IDENTIFYING THE EFFECTS OF ENERGY EFFICIENT HOUSES ON ENERGY COMSUMPTION

By

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To my mother Beatrice Aka in Tunis (Tunisia), my husband Kenneth Watkins and loving family in Abidjan (Cote d'Ivoire) and in the United States

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AECC	American Council for Energy-Efficient Economy
AR	Auto Regression
CMP	Cost Minimization Problem
DID	Difference-in-Difference
DOE	Department of Energy
EC	Energy Consumption
EPA	Environmental Protection Agency
ES	Energy Star
FE	Fixed Effect
FEMP	Federal Energy Management Program
GHG	Green House Gas
GISS	Goddard Institute for Space Studies
GLS	Generalized Least Squares
GRU	Gainesville Regional Utilities
HERS	Home Energy Rating System
IPCC	Intergovernmental Panel for Climate Change
kWh	Kilowatt hours
NASA	National Aeronautics and Space Administration
OLS	Ordinary Least Squares
PTSCS	Pooled Time Series Cross-Section
RESNET	Residential Energy Services Network
TSCS	Time Series Cross-Section
US	United States

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As environmental protection and conservation have become prominent policy issues in light of global warming, various proposals have been made regarding how to decrease greenhouse emissions, a key factor in raising global temperatures (IPCC, 2007). For example, Energy Star is a joint program of the United States Environmental Protection Agency (EPA) and the Department of Energy (DOE) that provides strict energy efficient guidelines which make an Energy Star home have a better performance in terms of energy use over time. By better performance, we mean lower energy consumption at the meter. Thus, those houses which are rated as Energy Star will use less energy than those houses which lack this rating. The first Energy Star home was built in Gainesville, Florida in 1997. Since then, the number of Energy Star homes built in Gainesville has steadily risen. Although energy savings of at least 15% are ratified for new homes, little is known of the performance of these homes over time. Results suggest that over time there is an increase of energy consumption of houses rated as Energy Star. We conclude that these guidelines are effective in reducing energy consumption when the house is built but they may not hold energy savings over time.

CHAPTER 1
INTRODUCTION

It is no secret today that the face of our planet is rapidly changing. In fact, according to the Intergovernmental Panel on Climate Change (IPCC) Annual report 2007, climate change or global warming due to increased greenhouse gas (GHG) emissions in the process of fossil fuel-based energy production (coal, oil and natural gas) is one of the most significant environmental challenges that we are facing as a global society.

According to the Earth Policy Institute, “since 1970, the earth’s average temperature has risen by 0.8 degrees Celsius, or nearly 1.4 degrees Fahrenheit. During this span, the rise in temperature each decade was greater than in the preceding one”. The same climate studies conducted by the Goddard Institute for Space Studies (GISS) show that the last two decades of the 20th century's were the hottest in 400 years and possibly the warmest for several millennia**.** Industrialization, deforestation, and pollution have greatly increased atmospheric concentrations of water vapor, carbon dioxide, methane, and nitrous oxide which are all greenhouse gases that help trap heat near Earth's surface. In other words, Humans are pouring carbon dioxide into the atmosphere much faster than plants and oceans can absorb it according to the IPCC**.** Based on the 2005 Residential Energy Consumption Survey, out of the four most populated states, Florida has the highest average electricity consumption per household with 15,862 kilowatts (kWh) followed by Texas (15,149 kWh), California (6,992 kWh) and New York (6,882 kWh).

According to the IPCC Annual Report 2001, with such temperature changes are associated lost of densely populated areas, such as low-lying coastal regions, glacier retreat, Arctic shrinkage, an altered patterns of agriculture. Secondary and regional effects include extreme weather events, an expansion of tropical diseases, changes in the timing of seasonal patterns in ecosystems, and an overall tremendous economic impact.

Since our environment is being threatened by significant environmental and economic consequences due to climate change, there is an apparent need for environmental protection and conservation efforts. Over the years, several energy efficiency policies have been initiated in the effort of reducing greenhouse gas emissions. One of those initiatives, the Energy Star (ES) program was created in 1993 as a joint program of the United States (US) Environmental Protection Agency (EPA) and the US Department of Energy (DOE) in the effort of reducing energy cost and protecting the environment through the implementation of energy efficient products and practices. Computers and monitors were the first labeled products. Today the EPA has extended the label to cover new homes, commercial and industrial buildings.

During the past years of execution of this voluntary program, the EPA has published several annual reports reflecting the performance of this initiative. In fact, the EPA 2001 report states that so far 80 billion kilowatt hours of energy have been saved; over 57,000 Energy Star rated homes were built which corresponds to savings of more than $15 million annually from lower energy costs. Although EPA reports claim significant energy savings and despite the theoretical as well as practical interest in energy efficient policies, a very slim body of the academic literature examines the performance of such programs over time.

Most studies in the current literature investigate the relationship between implementing energy efficiency policies, energy consumption and cost-effectiveness with a positive effect of such programs in reducing energy consumption as well as increasing energy savings. However, little is known about performance over time. This study will therefore help to further our understanding of efficiency programs by examining specifically how such initiatives like the ES program actually perform over time. We do so by identifying the effect of the ES rating on energy consumption in Gainesville, Florida. After performing a Difference-in-Difference

estimation (DID) using monthly energy consumption data of 5664 single-homes for the years 2000 and 2006, results suggest that over time there is an increase of energy consumption of houses rated as Energy Star of roughly 7.59%. These results lead to the conclusion that energy efficiency guidelines are successful in reducing energy consumption when the house is built but they do not maintain energy savings over time.

These results are even more compelling knowing that in terms of market penetration, Gainesville is one of the most productive markets for ES homes nationwide. In fact, the first ES home was built in 1997. Since then, the number of ES homes built in Gainesville has steadily risen (Smith and Jones, 2003). In fact, as in 2006 about "769 homes have been certified under the Energy Star program in Alachua County, which can include homes inside and outside the Gainesville city limits" (Crabbe, 2006). Energy Star certified home builders in the area include well known companies such as Atlantic Design Homes and G.W. Robinson. In addition, this study is the first to employ a DID estimator as a tool to evaluate the performance of the ES rating. It also includes four different control groups in the analysis in order to avoid the limitations of this evaluation method.

Since the initial DID uses only the years 2000 and 2006, the sample size is expanded to cover bill years from 1996 to 2008 with the intention of strengthening the results by capturing any existing trends in consumption. With this new yearly time series cross-sectional data created, the study adopts additional econometric methods such as pooled Ordinary Least Squares (OLS) and fixed effect models. Only yearly electricity consumption is analyzed and divided into a total, winter, summer and other consumption (i.e. off season consumption).With the pooled OLS estimation, ES homes consume 34.695 kWh more during the winter and 51.374 kWh more during the summer than non-ES homes. The results are statistically significant. ES homes'

consumption decreases by 18.54 kWh and 1.846 kWh respectively for the total and other consumption. However, these results are not significant. A downfall of the pooled OLS model is that is ignores heterogeneity between the houses and leads to inaccurate conclusions.

The panel data models on the other hand, incorporate a time trend variable that captures a time effect in the relationship between energy efficient construction and household electricity consumption, while controlling for house specific effects. With the fixed effect models, houses rated ES consume 89.63kWh of electricity more than traditional houses. During the summer these houses also consume 74.320 kWh more than traditional houses and 34.22 kWh more during the off season months. Consumption decreases by 61.57 kWh for ES homes during the winter. This change can be explained by the seasonality of electricity consumption. It is important to note that all of these results are statistically significant at the 5% significance level with a P-value of 0.000. Finally, another DID performed using the yearly time series cross-sectional data reveals that ES homes consumes 4.989 kWh more than traditional home during the winter, 12.086 kWh more during the summer and 13.13 kWh more in total consumption. Yet, ES houses consume 3.942l kWh less than traditional homes during the off-season months. Winter and off season results are not statically significant.

The main finding is that when using a longer time series cross-sectional data, ES houses on average consume more electricity that traditional homes, especially during the summer months. This difference in levels of consumption between the two types of homes also increases over time. The balance of the thesis is organized as follows: Chapter 2 presents the literature review. Chapter 3 discusses the conceptual framework, methodology, and data used in the study. Chapter 4 presents energy consumption analysis using a DID estimation for the years 2000 and 2006. In Chapter 5 a pooled cross sectional data and fixed effect estimation are performed as well as

another DID estimation using yearly electricity consumption. Finally, concluding thoughts and future research follow in chapter 6.

CHAPTER 2
LITERATURE REVIEW

The purpose of this chapter is to review the current literature on the effect of energy efficiency initiatives and policies on energy consumption, homeownership costs, public investments, land use patterns and regulations. In order to do so, a working definition of energy efficiency program is required. In addition, predictors of energy consumption are also outlined.

In this chapter, section 2.1 provides a working definition of energy efficiency and describes an example of an energy efficiency program of interest in this study implemented in the US: the Energy Star program. Section 2.2 summarizes the impact of energy efficiency efforts on homeownership costs, investment and land use patterns. Predictors of household energy consumption are also discussed. Finally, section 2.3 presents the conclusion of the literature review.

2.1 Energy Efficiency Programs

According to the American Council for Energy-Efficient Economy (AECC), an Energy Efficient Program is "an organized effort to try to encourage and facilitate customer implementation of energy efficiency improvements (residential and business)". By energy efficiency improvements the author means measures that result in producing the same or better levels of amenities such as light, space conditioning, heating, motor drive power, etc…while using less energy (Kushler, 2009).

The main idea of Energy Efficiency as a utility system resource is that utility systems need to have adequate supply resources to meet customer demand. Faced with an increasing energy demand, one can increase supply of energy resources; reduce customer demand or a combination of both in order to keep the system in balance. With the reality of rising greenhouse emissions due to human activity associated with climate change threatening our environment and

economy, it is literally in all cases today vital for the overall welfare of society to reduce consumer demand for energy consumption, especially demand for electricity and natural gas.

While Load Management programs only seek to reduce peak demand during specific, limited time periods, by temporarily restraining electricity use or shifting usage to other time periods, Energy Efficiency programs seeks to reduce energy demand at all times, reduce total energy consumption, lessen consumption of natural resources, decrease greenhouse gas emissions associated with energy consumption and thus trim down national energy import and energy dependence.

As a result according to the American Council for Energy-Efficient Economy, the following factors are key element in the implementation of an Energy Efficiency program:

- Public information, education and training
- Economic incentives for consumers (i.e. rebates, tax credit)
- Quality control, monitoring and evaluation

With the new administration in place putting forwards a new Stimulus Package, the government is furthermore active in the “implementation of sound, cost-effective energy management and investment practices to enhance the nation's energy security and environmental stewardship” according to the DOE's Federal Energy Management Program (FEMP). Thus, this study focus on a specific example of an Energy Efficient program: the Energy Star program, which is discussed in more details in the following sub-section.

2.1.1 The Energy Star Program

Energy Star is a term that includes a wide array of programs, all designed to promote energy efficient investments. In fact, the Energy Star initiative began with a limited agenda in the early 1990s, after the 1992 Energy Policy Act directed by the EPA. The idea was to implement a program that will identify and designate particularly energy efficient products and provide

estimates of the relative energy efficiency of those products. In addition, this legislation was designed to reward the most energy efficient products with positive advertising, thereby encouraging consumers to buy those products and other manufacturers to improve the energy efficiency of their own products. The Energy Star designation is completely voluntary and has been used by manufacturers as a selling point. Currently, the EPA and DOE jointly run the voluntary labeling program.

The program started with only computers and monitors and, by 1995, expanded to include additional office products and residential heating and cooling equipment. In 1996, EPA partnered with DOE to add other product categories to the labeling program. In the following years, the Energy Star voluntary labels were extended to cover a wide array of products, with over 35 product categories, including: major appliances, office equipment, home electronics, commercial and industrial equipment, lighting, plumbing even new homes and commercial and industrial buildings. The definition of qualifying Energy Star products is different for each product category, but tends to include only the most efficient products on the market - a small fraction of the total market. This is not always the case, however. The vast majority of computers, monitors, copiers, faxes, VCRs, TVs, and exit signs are Energy Star-qualified.

In addition to the Energy Star voluntary labeling program, Energy Star also encompasses a variety of public-private partnerships, many of which began as separate programs and were moved under the sponsorship of the Energy Star program in the late 1990s. For instance, the EPA Green Lights Program was started in 1991 to advance the adoption of energy efficient lighting systems in industrial and commercial facilities through information and demonstration activities. Similarly, the EPA Climate Wise program was created in the mid-1990s to provide information and assistance to industrial and commercial facilities to identify and implement

greenhouse gas emissions-reducing activities. These programs joined the Energy Star umbrella of programs in the late 1990s due to their similarity in mission to the core Energy Star mission. Other programs include: the Green Power partnership encouraging organizations to buy renewable energy, the Combined Heat and Power partnership between the government and industry, and Energy Star Home Sealing, which helps homeowners improve the energy performance of their homes during remodeling and renovation. By 2001, Energy Star facilitated partnerships between the government and over 7,000 public and private sector organizations based on the EPA 2003 Annual Report. The following sub-section describes the structural characteristics that make a house Energy Star qualified.

2.1.2 Energy Star Homes

As mentioned earlier, the Energy Star program extends to residential properties. In fact, an Energy Star rated home is expected to perform better than a conventional home due to an improved home envelope which includes:

- Energy efficient home sealing (insulation and air sealing),
- Energy efficient roof products, and
- Energy efficient windows, doors, ducts and skylights.

With such features energy consumption is therefore reduced due to the lessening of air leakages under doors, through roofs, windows and so forth. These physical attributes of a home in return translate into a Home Energy Rating System (HERS) score of 86 (or better) out of a 100 under the old rating system. In fact, following the ES rating system, the old HERS Score is a system in which a rated home is compared to another home of the same size and shape, built to the specifications of the HERS Reference Home (with a HERS Score of 80). However, based on the new HERS rating set up by the Residential Energy Services Network (RESNET) every additional point in the old HERS score increases a house‘s energy efficiency by 5% compared to

the HERS Reference House. In other words, the lower the HERS Index, the more efficient the home is. As result, under the new rating system which started in July 1st 2006, the minimum requirement for a home to be rated Energy Star is an index of 85 in climate zone 1 through 5 (i.e. cooler climates) and an index of 80 for climate zones 6 though 8 (i.e. hotter climate). The following sub-section outlines the determinants of energy consumption in the current literature.

2.2 Determinants of Energy Consumption

This section discusses several studies that investigated the relationship between efficient energy initiatives and homeownership cost savings. It also outlines the impacts of such initiatives on property value and corporate behavior. In addition, impacts of land use regulations on energy consumption are described. Finally the predictors of energy usage at the household level are discussed.

Colton (1995) found that energy efficient investment in a home has the equivalent effect of reducing initial price of the home from 1.5% to 8% depending on the location. These improvements have the potential to reduce operating costs and improve overall affordability for low-income and first-time home buyers.

Nevin and Watson (1998) investigated the effect of energy efficiency on property value and cost savings. Despite limited data and the difficulty of identifying consistent energy saving variables, the authors found a positive impact of energy efficiency on housing prices.

Smith and Jones (2003) analyzed the impact of energy efficient house construction on homeownership costs and property value. Their results suggest that, due to an energy saving of $180 per year for the average Energy Star home, operating costs are reduced and homeownership is thus made more affordable. In fact, residents can afford an additional $2,255 worth of mortgage. In addition, housing value increases by $4500 per unit due to green upgrades.

Since DeCanio and Watkins (1998) investigated the impact of Energy Star Green Lights program on investment in energy efficient equipment. The authors found that voluntary programs such as the Green Lights program can potentially create energy saving investment, improve corporate performance and reduce pollution. Yet, organizational and institutional factors can hinder investment.

