momentum for other agencies to adopt food security questions in surveys, such as the Panel Study of Income Dynamics (PSID), the Survey of Program Dynamics (SPD), and the Early Childhood Longitudinal Study (ECLS). The original questions have been slightly modified to constitute the "food security core survey module" (Bickel et al. 2000). The reliability of the food insecurity scale is quite strong; others have used alternative estimation techniques and observed similar results (Opsomer, Jensen and Pan 2003).

Four food security statuses are defined by the USDA: "food secure", "food insecure without hunger", "food insecure with hunger (moderate)", and "food insecure with hunger (severe)". Those who only worry about sufficient food or its quality are seen as food insecure without hunger. Households move into the category of food insecure with hunger (moderate) when adults within a household begin to suffer the physical effects of hunger and food insecurity with hunger (severe) is observed when all household members, including children, suffer from the physical effects of hunger. Households are placed into one of the categories based on their food insecurity score derived from their survey responses. It is important to note that the aggregate total of responses, not the response to individual questions, determines the household food insecurity status (Bickel et al. 2000).

There are some limitations to the food insecurity scale. First, there are several aspects of food insecurity that are not quantified. The idea of "entitlements", discussed by Sen (1981), are not addressed in the core module. Households could be considered "food secure", yet obtain their food through socially unacceptable methods, which would indicate high levels of food insecurity according to Sen. Second, in most surveys all questions in the core module ask households about conditions over the past year. It is easily conceivable that conditions within a household could have changed dramatically over such a long period of time. The USDA has varied the duration associated with the same core questions, only asking households about conditions experienced over the past 30 days. The results do not change much when using this shorter time frame, but are less reliable (Nord 2002).

Recently, the idea of creating a household energy insecurity scale (HEIS) has gained attention. The Administration for Children and Families (ACF), a division within the Department of Heath and Human Services, commissioned a first attempt in 2003 through similar questions to those within the food security core module. The questions ask households about energy usage during the previous 12 months and whether they altered their consumption behavior due to financial strain. Energy insecurity questions, however, are not simple yes/no questions like those in the food security core module. Instead, these questions ask households to determine how often they have adjusted their behavior during the past year.

The HEIS attempts to generate a home energy insecurity scale that captures "all aspects of low-income energy affordability" (Colton 2003, pg. 1). The report classifies five different components to household energy insecurity. Financial strain is considered a different component of energy insecurity compared to receiving aid from outside assistance. Additionally, reductions in energy consumption are differentiated from reductions in household necessities (like food or medicine). The last component to the energy insecurity scale concerns failure to pay energy bills. The USDA food insecurity scale, however, acknowledges that there are many aspects of food insecurity that are not measured by the scale, including nutritional quality of food, diet, and food safety (Bickel et al. 2000). The stated goal of the HEIS might be too broad to be achieved under such a short survey.

Some of the differentiated categories of energy insecurity should be combined into broader categories. Depending upon the level of financial strain, a household may reach out for assistance to help pay an energy bill, and eventually, under sufficient financial strain, not pay their energy bills. Similarly, households most likely jointly constrain energy use and household goods. The USDA acknowledges that their food insecurity scale cannot contain all aspects of food insecurity and that the scale measures only one part of household food insecurity. By trying to measure more components, the efficacy of the scale could be damaged.

The ACF HEIS defines five levels of energy security. Households are "thriving" if they exhibit no signs of energy insecurity. Households are "capable" if they worry about energy bill costs, but are generally energy secure otherwise. A "stable" household is one that occasionally requires external help to pay energy bills, but is not in danger of loss of service. Households that are "vulnerable" make choices between reducing consumption of basic commodities or reducing energy costs and often have significant unpaid energy bills. The worst classification of a household is one that is "in-crisis". These households face extended periods of discontinued service that can threaten their overall well-being. Households are assigned a unique category depending upon their response pattern.

This method of assignment is another major difference between the food and energy insecurity scales. The USDA food insecurity scale uses Rasch models to derive a continuous measure of food insecurity. The households are placed into one of the food security classifications based on their location along this continuum. Under the HEIS, criteria are used to determine if a household meets a specific energy security level. Households get eliminated from higher energy security categories based on question responses. If the criteria are not met, then the process is repeated for the subsequent energy insecurity category. This process continues until all households have been sorted (Colton 2003). Unfortunately, this method is not nearly as transparent as those associated with the food insecurity scale. The results and methods of the scale are difficult to use; in one of the few attempts to use this index since its creation, adjustments were needed to generate a "better" index (Division of Energy Assistance 2011).

Another household energy insecurity scale was created in 2008 (Cook et al. 2008). Using data from the Children's Sentinel Nutrition Assessment Program (C-SNAP), the authors created a scale that classified households into three levels of energy security. Within the C-SNAP survey, there were four questions that asked about household energy behavior during the previous 12 months. The questions are quite similar to those asked by the HEIS. Questions primarily ask about interactions with utility companies and delinquent energy bills. Households who responded negatively to all of the questions were considered "energy secure" by this study. Households who positively answered the first question were considered "moderately energy insecure" and if a household answered any other question affirmatively, the household was considered "severely energy insecure". These classifications differ from those designed by the ACF and the categorization of energy insecure households seems quite simplistic. However, with such a limited scope of the questions, it seems reasonable to assume that households could be energy insecure even if answering all four questions negatively.

Neither of these household energy insecurity indexes use methods like those used in the USDA food insecurity scale. This makes it impossible to compare levels of energy insecurity between the two surveys. It is, however, possible to create a new energy insecurity continuum from the nine RECS energy insecurity survey questions using the methods employed in the USDA food security index. The results from this approach also provides information that can improve survey design by identifying questions that do not adequately capture a specific trait of the energy insecure. The Rasch methods employed are detailed in section 4.4.

4.3 Data

The 2005 Residential Energy Consumption Survey (RECS), a nationally representative survey of almost 4,500 U.S. households, is the primary data set employed in the analysis. The RECS data is the first national survey that includes any questions regarding energy insecurity, though not all households are asked these questions. Households that are eligible for LIHEAP in that they have an income of less than 150 percent of the poverty level or less than 60 percent of the state's median income, whatever is greater, answer a special module of energy security questions that include nine questions about behavior and ten other questions about energy bills and consumption patterns. The energy behavior questions are used to construct a continuous household energy insecurity index across this sample.

States may offer LIHEAP benefits to households that are more generous than those used in determining who will be asked energy security questions, but may not employ more stringent eligibility requirements. Additionally, households that receive other entitlement benefits such as food stamps, aid to families with dependent children (AFDC), or supplemental security income (SSI) also qualify. Out of the 4,500 households, LIHEAP-eligible households are oversampled in the data and the final sample includes 1,223 eligible households, with 307 households actively receiving energy assistance benefits. Each household responded to all nine questions and there is no concern over omitted responses within the sample. The nine questions are shown in figure 4.1.

As seen from the questions, households are offered four response choices. To create an energy insecurity index using Rasch models, households who answer "never" to all questions are scored as a zero, indicating the lowest levels of energy insecurity. Households who answered "almost always" to questions would be the most energy insecure and have a score of 3. The simple transformation of data does not affect the ordering of households, nor does it affect the results.

In an alternative index, the questions are collapsed into dichotomous questions. If a household responded affirmatively to the question (indicating any response besides "never"), then the household receives a value of one. This means that total scores in the dichotomous model range from a low of zero to a maximum of nine. As part of the analysis we will examine whether household energy insecurity scores drastically change between a scale based on dichotomous or polytomous scaling.

Finally, since all households included in the sample are eligible for LIHEAP, there may be some fundamental differences between those who participate in LIHEAP and those who do not. Table 4.1 compares household demographic and residential summary statistics of the two groups of households. Several key differences exist between participants and non-participants. There is a greater proportion of black LIHEAP participants compared to non-participants, but significantly fewer other non-black, non-white races and fewer Hispanics. Additionally, single females account for 57 percent of LIHEAP participants, significantly more than in the non-participant group. Since one of the goals of LIHEAP is to target vulnerable households, including those with young children and elderly individuals, it is surprising that there is no statistical difference in the incidence of these groups in the participant and non-participant populations. However, there is some evidence that LIHEAP participants are worse off overall, as household income is $2,500 lower for LIHEAP participants. As expected, more LIHEAP participants receive cash and non-cash benefits compared to non-participants. It is striking, however, that the difference is so large. Almost 60 percent of households that receive LIHEAP benefits also receive non-cash benefits compared to roughly 25 percent of non-participants. A similar percentage gap exists for cash benefits. These differences in summary statistics of participants and non-participants support the idea of "bundled" assistance; households that participate in one government assistance program are more likely to participate in additional assistance programs as well (Higgins and Lutzenhiser 1995, Mills, Doraj-Raj, Peterson and Alwang 2001). A larger percentage of non-participant households earn wages through part-time work compared to households receiving LIHEAP benefits.

Several residential summary statistics also differ between participant and non-participant groups. Since the majority of LIHEAP funding assists households in paying their utility bills, it is not surprising that fewer households that have utilities included in their rent participate in LIHEAP. The difference in price per kilowatt hour is statistically significant, with non-participant households paying slightly higher costs per kilowatt hour. Household quality is a dummy variable created from two survey questions about insulation and draftiness of the residence. Households that indicated having poor insulation and heavy drafts within the residence receive a value of one. LIHEAP participant households, on average, have a lower opinion about their household quality compared to non-participants. The share of rural households that participate in LIHEAP is also smaller in comparison to non-participants. Household energy burden is significantly different between the two groups of households. Energy burden calculates a ratio of each household's total energy bill to its income. Households that participate in LIHEAP have higher energy burdens compared to non-participants, consistent with the LIHEAP objective of targeting those households with the highest energy burden.

4.4 Models

Several models exist that can provide more robust analysis compared to the ad hoc household energy insecurity index described by Colton or Cook et al.. First, there is the traditional Rasch family of models, which has been used previously by the USDA ERS to generate the food insecurity index. The USDA only asks yes or no questions within their food security supplement, allowing them to use the dichotomous (binary) Rasch model. The survey questions used in the RECS, however, use multiple response questions yielding polytomous data. The polytomous nature of the data requires a more general form of the Rasch model. Each model is described in detail below.

Dichotomous Rasch Model

The most basic model within the literature is the dichotomous Rasch model. In his seminal work, Rasch (1960) created a model based on probability theory to measure latent traits of individuals. Rasch noted that the probability of an individual answering a question correctly depended upon both the "ability" of the individual and the "difficulty" of the question. His model allows for measurement of both these properties on a uniform scale. The Rasch model creates a single index measurement from many questions that all try to measure one specific trait. One of the key assumptions of the model is that all questions are designed *only* to measure the trait of interest (in this case energy insecurity). This assumption is called *unidimensionality* in the literature and if it fails, the results of the Rasch model become less informative. The model has a specific measure of fit that allows researchers to test how well each question (and individual) conform to this assumption. Questions (and individuals) that fall outside of a 95% confidence interval constructed from the model are less informative and could possibly be associating the question with multiple traits (Bond and Fox 2001).

The dichotomous Rasch model uses a logarithmic transformation of the data (both individual and item) to convert ordinal data into interval data. Interval data is useful since it allows researchers to make direct comparisons between items and individuals. Comparisons such as "household a is more energy insecure than household b" or "answering question 1 in the affirmative denotes a higher level of energy insecurity than answering question 2" can now be answered. The model is identified up to any linear transformation, allowing the creation of an arbitrary mean. Item difficulty and ability levels are all described in terms of *logits* around this mean. Households with higher logit scores would indicate higher energy insecurity and questions with higher values along the logit scale are relatively more difficult to affirm, indicating higher levels of energy insecurity.

The dichotomous Rasch model is expressed as the probability of a response, conditional on a respondent's ability and the item difficulty in a logistic model,

$$\text{Prob}\left\{X_{vi} = x|\theta_v, \beta_i\right\} = \frac{\exp\left[x\left(\theta_v - \beta_i\right)\right]}{1 + \exp\left(\theta_v - \beta_i\right)} \tag{4.1}$$

where $v = 1 \dots n$ indexes the respondents and $i = 1 \dots k$ indexes the questions. X_{vi} is the vector of responses for each individual and x can be either 0 or 1. The parameter θ_v denotes the v^{th} person parameter and β_i is the i^{th} item parameter. The model for all questions and individuals aggregates to

$$\text{Prob}\left\{X_{vi} = x|\theta, \beta\right\} = \prod_{v}^{n}\prod_{i}^{k}\frac{\exp\left[x\left(\theta_v - \beta_i\right)\right]}{1 + \exp\left(\theta_v - \beta_i\right)} \tag{4.2}$$

There are several different methods for estimating the model. Traditionally, Rasch models are estimated through joint maximum likelihood estimation (JMLE). Under this procedure, the person parameters θ are assumed known and used to estimate the item parameters β. The item estimates, $\hat{\beta}$, are then treated as known to estimate the person parameters. The procedure is repeated until a specific convergence criterion has been met, providing item and person parameter estimates. Perfect (all ones) and zero scores for items or respondents cannot be estimated under JMLE.

An alternative procedure for estimating the Rasch model is the marginal maximum likelihood estimation (MMLE) approach. Instead of jointly estimating both unknown parameters, MMLE assumes a distribution for the person parameters, integrates them out and then directly estimates the item parameters. If the assumed distribution is wrong, these estimates could potentially have a greater bias than under JMLE. There are, however, some useful advantages to MMLE. Besides providing consistent and unbiased parameter estimates (assuming a proper distribution), MMLE provides parameter estimates for zero and perfect scores.[1] Both estimation methods will be estimated and compared in section 5.4.

Polytomous Rasch Models

A more general Rasch model is available when data are not dichotomous and instead have multiple response options. The framework is quite similar to the dichotomous Rasch model, but some slight differences are important to understand. The polytomous Rasch models also serve as the basis for other polytomous models.

