RESIDENTIAL ENERGY CONSUMERS RESPONSE TO ENERGY EFFICIENCY REBATES, INCENTIVES, AND PRICES

By

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A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2016

To my parents

ACKNOWLEDGMENTS

I am indebted to my dissertation chair and co-chair, Professor Jonathan Hamilton and Professor David Sappington for their useful guidance, comments, and constructive criticism. Their useful suggestions, not only on my analysis, but also on my writing has ushered me onto a path of successful and effective academic writing.

I'm also grateful to other members of my dissertation committee, Professor Chunrong Ai and Professor Charles Moss, as well as Dr. Ted Kury and other professors of the Economics Department for their invaluable support and motivation.

My sincere gratitude also goes to my parents, Mr. and Mrs. Boachie for their support and encouragement throughout my academic career.

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August 2016

Chair: Jonathan Hamilton
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Major: Economics

This dissertation is comprised of three chapters. In the Chapter 1, I estimate the energy savings effects of a Demand-Side Management (DSM) program, specifically Gainesville Regional Utility's (GRU) high-efficiency central Air Conditioner (AC) rebate program, in which GRU offers incentives to its customers to replace their old low-efficiency AC unit with a high-efficiency model. This research combines a Coarsened Exact Matching (CEM) methodology with a Difference-in-Difference (DD) approach. I estimate the impact of GRU's 2009 high-efficiency AC program on annual energy consumption. Also, because the primary reason for a DSM program is to reduce peak period consumption, I disaggregated the energy savings effects of the program into summer peak effects, winter peak effects, and non-peak effects. The results show substantial annual energy savings of the high-efficiency AC program. While the program has substantial effects on summer peak and non-peak consumption, it has little or no significant effects on winter peak usage.

Chapter 2 investigates if there is a "rebound effect" (increased energy consumption) once consumers learn of their energy cost savings after participating in a DSM program. I find no statistically significant rebound effects of the AC rebate program.

Chapter 3 analyzes whether automatic bill payment (or autopay) renders consumers electricity demand less price sensitive. I propose a conceptual model in which consumers make behavioral rules to their electricity consumption only after observing their bill from the previous

month. The model suggests that a consumer's current demand for electricity responds to the average price he paid for electricity in the preceding month. An implication of the model is that automatic bill payment which reduces the likelihood that a consumer will examine the charges on their bill makes him less price salient. We demonstrate, empirically, that consumers respond to their one-month lagged average price, consistent with the conceptual model. I also show that automatic bill payment users are 10% less price elastic than non-autopay users. I show further that enrolling in automatic bill payment makes a consumer's electricity demand elasticity 5% less (in absolute terms) than it was before he enrolled in autopay.

CHAPTER 1

EVALUATING THE ENERGY SAVINGS EFFECTS OF A UTILITY DEMAND-SIDE MANAGEMENT PROGRAM USING A DIFFERENCE-IN-DIFFERENCE COARSENED EXACT MATCHING APPROACH

1.1 Introduction

Since the late 1970's, there has been a wide variety of Utility Demand-Side Management (DSM) programs to reduce energy consumption. Price-based programs such as peak-load pricing and incentive-based Demand Response (DR) programs such as direct load control, demand bidding, and interruptible programs are considered most effective in reducing peak period energy demand. However, most utilities find it difficult to implement these measures due to program cost and problems with overpayment or underpayment of incentives due to unverifiable baseline mechanisms for obtaining consumption reductions (Bushnell et al., 2009). Residential home retrofitting programs thus appear as an alternative for energy savings that can avoid the problems of price-based or incentives-based demand response programs. Also, these traditional energy efficiency retrofit programs can help install the automation systems needed to allow customers to participate in an automated demand-response programs (Violette, 2008). Another significant advantage of residential retrofitting programs is that unlike price or incentive-based demand response programs, they "do not involve major adjustment to consumers' lifestyles and offer potential economic returns to consumers" (Gamtessa and Ryan, 2007). Currently, almost all electric utilities in the United States offer rebate programs to encourage customers to participate in retrofit programs.

As these energy efficiency retrofit programs grow in size and cost, there is the need to understand better their effects and cost-effectiveness. Since the 1990's, there has been a multitude of evaluation methodologies ranging from the crystal ball measures of savings (e.g. monthly energy savings in California's 20-20 program in the summer of 2005 was calculated as the difference in energy consumption relative to the same month in the previous year.[1]) to

[1] See Koichiro (2012) for a background of the program.

engineering simulation models [2] , and to various econometric models combining monthly meter readings and available data on customer characteristics to determine energy savings (e.g. Jones et al. (2010); Cohen et al. (1991)). Engineering methods use simulations to predict energy savings from specific measures at the individual building level or at the end-use equipment level. Since these engineering methods do not require customers' consumption data, they are theoretically appealing when customer information is not available. However, predictions from engineering models are normally flawed and misrepresents the actual energy savings since they do not account for the influences of confounding factors such as behavior and demographics of a household (Fels and Keating, 1993). Econometric methods, on the other hand, use customers billing information while controlling for weather and household-level and building level factors that might affect consumers' energy consumption.

Most econometric evaluations of the effects of a DSM program use the classic difference -in-difference (DD) methodology or a variant of it where the impact of the DSM program is estimated as the difference in mean outcomes between all households participating in the program and those not participating (e.g. Godberg (1986)). This approach leads to bias if there are unobserved characteristics that affect the probability of participating in the program that are also correlated with the outcome of interest. Further, the result might also be biased if program participants are very different from non-participants in terms of pre-treatment characteristics. Even controlling for pre-treatment characteristics in the DD regression does not necessarily reduce this bias since the estimated effect depends on the exact functional form used.

In this chapter, I evaluate the energy savings effect of a residential retrofitting program, GRU's high-efficiency AC rebate program. I combine a difference-in-difference (DD)

[2] See Architectural Energy Corporation (1992) for a review of various engineering simulation programs for estimating DSM program energy savings.

methodology with a Coarsened Exact Matching (CEM) approach[3] described in Iacus et al. (2008) to overcome the bias from confounding pre-treatment characteristics. Such an estimation approach is novel to the evaluation of energy savings from demand-side management programs and "they are arguably more appropriate compared to a simple instrumental variable approach (for dealing with the selection bias[4]) as no strong exclusion restrictions are needed"(Girma and Görg, 2007). This method is particularly important to evaluating DSM programs for other reasons; matching on neighborhoods allows us to compare participants and non-participants in the same neighborhood. Hence, we are able to disentangle the effects of weather from program effects since houses in the same neighborhood are more likely to experience the same weather. This method is particularly useful if the area under study has one or just a few weather stations which make it impossible to control for the effects of weather on energy consumption. Also, since houses built in the same year or a few years apart and in the same neighborhood are likely to be built with the same building materials and have similar characteristics, using neighborhoods and age of building in the matching methodology controls for the effects of building characteristics and materials on energy consumption. An added importance of the CEM method is that since the rebate program had a very low participation rate, it provides a way to select a reasonable control group from the high percentage of non-participating households. For example, only about 6% of households participated in at least one of GRU's rebate programs in the year 2009. This percentage is much lower (about 2%) when we consider only the high-efficiency AC program. Using all the 98% of households that did not participate as a control group may bias the energy savings estimate as the treatment group does not include all sections of the population.

[3] The idea of coarsened exact matching is described under the empirical strategy and methodology section (Section 1.3).

[4] Selection bias occurs when participation in a program is not random and depends on some observable or unobservable characteristics that are correlated with the outcome of interest.

I use data on household electricity and natural gas consumption and retrofit program participation from Gainesville Regional Utilities from 2008 to 2012. Specifically, I evaluate the savings effect of the 2009 high-efficiency AC rebate program. First, I estimate the energy saving effects on annual energy consumption. Next, since the main aim of DSM or energy efficiency programs is to reduce peak period consumption, I disaggregate the annual effect into summer peak effect, winter peak effect, and non-peak months effect to study the savings impact of the program on peak period energy consumption. The results indicate that while the program led to substantial energy consumption reductions in the summer peak and non peak months, winter peak reductions are statistically and economically insignificant. The remainder of this chapter is as follows: Section 1.2 gives a brief background of GRU's energy rebate programs, Section 1.3 describes the empirical strategy, Section 1.4 gives a brief description of the data, and Section 1.5 investigates selection into treatment based on pre-treatment characteristics. Section 1.6 presents the results of the program on annual energy consumption and peak period consumption while Section 1.7 concludes.

1.2 Background: Gainesville Regional Utilities Rebate Programs

Gainesville Regional Utilities (GRU) offers its consumers a mix of rebates and incentives to promote energy efficiency. GRU offers rebates for high-efficiency central air conditioners, room air conditioning units, heat pumps, water heaters, insulation, duct sealing, refrigerator recycling, pool pumps, installation of solar water heaters, and attic measures. GRU also offers incentives for a comprehensive whole system measure through its Energy Star Home Performance Program and Low-Income Energy Efficiency Program. In this chapter, I evaluate the energy savings effect of the high-efficiency central air conditioner rebate program. The high-efficiency central air conditioner program encourages homeowners to replace old, low-efficiency Heating Ventilation and Air-Conditioning (HVAC) system with a new high-efficiency unit. To qualify for the rebate, households must use a partnering Florida state licensed HVAC mechanical contractor in all retrofitting work. In 2009 about 3,226 single family households (representing about 6% of all single family homes in Gainesville) voluntarily participated in at least one of the rebate programs offered by GRU. Participants were allowed and even encouraged to participate in multiple rebate programs to maximize the energy savings. Table 1-1 lists the relevant financial incentives in GRU's 2009 rebate programs.[5]

Table 1-1. GRU's Rebate Programs and Incentives

Rebate Program	Amount	Maximum Incentive
Heat Pump Water Heater	\$200	
Central AC	\$ 550	
Home Performance with Energy Star	\$775 - 1400	
Low Income Energy Efficiency Program	\$3200	
Insulation	\$0.125 per square foot	\$375
Duct leak Repair	50% of cost	\$375
Pool pumps	\$250	
Refrigerator Buyback and Recycling	\$50	
Window Replacement	\$1.125 per square foot	\$300
Window Film/Solar Screen	\$1 per square foot	\$100

Source: Database of State Incentives for Renewables and Efficiency, http://www.dsireusa.org

Note: 1.One duct leak repair per HVAC system, 3 per location

1.3 Empirical Strategy and Method

This section motivates and summarizes our method. The aim is to overcome problems in the estimation of energy savings in the previous literature and also to provide a simple method of controlling for the effects of weather on Energy consumption when there is no proxy for household-specific weather. I use a difference-in-difference (DD) strategy in combination with the Coarsened Exact Matching (CEM) methodology described in Iacus et al. (2008).