Also using data on the Energy Star Green Lights and other voluntary labeling programs, Howarth et al. (2000**)** developed a similar model. According to their study, energy efficiency programs are effective in generating energy savings. In fact, they reduce market failures caused by imperfect information and bounded rationality.

Pigg (2002) examined the differences in energy use between participants in the Wisconsin Energy Star Homes program in 1999 and 2000. The study reveals that on average, participants of the program use 9% less natural gas in comparison to conventional new homes. This is due to reduced air leakage in Energy Star homes. Wisconsin Energy Star Homes program's participants also consume between 3% and 11% less electricity than non-participants .However the observed difference is not statistically significant. The rating system used in study captures well actual heating consumption but slightly over-predicts heating use on average.

Gillingham, et al. (2004) reviewed literature on a broad range of existing non-transportation energy efficiency policies including appliance standards, financial incentives, information and voluntary programs, and government energy use. Their results suggest that these "programs are likely to have collectively saved up to 4 quads of energy annually, with appliance standards and utility demand-side management likely making up at least half these savings" (Gillingham et al. 2004).

Glaeser and Kahn (2008) studied the relationship between greenhouse gas emissions associated with household energy consumption (from private and public transportation, home heating and household electricity usage) and new urban development in 66 major metropolitan areas within the United States. The results of the study show that in general households located in the central cities have significantly lower emissions than the ones living in the suburban area, with lowest emissions in California and highest emissions in Texas and Oklahoma. In addition, as land use regulations are stricter (which is the case in central cities) carbon dioxide emissions decrease. As a result, while current land use regulations restrict new urban sprawl in the "cleanest areas" (central cities) it has the unintended effect of pushing new construction toward higher emissions areas (suburban areas) and thus increasing greenhouse emissions as a whole.

Guerin, et al. (2000) reviewed numerous energy studies conducted since 1975 in order to identify occupant predictors of household energy-consumption behavior and energy-consumption change. The study revealed that household consumption is affected by three main factors: occupant characteristics, occupant attitudes and occupant actions. The most recurrent factors include age, income, education, homeownership, desire for comfort, weather and incentives.

Yohanis, et al. (2007) used a sample of 27 houses in United Kingdom and investigated how occupancy and characteristics of the dwelling affect domestic electricity use. This study suggests that type of dwelling, its location, ownership and size, as well as household appliances, attributes of the occupants (number of residents, income, and age) and occupant pattern have different but significant effect on electricity consumption. For instance, there is difference of 24% to 30% in consumption level between detached and terraced homes .There is a positive impact of floor area on electricity consumption. In addition, electricity consumption per

individual decreases as the number of residents increases. This is especially true for large houses with fewer occupants.

The review of the literature on energy consumption identifies the main elements that affect level of households or firms energy consumption. Of these elements are included energy efficiency initiatives, structural features of a house, characteristics its occupants, their behavior and actions and finally land use regulations. Researches show that energy efficiency programs such as the Energy Star program or the Energy Star Green Lights program reduce households or firms energy usage. Consequently such programs contribute in the decrease of homeownership costs while raising property value, affordability and corporate productivity. However, the majority of those studies are comparative studies that use little to no statistical tools in order to control for confounding factors influencing the results. As a dwelling get bigger in size (square footage for instance), energy consumption increases. Socio-economic characteristics such as income, education and age of its occupants also have a significant effect on the amount of energy consumed by the household. Finally as land regulations get stricter in the central cities, restricting energy consumption, consumption and therefore pollution levels are higher in newer development located in the outer cities where regulations are looser.

The review of the current literature shows that energy conversation and environmental protection represent a major area of interest for economists. Indeed, the environmentally conscious efforts of government are manifested by the implementation energy efficiency policies. However, despites the growing popularity of such “green” initiatives, academic research in this field is limited. For instance, there are very few studies focused on evaluating the performance of energy efficiency policies over an extended period of time.

2.3 Conclusion

This chapter defined the term “energy efficiency program” by summarizing the objectives of such an initiative and providing an illustration of it implemented here in the Unites States: the Energy Star program. The effects of energy efficient behavior on private cost savings, energy consumption and corporate investments was discussed, as well as impacts of land use regulations and urban development pattern. Finally determinants of household energy usage were discussed.

While individual energy efficient behavior and governmental efforts are critical in protecting the environment in the light of climate change, there is a very limited academic literature on the implementation and performance of such initiatives overtime. This constitutes a limitation of the current literature. The available literature on energy efficiency programs is certainly biased towards short- term energy use reductions and cost saving. In fact, it focuses more on the implementation of energy efficiency measures rather than evaluating the performance of these programs overtime. This study therefore stands to question whether or not energy efficiency programs work and if so, is this efficiency maintained overtime. For this reason, it is necessary to examine the performance of these programs as time goes by. Doing so will better guide policies aimed at protecting the environment through the reducing energy consumption and lessening of greenhouse emissions. This examination will achieve that goal by pointing out up-to-date challenges and changes faced by such efforts. It will also suggest adequate policy response to such changes.

CHAPTER 3
METHODOLOGY

In this chapter, the conceptual framework and econometric methods used for the study are discussed. To do so, definitions and applications from the current literature are provided. The objective of this chapter is also to define economic predictive models that allow for the determination of the impact of energy efficiency programs on household energy consumption overtime. Section 3.1 discusses the cost minimization behavior as the conceptual framework for the research. Section 3.2 describes the DID estimation, its application in the literature and its mechanisms. Section 3.3 introduces the different types of time series cross- sectional models used in the study. Section 3.4 describes the location of the study and the different types of data used to perform the analysis. Finally, the conclusions from the chapter are drawn in section 3.5.

3.1 Cost Minimization Behavior

Following previous studies in the literature, the underlying economic framework of this research is the cost minimization approach. The basic idea of the cost minimization problem (CMP) is to explain how firms find input combinations that minimize production cost given the quantity of outputs (Varian, 1992). The CMP can be stated as follows:

$$\text{Min } w*x \text{ with } x \geq 0 \text{ s.t. } f(x) \geq q, \tag{3-1}$$

where x is the nonnegative vector of inputs, w is the vector of input prices, f(x) is the production function and q is the amount of outputs. The optimized value of the CMP is then given by the cost function c (w,q) which is referred to as the cost curve on Figure 3-1. Conditional on the fact that the output level q is produced, the optimal set of inputs choices denoted $x^*(w,q)$ is obtained at the point of tangency where the constant slope of the cost curve is equal to the slope of the isoquant: the cost minimization point on Figure 3-1. At this point, the

optimal bundle of inputs (x_1^*, x_2^*) minimizes the cost of producing q outputs. See Figure 3-1.The CMP is analyzed by using the Lagrange multiplier method.

$$L(\lambda, x) = wx - \lambda(f(x) - q) \quad (3\text{-}2)$$

$$w_i - \lambda \frac{\partial f(x^*)}{\partial x_i} = 0 \quad (3\text{-}3)$$

$$\text{and } f(x^*) = q \quad (3\text{-}4)$$

In this specific study, the economic agent considered is a homeowner. The economic goal of that individual is to make a rational decision that will minimize his homeownership or operating costs which include energy cost denoted C_e. This framework also assumes that there are only two possible types of houses available to the homeowner in the market: a house that is ES rated or a traditional, non-ES house. Based on the current literature (Yohanis, et al. 2007; Smith and Jones, 2003; Pigg, 2002), one knows that the homeowner's energy costs C_e are a function of the type of the house he decides to choose (ES vs. non.ES), additional structural characteristic of the house such size, location, etc…denoted H and weather conditions denoted W. The CMP can be therefore stated as follows: Min C_e (ES, H, W) s.t. B (3-5)

where C_e (ES, H,W) is the homeowner's energy cost function and the constraint B is the homeowner's available income or his energy cost budget for his household. Assuming that the homeowner makes rational decisions and has full information in the market, the expectation is for him to choose a house that will minimize his operating expenditures in terms of reduced energy consumption. This will be materialized in a reduced energy bill. The homeowner is thus expected to choose a house that is ES.

Since pricing methods of utility consumption can be problematic and are often subject to changes, this study adopts a cleaner version of consumption such as direct energy consumption. By doing this, the study avoid the problem of measuring the effects of ES program on these pricing schemes. Having this economic framework in mind, the rest of this chapter discusses the

econometric methods adopted in this research. The goal is to model how the ES rating of a house impacts household energy consumption and therefore dictates homeowners' behavior.

3.2 The Difference-in-Difference Estimator

3.2.1 Definition and Applications

The main objective of this study is to identify the effect of the Energy Star rating on energy consumption in Gainesville, Florida. This section describes the framework used to evaluate the Energy Star program's performance over time: the Difference-in-Difference (DID) Estimator.

The DID estimation is often used in empirical economic research in order to assess the effects of public interventions and other treatments of interests in the absence of purely experimental data. The common objective of evaluation studies is to estimate the average impact of a treatment on some outcome variable of interest (Abadie, 2005). In this study, the treatment is the Energy Star rating of homes and the variables of interest are household energy consumption (EC) and property sale price.

There are many applications of a Difference-in-Difference estimation in the literature, especially in the area of labor economics. For example, Car and Kruger (1994) evaluated the effect of an increase in the minimum wage (the treatment) on employment (the outcome) in the Fast-Food Industry in New Jersey versus Pennsylvania. The DID estimator shows a small significant increase of 0.59% in employment in New-Jersey where the minimum wage increased. Another illustration of the DID estimation is Meyer, et al. (1995) paper which examined the effect of an increase in workers' compensation on time out of work in Kentucky versus Michigan. Their before and after analysis using Difference-in-Difference estimation shows that time out of work increased by approximately 50 percent for those eligible for higher benefits and remained the same for those whose benefits were constant.

More recent studies by Angrist and Krueger (1999), Abadie (2005), and Athey and Imbens (2006) utilizing DID estimations are at the fringe of econometrics. In fact, they relax the general assumptions that the conventional estimation hinges on. The authors then investigate the performance of the estimation under these new assumptions. For instance, Abadie's study in 2005 examines the event when the outcomes of the treated versus the control group do not follow a parallel trend in the absence of a treatment. This is explained by the fact that the "selection for treatment is influenced by individual-transitory shocks on past outcomes" (Abadie, 2005). In a DID estimation, in addition to a treatment and an outcome defined, two distinct groups as well as two time periods are also specify. The two groups are defined by their treatment status: the treatment group referred to as treated group and the control group not subject to the treatment studied referred to as the non-treated group. The first time period corresponds to the initial time period (let say $T = T_0$) in the study and the second period corresponds to another chosen time period ($T = T_1$). The following sub-section discusses the mechanics of the DID as well as how the outcome of interest is modeled.

3.2.2 Mechanics of the DID Estimator

The outcome interest Y_i is modeled by the flowing equation:

$$Yi = \beta_0 + \beta_1 \text{ Treatment}_i + \beta_2 T_i + \delta (\text{Treatment}_i * T_i) + \varepsilon_i \qquad (3\text{-}6)$$

Where the coefficients associated with β_0, β_1, β_2 and δ are all unknown parameters and ε_i is a random unobserved error term which includes all determinants of Y_i that the model omits.

The dependent variable, Y_i represents the variable of interest. The explanatory variables of the model are defined as follow: Treatment_i is a dummy variable which will take the value of one if there the observation is treated and zero if the observation is not treated. T_i is the time variable

identifying each time period defined in the analysis (T = 0 or T=1). ($Treatment_i$*T_i) is the interaction term between the two previous explanatory variables, $Treatment_i$ and T_i.

The purpose of this evaluation is to find a "good" estimate of δ, given the data available. The model is run using OLS estimation under the assumptions that the generalized standards hold. The parameter of interest in this analysis is $\hat{\delta}$ associated with the interaction term ($Treatment_i$*T_i). Indeed, δ hat gives the true effect to the treatment. It corresponds to the difference over time of the average difference in the dependent variable between the two groups. Mathematically, our DID estimator δ (delta hat) is written as:

$$\hat{\delta} = [\, Y_i \text{ (treatment group},T_1) - Y_i\text{(treatment group},T_1] - [Y_i\text{(control group},T_0) - Y_i\text{(control group},T_0)] \quad (3\text{-}7)$$

The other coefficients have the following interpretation:

β_0 = constant term , baseline

β_1 = treatment group specific effect accounting for average permanent differences between the treatment and the control group

β_2 = time trend common to both treatment and control groups: captures the changes in the dependant variable due to time

ε_i = error term containing any significant explanatory variables not included in the model.

3.2.3 Assumptions and Limitations

The main criteria for a "good" estimator in that this estimator is unbiased. In other words, the estimate of δ will be correct on average. Mathematically, the expected value of the estimator

$$E[\hat{\delta}] \text{ is equal to } \delta \text{ or } E[\hat{\delta}] = \delta \quad (3\text{-}8)$$

Consequently, the results of the DID estimation hinges on the following assumptions:

The model is correctly specified

The error term is on average equal to zero: $E[\varepsilon_i] = 0$ (3-9)

The error term is uncorrelated with the other variables in the equation:

$$\text{cov}(\varepsilon_i, \text{Treatment}) = 0 \tag{3-10}$$

$$\text{cov}(\varepsilon_i, T_i) = 0 \tag{3-11}$$

$$\text{and cov}(\varepsilon_i, \text{Treatment}*T_i) = 0 \tag{3-12}$$

The last assumption or parallel-trend assumption is the most critical (Abadie, 2005).Therefore, if any of the assumptions mentioned above do not hold, $\hat{\delta}$ is biased. The main issue when using a DID estimation is the failure of the parallel-trend assumption. For instance, if cov (ε_i, $\text{Treatment}_i * T_i$) = E [ε_i (Treatment_i *T_i)], the dependent variable for the treatment group and the control group follows a different trend T_i. If the control group have a time trend of $T_i^{control}$ and the treatment group has a time-trend of $T_i^{treatment}$, one will have in this case :

$$E[\hat{\delta}] = (T^{treatment} + \delta) - T^{control} = \delta^{+} \tag{3-13}$$

This problem is common in several program evaluation studies causing DID estimators to be biased (Wooldridge, 2007). However, econometricians such as Meyer (1995) and Wooldridge (1995) proposed simple ways to avoid these issues. One approach is to collect more data on other time periods before and after the treatment occurred. This helps capturing any pre-existing trend differences between the two groups. Another solution to having a biased difference-in-difference estimator is to find other control groups which can indicate additional underlying trends that the researcher might not be aware of.

In this study, the second approach is adopted as information on four different controls groups is gathered in order to avoid this limitation of the DID estimation. Based on the literature, additional ways to make sure that the DID estimator obtained in not biased is to test for heteroskedasticity using a White Test or a Breush-Pagan test. In addition, testing for

autocorrelation using a Durbin-Watson test will also help generate an accurate estimator. The following subsection discusses how to test for autocorrelation.

Testing for Autocorrelation: By definition, autocorrelation is a violation of the following statement: conditional on the explanatory variables, the error term in the two different time periods T=0 and T= 1 are uncorrelated: Corr ($U_{T=0,}$ $U_{T=1}$/ x) = 0 (3-14)

If the errors $U_{T=0,}$ $U_{T=1}$ are correlated across time, there is serial correlation also known as autocorrelation, which is always a potential issue for regressions using time series data (Wooldridge, 2003). In other words, errors associated with adjacent observations are correlated, and errors for observations which are "far apart" are not. The most common form of serial correlation is called the first- order serial correlation in what case errors in one time period are directly correlated with errors in the next time period.