The most crucial difference between dichotomous and polytomous models concerns *thresholds*. Thresholds identify critical points along the latent trait continuum. In a polytomous model, each response category has a unique probability density associated with it. At a threshold, the relative probability between two adjacent question response categories is equal. Movement from the threshold will cause the probability of one response to increase and the other decline, depending upon the direction of movement. Thresholds ideally are ordered, increasing in value along the scale. The values between thresholds do not have to be equal and can vary between response categories. This means that it is possible to have a large difference between two adjacent response options, and a very small difference between others. Finally, there are always one fewer thresholds than question response categories. For example, each question has four response categories (as seen in figure 4.1), but only three points along the continuum exist where adjacent probability curves intersect.

[1] The other major software packages, `BILOG` and `PARSCALE`, use MMLE to estimate Rasch models.

There are two widely used polytomous Rasch models. The major difference between the two types of polytomous models concerns threshold estimation. The Rating Scale Model (RSM), developed by Andrich (1978*a*, 1978*b*, 1978*c*) estimates a single set of fixed values to be applied to all questions. The fixed values are added to the question difficulty estimate to identify the threshold location for that question. Conversely, the Partial Credit Model (PCM), a generalization of the RSM developed by Masters (1982), does not equally apply the same estimates to each question to obtain thresholds. Instead, values between thresholds can vary among questions within a survey.

The RSM can be expressed as

$$\text{Prob}\left\{X_{vi} = x|\theta_v, \beta_i, \omega_h\right\} = \frac{\exp\left[\sum_{h=0}^{x}(\theta_v - (\beta_i - \omega_h))\right]}{\sum_{x=0}^{m}\exp\left[\sum_{h=0}^{x}(\theta_v - (\beta_i - \omega_h))\right]}, \tag{4.3}$$

where $v = 1, \ldots, n$ indexes the respondents, $i = 1, \ldots, k$ indexes the questions, $h = 0, \ldots, m-1$ indicate the number of thresholds, $x = 0, \ldots, m$ indicate the response categories, and X_{vi} is the response vector for each individual. The two parameters, θ and β still represent person and item parameters respectively and the parameter ω_h estimates the common set of thresholds applied to all questions.

The PCM varies slightly compared to the RSM since it calculates unique thresholds for each question. The PCM combines the two terms ω_h and β_i into one parameter, β_{ih} that varies across questions,

$$\text{Prob}\left\{X_{vi} = x|\theta_v, \beta_{ih}\right\} = \frac{\exp\left[\sum_{h=0}^{x}(\theta_v - \beta_{ih})\right]}{\sum_{x=0}^{m}\exp\left[\sum_{h=0}^{x}(\theta_v - \beta_{ih})\right]}, \tag{4.4}$$

with all notation the same as in equation 5.4, except that β_{ih} estimates the item difficulty and threshold parameters jointly for each question within the survey. As can be seen, the PCM is the most general model, but can reduce to both the RSM and dichotomous Rasch model if restrictions are applied.

4.5 Results

Dichotomous Results

Estimation of the dichotomous results was conducted using `WINSTEPS` and `BILOG`, two major proprietary programs used heavily in Rasch modeling. Results between the two programs are a bit different. Table 4.2 shows the item estimates obtained using `WINSTEPS`. The estimated difficulty ranking is shown in the last column. Leaving the residence due to extreme temperatures (Question 8) appears to be the most difficult to affirm, while reducing expenditures on basic necessities (Question 2) is the easiest to affirm. Looking at the results from the model, item "clumping" seems to be present between pairs of questions. Questions 7 and 8 are grouped closely near 6.30 along the latent energy insecurity continuum. This is not surprising since both discuss extreme temperatures within a residence. Questions 1 and 2 are grouped closely near 1.95 and inquire about expenditures. Ideally, there would be more differentiation between item difficulty within such a short survey. The large gap between the easiest questions (questions 1 and 2) and those moderately more difficult is quite large at almost two logits. This gap means that any households that fall between two and four on the scale are not accurately identified. Households within this range would be more energy insecure than those households who only answer affirmatively to questions 1 and 2, but less energy insecure than those who affirmatively answer question 4, which discusses skipping or reducing utility bill payments. Unfortunately, the survey design fails to pick up this difference.

A second problem when looking at the dichotomous results is seen in the fourth and fifth columns of table 4.2. Item infit and outfit statistics are relatively high for several of the items.

Infit and outfit are two measures of fit used in Rasch measurement to determine how well the data fit the model. Infit is an information weighted fit statistic that compares observed responses to those expected under the Rasch model. Conversely, outfit is an unweighted fit statistic that is sensitive to outliers. Outfit also compares observed responses to those expected from the Rasch model, but does not weight them. If the data conform perfectly to the Rasch model, then the outfit and infit statistics would be 1. As can be seen from the table, this is not the case with the data from the survey. There are, however, varying definitions of what constitutes a "good" fit. These statistics are t-distributed and with the large sample size approach normality. Some argue that as long as infit or outfit has values between 2 and -2, the item is satisfactory, since these values approximate the normal 95% confidence interval (Bond and Fox 2001). Negative values of infit and outfit indicate data that fits the model "too well" or overfit. Some experts then argue that only items with high positive values should be of concern. Regardless of the definition used to assess fit, some of the items within this survey exhibit significant misfit. Questions 1 and 5 have infit and outfit statistics with large negative values. Conversely, questions 6, 8, and 9 all have relatively good infit statistics, but positive outfit statistics well outside the range of acceptable fit.

There could be several potential reasons for the poor fit of the data. The most obvious one concerns the transformation of polytomous data into dichotomous. It is possible to see if the fit improves from the results of the polytomous models, though there does not appear to be evidence to support this hypothesis. Other reasons for the poor fit cannot be determined *ex post*, but it seems reasonable to believe that at least one (or more) assumption of the Rasch model has been violated. The most probable violation of the Rasch assumptions is that the survey questions are measuring more than just the single latent trait of energy insecurity.

Results are similar from table 4.3 which compute the dichotomous Rasch model using `BILOG`. One interesting difference between the program results is their overall item estimates. The maximum item estimate under `BILOG` is at roughly 3.5, while `WINSTEPS` has seven questions that have values greater than this. The overall pattern of results, however, is similar. There is no difference in the ranking of question difficulty between the two programs. The grouping of questions 1 and 2, and 7 and 8 are still present as well. The latent scale is a continuum, so it is not surprising that some item estimates have "negative" values, which just mean that they are relatively easy in comparison to other items.[2]

A major difference between the two programs is how they measure the fit of the model. Under `WINSTEPS`, fit is measured through infit and outfit. `BILOG`, however, uses a χ^2 statistic to calculate a p-value, which is shown in the fourth column of the table. The statistic tests the null hypothesis that the item fits the model. Failing to reject this hypothesis (high p-values) indicate good fit. Items that do not seem to fit the model would reject this null hypothesis and have low p-values. As can be seen from the table, six out of the nine questions have p-values lower than .05, indicating a rejection of the null hypothesis. This again seems to undermine the strength of the dichotomous survey questions in measuring only energy insecurity.

Polytomous Results

Results for the polytomous model are more complicated than the dichotomous results. As discussed in section 4.4, polytomous results have thresholds that should follow a sequential ordering, meaning that each threshold is higher than the previous threshold. Neither polytomous model could obtain sequential thresholds using the raw data. Table 4.4 shows the thresholds for both polytomous models. As can be seen, there is a substantial "dip" in the second threshold. The common solution used to fix these problems is to collapse response columns. For this survey, this meant collapsing the two response categories "one or two

[2]Estimates for all Rasch models are identified up to any linear transformation. Models were scaled so that respondents who did not affirm any response have an ability estimate of 0.0 and the same transformation is used to scale the items.

months" and "some months" into one category. This adjustment drastically improved the thresholds as can be seen in table 4.11. This collapses the data into a response pattern of "none", "some", and "always" which households would not find confusing.

It is also possible to see the difference in thresholds graphically. Figures 4.2 and 4.3 show the results of the raw and adjusted thresholds of the RSM for question 1. The curves represent the probability of each response. A question with well-behaved thresholds implies that each response has a portion of the latent continuum where it is the most likely response. This is shown graphically by being the highest curve. In figure 4.2 the blue line represents the probability of a response "one or two months" and is below all other curves, implying that it is never the most probable response when measuring energy insecurity. By collapsing the two lowest response categories and re-estimating the RSM, we see that the results have improved drastically. In figure 4.3, there is a clear section of the latent continuum where each response category is the most likely response. Results from the unadjusted models are uninformative and therefore omitted. Results from the collapsed data are presented instead.

Results between the RSM and PCM are similar and discussed together (Tables 4.6 and 4.7). The rankings between questions are almost identical in the two models and the overall item estimates do not differ dramatically. The fit statistics are somewhat different between the two models however. The RSM has worse fit statistics than the PCM, but the PCM results are still relatively weak. Under the PCM, there is a slight difference in rankings when compared to the RSM and dichotomous results. Question 9 is the second most difficult survey question instead of question 7. It is also possible to compare results between dichotomous and polytomous Rasch models. Estimates from the easiest question, questions 2, are approximately 1.3 logits higher under the polytomous models, but the difference for the hardest question, question 8, is only about 0.6 logits. These results show that it is not just a simple linear difference in location along the energy insecurity scale between polytomous and dichotomous estimates. The poor fit under the polytomous models confirms that the dichotomous model results were not an artifact of data transformation. Instead, the polytomous results cast further doubt that some questions are measuring the unique traits of energy insecurity.

Households Characteristics of the Severely Energy Insecure

Using the scores generated from the dichotomous and polytomous indexes, it is possible to identify characteristics of the most energy insecure households by focusing on the top decile of each index. Results for all indexes are consistent and show several significant differences compared to the rest of the population (table 4.8). First and foremost, almost 50 percent of households from the top decile receive LIHEAP benefits. Severely energy insecure households are also more likely to use other governmental assistance programs, such as food stamps, SSI, and AFDC. Further, average income for the most energy insecure households is significantly lower with some of the indexes, and a significantly higher percentage of income is used for energy expenses. A larger percentage of the energy insecure households are headed by a Black compared to the total population. Conversely, a smaller share of Hispanic households are severely energy insecure. Within the top decile, more households are headed by single females and have younger heads of household compared to the total population. There is no difference in the number of households with young children between the most energy insecure and the general survey population, but significantly fewer top decile households include elderly individuals. Finally, there is no significant difference observed in renters. The results generate a new portrait of the most energy insecure households.

4.6 Differential Item Functioning

Another benefit from collapsing the data into a dichotomous variable is simple differential item functioning (DIF) analysis. Differential item functioning identifies response patterns of unique subgroups and determines if they are statistically significant. For example, it is possible that those households receiving LIHEAP benefits answer questions differently than households that do not participate in the program. If a difference exists, it is identified through differential item functioning. There are several ways to conduct DIF analysis, but the most common method uses logistic regressions with dummy variables.[3]

To conduct a DIF analysis, each question is analyzed individually. Three nested logistic equations are estimated and the dependent variable for each equation is the question response vector. A likelihood ratio test compares the fit of the models. All equations include the summed household raw score from answers to all questions. The "full" equation additionally includes a dummy variable identifying the unique subgroup and an interaction term between the total raw score and the dummy variable. Two reduced equations are then estimated that omit the interaction term and the dummy variable to see if fit is better between models. A general model of the three equations is

$$y_i = \beta_{0i} + \beta_{1i}X_i + \gamma_{1i}D_i + \gamma_{2i}X_iD_i + \varepsilon_i \tag{4.5}$$

$$y_i = \beta_{0i} + \beta_{1i}X_i + \gamma_{1i}D_i + \varepsilon_i \tag{4.6}$$

$$y_i = \beta_{0i} + \beta_{1i}X_i + \varepsilon_i \tag{4.7}$$

where y_i is the response pattern for each individual survey question, X_i is the household raw score for all nine questions, D_i is an indicator variable for group membership, and $\{\beta_{0i}, \beta_{1i}, \gamma_{1i}, \gamma_{2i}\}$ are estimated model parameters.

[3] Differential Item Functioning is conducted abstractly from the problems of endogeneity that might exist with LIHEAP program participation. Significant research has shown that those who participate in assistance programs have to obtain net-positive utility from the additional money gained versus the disutility associated with the "welfare stigma" (Moffitt 1983). No conclusions about program effectiveness can be drawn from the DIF results. Differences in subgroup response patterns can be used to facilitate future research on program effectiveness.

If equation 5.9 fits significantly better than either equation 5.10 or 5.11, then this means that the question exhibits DIF. The three equations are necessary because two forms of DIF exist. Comparing equations 5.10 and 5.11 identifies uniform DIF. Uniform DIF exists when one group of households has a higher (or lower) probability of affirming the question than a different group of households throughout the entire energy insecurity continuum. Non-uniform DIF is identified through model fit comparisons of equations 5.9 and 5.10 and shows when there are portions of the continuum where a group has a higher or a lower probability of affirming the question in comparison to other groups. Analysis focuses on non-uniform DIF if both forms of DIF are observed in a model (Swaminathan and Rogers 1990). The difference in the Nagelkerke pseudo-R^2 between equations 5.9 and 5.10 help determine whether any revisions to the question are needed when significant non-uniform DIF is identified. When the difference in the pseudo-R^2 is small, the DIF is generally considered trivial and can be ignored. Similar calculations are used between equations 5.10 and 5.11 to examine the importance of uniform DIF.

Several comparisons between subgroups are of significant interest. First, it is useful to know if households that participate in LIHEAP answer questions differently compared to non-participants. Second, households headed by a single female are targeted by federal assistance programs and are often the most vulnerable households. It is possible to see whether they answer questions differently than other types of households. Finally, it is possible to test whether there any racial or ethnic response differences.