Let $\text{treat}_{it} \in \{0, 1\}$ be an indicator of whether household i participated in the rebate program under consideration in period t and let y_{it} be the energy consumption of household i in period t. Let y^1_{it+s} be the energy consumption of household i, s periods after participating in the rebate program. Also, let y^0_{it+s} be the counterfactual energy consumption of household i in period $t + s$ had it not participated in the rebate program. Thus the gain or energy savings

[5] I provide information for the 2009 rebate program since I specifically evaluate the 2009 program.

from participating in the rebate program for household i is:

$$\Delta_i = y^1_{it+s} - y^0_{it+s}. \tag{1–1}$$

If we could simultaneously observe y^1_{it+s} and y^0_{it+s} for the same household, then program evaluation would be straightforward. We could estimate Δ_i for every household that participated in the rebate program and average out to find the Average Treatment Effect on the Treated (ATT). The Average Treatment Effect on the Treated is defined in the evaluation literature as:

$$\mathrm{E}(y^1_{it+s} - y^0_{it+s}|\mathrm{treat}_{it} = 1, X) = \mathrm{E}(y^1_{it+s}|\mathrm{treat}_{it} = 1, X) - \mathrm{E}(y^0_{it+s}|\mathrm{treat}_{it} = 1,\ X). \tag{1–2}$$

X is a vector of control variables. Since $\mathrm{E}(y^0_{it+s}|\mathrm{treat}_{it} = 1, X)$ is unobserved, we need to construct an approximation for this value. The difference-in-difference literature uses the outcome of a control group of households that did not participate in the rebate program, $\mathrm{E}(y^0_{it+s}|\mathrm{treat}_{it} = 0, X)$, as an approximation to the average outcome of those who participated in the rebate program. One fundamental problem with the difference-in-difference approach is the creation of a comparison group of households who in the absence of the program would have similar outcomes to those who participated. Normally in experimental programs, participation in the program is randomized, and a credible comparison group is selected beforehand. When the program is voluntary, then those who participated in the program may differ from those who did not participate based on the pre-treatment household characteristics. This imbalance between participants and non-participants can lead to selection bias. In addition, if treat_{it} is correlated with some unobservable characteristics that affect the probability of participation in the program, then the analysis is plagued with endogeneity and simultaneity bias.

Controlling for pre-treatment variables in the difference-in-difference strategy does not completely overcome the selection bias nor the endogeneity bias. There is also the problem of common support (e.g., program participants may belong to a particular set of neighborhoods.

Including non-participants in other neighborhoods outside this set in the estimation leads to a common support problem that might bias the results). The common support problem, particularly with respect to neighborhoods, can greatly bias the estimated effects of DSM program on energy consumption. This is because we cannot accurately disentangle the effects of weather from program effects when there are just one or just a few weather stations in the area under study despite the fact that much of the variation in household energy consumption can be explained by changes in the weather (Acton et al. (1976); Parti and Parti (1980); Reiss and White (2005, 2003)). By including participants and non-participants from completely different neighborhoods and with no proxy for house-specific weather information, the estimated treated effect is likely to be biased.

Weather can differ from one location to another even in the same city. The ideal way of controlling for the effects of weather on energy consumption is to control for household specific weather. However, such information is not available. In Reiss and White (2003)'s study of the San Diego service area, the authors mapped each household to one of 21 weather stations in San Diego considering both proximity and elevation and used the weather information of the nearest weather station as a proxy for household specific weather. When there are only a few weather stations, this method does not allow for enough variation in the weather variable to obtain an accurate estimate of the effects of weather on energy consumption. The alternative to controlling for the effects of weather, in this case, is to compare only households in the same neighborhood. Further, by comparing households based on neighborhoods and age of building, we are able to control for building characteristics and house building materials since houses built in the same year or a few years apart and in the same neighborhood are usually built with the same construction materials and have similar characteristics.

In this study, I employ the Coarsened Exact Matching (CEM) methodology described in Iacus et al. (2008) with a difference-in- difference (DD) methodology in order to solve the common support problem, the selection bias problem, and also control for the effects of weather. The purpose of matching is to construct an accurate control group whose outcomes will be used as the counterfactual consumption of participants in the treatment group. The matching methodology pairs each treated household with a group of households in the comparison group based on pre-treatment characteristics so that the comparison group of households have similar pre-treatment characteristics as the treated households with whom they are paired. I specifically employ the coarsened exact matching methodology in order to circumvent the curse-of-dimensionality problem inherent in exact matching (adding one continuous variable to an exact matching methodology effectively kills the matching, since we are unlikely to find two observations with the same value on a continuous scale). The idea of Coarsened Exact Matching is to temporarily group each variable into meaningful strata and pair program participants to non-participants who belong to the same strata on each coarsened variable.[6] The original (uncoarsened) variables are, however, retained for analysis.

The Coarsening Exact Matching algorithm as described in Blackwell et al. (2009) is as follow:

1. Begin with the covariates $\mathbf{X}$ and make a copy, which we denote as $\mathbf{X}^*$.
2. Coarsen $\mathbf{X}^*$ according to user defined cutpoints or CEM's automatic binning algorithm.
3. Create one stratum per unique observation of $\mathbf{X}^*$, and place each observation in a stratum.
4. Assign these strata to the original data, $\mathbf{X}$, and drop any observation whose stratum does not contain at least one treated and one control unit.

I then perform exact matching on the matched strata. Let $\mathrm{A} = \{\mathrm{A}_1, \mathrm{A}_2, \cdots, \mathrm{A}_k\}$ be a set of matched strata with coarsened exact matching methodology. Let N^T and N^C be the total number of treated observations and control observations respectively. Also, let $N^T_{A_j}$ and $N^C_{A_j}$ be the number of treated and control observations in stratum A_j. Let y_{ij} be the post-treatment

[6] Not all variables need to be coarsened, some variables can be restricted from coarsening.

energy consumption of household i in stratum j. A standard matching estimator for the Average Treatment effect on the Treated (ATT) of a DSM program is:

$$\text{ATT} = \sum_{i \in N^T} \left\{ y_{ij} - \frac{\sum_{i \in N^C_{A_j}} y_{ij}}{N^C_{A_j}} \right\}. \tag{1–3}$$

The value in parenthesis in Equation 1–3 is the individual treatment effect of a program participant in stratum A_j. Summing and averaging over all treated participants gives the average treatment effect on the treated of the DSM program. Equation 1–3 uses only the post-treatment energy consumption to estimated the program effects. However, since we have panel data, we do not employ the Coarsened Exact matching estimator in levels. We use a difference-in-difference coarsened exact matching estimator on the matched observation in each stratum. The difference-in-difference coarsened exact matching relaxes the strong selection-on-observables assumption inherent in matching estimators. Combining a difference-in-difference methodology with a matching methodology has the additional advantage of eliminating unobservable time-invariant differences in energy consumption between treated control households that standard matching estimators fail to eliminate (Girma and Görg, 2007; Smith and Todd, 2005). Let Δy_{ij} be the difference in energy consumption between the post- and pre- treatment periods of household i in stratum A_j. Then the difference-in-difference coarsened exact estimator is defined as:

$$\delta = \sum_{i \in N^T} \left\{ \Delta y_{ij} - \frac{\sum_{i \in N^C_{A_j}} \Delta y_{ij}}{N^C_{A_j}} \right\}. \tag{1–4}$$

If I had performed exact matching, then there would be no imbalance left and Equation 1–4 perfectly estimates the energy savings effects of the demand-side management program. However, since I used coarsened variables, I use a variant of Equation 1–4 by also controlling for the actual (uncoarsened) values of the variables in a linear regression. This is the estimate we employ in the analysis below. I start with an initial equation of the form:

$$\log y_{it} = \beta_0 + \delta_0.\ d2 + \delta_1 treat_{it} + \delta_2 treat_{it} \cdot X_i + \beta_1 X_i + \beta_2\ d2 \cdot X_i + \gamma_i + u_{it}, \quad t = 1, 2 \quad (1\text{–}5)$$

where y_{it} is total energy consumption for household i in period t. Total energy consumption for household i is defined as the sum of electricity consumption and natural gas consumption.[7] $d2$ is a dummy variable for the second period, γ_i is the individual heterogeneity that is constant across time, and u_{it} is the idiosyncratic error that varies with time. X_i is a vector of household characteristics. All the household characteristics in our sample do not vary across time. However, I include an interaction term between these characteristics and the second-period dummy variable, $d2$, so that the household characteristics would have different effects on energy consumption in different periods.[8] I also allow for the treatment variable to have varied effects with respect to the household characteristics by including an interaction term between the household characteristics and the treatment dummy.

First differencing the two equations across the two time periods removes the individual heterogeneity as well as all the time constant explanatory variables so the final equation on which we applied the coarsened exact matching methodology is of the form:

$$\Delta y_i = \delta_0 + \delta_1.treat_i + \delta_2 treat_i \cdot X_i + \beta_2 X_i + \Delta u_{it} \quad (1\text{–}6)$$

[7] Natural gas consumption is originally measured in therms while electricity is measured in kilowatt hours. In order to combine electricity consumption to natural gas consumption, both were converted to equivalent kWh (ekWh) using the conversion rate 1 therm = 29.300111 ekWh and 1 kWh = 1 ekWh.