As it is the case with heteroskedasticity, if serial correlation is present, the least squares estimators will still be unbiased, however they are no longer B.L.U.E. In addition, in the case of positive serial correlation, estimates of the standard errors will be lower than they should be. There is therefore a downward bias .It will cause the confidence intervals to be smaller than they really are, and one will sometimes reject the null hypothesis when it should have been accepted. Finally, serial correlation will cause the value of R^2 to be higher than it should be, and estimates of the error variance will be smaller than they should be.

The Durbin-Watson test is a widely used method of testing for autocorrelation. The test statistic denoted d has a value that lies between 0 and 4. A value of 2 indicates there appears to be no autocorrelation. If the Durbin-Watson statistic is substantially less than 2, there is evidence of positive serial correlation. In fact, small values of d indicate successive error terms are, on average, close in value to one another, or positively correlated. Large values of d indicate

successive error terms are, on average, much different in value to one another, or negatively correlated.

3.3 Time Series and Cross-Sectional Models

3.3.1 Definitions and Applications

In conducting economic research, panel, cross-sectional and time series data represent the most widely type of information used for policy analysis or program evaluation at the micro or macroeconomic level. Indeed, with the increased availability of such information over time, researchers are able to conduct more complete and accurate economic analysis. This type of data not only allows the study of differences between subjects but also the study of these differences over time.

Panel data , also known as longitudinal data or time series cross-sectional data (TSCS) refers to a data set where a large number of cases, units, people , firms, counties, etc, (denoted i with $i = 1,\ldots, N$) are observed at two or more time periods (denoted t with $t = 1,\ldots, T$). Examples of the use of panel data include the National Election study in Political Science where over 2000 individuals are observed over a three years time period. In fact, political scientists have been using panel data for over fifty years (Adolph, et al.2005, Beck and Katz (1995), Garrett (1998)). Another example of panel data is the 1997 National Longitudinal Survey of Youth, where a representative sample of approximately 9,000 young individuals between the ages of 12 and 16 years old were repeatedly surveyed over several years on employment behavior and educational experience.

In this study, the data available is a pooled time series and cross-sectional data. An independently pooled time series and cross-sectional data (PTSCS) differs from a typical panel data in that fact that it is either dominated by time or just has fewer units relative to the number of time periods. Examples of PTSCS data include studies of countries, states, individuals

observed over periods of time that are longer compared to the number of units in the sample. According to Wooldrigde (2006), a PTSCS data is obtained by pooling a random sample of units, individuals, firms, countries, etc, i = 1, 2, …, N, from a large population at different points in time t= 1, 2,…, T, usually different years but not necessarily. In other words, a PTSCS data can be thought as groups of independent cross sections of all units i at time t piled on top of each other. The PTSCS also differs from a typical panel data since it does not follow the same units or individuals across time. In addition, in a PTSCS the distances between each time period t does not have to be identical within each cross section and finally there can be variables that are constant for each unit i across time. This type of data applies to this study since the data used is composed of monthly household energy consumptions observed across a 13-years time frame. In addition, at the cross sectional level, the sample of houses selected and household energy consumptions vary across time. At the time series level, household samples and their energy consumption levels change as well. However, the house structural characteristics such as number of bedrooms and bathrooms affecting energy consumption are time invariant. The panel is unbalanced.

According to the literature, there are many advantages from using PTSCS data which include increasing sample sizes, analyzing the effect of time or determining whether relationships have changed over time. In fact, "by pooling random samples drawn from the same population, but at different points of time, we can get more precise estimators and test statistics with more power" (Wooldridge, 2003). Using PTSCS data therefore allows for an explicit and dynamic comparison of groups by examining changes and differences over time between the groups. However, complications in using PTSCS data include accounting for heterogeneity across sections as well as within section serial correlation, which compromise estimation results.

As a result, particular models have been developed in order to effectively analyze such data. The following subsection discusses the mechanics of a general pooled cross section model, its assumptions and limitations.

3.3.2 The Pooled Ordinary Least Squares Model

A basic and general PTSCS model can be defined as followed:

$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it}$ with i = 1, 2,…, N and t = 1, 2,…, T (3-15)

Where Y_{it} is dependent variable, X_{it} is a vector of explanatory variables and ε_{it} is the error term

such that $E(\varepsilon_{it.} / X_{it}) = 0$ (3-15)

and $Var(\varepsilon_{it.} / X_{it}) = \sigma^2$ (3-17)

This model assumes that the data has rectangular structure where N units are observed for the same time periods T. This model relies on the following assumptions: all the usual Ordinary Least Squares (OLS) assumptions hold, the constant α is the same across all units i and the effect of any given explanatory variable X on the dependent variable Y is constant across observations assuming that there are no interactions in within each Xs (Cameron and Trivedi, 2005).The constant intercept and constant effects of X on Y assumption are essential to specify the model. Violation of these two assumptions will result in biased estimates due to variation of the intercept and change of the slope across units, over time or both. This general model can therefore take various forms. For instance, in case there are different intercepts at the unit level

the initial model becomes: $Y_{it} = \sum_{i=1}^{N} \alpha_i + \beta X_{it} + \varepsilon_{it}$ (3-18)

Assuming that the slope is the same for each unit but the intercepts are different over time,

the model can be written: $Y_{it} = \sum_{t=1}^{T} \alpha_t + \beta X_{it} + \varepsilon_{it}$ (3-19)

Intercepts can also very over time and across unit. The main idea is that in case the data is created by either model, a homogeneous intercept is estimated instead and there is a risk of biased results. The flip side of this situation is to have a constant intercept but the effects of X on Y change across time, across units or both. On one hand, in case there is a variation in slope across units: $Y_{it} = \alpha + \sum \beta_{i=1}^{N} X_{it} + \varepsilon_{it}$ (3-20)

On the other hand, if there is a variation in slope over time, the model is written:

$$Y_{it} = \alpha + \sum_{t=1}^{T} \beta_t X_{it} + \varepsilon_{it} \quad (3\text{-}21)$$

Nevertheless, it is important to note that all of these previous models assume that the error term ε_{it} is homoskedastic and serially uncorrelated across time. These events are very unlikely to happen with TSCS models since there is heterogeneity across units and over time in reality. In fact, $Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it}$ with stochastic errors ε_{it} where $E(\varepsilon_{it}./X_{it}) = 0$ (3-22)

but $\varepsilon_{it} = \rho\, \varepsilon_{i,t-1} + U_t$ (U_t meets all classical assumptions). (3-23)

In this particular study, the most restrictive model estimated based on the data available is the following pooled OLS model: $Y_{it} = \alpha + \beta X_i + \varepsilon_{it.}$; i= 1, 2,…, N; t= 1, 2,…,T. (3-24)

Y_{it} represents the amount of energy consumption at the household level that fluctuates with time. α is constant for all houses and across time. X_i represents the vector of house characteristics that affect energy consumption. These explanatory variables are time-invariant and therefore differ from the initial general model (3-21) defined earlier where X_{it} varies with time. Examples of such variables include number of bedrooms, bathrooms, age of the house, etc which are fixed across time. ε_{it} represents the error term including all relevant explanatory variables not accounted for in the model. i is individual houses in the sample and t represents the years of consumption.

In order to obtain consistent parameters estimates, OLS assumes that the idiosyncratic error tem ε_{it} is uncorrelated with X_i. Estimating this model with OLS ignores the heterogeneity in homes and thus generates estimates that are unbiased and consistent in terms of the slopes but inefficient since the standard errors are significantly underestimated. The correlation with units' errors therefore needs to be accounted for. Based on the current literature, in order to obtain efficient estimates, Generalized Least Square (GLS) estimation can be performed. Other approaches include estimating fixed and random effect, dynamic panel models or panel models for non- normal dependent variables. This study adopts as remedy a fixed effect method that not only accounts for a time-invariant individual specific effect and but also a time effect. The following subsection describes the fixed effects (FE) model in more details.

3.3.3 Fixed Effects Model

Following the basic framework in the literature, the standard FE model is:

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it}\ ;\ i= 1,2,\ldots,N;\ t= 1,2,\ldots,T. \tag{3-25}$$

The model assumes that: $E\ (\varepsilon_{it}/X_{it}, \alpha_i) = 0$ (3-26)

$Var\ (\varepsilon_{it}/X_{it}, \alpha_i) = Var\ (\varepsilon_{it}) = \sigma^2$ for all t=1,.., T (3-27)

and $Cov\ (\varepsilon_{it},\varepsilon_{i,t-1}\ /X_{it}, \alpha_i) = 0.$ (3-28)

The main advantage of a FE analysis is that it controls for any unmeasured time-invariant differences between units: α_i .In fact, α_i captures time-constant but unit-varying effect that is not accounted for in the previous restrictive pooled OLS model (3-23) and is therefore part of the error term. α_i is also called unobserved or fixed effect," which help to remember that α_i is fixed over time" (Wooldridge, 2003). In the literature, α_i is also known as the unobserved or individual effect. In addition, pooled OLS which does not account for this unobservable effect α_i is biased and inconsistent if α_i is correlated with the error term ε_{it}, even though it also assumes that ε_{it} and

X_{it} are uncorrelated. A major limitation of the FE estimation resides in the fact that only time-varying effects will be identified.

In order to overcome this limitation, for the purpose of this study, time-varying variables are incorporated into the analysis in order to capture a time trend. The following appropriate FE model is thus defined: $Y_{it} = \alpha_i + \beta X_i + \gamma C_{it} + \pi D_t + \varepsilon_{it,}$ (3-29)

The new explanatory variables in model are C_{it} and D_t . Indeed C_{it} represents the interaction term between the Energy Star status of a house and the bill years. D_t represents the vector of dummy variables representing years of consumption. Since C_{it} captures the unit-constant but time-variant effect, γ indicates variation in Y_{it} that is due to the effect of time. As it is likely the case for the error term ε_{it} to be serially correlated i.e. $\varepsilon_{it} = \rho\ \varepsilon_{i,t-1} + U_t$, the model is tested for autocorrelation.

With this model, the unobserved fixed effect can be differenced-out:

$$Y_{i,t-1} = \alpha_i + \beta X_i + \gamma C_{i,t-1} + \pi D_{t-1} + \varepsilon_{i,t-1} \quad (3\text{-}30)$$

$$\Delta Y_i = Y_{it} - Y_{i,t-1} = \gamma (C_{it} - C_{i,t-1}) + \pi (D_t - \pi D_{t-1}) + (\varepsilon_{it,} - \varepsilon_{i,t-1}) \quad (3\text{-}31)$$

Following this model, while controlling for the specific features of each house, the changes energy consumption over the years are explained by change in the ES feature overtime, changes occurred during the specific year and consumption pattern in the previous year. Based on the data available, for the purpose of this study this FE is considered the most appropriate estimation method. The following section describes the location of the study as well as the subdivisions of houses included in the sample.

3.4 Selection of Sample

3.4.1 Location of the Study

Located 50 miles from the Gulf of Mexico, 85 miles south of the Georgia state line, and 67 miles from the Atlantic Ocean, Alachua County is located in North Central Florida (See Figure

3-2). It extends over 977 square miles and includes the municipalities of Archer, Alachua, Gainesville, Hawthorne, High Springs, LaCrosse, Micanopy, Newberry, and Waldo. The population of Alachua County is approximately 247,000. According to the Alachua County Property Appraiser's 2008 Annual Report, the population of the city of Gainesville is approximately 120,000. Demographically, Gainesville ranks 15th among Florida's most populous cities; more than 27 percent of its population consists of individuals between the ages of 25 and 44 years. Over 55,000 of that population are students attending the University of Florida, the fourth largest public land grant university in the country.

The city of Gainesville, where the subdivisions are located, is characterized by a pleasant sub-tropical climate year round with mild winter averages in the upper 50's to mid-60's while warm and humid summer temperatures in the upper 80's and lower 90's. Average annual rainfall is around 35-40 inches. With Paynes Prairie State Park Preserve , 7,000-acre San Felasco Hammock Preserve State Park, several rolling hills, short climbs, sinkholes and upland forests , Gainesville offers numerous environmental amenities for outdoor activities including hiking biking and bird- watching. The Gainesville area is also well known for its numerous world class springs and rivers less than an hour drive which suitable for scuba diving, kayaking and snorkeling.

3.4.2 Characteristics of the Subdivisions

All homes selected for the study are single-family homes. The selection was done at the subdivision level since there is a large concentration of Energy Star houses in the Mentone Subdivision. This subdivision therefore represents the treatment group in the DID estimation performed in the following section.

All ES homes in Mentone have been built by Atlantic Design Homes. As an Energy Star homes certified builder since 1997, "Atlantic Design Homes has designed and built over 600 of

Gainesville's most elegant homes in subdivisions like Haile Plantation, Richmond, Mentone, and Town of Tioga" (Atlantic Design Homes, 2007). Other subdivisions include Burberry and Ridgemont in Gainesville, Florida. In addition to more than 20 years in the construction industry, Atlantic Design Homes was also been recognized by the EPA as "National Builder of the Year," in 2000. The company has received several awards over the years including the Grand Aurora Award for "Best Community in the Southeastern United States", a local "Ethics in Business"

Award and Alachua County's only designated "Clean Builder of the Year."Atlantic Design Homes has not only built more Energy Star homes than any other builder in the Gainesville area; it has also recently become certified by the Florida Green Building Coalition thanks to its environmentally conscious practices (Atlantic Design Homes, 2007).

Four other single-builder subdivisions with similar size, single story non-ES homes were also selected. These homes have multiple builders and are considered conventional homes representing the control groups in the study. They are located in the following subdivisions: Broadmoor, Capri, Eagle Point and Stillwind.

The Gainesville area is representative of the population of homes since similar houses with similar structural and environmental friendly features are also being built in several locations in the country. There are no specific conditions that apply to this region, making it a special case. Indeed, similarly hot climatic conditions can be found in different parts of the country including Arizona, California or Texas, as well as a nationwide demand for green construction.

Figure 3-3 provides a visual illustration of where the subdivisions are located within Alachua County. In addition based on location, each subdivision is zoned to a specific school by the Alachua County Public Schools' Zoning Department. For the purpose of the study, only middle schools are considered, three different middle schools in total. In fact, the subdivisions of

Mentone and Stillwind are zoned to Kanapaha middle school; the subdivisions of Eaglepoint and Broadmoore are zoned to FortClark middle school and the Capri subdivision is zoned to Westwood middle school.

The following subsection describes the energy data used for the study.

3.4.3 Energy consumption data

The data on energy consumption which includes electricity and natural gas was collected by the local utility company, Gainesville Regional Utilities (GRU) for all of the homes except for the electric consumption of the Mentone subdivision. In fact, Clay Electric provided the monthly electricity usage for homes located in Mentone. This data reflects monthly consumption measured in kilowatts for electricity and thermos for natural gas measured at the meter. Water consumption levels were also observed but not used in the study.

3.4.3 Other Data

Each home's data set also includes the conditioned/heated area, number of bedrooms, number of bathrooms, year built and Energy Star status of the home provided by the Alachua County Property Appraiser office. Houses are identified by their tax parcel identification number, street address as well as subdivision. All homes are singe-builder, single story and single family homes. All houses are equipped with central air conditioning and heating system. Most houses do not include individual swimming pools and other features of the homes including ventilation systems, sealing penetration are not observable. With similar construction style and comparable size, the comparison of homes is done at the subdivisions level: Energy Star homes versus traditional homes (Smith and Jones, 2003).

Average monthly temperatures used to control for the seasonality of energy consumption was gathered using the Florida Automated Weather Network database.

The ideal data for this study would also include socio-demographic data on households such as income level, education level, age, number of residents, household structure and so forth (Guerin, et al., 2000 and Yigzaw, et al., 2007) as well as occupants action and behavior such as thermostat setting (Pigg, 2002) . Data on occupant behavior and attributes would therefore add another dimension to the study by painting a more accurate picture how not structural features of a home (i.e. Energy Star upgrades) but also characteristics and attitude of its residents affect energy consumption of that specific home. Additional information can also include environmental and locational characteristics of the properties such as tree coverage in the area, distances to main roads, parks, lakes, shopping plaza and downtown center.