Table 4.9 shows the results from the DIF analysis. There does not appear to be any major difference between response patterns of LIHEAP participant and non-participant households. Results from the likelihood ratio tests show that question 6 exhibits non-uniform DIF and question 4 exhibits uniform DIF (p=.10), but generally the two groups answer the questions similarly. The differences in the pseudo-R^2 is small for both of these questions (0.0022 and 0.0001, respectively). There is little evidence of DIF when comparing heads of household as well. For most questions, households headed by single females answer questions in a similar manner. The two exceptions are questions 6 and 1. Question 6 exhibits significant non-uniform DIF, but the difference in the Nagelkerke pseudo-R^2 between the two equations is only 0.0027. The small difference in the pseudo-R^2 for question 1 (0.0017) also indicates that the observed DIF is minor at best. No other questions exhibit any differences between households headed by single females and other household types.

There is more evidence of potential DIF when comparing racial and ethnic response patterns. Questions 4 through 8 all show significant uniform DIF when comparing black households to white households and question 9 shows evidence of non-uniform DIF. Hispanic and non-Hispanic households also show different response patterns. Question 6 shows evidence of non-uniform DIF, while questions 1, 3, 5, and 8 all show evidence of uniform DIF. While the difference in the pseudo-R^2 is still small for all of these questions, the large number of questions exhibiting DIF merits further examination and implies that racial and ethnic differences in responses complicates measurement of energy insecurity with the current survey questions.

4.7 Conclusions

A continuous measure of household energy insecurity is created that places all households along a latent continuum. Households that have higher levels of energy insecurity are more likely to answer questions affirmatively. Question estimates are placed along the same latent continuum and those questions that are more difficult for households to affirm have a higher score. Comparisons of households and questions are now possible and can be used for future research. Original polytomous results seemed to cast doubt that any logical ordering could be observed from the survey responses, but collapsing the data into three response categories provides meaningful measures of energy insecurity. The dichotomous and polytomous models generate a relatively stable and consistent index with question difficulty not changing drastically between models. Questions that investigate household coping patterns, including leaving the house (question 8), setting thermostats to unhealthy or unsafe levels (question 7), or using non-traditional heating sources (question 9) are the most difficult questions for households to affirm. The survey questions show some evidence of DIF when comparing race and ethnicity, but households headed by single females and those receiving LIHEAP benefits do not seem to answer questions differently than other households. A more thorough testing of differential responses across racial and ethnic groups may be needed to reduce the observed differences in response patterns.

The identification of the severely energy insecure households allows policy makers to create assistance programs that better address insecure household needs. Instead of providing assistance based on poverty levels, policy makers should target households based on energy burdens. Households in the top decile of all indexes had significantly higher energy burdens compared to the total population. The results also suggest that energy assistance benefits cannot be directly tied to households with young children or elderly members, even though these households are considered particularly vulnerable under LIHEAP. Severely energy insecure households are less likely to include an elderly member and are just as likely to have young children as other households within the LIHEAP eligible population. On the other hand, households headed by single females are more likely to be severely energy insecure and more likely to use an assorted bundle of assistance programs, including AFDC, LIHEAP, and food stamps. The association between household energy insecurity and non-energy assistance program use suggests LIHEAP targeting could be improved if governmental agencies collaborated and provided information on LIHEAP whenever a household applied for benefits from other assistance programs.

The results from this paper also offer policy makers insight into improving measures of energy insecurity. The survey questions devised by the EIA in the Residential Energy Consumption Survey are modeled on food insecurity questions originally created by the USDA. In the adaptation to energy insecurity, it appears that the questions lose some of their effectiveness. When analyzed under a Rasch model, the food insecurity questions are well behaved and seem to conform to all necessary model assumptions (Bickel et al. 2000). It is unclear why modifying the questions to examine energy insecurity leads to less effective performance in the Rasch model framework, but we can speculate on the reasons. One major difference between the food security and energy security survey methods is the use of polytomous response patterns by the EIA. Food insecurity questions are all dichotomous questions that have follow up questions asking respondents about frequency only when they previously answer yes to a question. The EIA chose to use multiple response questions that asks about behavioral frequency within each question instead. This difference in survey design may contribute to the poorer performance. For this theory to hold, households must have responded differently to the survey only because of the choices presented. There is evidence within the food insecurity literature to substantiate this possibility. When polytomous variations of the original food insecurity questionnaire were used, researchers had to collapse two of the categories as well to derive meaningful results (Deitchler, Ballard, Swindale and Coates 2010).

It is also possible that the USDA food insecurity survey might not be a useful template for design of an energy insecurity questionnaire. While the results from the original 18 question survey have been extensively validated and used in many surveys within the United States, attempts to transfer the food insecurity questionnaire to foreign countries have had mixed results. A nine year study attempted to create a set of common questions to be used in developing countries worldwide. As the questions were used in different countries, results from the Rasch model showed that the questions were not accurately measuring overall food insecurity. Rather, the questions best identified household hunger levels (Deitchler et al. 2010). The difference between a food insecure household and a household experiencing hunger is subtle but important. Households do not have to experience hunger to be considered food insecure. Given the complications in creating a global food insecurity survey, it is not surprising that generalization of food insecurity questions to energy insecurity under a similar framework yields poor results in terms of generating an energy insecurity index.

Finally, the nine questions developed by the EIA appear to need more modification to conform to the Rasch model. Revisions to narrowly focus the survey questions on a single aspect of household energy insecurity and adjustments in questions asking households how they cope with high utility bills will likely improve the overall survey design. Rasch methods should also be used to validate the modified survey prior to its use in national surveys, such as the Residential Energy Consumption Survey.

4.8 Results from Item Response Theory Models

Two Parameter Logistic Model

The Two Parameter Logistic (2PL) model offers a greater range of values for the energy insecurity index compared to the dichotomous Rasch index (Table 4.10). The results from this more general index, however, are consistent to those of the Rasch model. Households that receive LIHEAP benefits continue to have lower EI scores compared to those households without the benefits. In terms of household demographics, all significant variables from both equations in the dichotomous Rasch index retained their significance, while no additional variables became significant. Households that include a young child still significantly lower household EI scores, but at an improved significance level ($p = 5\%$).

Residential characteristics still significantly affect household LP and EI scores. All residential characteristics that significantly affected the household LP decision retain the same type of effect and significance level. Under the 2PL model, households that lived in older residences no longer have significantly higher EI scores compared to those living in newer dwellings, though the sign is consistent between the two specifications. All other characteristics that significantly affected household EI scores continue to affect it under this alternative model as well.

Finally, regional effects show the biggest differences between the 2PL and dichotomous Rasch indexes. Under the 2PL, households that live in the Pacific census division (excluding California) now have a significantly ($p = 10\%$) lower EI score compared to households in the Mountain division. Households living in the other three divisions, the South Atlantic (excluding Florida), the Mid-Atlantic (excluding New York), and the East-South Central retained significantly lower EI scores as well.

Generalized Partial Credit Model

The generalized partial credit model (GPCM) is an Item Response Theory (IRT) model and the most general energy insecurity index considered. The GPCM index allows for over 300 different household energy insecurity scores. The results are consistent with the PCM results and the dichotomous results previously examined.

The generalized partial credit model (GPCM) is the index with the most relaxed assumptions of the four indexes considered (Table 4.11). The results from the GPCM EI index, however, are very consistent with those of the more restrictive indexes. All household demographic characteristics, residential characteristics, and locational differences that were significant in the PCM household LP decision are still significant. The only major difference in the household LP decision between this specification and the other specifications is the significance of mobile homes. Households residing in mobile homes are now less likely ($p = 10\%$) to participate in LIHEAP than those living in a single family home, which is different than expected. Since this result was only found in one index at a weak significance level, inference using this result should be extremely cautious. Households residing in mobile homes may be unaware that they are still eligible for all LIHEAP benefits.

Almost all attributes that are significant in the other models are also significant in the generalized index. Households headed by a Black still have a significantly higher EI score than households headed by a White. Larger households, households headed by a single female, and households receiving cash or non-cash federal entitlement benefits all significantly increase household EI scores. Households that include a child ($p = 10\%$), include an elderly member, have higher income, or are headed by a single male ($p = 10\%$) have lower household EI scores. The few residential characteristics that significantly affect EI scores under the PCM specification continue to affect EI scores when using the GPCM index

Table 4.1: Summary Statistics Between LIHEAP Participants and Eligible Non-participants

Variable	LIHEAP Participant	Std. Deviation	LIHEAP non-Participant	Std. Deviation	p-value
Head of Household, Black*	0.2508	0.434	0.1943	0.396	0.0443
Head of Household, non-White, non-Black*	0.1792	0.384	0.2325	0.423	0.0405
Hispanic**	0.1726	0.379	0.2566	0.437	0.0013
Household Age	50.1498	19.098	48.7260	19.620	0.2620
Number of household members	2.8730	1.861	2.8341	1.743	0.7476
Single Female Head of Household**	0.5700	0.496	0.4050	0.491	$5.88\times e^{-7}$
Household includes an elderly member	0.2606	0.440	0.2598	0.439	0.9791
Household includes a young child	0.2606	0.440	0.2489	0.433	0.6861
Household Income**	12565.15	6900.45	14978.17	7959.48	$4.67\times e^{-7}$
Receipt of cash benefits**	0.4169	0.494	0.1670	0.373	$4.88 \times e^{-15}$
Receipt of Non-cash benefits**	0.5863	0.493	0.2358	0.425	$9.88 \times e^{-26}$
Not Employed	0.1336	0.341	0.1354	0.342	0.9355
Part-time Employed**	0.1824	0.387	0.3199	0.467	$4.40 \times e^{-7}$
Renter	0.5668	0.496	0.5164	0.500	0.1249
Utilities included in rent**	0.1107	0.314	0.2216	0.416	$1.15\times e^{-6}$
Price per kilowatt hour**	0.0996	0.026	0.1079	0.082	0.0077
Household feels quality of house is low**	0.2313	0.422	0.1135	0.317	$9.64\times e^{-6}$
Urban Resident	0.4919	0.501	0.5317	0.499	0.2283
Rural Resident*	0.1498	0.357	0.2085	0.406	0.0166
Percent Burden**	0.1906	0.225	0.1507	0.218	0.0070

*: Significant at 5% level — **: Significant at 1% level

Table 4.2: Dichotomous Rasch Item Difficulty Estimates (`WINSTEPS`)

Question	Item Estimate	Std. Error	Infit	Outfit	Rank
Question 1	1.97	0.10	-4.40	-2.80	8
Question 2	1.94	0.10	0.40	0.32	9
Question 3	4.39	0.09	-0.12	0.74	6
Question 4	3.96	0.08	-1.91	-1.18	7
Question 5	4.51	0.09	-4.36	-3.70	5
Question 6	5.57	0.10	1.70	3.98	4
Question 7	6.28	0.11	0.02	1.92	2
Question 8	6.34	0.11	0.91	4.74	1
Question 9	5.98	0.10	1.22	4.26	3

Table 4.3: Dichotomous Rasch Item Difficulty Estimates (`BILOG`)

Question	Item Estimate	Std. Error	χ^2 p-value	Rank
Question 1	-0.25	0.05	0.000	8
Question 2	-0.27	0.05	0.000	9
Question 3	1.65	0.05	0.170	6
Question 4	1.27	0.05	0.007	7
Question 5	1.76	0.05	0.000	5
Question 6	2.77	0.06	0.146	4
Question 7	3.45	0.06	0.064	2
Question 8	3.51	0.06	0.024	1
Question 9	3.17	0.06	0.013	3

Table 4.4: Estimated Thresholds of Unadjusted Data

	PCM			RSM		
Question	Threshold 1	Threshold 2	Threshold 3	Threshold 1	Threshold 2	Threshold 3
Question 1	2.75	1.18	3.27	1.97	0.41	2.03
Question 2	2.68	1.11	3.20	1.95	0.39	2.01
Question 3	4.05	2.48	4.57	2.91	1.34	2.96
Question 4	3.89	2.32	4.41	2.81	1.25	2.86
Question 5	4.23	2.66	4.75	3.07	1.51	3.13
Question 6	4.51	2.94	5.03	3.27	1.71	3.32
Question 7	5.00	3.43	5.52	3.52	1.96	3.57
Question 8	5.16	3.59	5.68	3.92	2.36	3.98
Question 9	5.00	3.43	5.52	3.87	2.30	3.92

Table 4.5: Estimated Thresholds of Unadjusted Data

	PCM		RSM	
Question	Threshold 1	Threshold 2	Threshold 1	Threshold 2
Question 1	2.13	4.39	0.98	2.03
Question 2	2.05	4.31	1.00	2.05
Question 3	4.03	6.29	1.94	2.99
Question 4	3.76	6.02	1.68	2.73
Question 5	4.19	6.45	1.85	2.90
Question 6	4.80	7.06	1.02	2.06
Question 7	5.58	7.84	1.19	2.24
Question 8	5.78	8.04	3.55	4.60
Question 9	5.48	7.74	3.37	4.42

Table 4.6: Polytomous PCM Item Difficulty Estimates (Adjusted)

Question	Item Estimate	Std. Error	Infit	Outfit	Rank
Question 1	3.36	0.06	-5.47	-5.48	8
Question 2	3.28	0.06	0.29	-0.18	9
Question 3	5.28	0.07	-0.62	0.44	6
Question 4	5.12	0.07	-1.30	-1.05	7
Question 5	5.52	0.07	-2.75	-3.38	5
Question 6	5.56	0.07	2.60	4.12	4
Question 7	6.31	0.09	0.55	1.77	3
Question 8	6.99	0.10	1.16	4.77	1
Question 9	6.83	0.09	2.18	4.18	2

Table 4.7: Polytomous RSM Item Difficulty Estimates(Adjusted)