[8] An ideal way would be to include an interaction between the household characteristics and the total heating and cooling degree days so that the household characteristics have different effects based on the severity of the weather in different periods. While there are about 26 weather stations in and around Gainesville, the National Oceanic and Atmospheric Administration website has daily maximum and minimum temperature only for the weather station at the Gainesville Airport. Only precipitation, wind and/or water information is available at the other weather stations. Hence the total degree days, using information from only one weather station would be constant for all households in the dataset.

It should, however, be noted that Equation 1–6 is only an estimating equation to get rid of the individual heterogeneity and any other constant (time-invariant) unobservable factors that affect energy consumption. The estimates from these equations should, therefore, be interpreted in the context of the original level equation (Equation 1–5).[9] The intercept in this equation measures the average difference in consumption between the two time periods that can be attributed to the differences in the severity of the weather or any other unobserved time-variant factor that leads to changes in energy consumption across periods.

1.4 Data

I use data from three different sources: Gainesville Regional Utilities (GRU), the Alachua County Property Appraiser (ACPA) database, and the Census Bureau. The GRU datasets were obtained from the Program for Resource Efficient Communities, and they contain two distinct datasets. The first GRU dataset gives the monthly electricity and natural gas consumption for each residential household from 2008 to 2012. The second GRU dataset includes information about rebate program participants through 2011. I extracted the ACPA data from the ACPA website, and it contains information on the physical characteristics, location, and sales dates of all properties in Alachua County. I also geocode each property location address in our sample to link each property location address to a census tract or to a zip code to which they belong. The census tracts and zip codes serve as neighborhoods for each property so that by matching on the census tract or zip codes we can control for effects of weather on energy consumption without actually having weather data.[10] Since Gamtessa and Ryan (2007) found demographic

[9] Thus, the coefficients on the household characteristics in Equation 1–6 do not measure the effects of the characteristics on energy consumption or the effects of the characteristics on the differenced energy consumption, but rather the differences in the effects of the characteristics on energy consumption across the two periods as interpreted in Equation 1–5. For example the coefficient on the number of bedrooms in Equation 1–6 measures difference in the effects of bedrooms on energy consumption across the two years.

[10] The best way of controlling for weather is to include household-specific weather information. However, since household-specific weather information is not available, an

information such as income and household characteristics to play a role in the decision to undertake rebate programs, I extracted the mean income and mean household size for each census tract and imputed those values to all households in the census tract or zip code. Table 1-2 gives the variables contained in each dataset.

Table 1-2. Variables from Each Dataset

GRU Consumption Dataset	GRU Rebate Database	ACPA Dataset	Census Dataset
Parcel Number	Parcel Number	Parcel Number	Census tract codes
Month of consumption	Rebate type	Physical Address	Mean income
Year of consumption	Year installed	Year built	Median income
Monthly consumption	Month installed	Number of bedrooms	Average household size
Days of consumption		Number of bathrooms	
		Number of Stories	
		Base Area square feet	
		Total Area square feet	
		Heated Area square feet	
		Previous sales date	
		Pool ownership	

The GRU consumption dataset, the GRU rebate dataset, and the ACPA dataset were linked together by the parcel number identifier which is present in the three datasets. I geocode the location address of each house using ArcGIS and map the geocoded addresses into one of the 47 census tracts in Gainesville.[11] The base dataset with the geocoded addresses contains approximately 28000 single family households. Because the purpose of this research is to

approximation to controlling for weather information is to map each house location to a the nearest weather station and use the weather information for that weather station as an imputed value for the house-specific weather (Reiss and White, 2003). Such approach is only possible if there are enough weather stations in the area under study to allow for variation in the imputed weather information. As stated earlier, the National Oceanic and Atmospheric Administration website where I collected the temperature information has temperature information for only one weather station in Gainesville. Including the temperature information from only one weather station in the analysis will be redundant.

[11] ArcGIS successfully mapped 98% of the addresses into their respective census tracts. For the remaining 2% that were unsuccessful or where the location address is missing, I searched for the parcel number in Google Earth to find the address and census tract.

evaluate the energy savings effects of the high-efficiency central air conditioner rebate program, all households that participated in other rebate programs were dropped from the dataset. All households that participated in multiple programs were also dropped. The remaining dataset contains 24794 households. Further, households who made home improvements over the period that are likely to affect significantly their energy consumption were also dropped. For example, households that added a pool or solar heater during the period were dropped from the final dataset. Dropping these observations may lead to an underestimation of the energy savings; for example, households that participated in multiple programs are more likely to be the ones eager to save energy. It also makes our estimated savings effect a local treatment effect on those who participated only in the high-efficiency AC program. Nonetheless, since those who participated only in one program are more likely to have the same pre-treatment characteristics as non-participants, we are able to reduce the bias from confounding, unobservable characteristics. The final dataset for the evaluation of the 2009 high-efficiency AC rebate program contained 24010 households (about 40% of all single family residential households in GRU's service area in Gainesville). Energy consumption was calculated as the sum of electricity consumption and natural gas consumption (converted to ekWh).[12] Table 1-3 gives a summary statistics of the data.

Billing Timing and Standardization of Monthly Energy Consumption

Different households usually have different billing periods based on when their utility meter is read. When a household's billing meter is read, their billing period closes and a new billing period starts. Since the billing meter is read on different days for different households, the "monthly" electricity and natural gas consumption for different households in the same "month" have different dates of consumption. One way to exploit the billing method in our analysis so that no biases are resulting from the various billing periods is to follow Reiss and

[12] We converted natural gas consumption, originally measured in therms, to equivalent kilowatt-hour (ekWh) using the conversion rate 1 therm=29.300111 ekwh.

Table 1-3. Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Electricity 2008 (kwh)	24010	12485.23	6662.762	271.59	137633.7
Natural Gas 2008 (ekwh)	16035	8707.53	4887.221	14.65006	110128.3
Total Energy 2008 (ekwh)	24010	18300.53	8976.362	507.57	164589.2
Electricity 2009 (kwh)	24010	12583.85	6712.384	120.75	184895.7
Natural Gas 2009 (ekwh)	16034	9327.935	4946.789	29.30011	92101.09
Total Energy 2009 (ekwh)	24010	18813.1	9147.951	324	221120.9
Electricity 2010 (kwh)	24010	13256.47	7686.592	197.88	191181.8
Natural Gas 2010 (ekwh)	16035	11963.69	11221.91	142.1055	327575.8
Total Energy 2010 (ekwh)	24010	21246.37	13136.05	502.44	352763.3
Electricity 2011 (kwh)	24010	12317.82	7128.034	4.81	173417
Natural Gas 2011 (ekwh)	16078	8490.737	8889.289	3.809014	323516.3
Total Energy 2011 (ekwh)	24010	18003.54	11379.96	137.86	431242
Electricity 2012 (kwh)	24010	11609.13	7115.847	1	157079.6
Natural Gas 2012 (ekwh)	16070	7176.274	10121.62	7.032026	316227.9
Total Energy 2012 (ekwh)	24010	16412.25	11622.78	102.22	336224.8
Age of Building	24010	24.92936	10.89751	2	89
Bedrooms	24010	3.159142	0.6435316	1	5
Bathroomss	24010	2.027718	0.6515361	1	10
Total Area (square feet)	24010	2346.108	1009.164	399	20639
Heated Area (square feet)	24010	1784.903	732.8671	399	10855
Mean Income (dollars)	24010	73702.19	33029.68	17087	160823
Mean Household Size	24010	2.380901	0.2417656	1.34	3
Pool	24010	0.1436068	0.3506979	0	1

White (2005) and group households into billing cohorts (a group of households with the same billing dates for all months in a year). The billing cohorts (restricted from further coarsening) could be added to the variables on which the matching is performed so that we compare the energy consumption of households across cohorts. In the data, the billing cohort to which a household belongs sometimes changes across years so that I am not able to follow the same household in a particular billing cohort for two or more years. Also, since I have only a few program participants, comparing across billing cohorts will lead to more strata with only treated or non-treated observations. I might lose a significant percentage of the already limited treated group. The approach I took in this paper is to standardize energy consumption by calculating the average consumption for each calendar month. We achieve this by dividing each household's consumption in a billing period by the total number of days of consumption to find a daily average energy consumption. If consumption in a calendar month spans two billing periods, the number of days in the month that are in each billing period are multiplied by the average daily consumption in each period and summed together to calculate the energy consumption for the month.[13]

For example, suppose a household's billing period starts on the seventh of each month so that the household's electricity bill for two consecutive billing periods 7 May 2010 – 6 June 2010 and 7 June 2010 – 6 July 2010 are 868 kWh and 780 kWh respectively. There are 31 days in the first billing period and 30 days in the second billing period. Hence, the daily average electricity consumption for the two billing periods are 28 kWh and 26 kWh respectively. The first billing period contains 6 days in June while the second billing period contains 24 days in June. Hence, the average monthly usage for the month of June is $28 \times 6 + 26 \times 24 = 792$ kWh. A similar calculation is made for natural gas consumption. The "monthly" electricity and natural gas consumption for each household are then added up to obtain the "monthly" energy consumption for the household.

1.5 Self-Selection Based on Individual Pre-Treatment Characteristics for The Treatment and Control Groups

As stated above, one concern with using only a difference-in-difference methodology in the estimation of the treatment effect of a voluntary program is the bias from pre-treatment characteristics. Participants of the program may be those more likely to save energy from participating. For example, since newer homes are already more efficient and have more stringent building codes than older homes[14] , we expect older homes to save more energy from retrofitting programs than newer homes. There are also "halo" effects where people participate

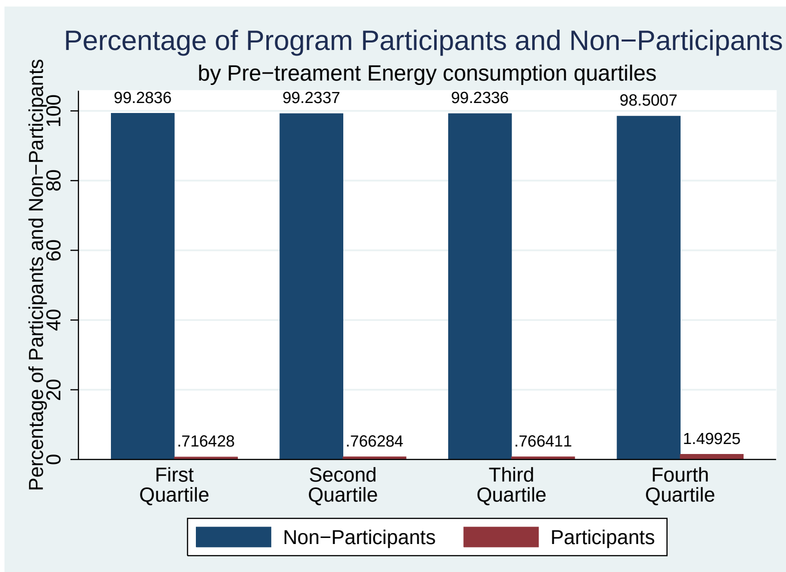
[13] This method was particularly useful when estimating the summer peak and winter peak effects. I thank Nick Taylor of the Program for Resource Efficient Communities at the University of Florida for providing us with the already standardized data.