3.4.4 Data Cleaning

The county appraiser data, containing structural characteristics of the houses and GRU data containing the energy consumption information were merged in order to create new energy data sets. Each new data set was examined and correct for anomalies in consumption and structural features. In fact, only positive energy consumptions were retained as 3005 observations were dropped (2943 observation for no consumptions and 62 observations for negative billed consumptions). 2460 additional observations were dropped due to missing billed consumption and 460 observations for missing bill year.764 observations made up of houses with no bathrooms and bathrooms were also deleted from the energy data set. For the panel data energy analysis only electricity consumption was retained, resulting in 205, 890 observations dropped.

3.5 Conclusions

In this chapter the methodology used in the study was discussed. First, the economic framework, the cost minimization problem was presented. Then the Difference-in-Difference estimation, pooled OLS and FE methods were discussed. Finally, a description of the location of the study was provided. The models discussed will be estimated using energy consumption data,

structural characteristics of the homes in the sample and seasonality. After describing the different types of data used, cleaning up process of the data is discussed.

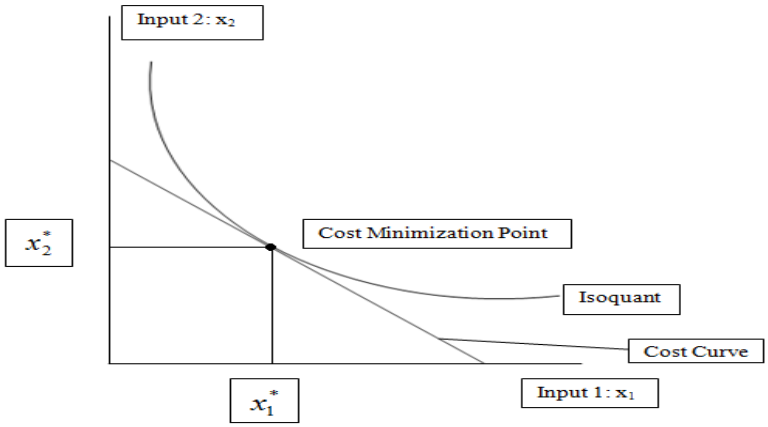

Figure 3-1 The Cost Minimizing Problem (CMP).

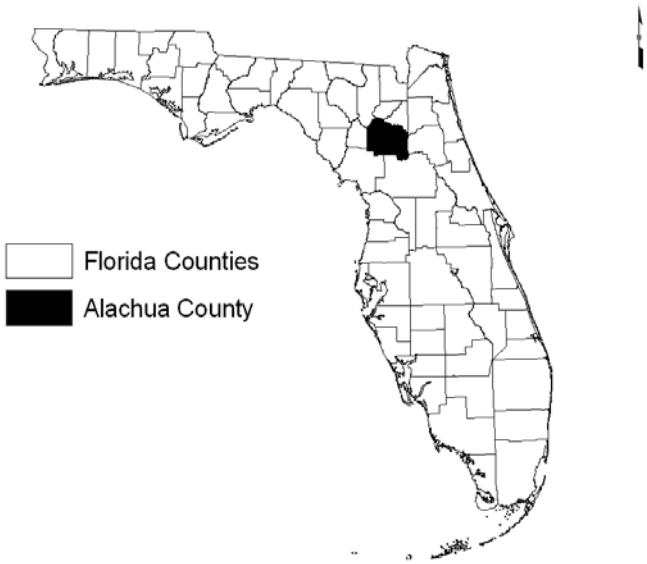

Figure 3-2. Map of Alachua County, Florida created using Alachua County GIS parcels data.

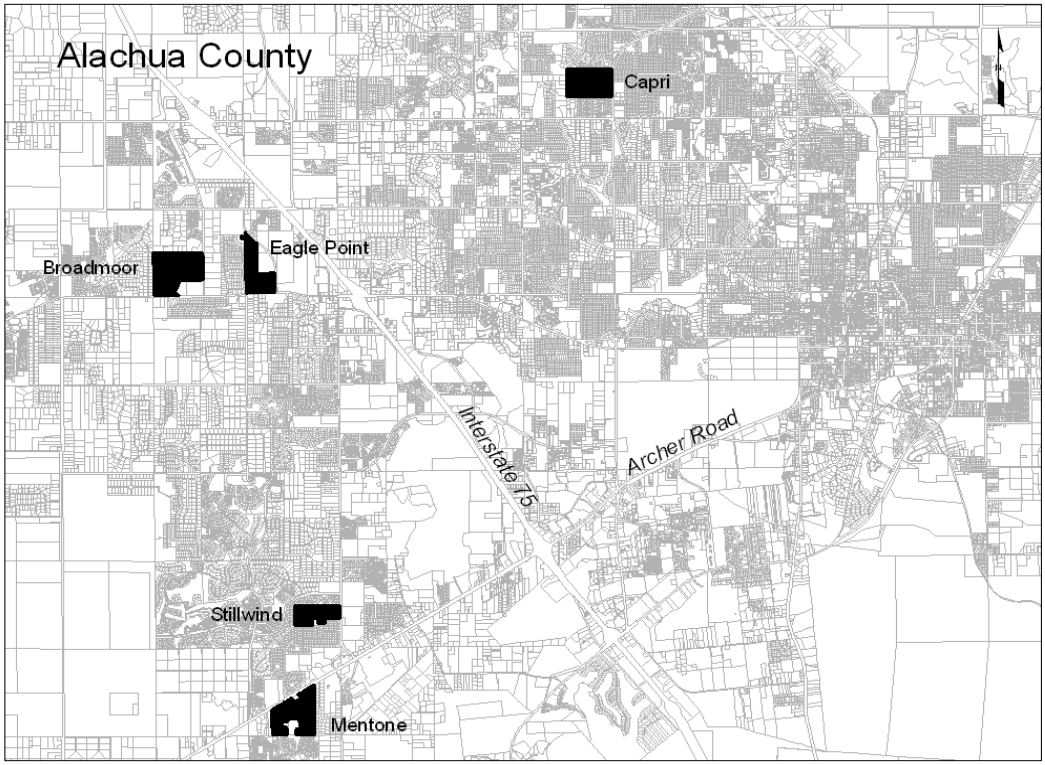

Figure 3-3. Map of all five subdivisions in Alachua County, Florida using Alachua County GIS parcels data

CHAPTER 4
ENERGY ANALYSIS USING DIFFERENCE IN DIFFERENCE ESTIMATOR

The objective of this chapter is to develop a model that can be used to identify the impact the Energy Star feature of a home on household energy consumption which includes electricity, natural gas and total consumption. To do so, five different models are developed and results are summarized. The DID framework adopted allows for an evaluation of the Energy Star program overtime and the formulation of policy implications. A limitation however in the implications of this analysis resides in the fact that only two time periods are considered. Another limitation is the unobservable pre-treatment or post-treatments characteristics of the sample between the treated and the untreated that could affect energy consumption. In most program evaluations, the research can observe how the subject behaves at the end of the treatment. It is not feasible in this study. In fact, once a house has been built ES for instance there is no way to observe it under any other conditions. To solve this issue, the study just considers the ES program as a natural experiment and attempt to control for any confounding factors outside the ES rating that affect the outcome, household energy consumption. Section 4.1 describes the sample. Section 4.2 describes the predictive models and summarized the results for the electricity, natural gas and total consumption analysis. Finally conclusions are drawn in section 4.3.

4.1 Characteristic of Sample

This section describes the sample of homes that was used in the initial estimation of the Difference- in-Difference estimator using electricity, natural gas and total energy consumption, which includes both electricity and natural gas usage, for the years 2000 and 2006. A total of 5684 homes were selected from both types of subdivision (conventional versus Energy Star rated). In fact, the sample includes 1,104 observations for homes rated Energy Star located in the Mentone subdivision and 4,560 observations Non-ES homes located in the four conventional

following subdivisions: Broadmoor, Capri, Eagle Point and Stillwind. This sample is referred to as sample 1 and is described in Table 4-1. As describe in Table 4.1, the houses in Mentone have the smallest areas with an average of 1670.27 square feet. The biggest heated/cooled areas are found in the houses located in Broadmoor with an average of 2778.76 square feet. Houses in Capri, Eagle Point and Stilllwind have heated/cooled areas that vary between 1778.67 to 1858.82 square feet.

Table 4-2 provides a definition of the variables used in the analysis of energy consumption patterns observed for each type of house. Electricity, natural gas and total (combined electricity and natural gas consumption) consumptions for the bill years 2000 and 2006 (t) are used for the analysis. The ES status of the house is also observed as well as the months of consumption. Table 4-3 provides the descriptive statistics of the variables. As described in Table 4-3, on average, houses in the sample consume about 939.5 kWh of electricity, 25 units of natural gas and 1678.6 units of total consumption. In the following section, an energy analysis is performed using electricity, natural gas and total consumption data for 2000 and 2006.

4.2 Energy Consumption Analysis

Results from the 2005 Residential Energy and Consumption Survey show that on average, when it comes to the energy expenditures, households in Florida spend a large percentage of their budget (35.2%) on air-conditioning. On the other hand only 5.1% of their budget is attributed to space heating. This is can be explained by the very hot temperatures during the summer time and mild winter temperatures which characterize this part of the country. 15.5% is attributed to water heating, 7.5% to refrigerators 36.7% to other appliances and lighting. See Figure 4-1.

4.2.1 Electricity Consumption

In this section, five different models are run in order to evaluate the impact of the Energy Star rating energy consumption using 2000 and 2006 monthly electricity consumption.

A simple model is used in a naïve analysis that estimates the effect of the Energy Star rating on emery consumption: $\text{Electric}_{2006} = \beta_0 + \gamma_1 ES$ (4-1)

The results are summarized in Table 4-4. The constant corresponds to an average annual electricity consumption of 1027.139 kWh in 2006. The coefficient of Energy Star, which corresponds to the difference in average electricity use between conventional homes and ES homes, shows that Energy Star homes consume on average 132.139 kWh less than the non-Energy Star homes. With significant estimates (t statistics greater than five in absolute value), one can strongly reject the hypothesis that the average electricity consumption for homes rated Energy Star and those without the rating is the same. Since this last estimation does not imply that the Energy Star rating is causing lower electricity consumption in 2006, the same regression is run for the year 2000. One can expect a lower consumption since the houses are newer. The following regression in then executed: $\text{Electric}_{2000} = \beta_0 + \gamma_1 ES$ (4-2)

The results are summarized in Table 4-5. Base on this naïve analysis, the average annual electricity consumption was 953.197 kWh in 2000. Homes rated Energy Star consumed on average 188.748 kWh less than conventional homes. The difference is also statistically different.

Nevertheless, it will be incorrect or misleading to conclude that homes that are rated Energy Star have been saving less and less electricity as time goes by or as houses are aging or they have actually increased electricity consumption over the years. The answer lies in the examination of how the coefficient on the Energy Star variable changed between 2000 and 2006. In fact, the difference in energy savings was much larger in 2000 than in 2006 (i.e. 188.748 versus 132.139 kWh). The difference in the two coefficients is 56.609 kilowatts: $\gamma_1 = -188.748 - (-132.139) = 56.609$

This is the estimate of the effect of the Energy Star rating on energy consumption between 2000 and 2006. In empirical economics, it is known as the Difference-in-Difference estimator (DID). It is equal to the difference overtime in the average difference of electricity consumption with the two building upgrades. In order to test whether the DID estimator is statistically different from zero; its standard error is obtained by using the following regression analysis defined in Model 2.

Model 2 introduces the effect of time and the interaction term between the time effect and the ES effect as discussed earlier in the methodology section. The following regression is then executed: $Electric_i = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i * T_i) + \varepsilon_i$ (4-3)

with DID = $\hat{\delta}$ = [Electric (ES,06) – Electric (ES,00)] - [Electric (Non-ES,06) - Electric (Non-ES,00)] (4-4)

β_0 = constant, baseline : average consumption of a Non-ES home

β_1 = treatment group specific effect accounting for permanent differences between ES and Non-ES homes (or consumption due to ES rating):

β_1 = Electric(ES,00)-Electric(Non-ES,00)

β_2 = time trend common to both groups: captures consumption changes due to time in all houses from 2000 to 2006:

β_2 = Electric(Non-ES,06)-Electric(Non-ES,00)

ε_i = error term

Under the parallel-trend assumptions, one can determine the expected value of the average consumptions for each group at both time periods. The expected values are summarized in Table 4-6.This table is valid for electricity, natural gas and total energy consumption analysis. Since energy consumption is seasonal and varies from month to month, it is important to control for

monthly fixed effects. Dummy variables (noted Feb through Dec) are therefore included in Model 2. These dummy variables will take the value of one if the reading goes with a certain month. This is model 3.

$$Electric_i = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i * T_i) + \pi (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + \varepsilon_i \quad (4\text{-}5)$$

An additional fourth model (Model 4) not only includes monthly fixed effects but also heated/cooled area of the house measured in square feet.

$$Electric_i = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i * T_i) + \pi (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + \varphi \text{ Heated/Cooled Area} + \varepsilon_i \quad (4\text{-}6)$$

There are two good reasons for including control variables in our estimation. On one hand, the energy consumption in 2000 may be different from the consumption observed in 2006. If so it is important to control for characteristics that might have been different .On the other hand, even if the average housing characteristic are the same for both years, including control variables can greatly reduce the error term variance, and in return shrink the error of our DID estimator (i.e. $\hat{\delta}$).When we introduce the monthly fixed effects we can see that our DID estimator is more significant than before (p-value of 0.062 versus 0.015).

Finally, Model 5 is logarithm model which provides an approximate percentage effect on energy consumption. In this last model, which is of main interest, 100 * $\hat{\delta}$ corresponds to the approximate percentage increase in energy consumption due to an ES rating.

$$Log (Electric_i) = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i * T_i) + \pi (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + \varphi \text{ Heated/Cooled Area} + \varepsilon_i \quad (4\text{-}7)$$

Based this analysis, there is an increase in electric consumption of about 7.59% for ES homes due to the ES rating. It is furthermore important to note that this coefficient is statistically significant or different from zero. The results of the analysis are summarized in the Table 4-7.

4.2.2 Gas Consumption

The same analysis is performed using monthly gas consumption for the years 2000 and 2006. Once again five separates models are defined in the attempt of quantifying the effect of the Energy Star rating on natural gas usage over time.

Model 1: $Gas_{2000} = \beta_0 + \gamma_1 ES$ (4-8)

and $Gas_{2006} = \beta_0 + \gamma_1 ES$ (4-9)

The results are summarized in the Tables 4-8 and 4-9.Table 4-8 shows that on average houses consumed 27.204 units of gas while ES homes consumed about 5.737 units less in 2000. In 2006, houses on average consumed 24.524 units of gas while ES homes consumed about 3.970 units less in 2006 based on Table 4-9. The results are statistically significant. The difference in the two coefficients is 1.767 units of gas

Model 2 is also defined as followed:

Model 2: $Gas_i = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i * T_i) + \varepsilon_i$ (4-10)

Similarly to the electricity consumption analysis, Model 2 for the natural gas data is tested for the presence of heteroskedasticiy using the the Breush-Pagan test. There is statistical evidence for the presence of heteroskedasticity in Model 2. As a result the rest of the natural gas analysis is conducted using hereteroskedasticity-robust standard errors models.