Question	Item Estimate	Std. Error	Infit	Outfit	Rank
Question 1	3.26	0.06	-7.15	-6.62	8
Question 2	3.18	0.06	-0.68	-0.99	9
Question 3	5.16	0.07	-0.61	0.16	6
Question 4	4.89	0.07	-2.67	-1.87	7
Question 5	5.32	0.07	-3.37	-3.71	5
Question 6	5.93	0.08	6.70	4.44	4
Question 7	6.71	0.10	2.55	1.60	2
Question 8	6.91	0.10	1.36	4.62	1
Question 9	6.61	0.09	2.18	4.01	3

Table 4.8: Characteristics of Severely Energy Insecure Households

Household Characteristic	Dich. Rasch	Poly. Rasch	All Index Mean
Receives LIHEAP benefits	0.4733**	0.4438**	0.2510
Receipt of cash benefits	0.4122**	0.3876**	0.2298
Receipt of non-cash benefits	0.4504**	0.5000**	0.3238
Average Household Income	12986.64†	12963.48*	14372.44
Head of Household, Black	0.3664**	0.3315**	0.2085
Hispanic	0.1985	0.1517**	0.2355
Single Female Head of Household	0.5267†	0.5169†	0.4464
Average Head of Household Age	46.32†	46.35*	49.08
Household includes a young child	0.1985	0.2191	0.2518
Household includes an elderly member	0.1450**	0.1404**	0.2600
Percent Burden	0.2135*	0.2292**	0.1607
Renter	0.5420	0.5281	0.5290

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

Table 4.9: Differential Item Functioning Likelihood Ratio test p-values

	LIHEAP		Single Female		Black		Hispanic	
	Non-uniform	Uniform	Non-uniform	Uniform	Non-uniform	Uniform	Non-uniform	Uniform
Question 1	0.6291	0.4867	0.0445*	0.0467*	0.8123	0.3733	0.6999	0.0878†
Question 2	0.1142	0.7217	0.6996	0.8665	0.1560	0.3238	0.8143	0.2595
Question 3	0.1386	0.7211	0.4425	0.9064	0.7927	0.3008	0.4283	0.0000**
Question 4	0.3191	0.0623†	0.2499	0.1426	0.8830	0.0303*	0.4331	0.1791
Question 5	0.6828	0.7482	0.9347	0.3604	0.7838	0.0176*	0.2735	0.0441*
Question 6	0.0363*	0.7217	0.0039**	0.1187	0.4454	0.0112*	0.0445*	0.0002**
Question 7	0.9208	0.3238	0.3925	0.2343	0.1354	0.0159 *	0.8092	0.1114
Question 8	0.9904	0.2559	0.9686	0.6846	0.7516	0.0132*	0.1847	0.0463*
Question 9	0.9400	0.9265	0.6625	0.1725	0.0203*	0.1931	0.4773	0.8555

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

K-1 INTERVIEWER INSTRUCTION: PLACE SHOW CARD 29 IN FRONT OF THE RESPONDENT. **As a result of energy price increases, some households have faced challenges in paying home energy bills. The next set of questions are about the challenges you may have faced. Please look at Card 29. In the past 12 months, did you *almost every* month, *some* months, *only 1 or 2 months*, or *never* do the following because there wasn't enough money for your home energy bill?**

		Almost Every Month	Some Months	Only 1 or 2 Months	Never
K-1a	SCALEA **Did you worry that you wouldn't be able to pay your home energy bill?**	1	2	3	4
K-1b	SCALEB **Did you reduce your expenses for what you consider to be basic household necessities?**	1	2	3	4
K-1c	SCALEC **Did you need to borrow from a friend or relative to pay your home energy bill?**	1	2	3	4
K-1d	SCALED **Did you skip paying your home energy bill or pay less than your whole home energy bill?**	1	2	3	4
K-1e	SCALEE **Did you have a supplier of your electric or home heating service threaten to disconnect your electricity or home heating fuel service, or discontinue making fuel deliveries?**	1	2	3	4
K-1f	SCALEF **Did you close off part of your home because you could not afford to heat or cool it?**	1	2	3	4
K-1g	SCALEG **Did you keep your home at a temperature that you felt was unsafe or unhealthy at any time of the year?**	1	2	3	4
K-1h	SCALEH **Did you leave your home for part of the day because it was too hot or too cold?**	1	2	3	4
K-1i	SCALEI **Did you use your kitchen stove or oven to provide heat?**	1	2	3	4

Figure 4.1: Survey questions used to measure Energy Security in 2005 RECS data

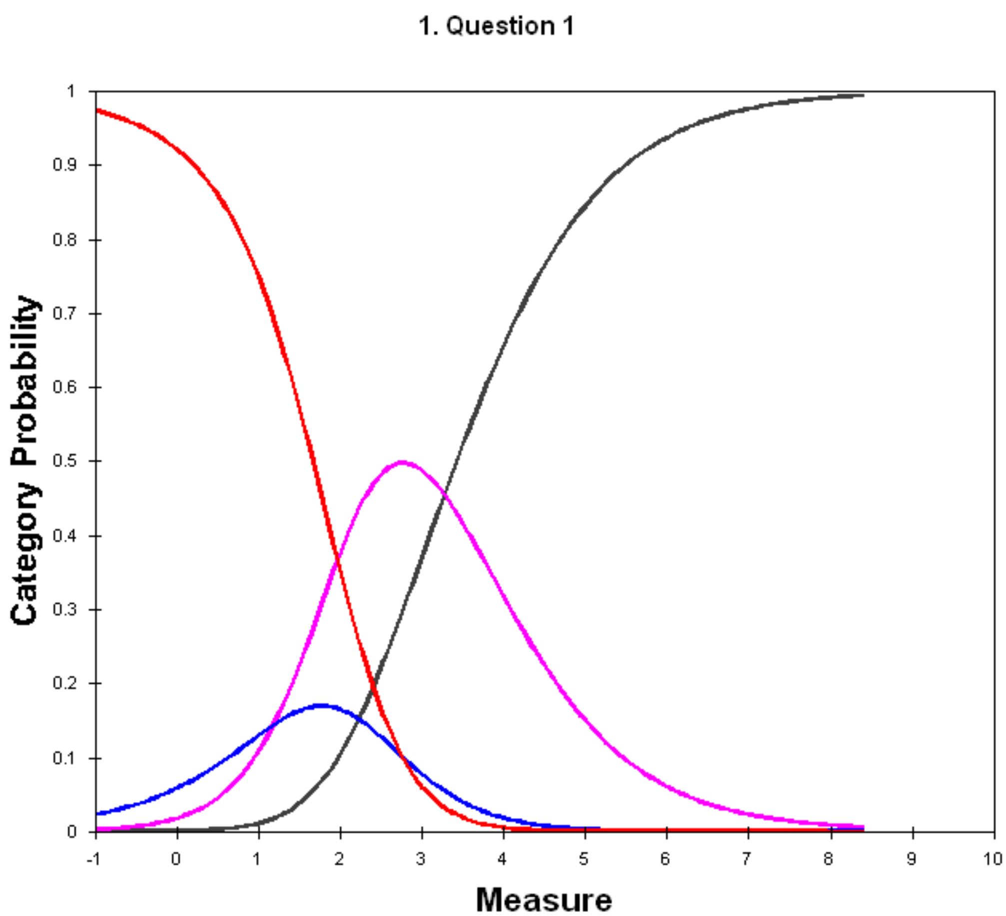

Figure 4.2: Unadjusted Category Response Probability Curves

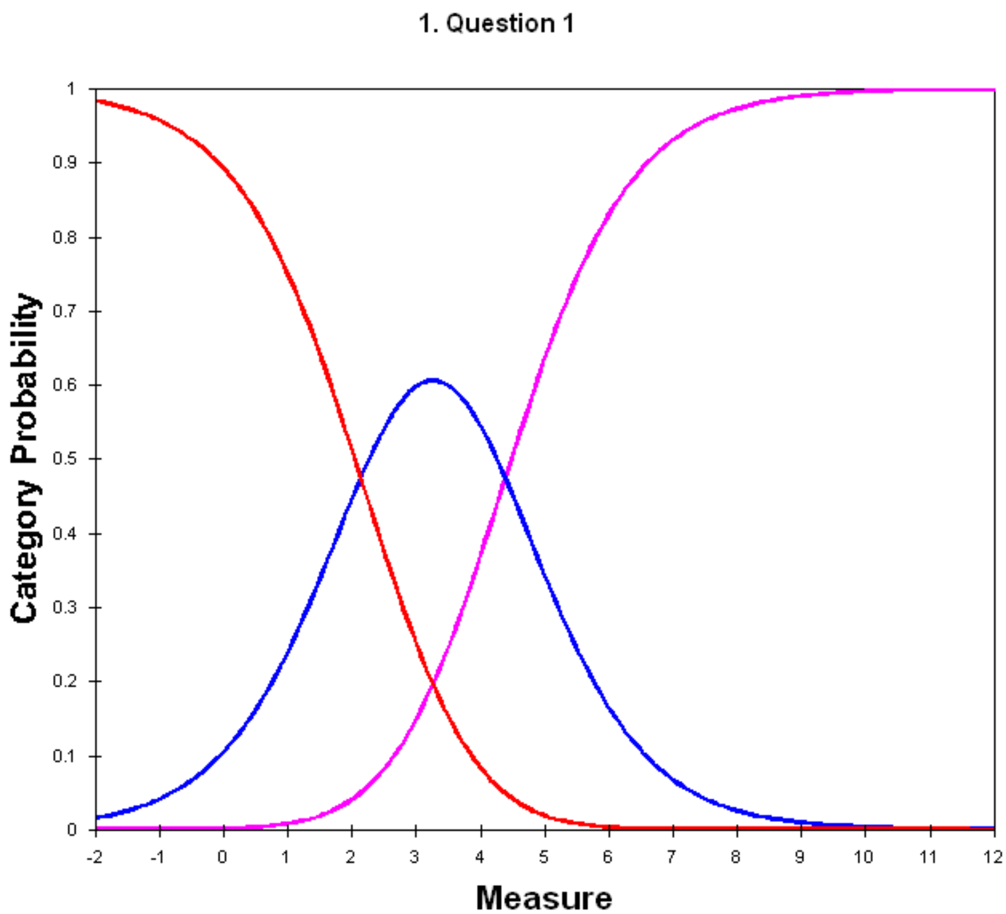

Figure 4.3: Adjusted Category Response Probability Curves

Table 4.10: Results using the Dichotomous Two Parameter Logistic Energy Insecurity Index

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits		—	-1.4373**	0.143
Black head of household	0.0760	0.125	0.4953**	0.120
Hispanic Head of household	-0.0164	0.147	0.0495	0.132
Non-White, Non-Black head of household	0.0617	0.141	-0.1080	0.126
Number of household members	0.0530	0.038	0.1658**	0.036
Household includes a child less than 6 years old	-0.0508	0.127	-0.2533*	0.116
House includes an elderly individual greater than 65	0.1798	0.123	-0.2968*	0.117
Household has someone at home during the day	-0.0104	0.101	-0.0502	0.095
Single-female head of household	0.2487*	0.112	0.2946**	0.105
Single-male head of household	-0.2920†	0.160	-0.2558†	0.146
Household Income ($\times$1000)	-0.0207**	0.007	-0.0201**	0.007
Receipt of cash benefits	0.5806**	0.118	0.4786**	0.117
Receipt of non-cash benefits	0.8520**	0.116	0.8427**	0.117
Household rents dwelling	0.0118	0.121	0.1695	0.112
Household resides in an apartment complex	-0.1496	0.138	-0.3992**	0.129
Household resides in a mobile home	-0.2703	0.171	-0.1119	0.152
Total square footage of dwelling	2.66 $\times e^{-5}$	4.96 $\times e^{-5}$	-2.31 $\times e^{-5}$	4.52 $\times e^{-5}$
Household has air conditioning	0.1668	0.125	0.1933	0.119
Price per kilowatt hour for electricity	-3.3724	2.335	-2.7394	2.206
Quality of house dummy variable	0.3948**	0.128	0.6863**	0.121
Dwelling built prior to 1970	—	—	0.1090	0.071
Household resides in a rural environment	-0.4038**	0.135	-0.2393†	0.128
Household resides in an urban environment	-0.2214*	0.109	-0.1914†	0.102
Annual cooling degree days	-3.53 $\times e^{-5}$	1.40$\times e^{-4}$	3.87 $\times e^{-5}$	1.25 $\times e^{-4}$
Annual heating degree days	1.63* $\times e^{-4}$	6.96 $\times e^{-5}$	1.33* $\times e^{-4}$	6.57 $\times e^{-5}$
New England	0.2741	0.282	0.0396	0.266
Mid Atlantic (excluding New York)	-0.2058	0.240	-0.5701*	0.225
East-North Central	-0.3029	0.224	-0.2992	0.208
West-North Central	-0.1640	0.248	-0.1546	0.226
South Atlantic (excluding Florida)	-0.0902	0.234	-0.4930*	0.210
East-South Central	-0.3295	0.253	-0.9844**	0.227
West-South Central (excluding Texas)	-0.7573†	0.457	-0.2491	0.285
Pacific (excluding California)	-0.5479*	0.275	-0.4157†	0.251
New York	-0.0694	0.345	-0.2063	0.317
California	0.1402	0.340	-0.1927	0.318
Texas	-0.2111	0.312	-0.1623	0.259
Florida	-0.1095	0.401	-0.1986	0.310
Constant	-1.2316	0.629	0.6254	0.587
ρ: 0.8871**			Log likelihood = -1636.16	

†: Significant at 10% level   *: Significant at 5% level   **: Significant at 1% level

Table 4.11: Results using the Polytomous Generalized Partial Credit Model Energy Insecurity Index