[14] Florida increased the stringency of its energy code in 2002 which is expected to make houses more energy efficient.

in a program if their neighbors are already involved in the program. Such effects concentrate program participants in a few neighborhoods so that including control observations from areas with no or fewer program participants may bias the results of the estimation. In this section, we examine the extent to which program participants and non-participants differ regarding their pre-treatment characteristics and pre-treatment energy usage.

Pre-Treatment Usage Pattern

Figure 1-1. Percentage of Program Participants and Non-Participants within Each Energy Consumption Quartile

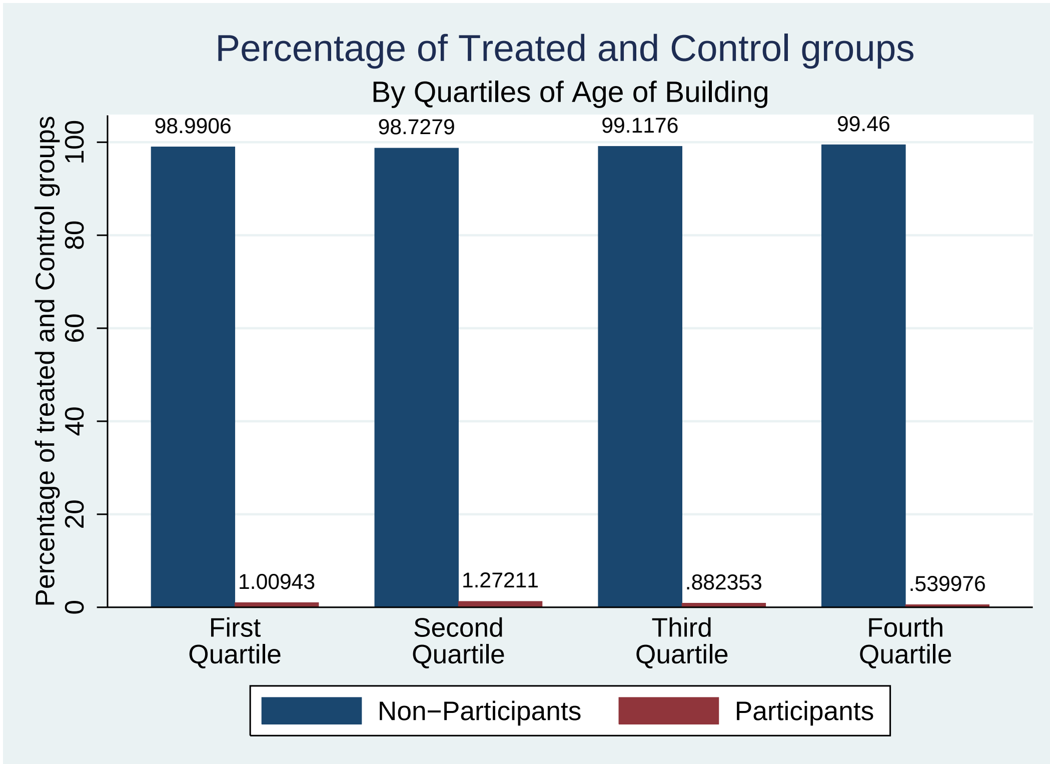


We expect that high energy consumers will be the ones more willing to save energy by switching to more energy efficient appliances. This is the case in Figure 1-1. The figure shows the percentage of program participants and non-program participants in each energy consumption quartile. It shows that majority of the treatment group (about 40%) are in the fourth quartile. The fourth quartile contains about twice the number of treated observation as the other quartiles. Thus, consumers with high energy usage are more likely to participate in the rebate program than consumers with low usage. The figure also shows that the number of treated observations is nondecreasing (or increasing) as we move from the lower quartile to the higher quartile.

Self-Selection Based on Age of The Building

Recent houses are more energy efficient and normally contains more energy efficient appliances than older homes. A change in an appliance in an older home is thus expected to have higher savings effects on total energy savings (since older AC units consume more energy than modern AC units). We expect that households in older building are more likely to participate in energy efficiency programs to take advantage of the high energy savings than households in newer homes. In 2002, Florida increased the stringency of its energy codes to make buildings more energy efficient. This increase in stringency is associated with a decrease in electricity consumption by 4% and natural gas by 6% (Jacobsen and Kotchen, 2013). Thus, since newer buildings are already energy efficient, there is less room for improvement in energy savings from rebate programs. Further newer buildings are likely to be installed with a high-efficiency AC unit, so replacing the already installed AC with a slightly more efficient AC will save only a fraction of the energy savings expected from replacing a very old AC in an old building. In Figure 1-2, we divided the age of the building into age of building quartiles. Each quartile contains about 6000 houses. The first quartile contains building aged less than 16 years, the second contains buildings between the ages of 16 and 28 years, the third contains buildings aged between 28 and 33 years while the fourth quartile is made up of buildings aged more than 33 years. The figure shows households in newer houses (less than 16 years) are less likely to participate in the rebate rebate as expected. Households in old houses over 33 years are also less likely to participate in the program. Perhaps these households had participated in a similar rebate program in the past so that there is lower expected energy savings from participating in the same program again. Program participation is rather high among households in houses with an age of building under 28 years (first and second). These houses make up about 63 % of all treated households in the data. Only 13.7% of the treated households are in the fourth quartile.

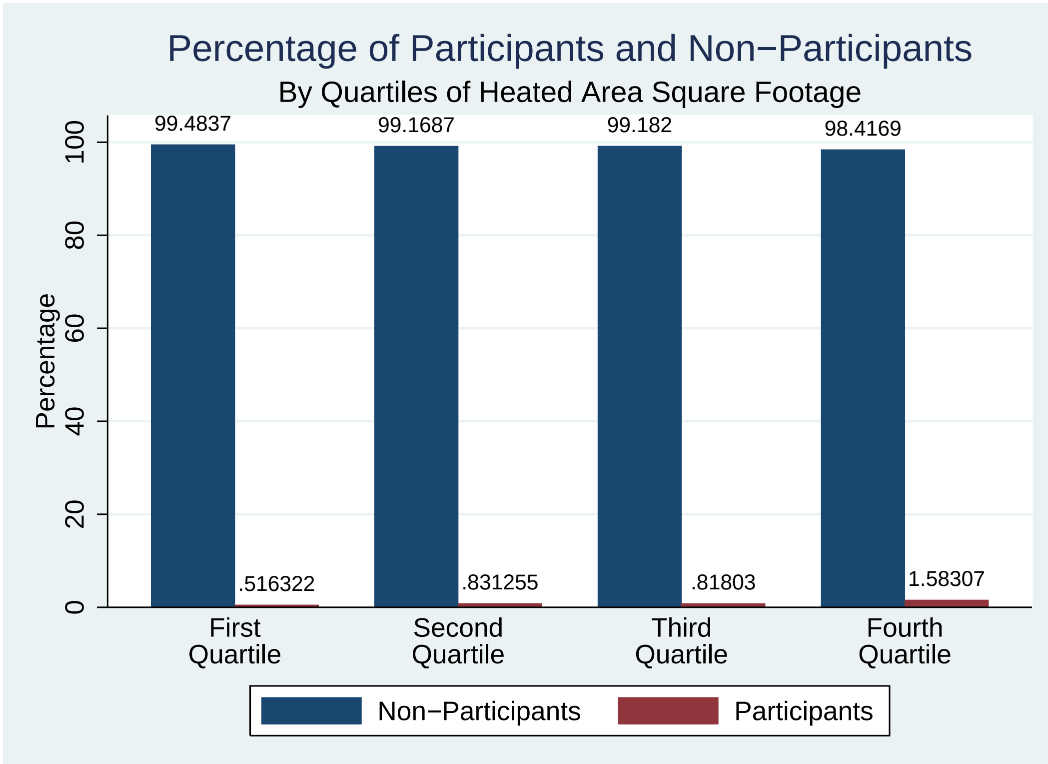
Figure 1-2. Distribution of Age of Building for Participants and Non-Participants



Self-Selection Based on Size of The Building

Bigger homes use more energy than smaller homes. A home's heating or cooling area square footage determines the amount of energy the household will use on air conditioning or heating. Thus, we expect households in bigger houses to participate more in the AC rebate program to reduce their energy usage than those in smaller houses. Figure 1-3 shows the distribution of the control and treatment groups among quartiles of the heated area square footage of the house. In the figure, bigger houses as determined by the size of the heated/cooling area participated more in the AC rebate program than smaller houses. Houses were grouped into quartiles based on the size of the heated area square footage. From the figure, a large percentage of the treated households (42 %) lies in the fourth quartile while the second and third quartile each has about 22%. The first quartile contains the least number of treated observations (13%). The figure, therefore, supports the argument that households in bigger houses are the ones more eager to reduce energy since they consume more.