The following models are run:

Model 3: $Gas_i = \beta_0 + \beta_1 ES_i + \beta_2 Ti + \delta (ESi*Ti) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) $+ \varepsilon_i$ (4-11)

Model 4: $Gas_i = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i*T_i) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + φ Heated/Cooled Area+ ε_i (4-12)

Model 5: $Log (Gas_i) = \beta_0 + \beta_1 ES_i + \beta_2 T_i + \delta (ES_i*T_i) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + φ Heated/Cooled Area+ ε_i (4-13)

The findings of Model 2 through 5 are summarized in Table 4-10. Based this analysis, there is an increase in electric consumption of about 10.09% for ES homes due to the ES rating (see table of results). It is also important to note that this coefficient is statistically significant or different from zero.

4.2.3 Total Consumption

The same analysis is performed using monthly total consumption including both electricity and natural gas for the years 2000 and 2006 in the attempt of quantifying the effect of the Energy Star rating on total energy consumption. The following regressions models are being applied and results are reported in Tables 4-11 and 4-12:

Model 1: $Total_{2000} = \beta_0 + \gamma_1 ES$ (4-14)

and $Total_{2000} = \beta_0 + \gamma_1 ES$ (4-15)

Table 4-11 shows that on average houses consumed 1749.808 units of total energy while ES homes consumed about 355.808 units less in 2000. Based on Table 4-12, in 2006 houses on average consumed 1745.893 units while ES homes consumed about 249.607 units less in 2006. The results are statistically significant. The difference in the two coefficients is 106.201 units of total energy. The following model is defined as follow:

Model 2: $Total_i = \beta_0 + \beta_1 ES_i + \beta 2 T_i + \delta (ES_i*T_i) + \varepsilon_i$ (4-17)

Model 2 for the total consumption data is also tested for the presence of heteroskedasticiy using the Breush-Pagan test. There is statistical evidence for the presence of heteroskedasticity in

Model 2 at the 5 % significance level. As a result the rest of the gas analysis is conducted using hereteroskedasticity-robust standard errors models

The following additional models are run:

Model 3: $Total_i = \beta_0 + \beta_1 ES_i + \beta 2\ Ti + \delta\ (ESi*Ti) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + ε (4-18)

Model 4: $Total_i = \beta_0 + \beta_1 ES_i + \beta 2\ T_i + \delta\ (ES_i*T_i) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + φ Heated/Cooled Area+ ε_i (4-19)

Model 5: $Log\ (Total_i) = \beta_0 + \beta_1 ES_i + \beta 2\ T_i + \delta\ (ES_i*T_i) + \pi$ (Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec) + φ Heated/Cooled Area+ ε_i (4-20)

The results are summarized in Table 4-13. Based this total consumption analysis, there is an increase in total energy consumption of about 7.16% for ES homes due to the ES rating. This coefficient is statistically significant or different from zero as well.

4.3 Conclusions

The application of the difference in difference estimator using sample1 provides evidence that energy consumption is affected by the presence of the Energy Star upgrades in a house. However, the most significant finding is that energy consumption actually increases over time due to those upgrades in a house that is rated Energy Star. In fact a house rated Energy Star consumes 7.59% more electricity, 10.09% more natural gas and 7.16% more in total energy consumption due to the Energy Star rating compared to a conventional house. The results are statistically significant. These findings suggest that the energy savings advertized by the Energy Star program are not sustainable over time. Major limitations of these findings include the lack of socioeconomic information on the occupants of the homes that can affect levels of energy observed (Guerin, et al., 2000 and Yohanis, et al., 2007). In addition, the lack of information on pre-treatment conditions of ES homes limits the analysis.

Nevertheless, the current analysis suggests important implications for both policy makers and homeowners. Indeed, these results are definitely in favor of promoting the construction of energy efficient homes, as they reduce energy consumption and thus greenhouse gas emissions. Yet, although energy efficient upgrades work, they need to be updated and maintained throughout the years, as they deteriorate with time. Policy makers should therefore encourage or even mandate the execution of periodic performance tests on ES homes in order to ensure the houses still meet the qualifications of energy efficient houses and are still protecting the environment. These results, on the other hand show that homeowners can be mislead over the years into thinking that their energy bill will remain low due to the fact that their houses are ES qualified. Homeowners will hence benefit from these periodic performance tests as they will help ensure that ES upgrades are still efficient thus minimizing still energy and homeownership cots overtime.

Given the evidence of short-term performance of the Energy Star upgrades in a house in terms of energy savings, the next step of the study is to expand this energy analysis to a larger sample of homes and a longer time period. Additional features of the homes affecting energy consumption will also be incorporated in the analysis in order to pint a full picture and make more adequate policy recommendations.

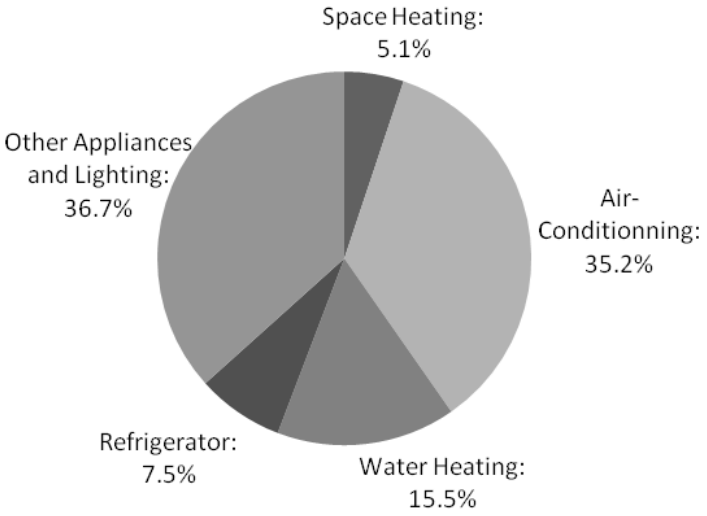

Figure 4-1. 2005 Average Household Energy Usage Expenditures in Florida created using 2005 Residential Energy and Consumption Survey

Table 4-1. Description of the Neighborhoods

Subdivisions	Mentone	Broadmoor	Capri	Eagle Point	Stillwind
Number of monthly	1104	1368	1272	1388	1104
Mean heated/cooled	1670.27	2778.76	1858.82	1778.67	1824.17

Table 4-2. Variable Names and Definition

Variables	Definitions
Dependent Variables	
Electric	Electricity consumption in kWh
Gas	Natural gas consumption in thermos
Total	Combined electricity and natural gas consumption
Independent Variables	
ES_i	Energy Star dummy variable (=1 if Yes,=0 if No)
T	Bill year dummy variable (=1 if 2006, =0 if 2000)
$(T*ES)_i$	Interaction term between ES and T
hdtarea	Heated/cooled area in square feet
month	Vector of dummy variables indicated month of consumption

Table 4-3. Descriptive Statistics of Variables

Variables	Mean	Std.Dev.	Min	Max
Dependent Variables				
Electric	939.5	470.5	118	2929
Gas	25	24.6	1	378
Total	1678.6	750.9	287	12669
Independent Variables				
ES_i	0.2	0.4	0	1
T	0.5	0.5	0	1
$(T*ES)_i$	0.1	0.3	0	1
hdtarea	1804.7	299.8	1051	2762
month	6.5	3.5	1	12

Table 4-4. Results of Model 1- Bill Year 2006

Variables	Estimates	P-values
Constant	1027.139	0.000
	(-11.415)	
ES	-132.139	0.000
	(-25.415)	

Table 4-5. Results of Model 1- Bill Year 2000

Variables	Estimates	P-values
Constant	953.197	0.000
	(-11.887)	
ES	-188.748	0.000
	(26.952)	

Table 4-6. Average Energy Consumptions (EC)

T Non-Es homes	ES homes
T EC = β_0	EC = $\beta_0 + \beta_1$
T EC = $\beta_0 + \beta_2$	EC = $\beta_0 + \beta_1 + \beta_2 + \delta$

Table 4-7. Results of Electricity Consumption Analysis using Sample 1

	Model 2	Model 3	Model 4	Model5
Dependent variable	$Electric_i$	$Electric_i$	$Electric_i$	Log ($Electric_i$)
Constant (β_0)	953.2 *** (12.632)	647.058*** (20.042)	102.990 (40.902)	5.813 (0.038)
ES_i (β_1)	-188.748*** (20.772)	-188.748*** (16.310)	-138.168 (16.337)	-0.146 (0.019)
T_i (β_2)	74.077*** (17.358)	74.077*** (23.286)	74.077 (13.651)	0.138 (0.027)
(ES_i*T_i) (δ)	56.609* (30.275)	56.609* (23.286)	56.609** (22.884)	0.0759 (0.026)
Monthly fixed effects	No	Yes	Yes	Yes
Heated/cooled area	No	Yes	0.288 (0.019)	0.00029 (0.00017)
N	5664	5664	5664	5664
R^2	0.0189	0.03750	0.4019	0.4819

Table 4-8. Results of Model 1- Bill Year 2000

Variables	Estimates	P-value
Constant	27.204	0.000
	(0.557)	
ES	-5.737	0.000
	(1.202)	

Table 4-9. Results of Model 1- Bill Year 2006

Variables	Estimates	P-value
Constant	24.524	0.000
	(-11.415)	
ES	-3.970	0.000
	(1.071)	

Table 4-10. Results of Natural Gas Consumption Analysis using Sample1

	Model 2	Model 3	Model 4	Model5
Dependent variable	Gas_i	Gas_i	Gas_i	Log (Gas_i)
Constant (β_0)	27.204 *** (0.583)	57.449*** (1.129)	40.439*** (1.681)	3.333*** (0.047)
ES_i (β_1)	-5.737*** (0.1.05)	-5.737*** (0.612)	-4.156*** (0.594)	-0.147*** (0.022)
T_i (β_2)	-2.680*** (1.388)	-2.680*** (0.493)	-2.680*** (0.484)	-0.093*** (0.014)
(ES_i*T_i) (δ)	1.767** (1.388)	1.767** (0.854)	1.767** (0.838)	0.1009 (0.031)
Monthly fixed effects	No	Yes	Yes	Yes
Heated/cooled area	No	Yes	0.009 (0.0007)	0.0003*** (0.00021)
N	5664	5664	5664	5664
R^2	0.0084	0.5954	0.6089	0.6635

Table 4-11. Results of Model1- Bill Year 2000

Variables	Estimates	P-value
Constant	1749.808	0.000
	(17.832)	
ES	-355.808	0.000
	(40.392)	

Table 4-12. Results of Model1- Bill Year 2006

Variables	Estimates	P-value
Constant	1745.893	0.000
	(15.367)	
ES	-249.607	0.000
	(34.808)	

Table 4-13. Results of Total Consumption Analysis using Sample 1

	Model 2	Model 3	Model 4	Model5
Dependent variable	$Total_i$	$Total_i$	$Total_i$	Log ($Total_i$)
Constant (β_0)	1749.753 *** (18.833)	647.058*** (20.042)	1288.47*** (67.544)	7.126*** (0.035)
ES_i (β_1)	-355.808*** (43.822)	-355.808*** (37.159)	-258.932*** (25.323)	-0.164*** (0.017)
T_i (β_2)	-3.859* (24.731)	-3.859* (21.583)	-3.859* (20.853)	0.048*** (0.026)
(ES_i*T_i) (δ)	106.201** (43.822)	106.201*** (37.159)	106.201*** (0.031)	0.0716*** (0.024)
Monthly fixed effects	No	Yes	Yes	Yes
Heated/cooled area	No	Yes	0.553*** (0.031)	0.00029 (0.00016)
N	5664	5664	5664	5664
R^2	0.0230	0.264	0.3123	0.3133

CHAPTER 5
ENERGY PANEL DATA ESTIMATION

The objective of this chapter is to develop a predictive model of energy consumption that can be utilized to identify how environmentally friendly upgrades such as Energy Star rating, structural characteristics of a house and environmental factors such seasonality influence changes in household energy usage. In this section only electricity consumptions are of interest since the area of study (Alachua County, Florida) is primarily a warm climate. This energy consumption model hinges on the premise that energy consumption of a household reflects the impact of environmental conditions as well as physical attributes of the house. This study takes a similar approach as previous researches in the literature suggesting that energy efficient investments result not only in energy cost savings but also in environmental protection in terms of greenhouse gas emission and pollution reduction (DeCanio and Watkins, 1998; Howarth et al., 2000; Pigg, 2002; Gillingham, et al., 2004). However, this study goes one step further by evaluating performance over an extended period of time.

Section 5.1 provides a description of the data sets used for the analysis. In the following sections the empirical models and results are presented. In fact, section 5.2 discusses the OLS models and results. Section 5.3 focuses on fixed effects estimation, statistical tests and findings. Section 5.4 presents Difference-in Difference estimation and results. Finally conclusions are made in section 5.5.

5.1 Description of the Datasets

Monthly electricity consumptions measured in kWh (97,515 observations) and measured at the meter were collected by Gainesville Regional Utilities. For the purpose of the study only positive monthly consumptions ranging from 1 kWh to 7,121 kWh have be retained for the analysis. Consumption years in the sample go from 1996 to 2008. Data on natural gas and water

consumption were also obtained. However, only electricity data is used for the current analysis. Following the Smith and Jones (2003) analysis, in order to account for the impact of climate variation on electricity consumption, the observed billed consumption is divided into three main categories: summer consumption, winter consumption and other consumption. The categories are created using average temperatures in Alachua County, Florida as reported by the Florida Automated Weather Network. The summer months extend from May through August. During these summer months, average temperature ranged from a minimum of 72 F to a maximum of 80.25F averaging at 79.10F. During the winter months (November through February) temperatures range from a low of 51F to a high of 59.75F averaging at 58.04F. During the remaining months of March, April, September and October temperatures range from a low of 60F to a high of 80F, averaging at 70.08F. The sample includes only single-residential family homes built between 1973 and 2005 with heated areas ranging from 1051 square feet to 4523 square feet. The number of bedrooms ranges from 2 to 5 bedrooms and the number of bathroom ranges from 2 to 4.5 bathrooms. Since the main objective is to measure the impact of Energy Star rating on household energy consumption, the comparison is made at the subdivision level with Energy Stars homes located in the Mentone subdivision. The rest of the homes located in the other four subdivisions are considered traditional and do not possess any energy saving upgrades.

From this monthly data, a time series data set is created using STATA. In fact, the monthly information is collapsed and aggregated at the yearly level. This new pooled TSCS data obtained contains 7793 observations and 956 groups.13 time dummy variables corresponding to each bill year are also created. Yearly consumption is divided in summer consumption (i.e. $summer\_con_{it}$), winter consumption (i.e. $winter\_con_{it}$), other consumption (i.e. $other\_con_{it}$) and finally total consumption (i.e. $total\_con_{it}$).The TSCS data is used later on in this chapter to

identify a time trend in the impact of ES upgrades on household energy consumption showing how ES upgrades and savings hold overtime. In addition to ES status of the house and the heated/cooled area, both data datasets also include additional descriptions of the house such as number of bedrooms and bathrooms and the year of construction (i.e. effective year) indicating the age of the house. The following section introduces the analytical framework as well as empirical econometric models adopted for the analysis and discusses the findings.