	LIHEAP Participation Equation		Energy Insecurity Equation	
Variable	Estimate	Std. Error	Variable	Std. Error
Household receives LIHEAP benefits	—	—	-1.3852**	0.146
Black head of household	0.0860	0.127	0.4037**	0.120
Hispanic Head of household	0.0090	0.149	0.0007	0.132
Non-White, Non-Black head of household	0.0298	0.142	-0.1129	0.125
Number of household members	0.0555	0.039	0.1586**	0.036
Household includes a child less than 6 years old	-0.0554	0.128	-0.2199†	0.116
House includes an elderly individual greater than 65	0.1885	0.124	-0.2930*	0.117
Household has someone at home during the day	-0.0096	0.103	-0.0652	0.095
Single-female head of household	0.2602*	0.113	0.2947**	0.104
Single-male head of household	-0.3296*	0.166	-0.2539†	0.146
Household Income (×1000)	-0.0207**	0.008	-0.0227**	0.007
Receipt of cash benefits	0.5840**	0.119	0.4976**	0.117
Receipt of non-cash benefits	0.8660**	0.118	0.8292**	0.117
Household rents dwelling	0.0225	0.123	0.1606	0.112
Household resides in an apartment complex	-0.1463	0.140	-0.3886**	0.129
Household resides in a mobile home	-0.2866†	0.172	-0.0577	0.152
Total square footage of dwelling	$2.06 \times e^{-5}$	$4.98 \times e^{-5}$	$-1.31 \times e^{-5}$	$4.51 \times e^{-5}$
Household has air conditioning	0.1728	0.126	0.1632	0.118
Price per kilowatt hour for electricity	-3.4374	2.353	-2.5682	2.201
Quality of house dummy variable	0.4015**	0.128	0.6600**	0.120
Dwelling built prior to 1970	—	—	0.0579	0.073
Household resides in a rural environment	-0.3795**	0.137	-0.2220†	0.128
Household resides in an urban environment	-0.2155†	0.111	-0.1377	0.102
Annual cooling degree days	$-3.97 \times e^{-5}$	$1.42 \times e^{-4}$	$6.65 \times e^{-5}$	$1.24 \times e^{-4}$
Annual heating degree days	$1.66^{*} \times e^{-4}$	$7.03 \times e^{-5}$	$1.46^{*} \times e^{-4}$	$6.56 \times e^{-5}$
New England	0.2143	0.284	0.0578	0.265
Mid Atlantic (excluding New York)	-0.2280	0.243	-0.4988*	0.225
East-North Central	-0.3291	0.227	-0.3112	0.208
West-North Central	-0.1916	0.251	-0.1064	0.226
South Atlantic (excluding Florida)	-0.1422	0.236	-0.4263*	0.210
East-South Central	-0.3488	0.255	-0.9198**	0.227
West-South Central (excluding Texas)	-0.8472†	0.440	-0.1376	0.284
Pacific (excluding California)	-0.5649*	0.280	-0.4149†	0.251
New York	-0.0631	0.345	-0.1372	0.317
California	0.1279	0.344	-0.0924	0.317
Texas	-0.2457	0.314	-0.1018	0.258
Florida	-0.2374	0.416	-0.0746	0.309
Constant	-1.2352*	0.639	0.5638	0.586
ρ: 0.8635**			Log likelihood = -1653.264	

†: Significant at 10% level *: Significant at 5% level **: Significant at 1% level

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Chapter 5

Essay 3: 'Food or Fuel': Calculating Elasticities to Understand 'Heat or Eat' behavior

5.1 Introduction

From 1999 through 2009 U.S. household energy costs increased rapidly. After adjusting for inflation, real electricity prices increased by almost 13 percent during the decade and real natural gas prices increased by almost 31 percent. As a share of household expenditures, energy expenditures increased by over one percent, while household food expenditures fell by 1.3 percent (Bureau of Labor Statistics). The sharp increase in costs to heat or cool a residence forces some consumers to make difficult choices. Researchers have examined the impact of higher prices on the increasingly constrained budgets of low-income households (Cassady, Jetter and Culp 2007, Bhattacharya et al. 2003). The core finding from this research is that many low-income households face an extremely difficult decision between heating a residence or eating. Rising prices and limited budgets of low-income households prevent them from choosing sufficient quantities of both, leading them to a choice of "heat or eat" (Bhattacharya et al. 2003). Empirical analysis of this trade-off, however, is far from complete. The results from most papers focus on health indicators, such as body mass index (BMI), while others look at changes in expenditure levels (Bhattacharya et al. 2003, Bhattacharya et al. 2004). But research to date has not generated elasticities to structurally determine how a change in energy prices affects household food consumption patterns.

Several papers do, however, provide significant insights on the heat or eat choice. Bhattacharya et al. (2003) focused on how unusually cold winters affect household consumption patterns using data on both expenditure patterns and dietary intake of households from the Consumer Expenditure Survey and the Third National Health and Nutrition Examination Survey, respectively. Harsh winters are found to force households of all income levels to increase expenditures on utilities to stay warm, but low-income households reduced food expenditures proportionally and high income households do not. The authors also acknowledge that southern households face different climatic conditions during the winter and estimate south-specific models. As expected, southern households did not increase fuel expenditures during the winter by as much as other households, but did react to cold-weather shocks by increasing their fuel consumption more than households in other regions of the country. Southern households do not, however, vary food expenditures in the face of cold weather shocks.

The Bhattacharya et al. (2003) article focuses on cold-weather shocks and primarily discusses how households adjust heating during the winter. While keeping warm in the winter is important, it is just as important to have residences cool during the summer in many regions, particularly in the South. According to the Energy Information Administration (EIA), over 81 percent of residences within the entire United States have some form of air conditioning. When only looking at those households residing in the southern Census region, over 96 percent of households have air conditioning. Air conditioning use during the summer significantly increases household energy consumption and expenditures. Southern households, with particularly high summer cooling needs, still may face a a "fuel or food" dilemma.

Nord and Kantor (2006) confirm the existence of a potential multi-seasonal "food or fuel" problem. They examine the link between food insecurity and household heating and cooling costs using logistic regressions and find that low-income households living in climates that require high-cost cooling or high-cost heating are more food insecure ceteris paribus. Further, low-income households living in cold climates experienced higher levels of food insecurity during the winter due to the costs of heating the residence, while low-income households that resided in warmer climates are more food insecure in summer because of the high-costs to cool their residence. Thus, low-income households make decisions between "cool or eat" as well as "heat or eat" depending on climate.

Household characteristics may also influence heat or eat choices. Due to their fixed income and physical conditions, elderly households may suffer most due to shocks in utility prices and rising energy needs with weather extremes. In fact, elderly households are found to be one of the most seasonally food insecure groups (Nord and Kantor 2006, O'Neill, Jinks and Squire 2006).

All of these studies have provided results supporting the existence of a food or fuel choice for low-income households within the United States, but none have attempted to calculate the cross-price elasticities associated with this trade-off. Elasticities are important because they provide a very simple, intuitive measure for how consumers react when prices change. Several studies have examined elasticities for food and electricity individually (e.g. Filippini 1995, Baker, Blundell and Micklewright 1989, Huang and Haidacher 1983, Huang 1996), but no study has attempted to estimate own and cross energy and food group price elasticities together in a demand system. Additionally, no study has used elasticity estimates to simulate how energy price shocks affect the food consumption levels of low-income households. While Nord and Kantor (2006) show that higher energy costs affect household food insecurity, quantifying energy-food trade-offs in low-income households will provide policy makers with information needed to understand the impacts that energy price shocks have on household food security and to design assistance programs and other safeguards to protect vulnerable households.

This paper generates own-price, cross-price, and expenditure elasticities using the Quadratic Almost Ideal Demand System (QUAIDS) of Banks et al. (1997), a refinement that better estimates non-linear Engel curves compared to the original Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980*b*). These elasticity estimates are then used to examine how energy price shocks impact household food consumption. There is significant evidence from many governmental reports that households in the South are unique. According to the 2008 LIHEAP Notebook, published by the Administration for Children and Families within the Department of Heath and Human Services, 10.1 percent of the low-income households in the South reported keeping temperatures at unsafe or unhealthy levels, a figure that is almost double other regions within the United States. Additionally, the report notes that Southern households report interruptions in service more frequently than the Midwestern or Northeastern regions. Finally, the South has a higher percentage of rural, low-income households compared to the rest of the United States (McGranahan, Cromartie and Wojan 2010). By uniquely identifying Southern households, it is possible to determine whether these differences result in different reactions to energy price changes.

5.2 Data

The paper relies on several data sources. Household expenditure data is obtained from the Bureau of Labor Statistics' Consumer Expenditure Survey (CES), a nationally representative survey that is published annually. Each annual publication includes four quarterly surveys that detail household expenditures and demographics. The survey includes very specific expenditure categories that encompass 95 percent of all expenditures within the household. Expenditures on housekeeping supplies, non-prescription drugs, and personal care products are the only excluded categories. The CES also reports aggregate quarterly household expenditures on food away from home, food at home, electricity, natural gas, fuel oil, and "other non-durables". The CES data cannot be considered a longitudinal survey because different households are interviewed over time. However, once a household is selected into the CES, it is interviewed for five consecutive quarters, allowing the BLS to track annual expenditures of each household. From 1999 until 2009, approximately 7,000 households are interviewed each quarter and 20 percent of the sample are first time respondents.[1]

One of the most difficult requirements for demand system estimation is finding accurate price data. The Council for Community and Economic Research (C2ER), which was formerly known as the American Chamber of Commerce Research Association (ACCRA) produces the ACCRA Cost of Living Index for the majority of metropolitan areas within the United States. The exact number of participating communities within individual states depends on the state size and fluctuates over time. Each quarter, enumerators record local prices for a specific set of goods. Since the enumerators are tasked with identifying prices for distinct goods, the local prices can be aggregated into quarterly state averages and compared across states. The ACCRA survey provides enough detail to generate a composite price for food at home, food away from home, and non-durable goods. The food away from home composite price includes prices of: McDonald's Quarter-Pounder with Cheese, a small 12 inch cheese pizza from Pizza Hut, and a two-piece fried chicken meal (dark meat) from Kentucky Fried Chicken or Church's. The food at home composite price is an average price of 24 produce,

[1] Future research should try to exploit the repeated quarterly observations of households to estimate the demand system as a panel.

meat, frozen, and dairy goods. Beginning in 2007, the ACCRA changed their reporting methodology. Instead of reporting four quarterly prices per year, they only report the first three quarters, meaning the index no longer reports a fourth quarter price. To include data from this time period, which includes the cold weather months, fourth quarter prices for 2007, 2008, and 2009 have to be imputed by averaging prices from the previous third quarter and subsequent first quarter.

The non-durable price index also needs to be highlighted. The ACCRA index only reports prices for a small set of goods and services. The CES "non-durable" category, however includes expenditures on a much broader range of goods. Additional data management is needed to limit the influence of expenditures on goods for which no price is recorded within the ACCRA index. Instead of using the non-durable household expenditures reported by the CES, household expenditures are extracted for 12 goods and services in the ACCRA index with prices.[2] These monthly expenditures are matched by household and aggregated into quarterly expenditures. A Paasche price index is then constructed from the price and expenditure information on these items. Households that do not consume any of non-durable goods are dropped from the price index and subsequent analysis.

Energy prices are reported from the Energy Information Administration (EIA). Quarterly averages are generated from monthly state electricity and natural gas prices available on the EIA website. Generating fuel oil prices, however, is not as simple. First, the EIA only reports fuel oil prices for half of the year and only for a few of the 50 states. During non-peak (spring and summer months) times, households still have expenditures on fuel oil, whether it be through payment agreements to smooth fuel oil costs over a longer time horizon or households purchasing it at lower prices during the off-season. An alternative measure of

[2]The set of goods include: residential phone line, vehicular tire balancing, doctor visit, dentist visit, men's haircut, women's salon, dry cleaning, men's dress shirt, washing machine repair, monthly newspaper service, one game bowling, and a movie theater ticket.

fuel oil prices has to be generated that reports quarterly prices for all states. The most feasible measure is monthly, non-taxed state gasoline prices. Several statistical measures validate this as a proxy for fuel oil prices. First, the correlation between the national spot price of gasoline and the spot price of fuel oil # 2 (the most common fuel oil) is over .90. Second, for those few states that have fuel oil prices reported, the state gasoline price and the fuel price also showed high correlation. Correlation can be seen in figure 1, where the monthly spot gasoline and fuel oil prices trend in a similar manner. A ratio of fuel oil to gasoline spot prices is used to weight state non-taxed gasoline prices to generate a valid quarterly fuel oil price for all states. Finally, monthly state level climate data are reported by the National Oceanic and Atmospheric Administration (NOAA) and freely available on their website. Since expenditure and pricing data are reported quarterly, monthly climate data are aggregated to quarterly averages as well.

The CES data suppresses identification of some states and some other states are only included in half of the 11 years of analysis. In total, 14 states are excluded from the analysis because of missing expenditure data.[3] Observations for Alaska and the District of Columbia have to be dropped as well since the NOAA does not report climate data for them. The 35 remaining state identifiers are used to match prices and climate data to consumers by state, quarter, and year.