Figure 1-3. Distribution of Heated Area Square Footage of Building for Participants and Non-Participants



1.6 Results

In this section, we present the results of the difference-in-difference coarsened exact matching methodology. We matched on neighborhoods, the age of the building, pre-treatment energy consumption, number of bathrooms, number of bathrooms, the number of stories, heated area square footage, and type of heating fuel. We assumed that pre-treatment consumption can be explained by building characteristics. Thus, by matching on pre-treatment consumption we are in effect matching on a single variable that aggregates the effects of all the building characteristics on energy consumption.[15] . We are mainly interested in the matching on neighborhoods to control for the effect of weather and the age of building to

[15] We didn't include all other building characteristics in the matching so as to reduce the number of strata and increase the number of treated observations in each stratum.

control for the effects of building characteristics. We use two neighborhood variables separately in the matching methodology: zip codes and census tracts. Zip codes and census tracts were restricted from further coarsening so that no two neighborhoods can be in the same stratum. That is, we compare only households in the same census tract or zip codes. The algorithm automatically imposes the common support condition, so all observations within any stratum that does not have at least one observation for each unique value of the treatment variable are discarded. The number of bathrooms was recoded with one-half bathrooms counting as full bathrooms in the matching methodology. Heated area square footage was coarsened into ten equal groups whereas pre-treatment energy consumption was divided by the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles of the distribution of pretreatment consumption.

Annual Effects of The High-Efficiency AC Rebate Program

Table 1-4 shows the total number of observations, and the number of treated and untreated observation in the original dataset before and after the coarsened exact matching. The table displays a summary of the result of the matching methodology with zip codes and census tracts as neighborhoods. Matching with census tracts as neighborhoods led to 135 matched strata with 1413 control observation and 139 treated observation. The matching with zip codes produced 159 matched strata with 7650 control observations and 193 treated observations. While matching on a the census tracts is expected to provide an accurate match, since census tracks are smaller, it produces fewer matches than matching on zip codes and we lose a larger number of the already few treated observations. The matching on the zip codes as neighborhoods, on the other hand, produced a high match since zip codes are bigger than census tracts, but houses within matched cell or the demographics of the households within the matched cells are more likely to be very difference. They may also experience different weather conditions which might bias the results. Thus, while smaller neighborhood categories produce fewer matches than bigger neighborhood categories, results using smaller neighborhood categories are likely to me more accurate than matching on bigger neighborhoods.

Table 1-4. Matching Summary–High-Efficiency AC Rebate Program

Census Tracts			**Zip Codes**		
Number of strata: 9771			Number of strata: 3653		
Number of matched strata: 135			Number of matched strata: 159		
	Control	Treated		control	Treated
All	23785	225	All	23785	225
Matched	1413	139	Matched	7650	193
Unmatched	22372	86	Unmatched	16135	32

The results in column I and IV of Table 1-5 (and Column I of Table A-1 in the appendix) show that the high-efficiency AC rebate program led to statistically significant energy savings under all three regressions. The difference-in-difference without matching shows average energy savings of about 8.5% per treated household. The DD CEM with census tracts as neighborhood shows a relatively higher savings of 9.5% per treated household.[16] Table A-1 in the appendix, which uses zip codes as neighborhoods, also shows that the AC rebate program led to savings of 8.6% per year. Thus even when matching on a few variables because of data unavailability, it can be seen that the regular DD marginally understates (or overstates) the effect of energy savings mainly because it fails to account for the differences in weather. The results also suggest that using smaller neighborhoods (in this case using census tracts) reduces bias and improves the treatment effect.

In columns II, III, V, and VI, we allowed the effects of treatment to vary by the size of the heated/cooling area square footage of the house and/or the age of the building. The age of a house does not significantly affect the savings effect (using both DD CEM and the regular DD). The size of the heated area square footage, on the other hand, reduces

[16] Matching on a refined neighborhood variable such as actual neighborhoods or subdivisions used by the Alachua County property appraiser might further reduce bias and lead to a more accurate estimate of the treatment effect. This is because houses in the same subdivisions are typically built in the same year, are usually constructed with the same construction material, and have similar characteristics. Houses in a smaller neighborhood category are also likely to have similar weather conditions than houses far apart, hence, we can accurately disentangle weather effects from program effects.

the energy savings from the program (under the DD CEM methodology). It is, however, not statistically significant using the regular DD. From Column II, the coefficient on Treat signifies that a treated household with zero heated area square footage reduces energy usage by 23.1% on average.[17] More importantly, a one-standard deviation increase in the heated area square footage (about 733 square feet) reduces the energy savings from the program by 5.4 percentage points. The energy savings effects of the program, therefore, becomes non-existent for a house with a heated area square footage of about 3080 square feet (about the 92nd percentile of the distribution of heated area in the sample). This negative effect of the heated area on the energy savings slightly increases when treatment is further allowed to vary with the age of the building (the coefficient on Treat*Heated Area increased from 0.075 in Column II to 0.077 in Column III), but the effects of age on the energy savings is statistically insignificant. In fact, the coefficient on Treat*Age is zero to three decimal places. The results were unexpected since households in bigger houses are more likely to participate in the program than those in smaller houses as seen in Figure 1-2. In columns V and VI, both heated area and age of building has no statistically significant effect on the size of the treatment effect using the regular DD. Thus, the regular DD without matching again fails to highlight the different treatment effects based on the size of the heated area.

Since we matched on only a few variables without any household demographics, much of the difference between the DD estimate and the DD CEM estimates can be attributed to the differences in how well the two methodologies accurately disentangle weather effects from program effects. As stated earlier, the coefficients on the household and housing characteristics in the regression measure the differences in the impact of these characteristics on energy consumption between the two years. The differences in the effects of theses characteristics on energy consumption are mainly attributed to the differences in weather between the years. For

[17] This figure is not interesting by itself since there is no house with a zero heated area square footage in the sample.

example, households in bigger houses are expected to increase their energy consumption far more than those in smaller houses during a year of severe weather conditions. Apart from the electric and gas dummy that is significant in all three regressions, the coefficients on the other variables are not significant in the DD CEM regression. This is mainly because there was only a slight imbalance in a matched strata using the DD CEM. The regular DD, however, has a lot of variables with significant effects. The age of the building, heated area, pool ownership, electric and gas dummy, and mean income are all statistically significant in the regular DD. Coefficients on the number of bedrooms, number of bathrooms, number of stories, mean household size and hot tub ownership are, however, not statistically significant. The lack of statistical significance of these house characteristics in the regular DD regression and the DD CEM suggests that the weather in the two time periods was not statistically significantly different from each other to allow these characteristic to have different effects on energy consumption.

I also evaluate the 2010 AC rebate program to check the robustness of 2009 program results. The 2009 AC rebate participants were deleted from the dataset so as not to bias the results of the estimation. The 2011 participants were also deleted. Our control group thus consist of households who from 2008 to 2011 never participated in any rebate program. The results of the estimation are presented in Tables A-2 and A-3 in the appendix. The results of the 2010 program are similar to that of the 2009 program. The program led to a statistically significant energy savings of 8.1% using the DD CEM with census tract as neighborhoods, 9.8% using the regular DD approach, and 8.9% using the DD CEM with zip codes as neighborhoods. The main difference in the treatment effect of the 2010 program with the 2009 program is that, while heated area square footage had an adverse effect on the size of the energy savings in the 2009 program, the effects of the heated area on the energy savings in the 2010 program is statistically insignificant. Rather, the age of building that had a statistically insignificant effect on the energy savings of the 2009 program has a statistically significant effect on the 2010 program in the regular DD methodology (the coefficient on

Table 1-5. Annual Energy Savings Effect of The 2009 High-Efficiency AC Rebate Program

Δlog(Energy Usage)	CEM DD (Census Tract)			Regular DD		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treat	-0.0946***	-0.2314***	-0.2424**	-0.0852***	-0.0983**	-0.0494
	(-4.11)	(-3.40)	(-2.64)	(-5.77)	(-2.77)	(-0.97)
Treat*Heated Area		0.0748*	0.0766**		0.0060	0.0036
(1000 square feet)		(2.52)	(2.68)		(0.50)	(0.30)
Treat*Age			0.0003			-0.0019
			(0.13)			(-1.14)
Bedrooms	0.0477	0.0475	0.0475	-0.0066	-0.0066	-0.0066
	(1.76)	(1.75)	(1.75)	(-1.55)	(-1.53)	(-1.53)
Stories	0.0175	0.0180	0.0179	-0.0073	-0.0072	-0.0072
	(0.76)	(0.78)	(0.78)	(-1.42)	(-1.42)	(-1.42)
Heated Area	-0.0475	-0.0546	-0.0547	0.0143***	0.0141***	0.0142***
(1000 square feet)	(-1.63)	(-1.84)	(-1.85)	(3.43)	(3.34)	(3.35)
Age	0.0025	0.0025	0.0025	0.0005*	0.0005*	0.0005*
	(1.84)	(1.83)	(1.71)	(2.23)	(2.22)	(2.27)
Pool	-0.0300	-0.0296	-0.0297	-0.0437***	-0.0437***	-0.0436***
	(-0.82)	(-0.81)	(-0.81)	(-7.51)	(-7.50)	(-7.49)
Electric and Gas	0.1014**	0.1013**	0.1013**	0.0865***	0.0866***	0.0865***
	(3.25)	(3.25)	(3.25)	(18.49)	(18.49)	(18.47)
Mean Income ($1000)	0.0003	0.0003	0.0003	-0.0002**	-0.0002**	-0.0002**
	(0.54)	(0.54)	(0.54)	(-3.10)	(-3.09)	(-3.09)
Mean Household Size	0.0584	0.0592	0.0592	0.0030	0.0030	0.0029
	(1.00)	(1.01)	(1.01)	(0.33)	(0.32)	(0.32)
Hot Tub	-0.0375	-0.0347	-0.0347	-0.0110	-0.0110	-0.0111
	(-0.88)	(-0.82)	(-0.82)	(-1.19)	(-1.20)	(-1.21)
cons	-0.2174	-0.2063	-0.2055	0.0892***	0.0895***	0.0892***
	(-1.44)	(-1.36)	(-1.35)	(3.36)	(3.36)	(3.36)
N	1552	1552	1552	24010	24010	24010

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Treat*Age in Column VI of Table A-2). This effect is however not economically significant. A 100-year change in the age of the building will reduce the treatment effect by 0.46 percentage points.