5.2 Estimations and Empirical Results

5.2.1 Monthly OLS Models and Results

In order to estimate the impact of energy saving investments such as Energy Star upgrades on the level of household electricity consumption the following econometric framework is used:

$$C_i = f\,(\,h_i,\, r_i\,, s_i\,;\, \pi,\, \delta,\, \lambda) \qquad (5\text{-}1)$$

where C_i is the consumption level of each individual i^{th} home, h_i is a vector of structural characteristics associated with the house, r_i is the energy efficiency rating or status of the house, s_i is a vector representing the seasonality of the consumption and π, δ, λ are the respective parameter vectors to be estimated . For the purpose of this study, using the available panel data, the following empirical model is then defined and parameters are estimated using regular OLS estimation[1]:

$$\text{billed\_con}_{it} = \beta_1\, \text{effyr}_i + \beta_2\, \text{beds}_i + \beta_3\, \text{baths}_i + \beta_4\, \text{htdarea}_i + \beta_5\, \text{htdarea}^2_i + \beta_6\, \text{ES}_i + \beta_7\, \text{summer} + \beta_8\, \text{winter} + \varepsilon_i \qquad (5\text{-}2)$$

As defined in Table 5-1, the dependent variable billed_con_{it} is monthly electricity consumption measured in kWh. The independent variables provided by the Alachua County Appraiser Office are as follow: effyr_i (effective year) represents the year built of the house. It is therefore used to account for the age of the property. As effyr_i increases, the house is newer and

[1] All OLS models are tested and corrected for the presence of heteroskedasticity using robust standard errors.

one therefore expects the energy consumption to decrease due to the newer construction knowing that older constructions retain less energy. The variable ES_i represents a dummy variable which will equal to 1 if a house is rated Energy Star and 0 is otherwise. Base on the literature, one expects ES rated home to consume less energy due to reduced leakage in ES homes (Pigg, 2002). $Beds_i$ and $baths_i$ are the number of bedrooms and bathrooms in the home. $htdarea_i$ is the size of total heated area in the home measured in square feet. As these variables increase, which indicate a bigger home, on expects the energy consumption to also increase. $htdarea^2_i$ is the squared value of the $htdarea_i$ variable to keep linearity of the variable. Summer and winter are dummy variables capturing the seasonality of energy consumption. Summer is equal to 1 if consumption was billed during that time frame or equal to 0 otherwise. Winter is equal to 1 if electricity consumption was billed during that the winter season or equal to 0 otherwise. It is expected to see an increase in consumption during the summer time and a decrease during the winter since air-conditioning system is mainly used during the summer for cooling purpose. ε_i is a residual capturing the errors.

Table 5-2 which provides the descriptive statistics of the variables shows that the houses in the sample were built between 1973 and 2005. They include on average 2 to 5 bedrooms and 2 to 4.5 bathrooms. The heated areas range from1051 to 4523 square feet. The average consumption in the sample is 944.067 kWh.

Based on the results of the electricity consumption model presented in table 5.3, the adjusted R2 is 0.2127. All variables are statistically significant at the 5% level. Results show that a house rated Energy Star consumes on average 51.428 kWh less in terms of electricity consumption every month than a house rated non-Energy Star. This corresponds to a yearly savings of about 617.136 kWh in electricity consumption. Knowing that the average monthly

consumption for the entire sample is about 944.07 kWh, Energy Star updates reduce that consumption by about 5.45%. It corresponds to a saving of about $5.50 each month and $ 66.00 per year in energy expenditure. Since it costs about $1200.00 to upgrade a home to Energy Star Standards (Smith and Jones), it will take a little over 18 months for home owners to capitalize their investments in terms of energy costs.

Compared to previous studies such as the Smith and Jones (2003), the current results are much more conservative. In fact while comparing traditional versus Energy Star rate homes, the Smith and Jones analysis (2003) found a 16% electricity savings in 2000 and a 10% savings in 2001 for Energy Star homes. On the other hand the results of the current study are more comparable to other studies such as the one by Pigg (2002) in terms of electricity savings.

The explanatory variables were square footage, number of individuals in the home and participation the program (Yes=1, No= 0). The data available actually indicated a 4% savings (400 kWh per year). However, the electricity consumption difference was not statistically significant and the study could therefore not come to the conclusion that Wisconsin Energy Star homes actually use less energy than non Energy Star comparable home.

As results in Table 5-3 show, when using a longer time period (from 1996 to 2008) for electricity consumption instead of only two years , 1999 and 2000 for Pigg (2002) or 2000 and 2001 for Smith and Jones (2003), the current analysis shows a significant decrease in energy savings due to the Energy Star rating . This finding begs the question knowing how well energy savings attributed to the Energy Star program hold over a long period of time.

The analysis shows a negative correlation between the year built of a house and the level of electricity consumption, as expected. In fact as a house is newer by one year, electricity consumption decreases by 13.136 kWh every month. This corresponds to a saving of 157.632

kWh each year or 1.4% reduction. In other words as the house ages and construction equipment slowly deteriorate as time goes by, each additional year will increase electricity consumption by 13.136 kilowatts every month or 157.632 kWh each year .

There is a positive relationship between the number of bedrooms, number of bathrooms and heated area of a house and monthly electricity consumption. Indeed, every additional bedroom increases the monthly electricity consumption by 59.588 kWh, 715.06 kWh yearly or 6.31%. Every additional bathroom increases, electricity usage by 35.720 kWh each month which corresponds to 428.64 kWh yearly or 3.78%. Since houses generally have more bedrooms than bathrooms, the larger impact of bedrooms than bathrooms on energy usage was expected. In addition, bedrooms are generally larger than bathrooms thus require more energy usage. As anticipated as heated area increase, consumption increases. An additional square foot in heated area results in a monthly increase of 0.0530 kWh in electricity consumption or an average 0.636 kWh a year or 0.0056%.

During the summer months, electricity consumption increases by 272.149 kWh per month, about 28.83%. This is predictable knowing that summers in North Florida are very warm and air-conditioning system constitutes 35.2% of average annual energy expenditure per household. On the other hand, during the winter months, electricity consumption decreases by 265.378 kWh per month or 28.11%. In fact, due to Florida temperate winter, space heating only constitutes 5.1% of yearly energy expenditure per household.

Like previous studies, the current analysis included physical attributes of homes (heated area, year built, number of bedrooms and number of bathrooms) as well as Energy Star status in predicting energy use level. Yet the analysis did not contain any information on occupants such as number of residents, age, income, education level and so forth as well as occupant behavior

such as average thermostat setting points (Pigg 2002). The lack of such information limits the findings and conclusions of the research. In the following sub section uses the same explanatory and dependent variables. Instead of a regular OLS model, the next analysis uses a pooled OLS model and the PTSCS data generated.

5.2.2 Pooled Ordinary Least Squares Estimation and Results

Using the monthly consumptions aggregated at the yearly level, a pooled OLS analysis is conducted using the four types of electricity consumption as the dependent variables: $total\_con_{it}$, $summer\_con_{it}$, $total\_con_{it}$ and $other\_con_{it}$. The sample includes 7050 observation for non-ES homes and 743 observations for ES homes. Conventional homes were built between 1973 and 2005. ES homes were built later from 1997 to 2005. Both groups shared very similar structural characteristics (number of barrooms, bathroom and heated area). The descriptive statistics of conventional homes are summarized in Table 5-4 .Table 5-5 summarized descriptive statistics of ES homes.

Based on Table 5-4 and 5-5, the average total annual electricity consumption for ES homes is 857.5 kWh versus 905.7 kWh for non-ES homes. The average annual summer electricity consumption for ES homes is 364 kWh versus 339.9 kWh for non-ES homes. On average, ES homes consume 206.8 kWh versus 268.1 kWh for non-ES homes during the winter. On average, ES homes consume 286.8 kWh versus 297.7 kWh for non-ES homes during other months. Based on tables, ES homes consume less electricity.

Using the PTSC data, the following restrictive pooled OLS models are estimated[2]:

(Model 1) pooled: $total\_con_{it} = \beta_0 + \beta_1\, ES_i + \beta_2\, effyr_i + \beta_3\, beds_i + \beta_4\, baths_i + \beta_5\, htdarea_i + \beta_6\, htdareai^2 + \varepsilon_{it}$ (5-3)

[2] All models are tested for heteroskedasticity and corrected for it using heteroskedasticity-robust standard errors.

(Model 2) $_{pooled}$: summer_conit = $\beta_0 + \beta_1$ $ES_i + \beta_2$ $effyr_i + \beta_3$ $beds_i + \beta_4$ $baths_i + \beta_5$ $htdarea_i + \beta_6$ $htdareai^2 + \varepsilon_{it}$ (5-4)

(Model 3) $_{pooled}$: winter_conit = $\beta_0 + \beta_1$ $ES_i + \beta_2$ $effyr_i + \beta_3$ $beds_i + \beta_4$ $baths_i + \beta_5$ $htdarea_i + \beta_6$ $htdareai^2 + \varepsilon_{it}$ (5-5)

(Model 4) $_{pooled}$: other_conit = $\beta_0 + \beta_1$ $ES_i + \beta_2$ $effyr_i + \beta_3$ $beds_i + \beta_4$ $baths_i + \beta_5$ $htdarea_i + \beta_6$ $htdareai^2 + \varepsilon_{it}$ (5-6)

The results summarized in Table 5-6 show that the variable of interest ES_i is statistically significant only in the summer months and winter months at the 5% significance level with a P-value of 0.000. During the rest of the year it does not play a statically significant role in predicting household yearly electricity consumption (P-value = 0.197 for the total consumption and P-value= 0.734 for the other consumption). This finding shows the importance that weather plays in predicting the effect of ES rating on electricity consumption.

The summer estimation shows that consumption will actually increase by 34.695 kWh due to these rating of a house. This can be in part explained by the extremely hot temperatures of the region during the summer time. It is also during this time of the year that residents heavily rely on air conditioning systems for cooling purposes. In the contrary, the winter estimation reveals that electricity consumption decreases by 51.374 kWh due to the ES rating of the house. This result is also somewhat anticipated since less air condition systems are turn on during the winter. However, this model does not account for heterogeneity in the houses and produce a single constant intercept with underestimated standard errors. In order to account for the house specific effect, a FE model is estimated. In addition, a time trend is also included in the analysis. The following section discusses the estimation. Since this new variable is time sensitive, it will allow for the evaluation the effects of the ES features on electricity consumption over time.

5.2.3 Panel Data Estimations and Results

In the FE models, house characteristics of a house which are time-invariant cannot be identified. As a remedy, a new variable of interest, the interaction term between the ES_i dummy and the $billyear_t$: $(ES*billyear)_{it}$. A series of time dummy variables (D_t) are also created for each billing year going from 1996 to 2008. A total of 13 binary variables (D_{96}, D_{97}, D_{98},..., D_{08}) are included in the estimation. Each dummy takes value of 1 if billing occurred during the specific year; otherwise it is equal to 0. Since these variables are time sensitive they are also identified. The dependent variables are still four types of electricity consumptions.

Using xtreg …, fe command in STATA, the following models are estimated as FE models[3]:

$$(\text{Model 5})_{FE}: total\_con_{it} = \beta_0 + \gamma(ES*billyear)_{it} + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_{it} \quad (5\text{-}7)$$

$$(\text{Model 6})_{FE}: summer\_con_{it} = \beta_0 + \gamma(ES*billyear)_{it} + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_{it} \quad (5\text{-}8)$$

$$(\text{Model 7})_{FE}: winter\_con_{it} = \beta_0 + \gamma(ES*billyear)_{it} + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_{it} \quad (5\text{-}9)$$

$$(\text{Model 8})_{FE}: other\_con_{it} = \beta_0 + \gamma(ES*billyear)_{it} + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_{it} \quad (5\text{-}10)$$

The parameter $\hat{\delta}$ in the equations tells whether the ES rating of a house helped increase or decrease household electricity consumption over time and by how much. Each individual $\hat{\pi}_j$ (j = 1,…, 13) corresponds to the increase or decrease in electricity consumption specific that particular year only. β_0 and ε_{it} respectively represent the constant and error terms.

[3] All models are tested for heteroskedasticity and corrected for it using heteroskedasticity-robust standard errors.

Now that the models have been described, a joint significance and autocorrelation tests are carried out in order to ensure the use the appropriate modeling strategy before diving into the discussing of the results.

Joint Significance Test Results: Consider then, the hypothesis:

H_o: $\hat{\pi}_1 = \hat{\pi}_2 = \hat{\pi}_3 = \ldots = \hat{\pi}_{13} = 0$ (5-11)

H_a: H_o is not true

where the null hypothesis (H_o) indicates that the time dummy variables have no effect on the level of household electricity consumption. The alternative hypothesis (H_a) is that the time dummy variables are not jointly equal to zero. There are k = 13 restrictions that are being tested. Using STATA, F statistic obtained is 228.89 and the P-value is 0.000.

Based on the results of the joint significance test, the decision is to reject H_o. The time dummy variables are statistically and jointly not equal to zero at the 5% significance level. They are therefore statistically significant in explaining the variation in electricity consumption over time. This result confirms the importance of a time trend in examining electricity consumptions over time. Next, an autocorrelation test is carried out and the results are presented.

Serial Correlation Test Results: Since most TSCS datasets are a very likely to be plagued by the presence of serial correlation, all four FE models are tested for it and results are discussed. In case there is the presence of autocorrelation, the error term is: $\varepsilon_{it} = \rho\varepsilon_{i,t-1} + U_t$ where U_t meets all classical assumptions. The following hypotheses are therefore tested using the Durbin-Watson Test, assuming that all X variables are strictly exogenous with $\alpha = 0.05$, the significance level. Consider the hypothesis:

H_o: $\rho = 0$ (5-12)

H_a: $\rho \neq 0$ (5-13)

where the null hypothesis (H_o) is no serial correlation in the error term and the alternative hypothesis (H_a) is that there is autocorrelation . Based on the results of the test summarized in Table 5-7, the decision is to reject H_a since the P values of all four models are 0.000 and less than $\alpha = 0.05$.There is statistical evidence that the error terms are serially correlated at the 5% significance level.

In other words, the level of electricity consumption at time period t is not only determined by the changes in consumption that occurred during this time period but also by the "memory" of the level of consumption in the last time period t-1. This is defined as an autoregressive process of order one or AR (1). As mentioned previously in the study, if not accounted for, autocorrelation will affect OLS results: standard errors will be too small; test statistics will be too big and thus OLS will create a false confidence in results.

Since the time dummy variables are jointly significant and there is evidence of serial correlation, $(\text{Model 5})_{FE}$ through $(\text{Model8 })_{FE}$ described earlier are run as FE models using the xtregar…fe STATA command.

The results from the FE estimation which are summarized in Table 5-8 show that the variable of interest $(\text{ES*billyear})_{it}$ increases the level of total annual electricity consumption by 89.63 kWh. Because of the time effect, ES rating increases annual electricity usage by 74.320 kWh for the summer consumption. This result is also statistically significant with a P-value of 0.000. Over time, annual winter consumption decreased by 61.57kWh while other consumption increased by 34.222 kWh due to the ES rating. It is important to note that all these results are statistically significant at the 5% significance level with a P-value of 0.000.

When not corrected for serial correlation, the FE estimations generate the results summarized in Table 5-9. The variable of interest $(\text{ES*billyear})_{it}$ increases the level of total

annual electricity consumption by 11.609 kWh. ES rating increases annual summer electricity consumption by 12.044 kWh. Over time, annual winter consumption increases by 3.904 kWh while other consumption decreases by 4.338 kWh due to the ES rating. All these results are statistically significant at the 5% significance level.

The FE estimation tells a similar story of the effect energy efficient features of a house being dependent on the climatic conditions: more during the summer season than the winter season due to hotter temperatures. Based on this FE model, ES rating of a house actually increases electricity consumption as time goes by. This phenomenon can be explained by the gradual degradation over an extended period of time of energy efficiency features built into the house. The examination of such time trend introduced in this research is lacking in the current literature, as most studies only focus on the stationary effect of the ES rating which does not allow for the estimation of effect on time on ES performance. This positive time trend therefore shows that on average, from one year to the other, ES rating increases electricity consumption. In summary, the current analysis shows that changes in electricity consumption are explained by:

Structural characteristics of the house accounted for as unit-specific effect

Changes in consumption pattern occurred during a given year which can be explained for instance by changes in climate (i.e. summer, winter or off-seasons)

Changes in consumption pattern which occurred in the previous year

Changes in the performance of ES upgrades due to gradual degradation over time.