Pooling the 44 quarters of data led to over 200,000 observations. Households who have negative expenditures in any category are omitted. Additionally, households who indicate no expenditures on food or fuel are dropped from the analysis. Out of the over 200,000 observations, only 3,470 households indicated having positive fuel oil expenditures. Not

[3]The 14 states dropped are: Arkansas, Hawaii, Iowa, Maine, Mississippi, Montana, New Mexico, North Carolina, North Dakota, Oklahoma, Rhode Island, South Dakota, Vermont, and Wyoming. Omission of these states is unavoidable, but should not significantly affect results since omitted states are from various regions of the country with different climates.

surprisingly over 75 percent of these households live within the Northeast region of the U.S. Therefore, the primary specification of the model only includes electricity and natural gas energy expenditure categories. The remaining three expenditure categories included in the five share demand system are food at home, food away from home, and non-durable goods. An alternative specification that includes fuel oil expenditures for those households with positive fuel oil costs is estimated in the appendix (table 5.8). Observations outside three standard deviations of the expenditure mean are trimmed from the sample, leading to a final sample of 122,218 households.[4]

Summary statistics on sample distribution by year, quarter, and region and dependent variable mean shares are listed in table 5.1. Summary statistics on sample household characteristics are listed in table 5.2. The number of observations per year (between 10,000 and 12,000) and quarter (all around 30,000) are roughly equal. There are larger differences in the number of observations per region, but this mainly stems from the southern region including both Texas and Florida, two of the four most populated and heavily surveyed states. Summary statistics reported within table 5.1 show the average share of each of the five commodity groups. A large portion of household expenditures are used for food purchases. Food at home expenditures average almost 39 percent of a household's total expenditures and food away from home use an additional 14 percent. Energy expenditures seem low for the sample, with natural gas and electricity shares averaging 4.5 and 11.6 percent respectively. The remainder of household expenditures are dedicated to the aggregated other non-durable share category. Poor households expenditure shares are different compared to

[4]Original sample includes 202,058 observations. Observations are omitted for the following reasons: All expenditures zero (1,734); Negative expenditure (1,313); Income less than zero (759); No expenditures on: non-durables (3,539), food and fuel (64,778), food (178), energy (7,087); Trim data to within three standard deviations of the mean of log expenditures (452). This leads to a final sample of 122,218. Table 5.7 shows that demographics did not change drastically due to the reduction in sample size, though there is a somewhat lower share of poor households in the final sample.

the full sample. Poor households spend a larger share on food at home (45.1 percent), less on food away from home (8.5 percent), slightly more on natural gas (4.9 percent), more on electricity (14.3 percent), and less on non-durables (27.1 percent).

Households headed by a Black represent 10.5 percent of the sample and 11.5 percent of the sample are households headed by a Hispanic (table 5.2). Households headed by a single female, traditionally one of the most vulnerable groups, account for 25.9 percent of the sample. The majority of the sample indicate having completed a high school degree and attended at least some college (53.5 percent) or actually completed a four year degree (36.1 percent). Only 12.2 percent of the sample include a child below the age of six, while almost twice as many households (23.9 percent) include an elderly individual older than 65 years of age. Less than ten percent of the sample indicate incomes that place them below the poverty line. Rural households are a very small portion of the sample as well. Only 1.34 percent of the entire sample live in a rural area due to the strict survey definition of what constitutes a rural household. According to the CES, only those households that live in an area with less than 2,500 people are considered rural households. Additionally, all rural households living within one of the 366 Metropolitan Statistical Areas (MSA) are defined as urban.

Several residential characteristics are included as well. The CES does not report total square footage of a residence, but does report the total number of rooms. While not always true, a house with more rooms generally has more square footage than a house with fewer rooms and requires more energy to cool or heat the residence. In this way, the number of rooms within a residence serves as a proxy for the square footage. Over 80 percent of the residences include some form of air conditioning as well. As expected, natural gas is the primary source of heat, used by over 59 percent of sample households and 28 percent of households use electricity to heat their homes. The remaining households use a mix of fuel oil, propane, kerosene, wood, or no fuel at all.

5.3 Demand System Estimation

Demand system estimation begins from the idea of utility maximization by rational consumers, providing a theory based foundation for analysis. Consumers are assumed to have continuous, strictly quasi-concave, and monotone utility functions and try to maximize these function values based on their constraints (Deaton and Muellbauer 1980*a*).

$$\max_{q} U(\mathbf{q}), \quad \text{subject to: } \mathbf{p}'\mathbf{q} = x, \tag{5.1}$$

where $\mathbf{p}$ and $\mathbf{q}$ are $n \times 1$ vectors of prices and quantities, and x indicates total expenditures. It is much easier for demand system estimation, however, to study the dual of utility maximization, cost or expenditure minimization.

$$c(u, p) = \min_{q} \mathbf{p}'\mathbf{q}, \quad \text{subject to: } U(x) = \bar{u}, \tag{5.2}$$

where $\bar{u}$ is some specified level of utility. The cost function shows the minimum level of expenditures needed to attain a given level of utility.

Additionally, demand analysis often uses the concept of weak separability or multi-stage budgeting to facilitate analysis. Consumers first allocate a portion of their budget to a specific bundle of goods. Consumers maximize their utility for that bundle of goods conditional on this original allocation. This assumption makes it possible to focus on a specific set of goods while ignoring other baskets, particularly savings and durable goods. Once a consumer partitions his budget into each weakly separable category, information on prices and total expenditure on goods within that category are the only relevant information needed (Deaton and Muellbauer 1980*a*).

The Almost Ideal Demand System of Deaton and Muellbauer (1980*b*) uses a representative consumer from the Price Independent Generalized Logarithmic (PIGLOG) class of models, meaning all consumers have the same set of preferences allowing for aggregation and utility maximization. The cost function is defined

$$\ln c(u,p) = \ln a(p) + ub(p), \tag{5.3}$$

The AIDS defines a specific parameterization for both $\ln a(p)$ and $b(p)$:

$$\ln a(p) = \alpha_0 + \sum_k \alpha_k \ln p_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj} \ln p_k \ln p_j \tag{5.4}$$

$$b(p) = \beta_0 \prod_k p_k^{\beta_k}, \tag{5.5}$$

leading to the cost function:

$$\ln c(u,p) = \alpha_0 + \sum_k \alpha_k \ln p_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj} \ln p_k \ln p_j + u\beta_0 \prod_k p_k^{\beta_k} \tag{5.6}$$

The AIDS model is normally written in budget share equations, which are simply the expenditures on good i over total expenditures. Equation 5.6 can be put in terms of x and p by substitution of the indirect utility function, leading to a budget share equation of:

$$\omega_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{x}{a(p)}\right), \quad \text{where} \tag{5.7}$$

$$x = \sum_{i=1}^{n} p_i q_i \quad \text{and} \tag{5.8}$$

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j \tag{5.9}$$

The budget share of each commodity is denoted as ω_i and total expenditures for all commodities are denoted as x. The parameters $\{\alpha_i, \beta_i, \gamma_{ij}\}$ are unknown parameters to be estimated.

The model must satisfy the Engel aggregation conditions (commonly referred to as the adding up restrictions), which require $\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \beta_i = 0$, and $\sum_{i=1}^{n} \gamma_{ij} = 0$. The model must also satisfy the homogeneity restriction,and the symmetry restriction,$\gamma_{ij} = \gamma_{ji}$. With all of these restrictions in place, the AIDS model conforms to the requirements of a flexible functional form, implying that it has sufficient parameters to be a feasible approximation to the true unknown cost function.

The AIDS model is one of the most common specifications to estimate many different types of demand systems. Its flexibility lends itself to estimation of very specific topics like differentiated carbonated beverages (Dhar, Chavas and Gould 2003) and more aggregate categories like food, clothing, and shelter (Deaton and Muellbauer 1980*b*). The model also allows for testing of economic theory. By estimating restricted and unrestricted demand equations, the homogeneity and symmetry restrictions can be tested. However, data must still conform to the assumptions of the AIDS model for it to be valid.

A strong, and often violated, assumption of the AIDS model is that Engel curves, the relationship between the share equation and log expenditure, are linear. If the Engel curves are non-linear in shape, the AIDS model will not accurately estimate the demand system, leading to flawed estimates. Instead, a slightly modified model must be estimated. This model, known as the Quadratic Almost Ideal Demand System (QUAIDS) developed by Banks et al. (1997), has many of the appealing features of the AIDS model, while allowing for the possibility of non-linear Engel curves.

The QUAID model is a “rank 3” model compared to the AIDS model which is only of “rank 2”. A rank 3 model is the highest rank any demand system can achieve that is linear in expenditures (Gorman 1981). Intuitively, higher ranking models allow for more flexibility and can better approximate non-linear Engel curves. Non-linear models, like the QUAIDS, allow goods to vary between necessities and luxuries depending upon income or expenditure levels (Fisher, Fleissig and Serletis 2001). Additionally, U.S. expenditure data has often been found to be best modeled by a rank 3 system (Lewbel 1990).

As expected, the QUAIDS model starts from generalized PIGLOG preferences. The original PIGLOG indirect utility function is modified by adding an additional term, $\lambda_i(\mathbf{p}) = \lambda_i \sum_i^n \ln p_i$. When this term approaches zero, the original PIGLOG preferences return (See Banks et al. (1997), Theorem 1 for full derivation). Using Roy's identity, the QUAIDS model in budget share form is

$$\omega_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{x}{a(p)}\right] + \frac{\lambda_i}{b(p)} \left\{ \ln \left[\frac{x}{a(p)}\right] \right\}^2 , \tag{5.10}$$

where x is total expenditures and $\ln a(p)$ is defined as in equation 5.4 and homogeneous of degree one in price. The term $b(p) = \prod_i^n p_i^{\beta_i}$ is homogeneous of degree zero in price.

Theory continues to require homogeneity, and symmetry to hold so that $\sum_j^n \gamma_{ij} = 0, \forall i$ and $\gamma_{ij} = \gamma_{ji}$. Engel aggregation requires an additional restriction due to the λ parameter that is part of the specification. Now, adding up requires $\sum_{i=1}^n \alpha_i = 1$, and $\sum_i \gamma_{ij} = \sum_i \beta_i = \sum_i \lambda_i = 0$. The QUAIDS model nests the AIDS model if $\lambda_i = 0, \forall i$.

Non-parametric local linear regressions shows the shape of the five Engel curves. A Gaussian kernel and rule of thumb bandwidth are used to estimate the regressions. If these nonparametric Engel curves reflect a linear relationship, the AIDS model can be used. Figure 2, however, suggests the Engel curves for most commodity groups are not linear. Therefore, the QUAIDS model is the preferred estimation method.

Demographics, time trends, and the QUAIDS model

Demand for goods and services often differ depending upon demographic characteristics and several different methods exist to incorporate demographic characteristics (such as race, ethnicity, or size of the residence) into a demand system. One of the simplest involves demographic translating (Pollak and Wales 1992), which is often used when estimating a QUAIDS model. Demographic translating decomposes the original intercept term, α_i. Instead of a single intercept term, it becomes $\tilde{\alpha}_i = \alpha_{0i} + \sum_{k=1}^{K} \delta_{ik} Z_k$, where $i = 1, \ldots, n$ indexes the number of share equations, and $k = 1, \ldots, K$ indicates the number of demographic characteristics included (Dhar et al. 2003). When demographics are added, theory restricts $\sum_{i=1}^{n} \delta_{ik} = 0, \forall k$.[5]

Additionally, seasonality and a time trend are added to the QUAIDS model. One method for incorporating time into the model is through the addition of "harmonic" variables. Harmonic variables are trigonometric variables that allow purchases to vary cyclically depending upon the season. The three harmonic variables used in the model are $\sin(.5\pi t), \cos(.5\pi t)$, and $\cos(\pi t)$. Past research in demand analysis has used harmonic variables to account for seasonality (e.g. Gould, Cox and Perali 1991, Arnade, Pick and Gehlhar 2004). A time trend t is also included in the data and parameter estimates, $\{\tau_{1i}^s, \tau_{1i}^c \tau_{2i}^c, \text{ and } \tau_i^t\}$, for the seasonal and time trends must sum to zero for the properties of the demand system to hold.

Therefore the QUAIDS model, including demographics and time variables, is defined as:

$$\begin{aligned} \omega_i &= \alpha_{0i} + \sum_{k=1}^{K} \delta_{ik} Z_k + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{x}{\tilde{a}(p)} \right] + \frac{\lambda_i}{b(p)} \left\{ \ln \left[\frac{x}{\tilde{a}(p)} \right] \right\}^2 \\ &\quad + \tau_{1i}^s \sin(.5\pi t) + \tau_{1i}^c \cos(.5\pi t) + \tau_{2i}^c \cos(\pi t) + \tau_i^t t \end{aligned} \tag{5.11}$$

where

$$\ln \tilde{a}(p) = \alpha_0 + \sum_{i=1}^{n} \alpha_{0i} \ln p_i + \sum_{i=1}^{n} \sum_{k=1}^{K} \delta_{ik} Z_k + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j \tag{5.12}$$

The sets of restrictions under this specification are:

[5] Future research might try to relax the assumption of linear demographics since economies of scale might exist for heating and cooling expenditures.

$$\gamma_{ij} = \gamma_{ji}, \qquad \textstyle\sum_{i=1}^{n} \alpha_{0i} = 1, \qquad \sum_{i=1}^{n} \gamma_{ij} = 0, \forall j,$$

$$\textstyle\sum_{i=1}^{n} \beta_i = 0, \qquad \sum_{i=1}^{n} \lambda_i = 0, \qquad \sum_{i=1}^{n} \delta_{ij} = 0, \forall k \tag{5.13}$$

$$\textstyle\sum_{i}^{n} \tau_{1i}^{s} = \sum_{i}^{n} \tau_{1i}^{c} = \sum_{i}^{n} \tau_{2i}^{c} = \sum_{i}^{n} \tau_{i}^{t} = 0$$

Elasticities

Elasticities are generated from differentiating equation 5.11 with respect to $\ln x$ and $\ln p_j$ (Banks et al. 1997).

$$\mu_i \equiv \frac{\partial w_i}{\partial \ln x} = \beta_i + \frac{2\lambda}{b(\mathbf{p})}\left\{\ln\left[\frac{x}{\tilde{a}(\mathbf{p})}\right]\right\} \tag{5.14}$$

$$\mu_{ij} \equiv \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum_k \gamma_{jk}\ln p_k\right) - \frac{\lambda_i\beta_j}{b(\mathbf{p})}\left\{\ln\left[\frac{x}{\tilde{a}(\mathbf{p})}\right]\right\}^2 \tag{5.15}$$

Using equations 5.14 and 5.15, the budget elasticity is defined as $e_i = \mu_i/\omega_i + 1$, the uncompensated price elasticity is $e_{ij}^{u} = \mu_{ij}/\omega_i - \delta_{ij}$, where δ_{ij} is the Kronecker delta, which equals one when $i = j$ or zero otherwise. Compensated demand uses the Slutsky equation, $e_{ij}^{c} = e_{ij}^{u} + e_i\omega_j$.