Peak and Non-peak Month Effect

The main reason for demand management programs is to "allow a utility to control the balance of its resources and demands for energy by managing the consumers' needs for energy rather than by simply adding more supply" (Fels and Keating, 1993). Since utilities operate under capacity during non-peak periods, and there is no need to worry about adding more supply or buying power at the market rate, Utilities are particularly interested in how demand-side management programs affect peak-period demands. Florida has two peak periods: the summer peak which starts in mid-may and ends in September and the winter peak which begins in December and ends in February. A high percentage of Florida's energy is consumed in those two peak periods. In this part of our analysis, we allow the effects of the demand-side management program to differ by season: summer peak, winter peak and non-peak to evaluate the impact of the program on peak period consumption. December, January, and February were considered as the winter months. June, July, August, and September were considered as summer months. The remaining months were considered as non-peak. This classification is based on the historical distribution of cooling and heating degree days in north-central Florida in the literature.

Non-peak months

The non-peak months in Florida comprise the Spring months of March, April, and May and the Fall months of October and November. These months are normally the most pleasant months in the state in terms of the comfort index, the sum of heating and cooling degree days. Households require less energy for heating or cooling than in the other months. Air conditioners are usually used only minimally during this period. We, therefore, expect lower energy saving in the non-peak months for the AC rebate program. The results of the energy savings effect of the program in the non-peak months are presented in Table 1-6. The table shows that the AC rebate program led to a statistically significant energy reduction of about 4.8% in the non-peak months using both the DD CEM with census tracts as neighborhoods and the regular DD (Columns I and III). The 4.8% energy savings in this period is however not surprising since there is about 58% percent of days in this period in Gainesville where the daily maximum temperature is above 80^0F, and thus households require the AC to cool their homes. [18] In regular DD regression, age and heated area square footage do not affect the size of the energy savings. However, in the DD CEM regression with census tracks as neighborhoods, heated area has a statistically significantly negative effect on the magnitude of the energy savings once the age of the building is also allowed to vary with the treatment effect (coefficient of Treat*Heated Area in Column III) of Table 1-6). The effect is not economically significant as a one standard deviation increase in the heated area square footage of a house (an increase of about 733 square feet) reduces the energy savings by only 0.047 percentage points. The results using DD CEM with zip codes as the neighborhoods in shown in Table A-4 in the appendix. The results presented in Table A-4 are similar to the results using the regular DD.

Summer peak

Florida's hot, humid summer begins in mid-May or later with average maximum temperatures reaching about 90^0F during the day but with high humidity, the real feel of the temperature is about 108^0F. Night time provides little relief from the heat as the temperature reduces by just a little during the night, with night time temperatures still about 76^0F and with a real feel of about 87^0F. Air conditioning thus becomes the main driver of energy usage and cost during the summer. "When combined peak monthly demand for the months of June, July, and August (the hottest months) is compared to that of the combined months of December, January and February (the coolest months), except for a handful of power companies, the

[18] There is also about 83% of days in which the daily minimum temperature is below 65^0F in Gainesville so that households would require their AC for heating.

Table 1-6. Non-Peak Months Effects Of The 2009 AC Rebate Program

Δlog(Energy Usage)	DD CEM (Census Tract)			Regular DD		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treat	-0.0488*	-0.1439*	-0.2196*	-0.0487***	-0.0524	-0.0456
	(-2.15)	(-2.15)	(-2.16)	(-3.36)	(-1.53)	(-0.82)
Treat*Heated Area		0.0520	0.0646*		0.0017	0.0013
		(1.72)	(2.11)		(0.14)	(0.12)
Treat*Age			0.0023			-0.0003
			(0.83)			(-0.15)
Bedrooms	0.0433	0.0432	0.0432	-0.0050	-0.0050	-0.0050
	(1.47)	(1.47)	(1.47)	(-1.06)	(-1.06)	(-1.06)
Stories	0.0237	0.0240	0.0238	-0.0056	-0.0056	-0.0056
	(0.96)	(0.98)	(0.97)	(-1.04)	(-1.04)	(-1.04)
Heated Area	-0.0401	-0.0451	-0.0459	0.0109*	0.0109*	0.0109*
(1000 square feet)	(-1.42)	(-1.55)	(-1.58)	(2.40)	(2.35)	(2.35)
Age	0.0016	0.0016	0.0014	-0.0004	-0.0004	-0.0004
	(1.21)	(1.20)	(1.01)	(-1.83)	(-1.83)	(-1.82)
Pool	-0.0639*	-0.0636*	-0.0644*	-0.0340***	-0.0340***	-0.0339***
	(-2.04)	(-2.03)	(-2.05)	(-5.36)	(-5.35)	(-5.35)
Electric and Gas	0.0729*	0.0729*	0.0727*	0.0528***	0.0528***	0.0528***
	(2.43)	(2.42)	(2.42)	(10.33)	(10.33)	(10.33)
Mean Income ($1000)	0.0015**	0.0015**	0.0015**	0.0005***	0.0005***	0.0005***
	(2.88)	(2.88)	(2.88)	(6.40)	(6.40)	(6.40)
Mean Household Size	0.0574	0.0580	0.0583	0.0255*	0.0255*	0.0255*
	(0.94)	(0.94)	(0.95)	(2.50)	(2.49)	(2.49)
Hot Tub	-0.0182	-0.0163	-0.0163	-0.0164	-0.0165	-0.0165
	(-0.43)	(-0.38)	(-0.38)	(-1.63)	(-1.63)	(-1.63)
cons	-0.4047*	-0.3969*	-0.3914*	-0.1076***	-0.1075***	-0.1075***
	(-2.47)	(-2.41)	(-2.38)	(-3.68)	(-3.67)	(-3.67)
N	1552	1552	1552	24010	24010	24010

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

demand for electricity during the three hottest months is about 20% higher than for the three coolest ones. Air conditioning accounts for most of that difference"(Winsberg and Simmons, 2009). GRU generates about 30% more electricity per month in the summer months than in the winter months and 40% more electricity per month than in the non-peak months.

The results of the summer peak effects of the program are shown in Table 1-7 . As expected the AC rebate program led to substantial energy savings about 20% in the summer months using the DD CEM with census tracts as neighborhoods (Column (I) of Table 1-7). The regular DD without matching also produced a statistically significant but relatively lower energy savings estimate of 16.77% (Column IV of Table 1-7). These higher estimates in the summer months are expected since air conditioning accounts for a greater percentage of the energy usage during the summer months. In Columns II, III, V, and VI, we allowed the summer peak effects to vary by the size of the house as measured by the heated area square footage (Columns II and VI) and by heated area and age of the building (Columns III and VI). As was the case in the non-peak months, the age of the building has no significant effects on the energy savings. The coefficient of Treat*Age in both the regular DD and the DD CEM regressions (Columns III and VI) is statistically and economically insignificant. Heated area square footage, however, has a statistically significant inverse effect on the energy savings in the summer. In column II, an increase in the heated area by one standard deviation (732.866 square feet) reduces the treatment effect by 7 percentage points. In the regular DD regression (Column V), a one standard deviation increase in the heated area square footage reduces the treatment effect by 2.2 percentage points. Thus, both regressions show that households in smaller houses had a higher energy savings rate than those in bigger houses. Nonetheless, households in larger houses are more likely to have a greater impact on their bill than households in smaller houses.

Winter peak

Florida's relatively lower energy peak period is in the winter months when the maximum temperatures averages about 70^{0}F. The winter in Florida or Gainesville to be specific is not

Table 1-7. Summer Peak Effects of The 2009 AC rebate program

Δlog(Energy Usage)	DD CEM(Census Tract)			Regular DD		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treat	-0.2063***	-0.3829***	-0.4227***	-0.1677***	-0.2362***	-0.2447***
	(-6.77)	(-4.18)	(-3.36)	(-8.68)	(-5.38)	(-3.83)
Treat*Heated Area		0.0966*	0.1032*		0.0310*	0.0315*
		(2.17)	(2.25)		(2.01)	(2.05)
Treat*Age			0.0012			0.0003
			(0.36)			(0.16)
Bedrooms	0.0490	0.0487	0.0487	-0.0020	-0.0017	-0.0017
	(1.45)	(1.44)	(1.44)	(-0.35)	(-0.31)	(-0.31)
Stories	0.0203	0.0209	0.0208	0.0002	0.0004	0.0004
	(0.69)	(0.71)	(0.71)	(0.04)	(0.06)	(0.06)
Heated Area	-0.0565	-0.0656	-0.0660	0.0021	0.0012	0.0012
(1000 square feet)	(-1.36)	(-1.57)	(-1.57)	(0.38)	(0.21)	(0.21)
Age	0.0040	0.0040	0.0039	0.0000	-0.0000	-0.0000
	(1.95)	(1.95)	(1.77)	(0.02)	(-0.01)	(-0.01)
Pool	0.0200	0.0205	0.0201	-0.0271***	-0.0269***	-0.0269***
	(0.42)	(0.44)	(0.43)	(-3.79)	(-3.76)	(-3.76)
Electric and Gas	0.0185	0.0184	0.0183	0.0197**	0.0197**	0.0197**
	(0.43)	(0.43)	(0.43)	(3.16)	(3.16)	(3.16)
Mean Income	-0.0000	-0.0000	-0.0000	-0.0003**	-0.0003**	-0.0003**
($1000)	(-0.04)	(-0.04)	(-0.04)	(-2.66)	(-2.62)	(-2.62)
Mean Household Size	0.0452	0.0462	0.0464	0.0007	0.0004	0.0004
	(0.75)	(0.76)	(0.77)	(0.06)	(0.03)	(0.03)
Hot Tub	-0.1084*	-0.1049*	-0.1049*	-0.0140	-0.0142	-0.0142
	(-2.25)	(-2.21)	(-2.21)	(-1.30)	(-1.32)	(-1.32)
cons	-0.2178	-0.2034	-0.2005	0.0655	0.0668	0.0669
	(-1.38)	(-1.28)	(-1.26)	(1.87)	(1.91)	(1.91)
N	1552	1552	1552	24008	24008	24008