In the following section another DID estimation is performed and compared to the initial one conducted in chapter 4.

5.3 Difference-in-Difference Estimations and Results

Based on the previous analysis in previous sections, there is a statistically significant difference in the level of electricity consumption from one year to the other due to ES rating. The

following models examine how that difference actually behaves overtime. A DID estimation is therefore carried out with the parameter of interest being $\hat{\gamma}$ .This parameter corresponds to the change over time in the difference in electricity consumption due to the ES rating.

This estimation differs from the previous one in chapter 4 in the sense that the dependent variables are here all electricity consumptions (summer, winter and off-season consumptions) instead of electricity, natural gas and a combination of electricity and natural gas.

The current estimation also differs from the previous one since it is carried out using billed years from 1996 to 2008 instead of only two years (2000 and 2006). By adding data on other time periods, the study hopes to capture any underlying existing trends and confounding factors affecting the results (Meyers, 1995).

3 models are specified. The first model, (Model 9) $_{DID}$, includes the ES dummy variable as well as time dummy variables as explanatory variables:

(Model 9) $_{DID}$: $total\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_{it}$ (5-14)

Similarly to the DID estimation conducted in chapter 4, the constant term represents the average yearly electricity consumption for conventional or non-ES house. $\hat{\beta}_1$ associated with the ES dummy variable represents the change in electricity consumption due to the treatment specific effect: ES rating of the house. Each $\hat{\pi}_j$ (j= 1,…, 13) represents the variation in electricity consumption specific to that year. It corresponds to the time trend impacting household electricity consumption common to both types of houses.

In the second model, (Model 10) $_{DID}$, the interaction term between the ES dummy and the bill year is added: (ES*billyear) $_{it}$. $\hat{\gamma}$ Associated with this variable captures the change overtime in the difference in electricity consumption between ES house and non-ES houses.

(Model 10)$_{DID}$: $total\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \gamma(ES*billyear)_{it} + \varepsilon_{it}$ (5-15)

In the last model, (Model 11)$_{DID}$, structural characteristics the houses are added in the attempt to explain better the variations in consumption. They include effective year, number of bedrooms, bathrooms and heated area.

(Model 11)$_{DID}$: $total\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \gamma(ES*billyear)_{it} + \beta_2 effyr_i + \beta_3 beds_i + \beta_4 baths\ \beta_5 htdarea_i + \beta_6 htdarea_i^2 + \varepsilon_i$ (5-16)

$\hat{\beta}_2, \ldots, \hat{\beta}6$ represent the change in household s electricity consumption due the structural characteristics of a house. The models are run[4] using OLS estimation and the results are summarized in the Table 5-10 using total consumption data. The average consumption for traditional homes is 862.281kWh and ES homes consume about 17.481kWh less based on (model 9)$_{DID}$. The results are statistically significant at the 5% level. As additional explanatory variables are added in to the analysis, R^2 increases from 0.0849 to 0.1824. The results of (Model 11) $_{DID}$ show that total electricity consumption increased by 13.133 kWh due to the impact of the ES features overtime. The results are statistically significant at the 5% significance level. Knowing that the average total electricity consumption is 910.010 kWh, ES qualified homes consume about 1.46% more energy than conventional homes. This result is much more conservative than the previous results in chapter 4 (i.e. 7.59%).

The following 3 models are also estimated using summer consumption data and the results are summarized in Table 5-11.

[4] All models are tested for heteroskedasticity and corrected for it using heteroskedasticity –robust standards errors.

(Model 12)$_{DID}$:summer_con$_{it}$ = $\beta_0 + \beta_1$ ES$_i$+ $\pi_1 D_{97}$+ $\pi_2 D_{98}$+ $\pi_3 D_{99}$+ $\pi_4 D_{00}$+ $\pi_5 D_{01}$+ $\pi_6 D_{02}$+ $\pi_7 D_{03}$+ $\pi_8 D_{04}$+ $\pi_9 D_{05}$+ $\pi_{10} D_{06}$+ $\pi_{11} D_{07}$+ $\pi_{12} D_{08}$+ε_{it} (5-17)

(Model 13)$_{DID}$: summer_con$_{it}$ = $\beta_0 + \beta_1$ ES$_i$+ $\pi_1 D_{97}$+ $\pi_2 D_{98}$+ $\pi_3 D_{99}$+ $\pi_4 D_{00}$+ $\pi_5 D_{01}$+ $\pi_6 D_{02}$+ $\pi_7 D_{03}$+ $\pi_8 D_{04}$+ $\pi_9 D_{05}$+ $\pi_{10} D_{06}$+ $\pi_{11} D_{07}$+ $\pi_{12} D_{08}$+ γ(ES*billyear)$_{it}$ + ε_{it} (5-18)

(Model 14)$_{DID}$: summer_con$_{it}$ = $\beta_0 + \beta_1$ ES$_i$+ $\pi_1 D_{97}$+ $\pi_2 D_{98}$+ $\pi_3 D_{99}$+ $\pi_4 D_{00}$+ $\pi_5 D_{01}$+ $\pi_6 D_{02}$+ $\pi_7 D_{03}$+ $\pi_8 D_{04}$+ $\pi_9 D_{05}$+ $\pi_{10} D_{06}$+ $\pi_{11} D_{07}$+ $\pi_{12} D_{08}$+ γ(ES*billyear)$_{it}$ + β_2 effyr$_i$+ β_3 beds$_i$+ β_4 baths β_5 htdarea$_i$+ β_6 htdarea$_i^2$+ ε_{it} (5-19)

The results show that summer electricity consumption increased by 12.086 kWh due to the impact of the ES features overtime. The results are statistically significant at the 5% significance level with a P-value of 0.003. Since the average summer consumption in the sample is 342.21 kWh, it corresponds to a 3.53% increase for ES qualified homes. The average consumption for traditional homes is 376.425 kWh and ES homes consume about 36.385 kWh more based on (model 12)$_{DID}$. The results are statistically significant at the 5% level. As additional explanatory variables are added in to the analysis, R^2 increases from 0.4435 to 0.4863. The lager effect of the rating can be explained by the hot temperatures during the summer months and which reinforced the seasonality of consumption. The same analysis is carried out using winter consumption data and the results are summarized in Table 5-12. The 3 models are:

(Model 15)$_{DID}$: winter_con$_{it}$ = $\beta_0 + \beta_1$ ES$_i$+ $\pi_1 D_{97}$+ $\pi_2 D_{98}$+ $\pi_3 D_{99}$+ $\pi_4 D_{00}$+ $\pi_5 D_{01}$+ $\pi_6 D_{02}$+ $\pi_7 D_{03}$+ $\pi_8 D_{04}$+ $\pi_9 D_{05}$+ $\pi_{10} D_{06}$+ $\pi_{11} D_{07}$+ $\pi_{12} D_{08}$+ε_{it} (5-20)

(Model 16)$_{DID}$: winter_con$_{it}$ = $\beta_0 + \beta_1$ ES$_i$+ $\pi_1 D_{97}$+ $\pi_2 D_{98}$+ $\pi_3 D_{99}$+ $\pi_4 D_{00}$+ $\pi_5 D_{01}$+ $\pi_6 D_{02}$+ $\pi_7 D_{03}$+ $\pi_8 D_{04}$+ $\pi_9 D_{05}$+ $\pi_{10} D_{06}$+ $\pi_{11} D_{07}$+ $\pi_{12} D_{08}$+ γ(ES*billyear)$_{it}$ + ε_{it} (5-21)

(Model 17)$_{DID}$: $winter\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \gamma(ES*billyear)_{it} + \beta_2 effyr_i + \beta_3 beds_i + \beta_4 baths\ \beta_5 htdarea_i + \beta_6 htdarea_i^2 + \varepsilon_{it}$ (5-22)

The results of (Model 17) $_{DID}$ show that winter electricity consumption increased by 4.989 kWh due to the change in the impact of the ES features overtime. Since the average winter consumption in the sample is 262.23 kWh, it corresponds to a 1.90% increase for ES qualified homes. Yet, the results are not statistically significant with a P-value of 0.123. The average consumption for traditional homes is 203.144 kWh and ES homes consume about 68.705 kWh less based on (model 15)$_{DID}$. The results are statistically significant at the 5% level. As additional explanatory variables are added in to the analysis, R^2 increases from 0.2825 to 0.3436. The smaller effect of the rating can be explained by the cooler temperatures during the winter months. The following 3 models are run using other consumption data and the results are summarized in Table5-13:

(Model18)$_{DID}$: $other\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \varepsilon_i$ (5-23)

(Model 19)$_{DID}$: $other\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \gamma(ES*billyear)_{it} + \varepsilon_{it}$ (5-24)

(Model 20)$_{DID}$: $other\_con_{it} = \beta_0 + \beta_1 ES_i + \pi_1 D_{97} + \pi_2 D_{98} + \pi_3 D_{99} + \pi_4 D_{00} + \pi_5 D_{01} + \pi_6 D_{02} + \pi_7 D_{03} + \pi_8 D_{04} + \pi_9 D_{05} + \pi_{10} D_{06} + \pi_{11} D_{07} + \pi_{12} D_{08} + \gamma(ES*billyear)_{it} + \beta_2 effyr_i + \beta_3 beds_i + \beta_4 baths\ \beta_5 htdarea_i + \beta_6 htdarea_i^2 + \varepsilon_{it}$ (5-25)

The results of (Model 20) $_{DID}$ show that other electricity consumption decreased by 3.942 kWh due to the impact of the ES features overtime. Since the average other consumption in the sample is 296.65 kWh, it corresponds to a 1.32% increase for ES qualified homes. However,

these results are not statistically significant with a P-value of 0.135. The average consumption for traditional homes is 282.717 kWh and ES homes consume about 14.837 kWh more based on (model 18) $_{DID}$. The results are statistically significant at the 5% level. As additional explanatory variables are added into the analysis, R^2 increases from 0.1693 to 0.2361.

5.4 Conclusions

This chapter presented predictive models of household electricity consumption in order to f identify the effect of its energy efficiency status (Energy Star rated or not), physical attributes of the house and climatic conditions on levels of household energy usage. First, the two different types of energy datasets used in this part of the study were described. Secondly, a simple OLS and pooled OLS estimations were carried out. Then a FE and DID analysis were performed. Results from joint significance and autocorrelation tests were also outlined. Finally, findings from the estimations were presented as well as their interpretations and implications in terms energy consumption and energy savings outcomes.

Monthly electricity consumption from 1996 to 2008 is estimated as function of structural characteristics, Energy Star status and seasonality of consumption. The findings show that Energy Star rated homes consume about 5.45% less electricity each month than traditional homes. These results are much more conservative than previous studies in the current literature that estimated saving of 3% all the way to 16% at the household level. The study therefore shows that a short time frame (for instance two years in the current literature) does not allow for a true assessment of the effectiveness of the Energy Star program in term of electricity savings at the household level. Over a longer time period, energy savings shrink significantly (i.e. by about half) as well thus in effectiveness in greenhouse gas emission reduction, energy security and environmental protection. The study also shows that physical characteristics of the house, for instance number of bedrooms, bathrooms and heated area positively affect household electricity

consumption, as predicted. Environmental factors such as seasonality (winter and summer months) have a significant influence on monthly electricity consumption. Indeed, as the temperature rises during the summer so does electricity consumption as households heavily rely on air conditioning systems to cool off. In the contrary, during the winter months, as climate cools down, consumption decreases since household use less on air conditioning.

The short-comings of the model rise in the fact that it does not include information on occupants of the homes such social characteristics (income, education levels, number of occupants, household composition, and so forth) or occupant behavior such as thermostat setting. As a result, the low predictive power of the model (21.24%) can be improved by including such explanatory variables.

There is a very slim body of literature on the impact of energy saving investments such as the Energy Star program on household energy consumption over an extended period of time. The current research consequently contributes to this body of literature since it allows for the evaluation of an energy efficiency initiative, the Energy Star program over time. Results from the study mainly address the issue of sustainability of energy savings generate by such voluntary programs and therefore motivate a serious examination of the following questions: how much energy is actually saved over time by voluntary energy efficiency programs at the household level? Are those savings sustainable in the long-run? Are the investments actually worth it for the average homeowner participating in the Energy Star program? To what existent are such voluntary programs protecting the planet at the household level?

In the attempt to answer the previous questions, the original monthly data was collapsed and aggregated at the yearly level as TSCS data using STATA. With a dataset that is time sensitive, the evaluation of the ES program over time is made more accurate.

The pooled OLS estimation shows that during summer months, electricity consumption rises by 34.695 kWh for homes rated ES. Consumption decreases by 51.374 kWh during the winter for ES homes. Both results are statistically significant. When considering total consumption and other consumption, levels of energy usage decrease respectively by 18.54 kWh and 1.846 kWh. These results are however not statistically significant.

Since this estimation does not take in account house specific effect, FE estimation corrected for autocorrelation is carried out accounting for not only heterogeneity at the house level but also a time effect. Indeed the interaction term $(ES*billyear)_{it}$ captures the time trend in the impact of ES rating on electricity consumption. All estimates are statistically significant. ES homes have a higher consumption overall for total consumption (89.63 kWh more), summer consumption (74.320 kWh more) and other consumption (34.22 kWh more) than non -ES except during the winter when ES homes consumed about 61.57 kWh less than traditional homes.

This shows that the effects of the energy efficiency upgrades do change over time and they are not stagnant as assumed by the current literature. The changes can be attributed to the natural degradation of construction over the years. The 13 time dummy variables created to indicate the bill years are all jointly statistically significant.

Finally, the DID estimation reveals a similar conclusion. In fact, with ES homes consuming 13.133 kWh more in total consumption or 1.46%, 12.086 kWh more in summer consumption or 3.53% and 4.989 kWh or 1.90% more in winter consumption than non -ES except for the off season months when ES homes consumed about 3.942 kWh or 1.32% less than traditional homes. The results during the winter and off season are not statistically significant. The DID conclusion however shows how the changes observed previously with the FE model change over time: they increase overtime revealing that the ES upgrades become less

and less efficient in conserving energy to a point that they actually increase household energy consumption.