Empirical Strategy

Equation 5.11 is used to estimate the model and includes demographic variables for household size (number of members), residential size (number of rooms), logged climate data, and dummy variables for a black headed household, a Hispanic headed household, a rural household, a household residing in the Southern Census region, a single female headed household, a poor household, having less than a high school degree, and for not completing a four year college degree. These demographic characteristics have often been shown to significantly affect expenditures (e.g. Baker et al. 1989, Bhattacharya et al. 2004). Own-price, cross-price, and expenditure elasticity estimates are generated from this demand system. Since poor households often face the most severe "heat or eat" decision, elasticities are also estimated separately for the sub-sample of poor households.[6]

5.4 Results

Parameter estimates for the models will not be discussed as they provide no useful information by themselves.[7] Instead, elasticities are calculated from the parameter estimates using mean prices, expenditures, and demographics.

Elasticities for the full model and standard errors (in parentheses) are reported in table 5.3. All elasticity estimates are significant at conventional levels ($p = 0.05$). Expenditure elasticities indicate that food at home, natural gas, and electricity are all necessities, as expenditure elasticities are below one. Food away from home has an expenditure elasticity of 1.46, indicating it is a luxury good. It is not surprising to think of food away from home as a luxury good since it is not something essential to a household and can easily be substituted. By definition, demand for luxury goods increases more than a proportional increase in income. As income increases, a household's time for preparing food might become more valuable, leading to higher demand for quick, prepared meals out of the house. Previous research has found a similar expenditure elasticity for food away from home during a different time period (Reed, Levedahl and Hallahan 2005). Finally, the non-durable category has an expenditure

[6]Under this specification, only ten demographic variables are included and the data is subset to only include those households who earn an income below the poverty line.

[7]See table 5.9 in the Appendix for a detailed list of estimates for the full sample. Most parameters are significant at conventional levels ($p = 0.05$).

elasticity close to one. Attempting to define the category as a luxury good or necessity seems ill-advised. Only a few non-durable products are included within this category and caution must be used when interpreting this expenditure elasticity as representative of a more comprehensive set of goods.

Own-price elasticities are consistent with expectations as well. Food at home and food away from home show inelastic own-price elasticities of -0.75 and -0.64 respectively. It is not surprising that both exhibit inelastic demands since food is necessary for survival and the aggregate nature of the commodities leave few products as substitutes. Own-price elasticities for natural gas and electricity, however, show more elastic demand with estimates of -0.90 and -0.84. Taylor and Houthakker (2010) obtains a similar own-price electricity elasticity estimate of -0.7 using the ACCRA and CES data from 1996. As prices increase, households often use an assortment of "low cost curtailment" techniques to substitute away from energy costs, such as adjusting the thermostat to reduce energy costs, increasing passive heating and cooling measures within a residence (such as opening windows), or adding or removing layers of clothing instead of adjusting the thermostat (Black, Stern and Elworth 1985). Methods like these can be used to reduce energy consumption and as prices increases, these cost-saving methods are often highlighted by the media. Finally, non-durable goods exhibit slightly elastic own-price demand.[8]

Table 5.3 also includes the cross-price elasticities between goods. Cross-price elasticity estimates are described by row, then column. As an example, the cross-price elasticity for

[8]Results from the 6 share equation model (table 5.8) indicate problems in the estimation strategy when including fuel oil. Natural gas has an expenditure elasticity estimate greater than one. Elasticity estimates are the weakest of any specification, with only 14 of the 36 price elasticities being statistically significant ($p = 0.05$). Two of the three cross-price elasticity estimates for energy commodities and food at home are insignificant, while the third is only marginally significant ($p = 0.10$). Therefore little analysis could be drawn from the results. Future research should try to identify problems when incorporating fuel oil into the demand system.

electricity-food at home is -0.14, which shows how an electricity price shock impacts food at home expenditures. Alternatively, the cross-price elasticity of food at home-electricity is -0.06 and relates food at home price changes to electricity expenditures. Price shocks impact row commodities and depict the change in demand to the column commodity. Cross-price elasticities are of particular importance because they describe the heat or eat behavior of households. Results will focus on explaining the energy and food cross-price elasticity estimates because they describe how food expenditures change with an energy price shock.

Households in the full sample consider food and energy complements. Cross-price elasticity estimates reveal that expenditures on food fall when energy prices increase and expenditures on energy fall when food prices increase. Specifically, the cross-price estimate indicates that if electricity prices increase by one percent, demand for food at home falls by 0.14 percent. Natural gas price increases cause reductions in food at home expenditures with a cross-price elasticity estimate of -0.47. As expected, households view electricity and food away from home as weaker complements than electricity and food at home.

Cross-price elasticities within the energy commodities illustrate that natural gas and electricity are substitutes. When the price of electricity rises, households substitute away from it towards natural gas. It is not surprising that the two are substitutes since both provide services like heat. Even though electricity is used for power generation and heating, the cross-price elasticity estimates are very similar between natural gas and electricity (0.116 versus 0.113).

Poor households

Poor households are the most likely to face the “heat or eat” dilemma. Elasticity estimates for poor households (table 5.4) seem to confirm a more pronounced reaction to price changes. Own-price elasticity estimates for poor households are higher for food at home, natural gas, and electricity compared to the non-poor. As Bhattacharya et al. (2003) demonstrate, poor households have lower expenditure increases when prices increase and the elasticity estimates confirm this behavior. A price increase reduces demand of basic commodity groups more for poor households compared to non-poor households.

Many cross-price elasticities continue to show poor households react differently to price changes compared to the non-poor. While poor households have more elastic own-price elasticity estimates, the trade-off between goods is not as clear. Cross-price elasticity estimates for poor households are lower (in absolute value) for both natural gas-food at home (-0.38) and electricity-food at home (-0.03) compared to the full model, though the electricity-food at home estimate is statistically insignificant. Alternatively, it is possible to calculate elasticities for poor households using the full sample parameter estimates isolating only those households that indicate being poor (table 5.5). Using the sub-sample and full-model parameter, the cross-price elasticity estimate is significant (-0.11) and indicates that poor households still consider electricity and food at home complements. Under this specification, the cross-price elasticity estimate between natural gas and food at home is higher (-0.50) than either the full model or the specification that when poor households are estimated separately. It is not possible from the elasticity estimates alone to determine why poor households reduce food expenditures less with energy price shocks. Lower cross-price elasticity estimates might imply extremely constrained budgets for poor households who operate at a minimum necessary expenditure level for survival. Reductions in expenditures below these levels might endanger the well-being of family members, making elasticity estimates smaller and masking a more dangerous underlying problem.

Alternatively, true "heat or eat" behavior would indicate that poor households view food and fuel as substitutes. The lower cross-price elasticity estimates mean that poor households view food and fuel as weaker complements than the full sample for natural gas. The insignificant cross-price electricity-food at home estimate prevents establishment of any relationship between electricity and food. However, it is very unlikely that they are truly independent of each other. When using the precise definition of complements and substitutes, it is not surprising that the cross-price elasticities are smaller for poor households since this indicates that a weaker complementary relationship.

Southern households

Southern households are often categorized as regionally different based on climate and regional preferences compared to the rest of the United States. Most elasticity estimates do not support this characterization (table 5.6) when calculated using the Southern sub-sample population and full model parameter estimates. Both own-price and cross-price elasticity estimates for all commodity groups *except* natural gas are relatively similar to those from estimated under the full model. Southern households, however, do have significantly different cross-price elasticity estimates for natural gas. The natural gas own-price elasticity estimate for Southern households is quite similar to the full model estimate (-0.85 compared to -0.84). However, other cross-price elasticities, especially the natural gas-food at home cross-price elasticity estimate are quite different. Southern households view natural gas as a much stronger complement to food at home compared to the full model (-0.80 versus -0.47). Southern households continue to have a statistically significant negative cross-price elasticity estimate for electricity and food at home, but Southern households view the two commodity groups as weaker complements (-0.11 vs -0.14) compared to the full model. The differences in fuel-food cross-price elasticity estimates supports the notion that Southern households have unique preferences when looking at these two commodity groups, but many other elasticity estimates are quite similar between the full model.

5.5 Conclusions

Poor households exhibit heat or eat trade-offs in consumption behavior. When an energy shock causes energy prices to rise, poor households reduce consumption of food expenditures as well as the energy commodity. Specifically, estimates show that an energy price shock of 10 percent can lead to reductions in food at home expenditures up to five percent. Policy makers must realize that these energy shocks can lead to significant impacts on households in goods, especially food at home, that are not directly related to energy consumption.

Additionally, policy makers should expand and improve upon federal energy assistance programs. Future energy assistance programs can help safeguard poor households in ways not directly tied to utility bills. Energy assistance benefits that help poor households maintain food expenditure levels equal to pre-shock status would reduce the food or fuel trade-offs that low-income households make. The largest program, Low Income Home Energy Assistance Program (LIHEAP) has an annual budget less than one-tenth of the Supplemental Nutrition Assistance Program (SNAP), formerly called the food stamps program. Further, the LIHEAP currently has no method to help protect poor households from energy price shocks, nor a way to help maintain food expenditures. The low level of assistance suggests that improved energy assistance programs likely will lead to improved welfare for poor households in terms of both food and energy security.

Table 5.1: Year, Quarter, and Region Summary Statistics

Year	Sample Size	Quarter	Sample Size	Census Region	Sample Size
1999	10,358	1	30,667	Northeast	23,127
2000	10,518	2	30,656	Midwest	27,889
2001	10,706	3	30,459	South	40,947
2002	11,739	4	30,436	West	30,255
2003	12,185				
2004	11,711				
2005	12,329				
2006	11,445				
2007	10,386				
2008	10,449				
2009	10,392				
Total:	122,218		122,218		122,218

	Full Sample		Poor Households	
Expenditure Share	Mean	Std. Err	Mean	Std. Err
Food at home	0.386	0.159	0.451	0.172
Food away from home	0.139	0.130	0.086	0.112
Natural gas	0.045	0.065	0.049	0.076
Electricity	0.116	0.079	0.144	0.098
“Other” non-durables	0.314	0.167	0.271	0.163
		$N = 122,218$		$N = 10,784$

Table 5.2: Household Summary Statistics

Variable	Mean	Std. Error
Household headed by a Black	0.105	0.306
Household headed by a Non-White, Non-Black	0.040	0.196
Household headed by a Hispanic	0.115	0.319
Household head is married	0.579	0.494
Household headed by a single female	0.259	0.438
Household headed by a single male	0.162	0.368
Age of head of household	49.32	16.75
Head of Household did not graduate high school	0.104	0.305
Head of Household attended some college, but did not graduate	0.535	0.499
Head of household completed college or higher degree	0.361	0.480
Household size	2.64	1.50
Household includes a child less than 6	0.122	0.328
Household includes elderly individual $>$ 65	0.239	0.427
Log of household income	10.634	0.937
Household rents dwelling	0.267	0.442
Household earns income at or below poverty line	0.088	0.284
Household is in a rural environment	0.013	0.115
Number of rooms within residence	6.058	2.22
Residence has air conditioning	0.811	0.392
Household heated by natural gas	0.591	0.492
Household heated by a electricity	0.281	0.450
Log climate (degrees Fahrenheit)	3.976	0.312
Log total expenditures	7.122	0.609
N = 122,218		

Table 5.3: Own-, Cross-price, and Expenditure Elasticities and Standard Errors: Full Model

	Food: Home	Food: Away	Natural Gas	Electricity	Non-durables	Expenditure
Food: Home	-0.746*	-0.080*	-0.034*	-0.059*	0.023*	0.896*
	(0.015)	(0.013)	(0.004)	(0.005)	(0.010)	(0.004)
Food: Away	-0.346*	-0.639*	-0.139*	-0.077*	-0.263 *	1.463*
	(0.035)	(0.041)	(0.010)	(0.011)	(0.025)	(0.007)
Natural Gas	-0.474*	-0.069*	-0.902*	0.113*	0.495*	0.838*
	(0.033)	(0.030)	(0.017)	(0.014)	(0.031)	(0.015)
Electricity	-0.143*	-0.047*	0.116*	-0.836*	0.217*	0.693*
	(0.015)	(0.014)	(0.006)	(0.009)	(0.013)	(0.004)
Non-durables	-0.039*	-0.035*	0.047*	0.030*	-1.062*	1.059*
	(0.012)	(0.011)	(0.004)	(0.005)	(0.015)	(0.005)

$N = 121,435$ $\quad$ * = significant at $p = 0.05$

Table 5.4: Own-, Cross-price, and Expenditure Elasticities and Standard Errors: Poor households

Poor households

	Food: Home	Food: Away	Natural Gas	Electricity	Non-durables	Expenditure
Food: Home	-0.851*	-0.069*	-0.039*	-0.034*	0.012	0.982*
	(0.047)	(0.035)	(0.012)	(0.015)	(0.031)	(0.011)
Food: Away	-0.523*	-0.224	-0.312*	-0.049	-0.364*	1.471*
	(0.184)	(0.209)	(0.049)	(0.059)	(0.121)	(0.035)
Natural Gas	-0.384*	-0.382*	-0.997*	0.167*	0.634*	0.962*
	(0.114)	(0.085)	(0.061)	(0.054)	(0.100)	(0.049)
Electricity	-0.033	-0.014	0.102*	-0.946*	0.123*	0.768*
	(0.048)	(0.036)	(0.018)	(0.031)	(0.040)	(0.012)
Non-durables	0.004	-0.053	0.109*	0.013	-1.085*	1.012*
	(0.051)	(0.038)	(0.017)	(0.021)	(0.053)	(0.019)