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

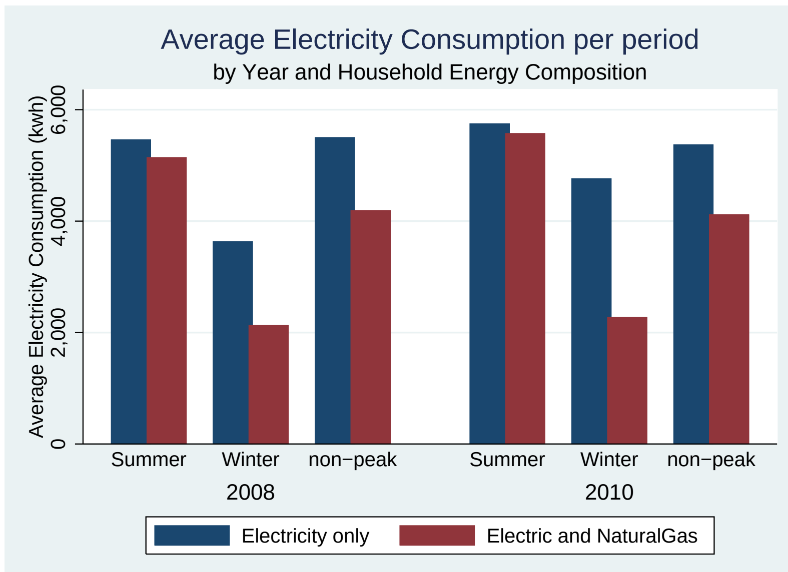
as severe and requires less energy for heating than in the summer for cooling. The percentage of days from December through February that the daily maximum temperature exceeded 80^0F is about 70% in Gainesville and 50% in other parts of central Florida. Most Floridians uses their AC system to heat their homes in the winter. Therefore, the AC rebate program is expected to have a significantly higher effects in the winter months than in the non-peak months. The results of the impact of the rebate program on energy consumption in the winter peak are presented in Table 1-8. While the impact on winter-peak consumption is still negative as expected, the magnitude is small compared even to the effects in non-peak months. It is again statistically insignificant using the DD CEM with census tract as neighborhoods and significant at the 5% level using the regular DD.[19] The relatively small magnitudes and the statistical insignificance of the estimated effects are surprising as we expect the high-efficiency AC to have a large impact in the winter months particularly because most Floridians depend on their air conditioner to heat their homes during winter. About 53% of households in our sample uses electricity as their primary heating fuel. Nevertheless, the result lends support to the observation that the temperatures in Florida's winter are sufficiently mild to require much less energy for heating than in the summer for cooling (Winsberg and Simmons, 2009).

One reason for the no or little winter peak effect may be that there is fuel switching in the winter months so that households in Gainesville use gas for heating in the winter and electricity for cooling in the summer. Because the AC rebate program is expected to have a high effect on electricity consumption than on gas consumption, this substitution of gas for electricity in the winter months reduces electricity consumption and thus there is little room for energy savings compared with if households continued to use their electricity for heating. Figure 1-4 compares the winter, summer and non-peak months electricity consumption of households who use electricity only to households who use both electricity and natural gas. The

[19] A similar results in obtained with the DD CEM using zip codes as neighborhoods in Table A-6 in the appendix.

bar charts show that while electricity consumption in the summer between the two households groups is similar, there is a large difference in electricity consumption between the two groups in the winter months. There is also a significant difference in the electricity consumption between the households in the non-peak months but as expected, this difference is lower than the difference in the electricity consumption in the winter months. To further test the fuel

Figure 1-4. Average Electricity Consumption in The Summer, Winter, and Non-peak Months by Household Energy Composition



switching proposition, we compared the electricity and natural gas consumption in the summer, winter, and non-peak months for households that use both electricity and natural gas. This is shown in Figure 1-5. The figure shows that while a greater proportion of the households energy usage comes from electricity in the summer, natural gas becomes main fuel in the energy mix in the winter. There is still relatively high electricity usage in the non-peak months. This further lends more support to the results that the high-efficiency AC reduced energy consumption in the summer and non-peak months but has no statistically significant effect on winter peak consumption. While the high-efficiency AC program is expected to have a high effect on electricity usage than on natural gas usage, households, especially those with both electricity and natural gas reduces their consumption of electricity and increases their natural gas usage so that the energy savings on the "little" energy consumption is almost negligible.

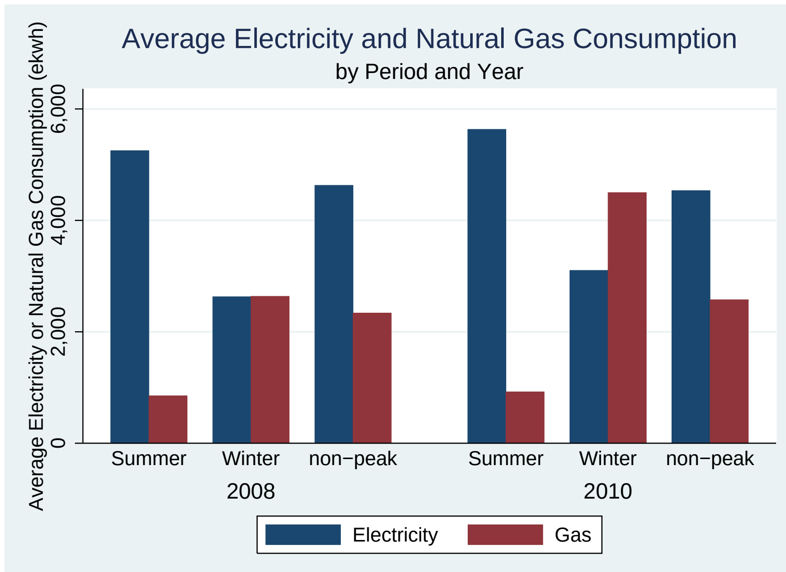
Table 1-8. Winter Peak Effects of The 2009 AC Rebate Program

Δlog(Energy Usage)	DD CEM (Census Tract)			Regular DD		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treat	-0.0404	-0.1599	-0.1118	-0.0403*	-0.0283	0.0605
	(-1.44)	(-1.92)	(-0.93)	(-2.26)	(-0.71)	(0.99)
Bedrooms	0.0556	0.0554	0.0554	-0.0043	-0.0043	-0.0043
	(1.78)	(1.77)	(1.77)	(-0.86)	(-0.87)	(-0.87)
Stories	0.0081	0.0085	0.0086	-0.0159**	-0.0159**	-0.0159**
	(0.24)	(0.25)	(0.25)	(-2.70)	(-2.71)	(-2.70)
Heated Area	-0.0453	-0.0515	-0.0509	0.0171***	0.0173***	0.0174***
(1000 square feet)	(-1.19)	(-1.31)	(-1.30)	(3.56)	(3.54)	(3.56)
Age	0.0015	0.0015	0.0016	0.0004	0.0004	0.0004
	(0.90)	(0.90)	(0.92)	(1.62)	(1.63)	(1.70)
Pool	-0.0530	-0.0526	-0.0521	-0.0532***	-0.0532***	-0.0532***
	(-1.15)	(-1.15)	(-1.13)	(-8.15)	(-8.14)	(-8.13)
Electric and Gas	0.1567***	0.1567***	0.1568***	0.1375***	0.1375***	0.1374***
	(4.07)	(4.08)	(4.08)	(25.24)	(25.24)	(25.21)
Mean Income	-0.0010	-0.0010	-0.0010	-0.0009***	-0.0009***	-0.0009***
($1000)	(-1.63)	(-1.63)	(-1.63)	(-10.08)	(-10.08)	(-10.09)
Mean Household Size	0.0979	0.0986	0.0984	-0.0235*	-0.0235*	-0.0236*
	(1.15)	(1.16)	(1.15)	(-2.16)	(-2.16)	(-2.16)
Hot Tub	-0.0048	-0.0024	-0.0024	-0.0017	-0.0016	-0.0018
	(-0.07)	(-0.03)	(-0.04)	(-0.16)	(-0.15)	(-0.17)
Treat*Heated Area		0.0653	0.0573		-0.0055	-0.0098
		(1.72)	(1.47)		(-0.39)	(-0.72)
treatage			-0.0015			-0.0034
			(-0.48)			(-1.74)
cons	-0.0195	-0.0097	-0.0132	0.3742***	0.3740***	0.3735***
	(-0.09)	(-0.04)	(-0.06)	(12.15)	(12.12)	(12.11)
N	1552	1552	1552	24010	24010	24010

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

The two figures (Figure 1-4 and Figure 1-5) suggest that there is fuel substitution among

Figure 1-5. Average Electricity Consumption in the Summer, Winter, and Non-peak months by Household Energy Composition



households with both natural gas and electricity consumption which accounted for the low or statistically insignificant energy savings effects in the winter months. To test whether energy savings would have been higher without the substitution of gas for electricity , we consider only the subset of households who use only electricity and estimate the treatment effect in the summer peak, winter peaks, and non-peak months. The estimated effects are shown in Table 1-9.