Keeping the main research question in mind, determining if energy efficient program such as the ES program saves energy and if the savings are sustainable over time, important lessons can be learned from this study. In fact, this study shows that if not maintained or updated, energy efficient features built into ES qualified homes can result in an increase of energy consumption at the household level over time. As these upgrades degrade overt time, the effect of ES rating on energy consumption in negatively affected. ES houses could be actually consuming more energy and thus hurting more the environment instead of protecting it. Some policy implications include the risk of investing into short-term solutions instead of really assessing long-term performance of such initiatives in order to make adequate changes. As suggested earlier, a policy recommendation can be a mandatory periodic evaluation of ES homes to ensure that energy savings are still maintained. In the following the main conclusions and policy implications of the study are outlined

Table 5-1. Variables Description

Variable	Variables Description
billed_con	Monthly billed electricity consumption in kWh
ES	Energy Star dummy
effyr	Year built of the house
beds	Number of bedrooms
baths	Number of bathrooms
htdarea	Heated area in the house in square feet
summer	Dummy variable indicating summer consumption (1=Yes ,0=No)
winter	Dummy variable indicating winter consumption (1=Yes ,0=No)

Table 5-2. Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
billed_con	97515	944.0672	548.574	1	7121
effyr	97515	1998.495	2.179315	1973	2005
ES	97515	0.087299	0.282275	0	1
beds	97515	3.274286	0.46689	2	5
baths	97515	2.116521	0.320358	2	4.5
htdarea	97515	1850.127	342.7187	1051	4523

Table 5-3. Monthly OLS Estimation Results

Variables	Estimates	P value
effyr	-13.136	0.000
	(0.779)	
ES	-51.428	0.000
	(5.513)	
beds	59.588	0.000
	(4.441)	
baths	35.72	0.000
	(6.895)	
htdarea	0.053	0.000
	(0.063)	
$htdarea^2$	-0.000056	0.001
	(1.65E-06)	
summer	272.149	0.000
	(-4.329)	
winter	-265.378	0.000
	(3.583)	

Table 5-4. Descriptive Statistics of Conventional Non-ES Homes

Variables	Obs.	Mean	Std. Dev.	Min	Max
total_con_m	7050	905.7	375.5	6	3333.8
sum_con_m	7050	339.9	213.0	0	1368.6
winter_con_m	7050	268.1	169.6	0	2051
other_con_m	7050	297.7	140.8	0	1141.8
effyr	7050	1998.5	2.3	1973	2005
beds	7050	3.3	0.5	2	5
baths	7050	2.1	0.3	2	4.5
htdarea	7050	1869.1	357.6	1051	4523
htdarea2	7050	3621507	1457106	1104601	2.05E+07

Table 5-5. Descriptive Statistics of ES Homes

Variables	Obs.	Mean	Std. Dev.	Min	Max
total_con_m	743	857.5	387.8	23	3557.2
sum_con_m	743	364	174.5	0	1242.3
winter_con_m	743	206.8	112.6	16.5	1124.5
other_con_m	743	286.8	145.5	0	1319
effyr	743	1998.5	2.2	1997	2005
beds	743	3.2	0.4	3	4
baths	743	2.1	0.3	2	3
htdarea	743	1790.7	328.9	1329	2911
htdarea2	743	3314436	1332876	1766241	847392

Table 5-6. Parameter Estimates, Standard Errors, and P-values of Pooled OLS Estimation using Annual PTSCS Data

Models	$(\text{Model 1})_{pooled}$		$(\text{Model 2})_{pooled}$		$(\text{Model 3})_{pooled}$		$(\text{Model 4})_{pooled}$	
Explanatory variables	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
Constant	28963	0.000	9834.77	0.000	14470.11	0.000	4658.12	0.001
	(3627.498)		(2274.653)		(1955.712)		(1425.936)	
ES_i	-18.524	0.197	34.695	0.000	-51.374	0.000	-1.846	0.734
	(14.362)		(6.719)		(4.518)		(5.435)	
$Effyr_i$	-14.444	0.197	-4.941	0.000	-7.229	0.000	-2.273	0.001
	(1.811)		(1.137)		(0.977)		(0.712)	
$beds_i$	52.67	0.00	14.336	0.035	22.977	0.000	15.356	0.001
	(12.032)		(6.803)		(5.429)		(4.552)	
$baths_i$	18.724	0.303	-0.814	0.935	19.419	0.026	0.119	0.986
	(18.185)		(9.961)		(8.746)		(6.879)	
$htdarea_i$	0.35	0.014	0.249	0.000	0.048	0.519	0.053	0.195
	(0.142)		0.067		0.075		0.04	
$htdarea_i^2$	1.62E-05	0.661	-3.80E-05	0.038	1.05E-05	0.59	9.35E-06	0.375
	(3.70E-05)		(1.74E-05)		(1.94E-05)		(1.50E-05)	
R^2	0.0966		0.0389		0.0761		0.0635	

Table 5-7. F Statistics and P-values of Autocorrelation Test

Models	F statistic	P-value
(Model 5)$_{FE}$	867.154	0.000
(Model 6)$_{FE}$	437.143	0.000
(Model 7)$_{FE}$	952.973	0.000
(Model 8)$_{FE}$	981.422	0.000

Table 5-8. Parameter Estimates, Standard Errors, and P-values of Interaction Term Variable in FE Estimation after Accounting for Autoregressive Disturbances AR (1)

Variable	(ES*billyear)$_{it}$		Value of Rho
Models	Estimates	P-value	
(Model 5)$_{FE}$	89.63	0.000	0.5474
	(8.24)		
(Model 6)$_{FE}$	74.32	0.000	0.3642
	(3.3147)		
(Model 7)$_{FE}$	-61.57	0.000	0.5133
	(3.428)		
(Model 8)$_{FE}$	34.222	0.000	0.4737
	(2.860)		

Table 5-9. Parameter Estimates, Standard Errors, and P-values of values of Interaction Term Variable in FE Estimation without Accounting for Autoregressive Disturbances AR (1)

Variable	(ES*billyear)$_{it}$	
Models	Estimates	P-value
(Model 5)$_{FE}$	11.609	0.003
	(3.949)	
(Model 6)$_{FE}$	12.044	0.000
	(2.126)	
(Model 7)$_{FE}$	3.904	0.032
	(1.823)	
(Model 8)$_{FE}$	-4.338	0.007
	(1.595)	

Table 5-10. Parameter Estimates, Standard Errors, and P-values of the DID Estimation using Total Annual Electricity Consumptions

Dependent variable	$total\_con_{it}$					
Models	(Model 9) $_{DID}$		(Model 10) $_{DID}$		(Model 11) $_{DID}$	
Explanatory	Estimates	P-value	Estimates	P-value	Estimates	P-value
Constant	862.281	0.000	866.759	0.000	39991.93	0.000
	(12.826)		(12.936)		(3709.649)	
ES_i	-17.481	0.007	-34860.97	0.007	-263000.03	0.035
	(16.862)		(12878.79)		(12442.44)	
$(Es*billyear)_{it}$	No		17.392	0.007	13.133	0.035
			(6.431)		(6.213)	
D_t	Yes		Yes		Yes	
House $features_i$	No		No		Yes	
R^2	0.0849		0.0858		0.1824	

Table 5-11. Parameter Estimates, Standard Errors, and P-values of the DID Estimation using Summer Annual Electricity Consumptions

Dependent variable	$summer\_con_{it}$					
Models	(Model 12) $_{DID}$		(Model 13) $_{DID}$		(Model 14) $_{DID}$	
Explanatory variables	Estimates	P-value	Estimates	P-value	Estimates	P-value
Constant	376.425	0.000	379.901	0.000	15550.41	0.000
	(5.700)		(7.076)		(1717.59)	
ES_i	36.385	0.000	-27046.39	0.001	-24165.41	0.003
	(6.658)		(8142.163)		(12442.44)	
$(Es*billyear)_{it}$	No		13.519	0.001	12.086	0.003
			(4.065)		(4.051)	
D_t	Yes		Yes		Yes	
House $features_i$	No		No		Yes	
R^2	0.4435		0.4463		0.4863	

Table 5-12. Parameter Estimates, Standard Errors, and P-values of the DID Estimation using Winter Annual Electricity Consumptions

Dependent variable	$winter\_con_{it}$					
Models	(Model 15) $_{DID}$		(Model 16) $_{DID}$		(Model 17) $_{DID}$	
Explanatory	Estimates	P-value	Estimates	P-value	Estimates	P-value
Constant	203.144	0.000	204.819	0.000	11149.95	0.000
	(5.122)		(4.543)		(1531.77)	
ES_i	-68.705	0.000	-13119.77	0.048	-10055.91	0.121
	(5.983)		(6643.96)		(6484.65)	
$(ES*billyear)_{it}$	No		6.514	0.049	4.989	0.123
			(3.315)		(4.051)	
D_t	Yes		Yes		Yes	
House $features_i$	No		No		Yes	
R^2	0.2825		0.2844		0.3436	

Table 5-13. Parameter Estimates, Standard Errors, and P-values of the DID Estimation using Other Annual Electricity Consumptions

Dependent variable	$other\_con_{it}$					
Models	$(Model\ 18)_{DID}$		$(Model\ 19)_{DID}$		$(Model\ 20)_{DID}$	
Explanatory	Estimates	P-value	Estimates	P-value	Estimates	P-value
Constant	282.717	0.000	282.038	0.000	10291.57	0.000
	(4.688)		(5.173)		(1507.63)	
ES_i	14.837	0.007	5305.195	0.324	7921.286	0.134
	(5.477)		(5379.202)		(5286.957)	
$(ES*billyear)_{it}$	No		-2.640	0.325	-3.942	0.135
			(2.685)		(2.639)	
D_t	Yes		Yes		Yes	
House $features_i$	No		No		Yes	
R^2	0.1693		0.1708		0.2361	

CHAPTER 6
CONCLUSIONS

This chapter outlines general conclusions and policy implications of the research. Section 6.1 presents an overview of the research. Then section 6.2 discusses the limitation of the study. Finally, policy implications as well as future steps are summarized in Section 6.3.

6.1 Overview of the Research

With a current U.S. greenhouse gas emissions increasing each year, policy makers are face with the overwhelming challenge of climate change. Energy efficiency policies or voluntary programs such as the Energy Star program is one way the current government attempts to conserve energy and preserve our environment. This study investigates the effect of the Energy Star rating on energy consumption in Gainesville, Florida. The main research question is therefore to determine if energy efficient upgrades save energy and if so, if this efficiency maintained overtime. Difference-in-Difference, pooled OLS and FE estimations are adopted as tools to evaluate the performance of the Energy Star rating (the treatment) overtime on household energy consumption (the outcome). Two groups (ES homes and Non-ES homes) are defined and a 13 years' time period is used. Dummy variables capturing seasonality of energy consumption and bill years are created. Energy consumption of homes initially included electricity consumption measured in kilowatts and natural gas consumption measured in thermos. The study focuses later on electricity consumption due the hot climate of the region of study.

In recent years, EPA reports claimed significant energy savings due to the execution of the Energy Star strict energy efficiency guidelines. However, the different empirical models used in this study reveal unexpected findings. In fact, estimates show an increase energy consumption for homes rated Energy Star as a result of the Energy Star rating in Gainesville, Florida overtime from a minimum of 4.989 kWh per year to a maximum of 89.63 kWh depending on the model.

The latest result is believed to be the most accurate prediction since it results from the most appropriate modeling approach for the data available. These results are statistically significant. These findings challenge the long-term performance of the Energy Star program. Indeed, they lead to the conclusion that Energy Star guidelines are effective in reducing energy consumption when the house is built but these guidelines do not sustain energy savings over time.

6.2 Limitations of the Study

A limitation in the study is the lack of data on occupant behavior or "occupant actions" (Guerin, et al., 2000) such as thermostat setting. In fact, there is lack of information on whether residents of ES rated homes tend to set their thermostat higher during the summer and lower during the winter in a way that expected energy savings are reduced (Smith and Jones, 2003). Characteristics of the occupants such as age, income, number of occupants, education and so forth, that explain energy consumption are also not observable (Guerin, et al., 2000, and Yohanis, et al., 2007). Adding more time-invariant variables that affect energy consumption such as tree coverage can also provide a better measure to the effect of time on energy consumption. Incorporating these elements to the current information available would make the ideal data for this research and produce stronger results.

6.3 General Conclusions and Policy Implications

This analysis has important policy implications. In fact, it forces policy makers to look closer at the long-term effects of energy efficiency programs in addition to the short-tem impacts. For instance, without long-term examination of programs such as the Energy Star program, there is the risk of attributing energy efficiency tax credits to homeowners that are actually polluting more. In fact, the energy efficiency tax credits were initially established in 2006 as a result of the Energy Policy Act of 2005. The main objective of energy efficiency tax credits is to encourage environmental stewardship by monetarily rewarding individuals or

organizations that invest in environmental friendly equipment or construction. Since then, energy efficiency tax credits have evolved. Starting at 10% of the cost or up to $500 in 2006 and 2007, credits have increased to a significant 30% or up to $1,500 today. Federal efforts such as the Economic Stabilization Act of 2008 signed by former President Bush and the American Recovery and Reinvestment Act of 2009 under the new Obama administration are examples of policy initiatives reinforcing the implementation of energy efficiency tax credits. Federal tax credits for Energy Efficiency includes installation of energy-efficient windows and doors, insulation, roofs, heating and cooling equipment such as water heater (non-solar) and biomass stoves. Such features are built into ES qualifies homes. Other tax credits such as the "Residential Renewable Energy Tax Credits reward consumers who have installed solar energy systems (including solar water heating and solar electric systems), small wind systems, geothermal heat pumps, and residential fuel cell and microturbine systems" (ENERGY STAR, 2007).

In addition to federal tax incentives, some consumers will also be eligible for utility or state rebates, as well as state tax incentives for energy-efficient homes, vehicles and equipment. As a result, if periodic evaluations are not conducted and long-term performance not assessed, the attribution of energy efficient tax credits can simply turn into a marketing tool for homebuilders or energy efficient equipment manufacturers. This will in return hinder the purpose of the initiative which is to encourage behavior that actually decreases GHG emissions and thus protects the environment.

Future works of this study will consist in incorporating more time-varying and spatial explanatory variables which characterize each house and thus influence household energy consumption. For instance, change in tree coverage in the area. Appraised home values or sale prices of the homes can be incorporated to see how ES features are being capitalized by

homeowners. Indeed, the sale transaction information can be used to proxy the changes in household composition over time. It will help measure how many times the home has changed owner. This will therefore account for the fact that different household types have different characteristics and habits and therefore different energy use levels.

On one hand, the results of this study can be used as a tool to market energy efficient home upgrades to home buyers in terms of reduced homeownership operating cost due to energy savings. On the other hand, it sheds some light on the need for constant evaluation and assessment of the performance of such initiatives over time. Frequent evaluation will in return inspire more up- to-date and relevant policies aimed at promoting efficient energy usage and environment protection. The major implication from this study is that houses rated ES need to be evaluated periodically in order to ensure that the energy efficient upgrades built into the house are still efficient since they gradually degrade overtime. Another extension of this study can thus be to estimate the point at which an ES house loses its energy saving and environmentally friendly capabilities.

As described in the new Stimulus Package, environmental protection and natural resource conservation have an important place on the new administration's agenda. It accordingly follows that a proper evaluation of energy efficiency programs such as the Energy Star program is crucial. Indeed, this study shows that it constitutes a vital step toward meeting governmental goal of "implementation of sound, cost-effective energy management and investment practices to enhance the nation's energy security and environmental stewardship" (US DOE, 2009).

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BIOGRAPHICAL SKETCH

Eloise Francesca Aka was born in 1984 in Abidjan, Cote d'Ivoire (West Africa). The middle child of three children, she graduated from Lycee Blaise Pascal High School, Abidjan in 2002. She moved to the United States in August 2002 and earned her Associates of Arts degree in accounting from Santa Fe Community College in December 2004. Eloise then transferred to the University of Florida and earned her Bachelor of Science degree in food and resource economics in May 2007. During her undergraduate years, Eloise interned as a Management Consultant with East Gainesville Development Corporation, volunteered at Shands Hospital and represented the University of Florida at the first annual Florida International Leadership Conference in February 2007. After graduation, she also interned in the summer of 2007, working with IFAS professors on investigating consumers' willingness to pay for locally grown fruits and vegetables in Gainesville, FL.

She was admitted in August 2007 into the Food and Resource Economics Graduate Program. Her areas of interest were international development and environmental economics. As a graduate Research Assistant, Eloise worked on a grant sponsored the Center for International Business and Research analyzing EUREPGAP certification for Florida growers. During her second year of graduate studies, she provided consulting services to the Gainesville Energy Efficient Communities by analyzing energy consumption data for the Gainesville area and making energy efficient policy recommendations. She also served as a Teaching Assistant of Agribusiness Marketing and Econometrics courses. She received her Master of Science in food and resource economics in August 2009. Eloise plans to pursue a career as natural resource economist in the public utility sector, a private organization or an international institution.