$N = 10,715$ $\quad$ * = significant at $p = 0.05$

Table 5.5: Own-, Cross-price, and Expenditure Elasticities: Poor Households (full model parameters)

Poor households	Food: Home	Food: Away	Natural Gas	Electricity	Non-durables	Expenditure
Food: Home	-0.797*	-0.064*	-0.039*	-0.051*	0.020*	0.932*
	(0.013)	(0.011)	(0.003)	(0.004)	(0.009)	(0.004)
Food: Away	-0.518*	-0.426*	-0.198*	-0.125*	-0.424*	1.691*
	(0.056)	(0.067)	(0.016)	(0.018)	(0.041)	(0.014)
Natural Gas	-0.498*	-0.049†	-0.948*	0.104*	0.459*	0.933*
	(0.031)	(0.028)	(0.016)	(0.013)	(0.029)	(0.012)
Electricity	-0.112*	-0.039*	0.095*	-0.868*	0.175*	0.749*
	(0.012)	(0.011)	(0.005)	(0.007)	(0.011)	(0.003)
Non-durables	-0.024	-0.045*	0.068*	0.035*	-1.073*	1.039*
	(0.015)	(0.013)	(0.005)	(0.006)	(0.017)	(0.004)

$N = 10,715$ * = significant at $p = 0.05$

† = significant at $p = 0.10$

Table 5.6: Own-, Cross-price, and Expenditure Elasticities and Standard Errors: Southern households

Southern Households	Food: Home	Food: Away	Natural Gas	Electricity	Non-durables	Expenditure
Food: Home	-0.746*	-0.080*	-0.036*	-0.060*	0.022*	0.899*
	(0.015)	(0.013)	(0.004)	(0.005)	(0.010)	(0.004)
Food: Away	-0.345*	-0.634*	-0.139*	-0.079*	-0.268*	1.465*
	(0.035)	(0.042)	(0.010)	(0.011)	(0.026)	(0.008)
Natural Gas	-0.799*	-0.111*	-0.846*	0.185*	0.817*	0.755*
	(0.055)	(0.050)	(0.029)	(0.024)	(0.052)	(0.025)
Electricity	-0.114*	-0.037*	0.091*	-0.870*	0.172*	0.758*
	(0.012)	(0.011)	(0.004)	(0.007)	(0.011)	(0.003)
Non-durables	-0.038*	-0.036*	0.049*	0.031*	-1.063*	1.056*
	(0.013)	(0.011)	(0.004)	(0.005)	(0.015)	(0.005)

$N = 40,778$ * = significant at $p = 0.05$

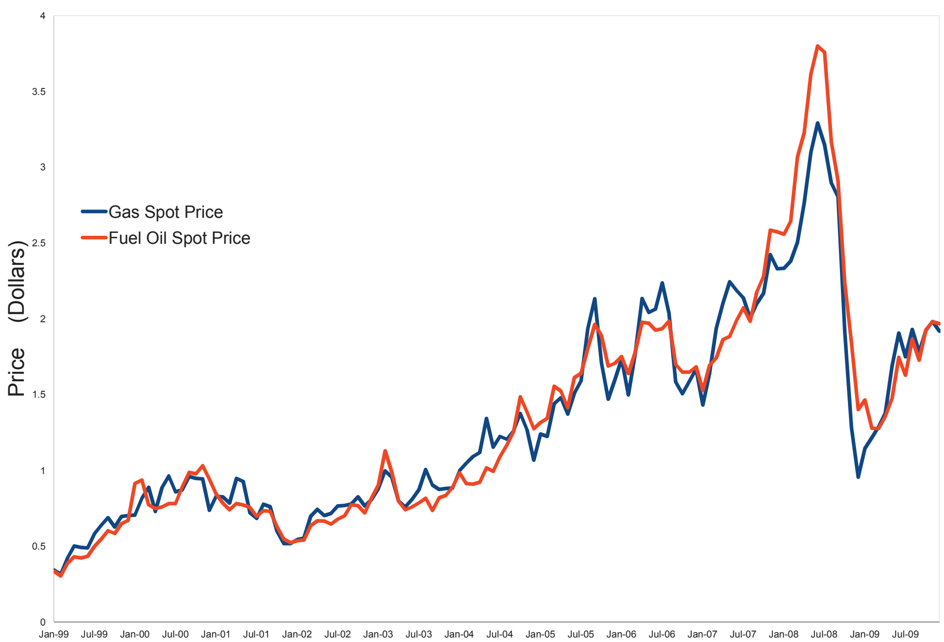
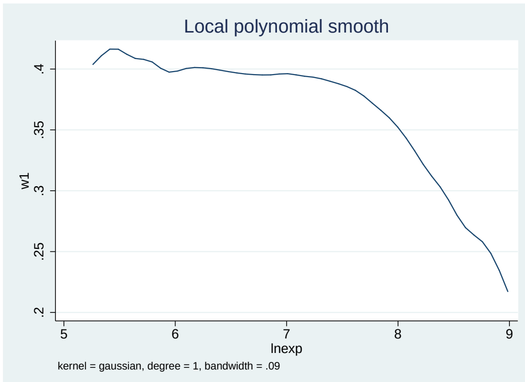
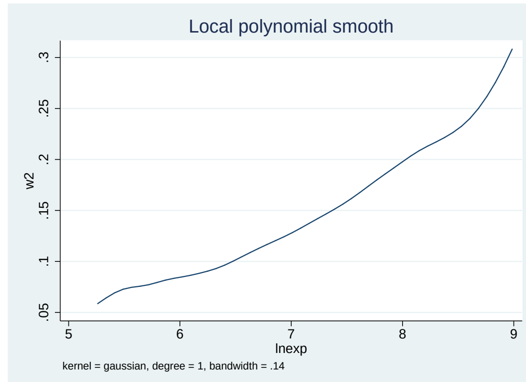


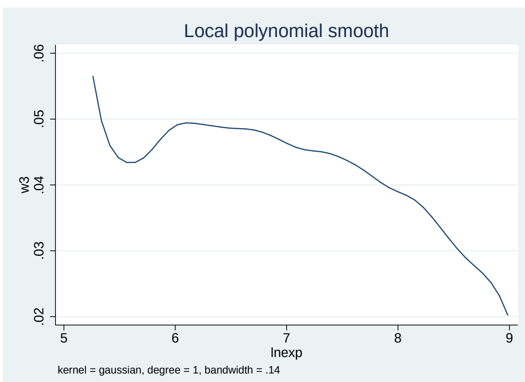
Figure 5.1: Monthly National Spot Prices of Gasoline and Fuel Oil # 2



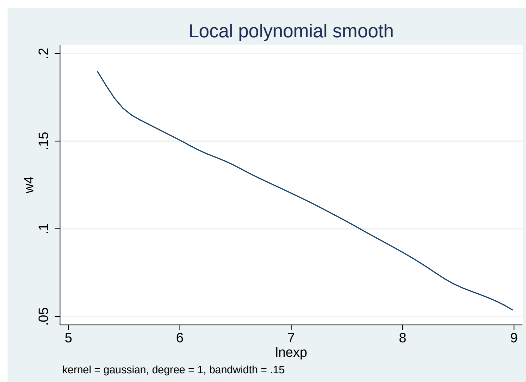
(a) Food at home budget share



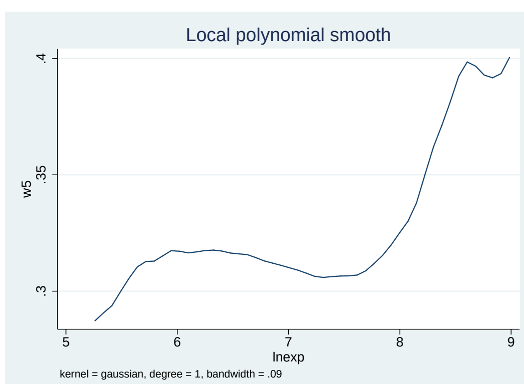
(b) Food away from home budget share



(c) Natural gas budget share



(d) Electricity budget share



(e) Non-durables budget share

Figure 5.2: Nonparametric Engel Curves by Share

Table 5.7: Parameter Estimates: Full Model

					No expenditures on:				
	Initial Sample	All Expend. = 0	Expenditures < 0	Income < 0	Non-durables	Food and Fuel	Food	Fuel	Trimmed Data
Percentage Hispanic	11.8	11.73	11.76	11.77	11.57	11.67	11.67	11.48	11.5
Percentage Black	10.48	10.4	10.44	10.45	10.3	40.52	10.51	10.45	10.46
Percentage Poor	10.08	9.89	9.92	9.83	9.44	9.51	9.47	8.87	8.83
Sample observations	202058	200324	199011	198252	194713	129935	129757	122670	122218
Observations Dropped	—	1734	1313	759	3539	64778	178	7087	452

5.6 Appendix Tables

Table 5.8: Own, Cross, and Expenditure Elasticities, 6 share equations including fuel oil

	Food: Home	Food: Away	Natural Gas	Electricity	Fuel Oil	Non-durables	Expenditure
Food: Home	-1.113*	-0.106	0.012	0.037*	-0.062	0.296*	0.937*
	(0.104)	(0.076)	(0.019)	(0.029)	(0.053)	(0.071)	(0.048)
Food: Away	-0.441*	-0.762*	-0.028	-0.022	-0.190*	-0.183	1.618*
	(0.213)	(0.247)	(0.054)	(0.067)	(0.074)	(0.152)	(0.037)
Natural Gas	0.498	-0.585	-2.350*	0.821*	0.120	0.404	1.091*
	(0.728)	(0.703)	(0.318)	(0.254)	(0.269)	(0.524)	(0.137)
Electricity	0.177†	0.012	0.073*	-0.928*	-0.045	-0.051	0.765*
	(0.095)	(0.084)	(0.024)	(0.048)	(0.044)	(0.079)	(0.022)
Fuel Oil	-0.097	0.044	0.001	-0.057*	-0.639*	0.003	0.749*
	(0.060)	(0.051)	(0.013)	(0.024)	(0.052)	(0.057)	(0.028)
Non-durables	0.302*	0.010	0.015	-0.044†	-0.077†	-0.944*	1.057*
	(0.075)	(0.065)	(0.016)	(0.027)	(0.044)	(0.219)	(0.031)

$N = 121,435$

* = significant at $p = 0.05$

† = significant at $p = 0.10$

Table 5.9: Parameter Estimates: Full Model

Parameter	Estimates	Std. Error	Parameter	Estimates	Std. Error
α_1	0.082*	0.0311	δ_{22}	0.022*	0.0023
α_2	-0.081*	0.0262	δ_{32}	-0.056*	0.0011
α_3	0.086*	0.0122	δ_{42}	0.006*	0.0013
α_4	0.245*	0.0149	δ_{13}	-0.007*	0.0002
β_1	0.125*	0.0098	δ_{23}	-0.004*	0.0002
β_2	-0.022*	0.0077	δ_{33}	0.004*	0.0001
β_3	0.063*	0.0040	δ_{43}	0.004*	0.0001
β_4	-0.044*	0.0047	δ_{14}	0.063*	0.0016
γ_{11}	0.035*	0.0098	δ_{24}	-0.044*	0.0013
γ_{12}	-0.018*	0.0058	δ_{34}	0.013*	0.0007
γ_{13}	-0.049*	0.0029	δ_{44}	0.025*	0.0008
γ_{14}	-0.011*	0.0029	δ_{15}	0.027*	0.0010
γ_{22}	0.042*	0.0058	δ_{25}	-0.015*	0.0008
γ_{23}	0.002	0.0021	δ_{35}	0.004*	0.0004
γ_{24}	-0.005*	0.0019	δ_{45}	0.016*	0.0005
γ_{33}	-0.010*	0.0018	δ_{16}	-0.009*	0.0010
γ_{34}	0.013*	0.0013	δ_{26}	-0.021*	0.0009
γ_{44}	0.008*	0.0017	δ_{36}	0.005*	0.0004
α_1^c	0.006*	0.0007	δ_{46}	0.003*	0.0005
α_2^c	$3.60\times e^{-4}$	0.0006	δ_{17}	0.035*	0.0016
α_3^c	-0.014*	0.0003	δ_{27}	-0.016*	0.0013
α_4^c	0.006*	0.0004	δ_{37}	0.004*	0.0006
α_1^s	0.004*	0.0011	δ_{47}	0.010*	0.0008
α_2^s	-0.003*	0.0009	δ_{18}	0.013*	0.0015
α_3^s	$-8.93\times e^{-6}$	0.0004	δ_{28}	0.008*	0.0012
α_4^s	$-1.02\times e^{-6}$	0.0005	δ_{38}	$-0.001^\dagger$	0.0006
α_1^t	$4.69^* \times e^{-4}$	$4.56\times e^{-5}$	δ_{48}	-0.011*	0.0007
α_2^t	0.002*	$3.95\times e^{-5}$	δ_{19}	0.029*	0.0037
α_3^t	$3.40^* \times e^{-4}$	$1.70\times e^{-5}$	δ_{29}	-0.015*	0.0030
α_4^t	$4.28^* \times e^{-4}$	$1.94\times e^{-5}$	δ_{39}	-0.024*	0.0015
λ_1	-0.014*	0.0009	δ_{49}	0.010*	0.0018
λ_2	0.008*	0.0006	δ_{110}	-0.026*	0.0014
λ_3	-0.006*	0.0004	δ_{210}	-0.024*	0.0012
λ_4	$0.001^\dagger$	0.0004	δ_{310}	0.018*	0.0006
δ_{11}	0.028*	0.0003	δ_{410}	0.009*	0.0007
δ_{21}	-0.015*	0.0003	δ_{111}	-0.009*	0.0013
δ_{31}	-0.002*	0.0001	δ_{211}	-0.001	0.0010
δ_{41}	0.002*	0.0002	δ_{311}	-0.019*	0.0005
δ_{12}	0.030*	0.0028	δ_{411}	0.040*	0.0006

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