The results in Table 1-9 show statistically significant 14% energy savings in the summer using the CEM DD regression (Column I). The regular DD gives a 11% energy savings in the summer. These estimates are quite less when compared to the estimates using all households. This implies that the high-efficiency AC rebate program has greater energy savings effects on households with both electricity and gas than on households with electricity as their only energy source during the summer months. I.e., the high-efficiency AC significantly reduces the already low natural gas consumption during the summer months. The electricity savings estimates in the winter peak are doubled and statistically significant in the DD CEM regression with an estimated 8% reduction in winter peak consumption (Column II). The estimated

Table 1-9. Summer, Winter, and Non-Peak Months Effects of The High Efficiency AC Rebate Program for The Electric-Only Households

Δlog(Electricity Usage)	DD CEM (Census Tract)			Regular DD		
	Summer	Winter	Non-Peak Months	Summer	Winter	Non-Peak Months
Treat	-0.1391***	-0.0804*	-0.0376	-0.1110***	-0.0659**	-0.0348
	(-3.73)	(-2.16)	(-1.20)	(-3.51)	(-2.64)	(-1.60)
Bedrooms	0.0431	0.0395	0.0617	-0.0012	0.0014	0.0017
	(1.14)	(0.82)	(1.65)	(-0.12)	(0.14)	(0.20)
Stories	-0.0088	-0.0032	-0.0199	0.0063	-0.0227*	-0.0050
	(-0.39)	(-0.11)	(-0.75)	(0.65)	(-2.55)	(-0.63)
Heated Area	-0.0090	-0.0523	-0.0272	-0.0033	0.0131	0.0096
(1000 square feet)	(-0.24)	(-1.88)	(-1.14)	(-0.33)	(1.48)	(1.17)
Age	-0.0022	0.0016	-0.0015	0.0002	0.0003	-0.0002
	(-1.06)	(0.74)	(-0.78)	(0.34)	(0.70)	(-0.50)
Pool	0.0480	0.0423	0.0064	-0.0051	-0.0454***	-0.0234*
	(0.88)	(0.94)	(0.16)	(-0.41)	(-3.84)	(-2.09)
Mean Income ($1000)	-0.0013	-0.0011	-0.0001	-0.0003*	-0.0011***	0.0000
	(-1.65)	(-1.23)	(-0.24)	(-1.96)	(-7.28)	(0.08)
Mean Household Size	0.0748	0.1777	0.1121	0.0154	0.0108	0.0310
	(0.76)	(1.16)	(1.27)	(0.70)	(0.61)	(1.87)
Hot Tub	-0.0937	-0.0003	0.0229	-0.0156	0.0100	-0.0068
	(-1.39)	(-0.00)	(0.50)	(-0.77)	(0.42)	(-0.32)
cons	-0.0936	-0.1560	-0.3755	0.0272	0.3067***	-0.1127*
	(-0.41)	(-0.38)	(-1.74)	(0.45)	(6.10)	(-2.39)
N	502	502	502	7975	7975	7975

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

energy savings in the winter months using the regular DD is also higher (6.6%) than previously estimated using the combined group of all households. These indicate that the AC rebate program had a large effect on electricity consumption in the winter months. However, the substitution of electricity for gas in the winter months by those with gas in their energy mix overshadows this effect so that the aggregate effect is statistically insignificant. The estimated effects in the non-peak months are statistically insignificant in the DD CEM with census tracks as well as in the regular DD. It is, however, significant at the 5% level in the DD CEM regression with zip codes as neighborhoods.[20]

We also estimate the effect of the AC rebate program on electricity consumption for those households with both gas and electricity in their energy mix to give more support to our fuel switching hypothesis. We posit that since those with natural gas switch to natural gas to heat their homes in the winter, there is little AC or electricity usage in the winter, so there should be little or no energy savings for this group of households in the winter. We also expect a relatively higher summer peak effect since the AC rebate program is expected to have bigger effects on both summer electricity and natural gas consumption. Table 1-10 summarizes our results. From the table, the summer peak effect of the AC rebate program is about 24% in the CEM DD with census tracks as neighborhoods (Column 1) and a about 21% in the regular DID (Column IV). There are also energy savings in the non-peak months (7.8% reduction using the DD CEM with census tracts as neighborhoods (Column III) and 6.5% using the regular DID (Column VI). However, as expected, there are no statistically significant energy savings in the winter peak using the DD CEM regression. The regular DD shows that electricity usage increased in the winter for the program participants, but the result is only marginally significant at the 5% level.

[20] See Table A-7 in the appendix.

Table 1-10. Summer, Winter and Non-Peak Months Effects of The 2009 AC Rebate Program on Electricity Consumption for Households with Both Electricity and Natural Gas in Their Energy Mix

Δlog(Energy Usage)	DD CEM (Census Tract)			Regular DD		
	Summer	Winter	Non-Peak Months	Summer	Winter	Non-Peak Months
Treat	-0.2408***	0.0262	-0.0780***	-0.2168***	0.0552*	-0.0658***
	(-7.62)	(0.91)	(-3.58)	(-7.52)	(1.96)	(-3.50)
Bedrooms	0.0514	-0.0324	-0.0212	0.0005	-0.0107	-0.0063
	(1.32)	(-0.88)	(-0.79)	(0.07)	(-1.65)	(-1.01)
Stories	0.0814	0.0416	0.0145	-0.0079	0.0237*	0.0043
	(1.63)	(1.06)	(0.46)	(-0.92)	(2.58)	(0.53)
Heated Area	-0.0451	0.0592	0.0372	0.0018	0.0109	-0.0028
(1000 square feet)	(-1.71)	(1.75)	(1.22)	(0.27)	(1.77)	(-0.48)
Age	-0.0013	0.0008	-0.0019	-0.0000	0.0016***	-0.0006
	(-0.89)	(0.64)	(-1.73)	(-0.13)	(4.79)	(-1.70)
Pool	-0.0245	-0.1126**	-0.0810	-0.0479***	-0.0388***	-0.0304***
	(-0.54)	(-2.65)	(-1.92)	(-5.53)	(-4.44)	(-3.70)
Mean Income ($1000)	0.0006	-0.0011*	-0.0006	-0.0002	-0.0009***	0.0000
	(1.20)	(-1.97)	(-1.29)	(-1.90)	(-7.65)	(0.07)
Mean Household Size	-0.0241	0.1358	0.1407*	-0.0086	0.0259	0.0297*
	(-0.38)	(1.69)	(2.53)	(-0.55)	(1.61)	(2.10)
Hot Tub	-0.0849	-0.0075	-0.0157	-0.0022	0.0061	-0.0085
	(-1.61)	(-0.22)	(-0.46)	(-0.19)	(0.47)	(-0.69)
cons	-0.0404	-0.2477	-0.2671*	0.1347**	0.0046	-0.0514
	(-0.20)	(-1.33)	(-2.08)	(3.15)	(0.11)	(-1.31)
N	4107	4437	4437	16030	16035	16035

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

1.7 Conclusion

Understanding the actual energy saved at the whole building level, and not just at the appliance level is important to consumers, the utility company and regulators. All stakeholders want to know the exact energy savings to determine the cost-effectiveness of the program from their perspective. Consumers are interested in whether the discounted monthly savings would outweigh the initial cost of participating in the DSM program. Regulators and utility companies are interested in the overall cost-effectiveness of the rebate program and whether the program should be continued in future years. This study provides an analysis of the energy savings effects of a demand-side management program particularly GRU's high efficiency AC program where GRU offers incentives to its customers to replace their old low-efficiency AC unit with a high-efficiency model. The results show that the high-efficiency AC program has significant effects on annual energy savings in both our proposed difference-in-difference coarsened exact matching methodology or the regular difference-in-difference methodology without matching. The results also show that while the high-efficiency AC program had significant effects on summer peak energy consumption and non-peak months consumption, it had little or no statistically significant effect on winter peak consumption

While the empirical analysis presented here is specific to Gainesville and to the high efficiency AC rebate program, and the analysis is limited by problems of data availability and reliability, using the difference-in-difference coarsened exact matching approach to reduce the imbalance between the treated and untreated observation as well as matching on neighborhoods (without further coarsening) to control for the effects of weather on energy consumption is one of the contributions of this paper. The results also indicate that when the area under study has only one weather station so that there is no proxy for household specific weather, the difference-in-difference methodology (without marching) overstates (or understates) the energy savings effects of DSM programs.

CHAPTER 2
THE "REBOUND" EFFECT

2.1 Introduction

In this chapter, I present an estimate of the rebound effect. Rebound occurs when DSM program participation results in a decline in participants' energy cost so that participants adjust their thermostat setting or other energy use levels, thereby decreasing energy savings. Rebound effects, therefore, imply that DSM investments would not lead to proportionate reductions in energy consumption. The reason for this is that DSM measures reduce the effective price of operation of energy-consuming equipment. Hence, consumers use some of the money saved to purchase increased comfort, increasing the use of energy-consuming equipment (e.g. adjusting thermostat setting or increased hours of operation). The term "rebound effect" first appeared in a seminal paper by Daniel Khazzoom in which the author argued that mandated energy efficiency standards for household appliances would not lead to a proportionate decrease in energy consumption (Khazzoom, 1980). Since the term's appearance in the literature, there has been extensive research on the size of the rebound effect. However, there is a wide range and variation of estimates of the rebound effect in the literature. Depending on the energy efficiency measure, the theoretical literature posits rebound effects of between zero (no rebound effect) and 100% rebound (back fire), while estimated rebound effects in the empirical literature lie between 0% and about 75%.

The stark variation in the estimates of the rebound effect stems from the definition and the empirical methodology used. Some empirical studies use survey data where consumers' responses to questionnaires are used to investigate the rebound effect (e.g. Fowler et al. (2015)). Other studies use observed thermostat settings and hot water temperatures to estimate a direct rebound effect (e.g. Dubin et al. (1986)). A direct rebound effect measures increases in the consumption of the appliance that has received the energy efficiency improvement.[1] A majority of the empirical studies, especially literature in the transportation sector, however, rely on observational data on energy use and energy prices. In these cases, the rebound effect is investigated using variation in energy prices rather than variation in energy efficiency.

The intuition for using price variation is that energy efficiency improvements reduce the cost of using the energy-consuming appliance, in the same way, an energy price reduction would. Therefore, we can expect consumers to response to a decrease in energy cost as a result of energy efficiency, in the same way, they would respond to a decline in energy prices. Further, prices are exogenously fixed, and consumers have no control over them compared to energy efficiency improvements that are endogenously chosen by households. Although using price variation helps to circumvent the problem of endogeneity with energy efficiency investments, the elasticities for prices and efficiency can be statistically different from each other (Greene, 2012). Another recent empirical study further suggests that consumers respond comparatively less to changes in the fuel economy of vehicles than to fuel prices (Gillingham, 2011).

Again in the electricity sector, since a change in price affects the consumption of all other energy-consuming appliances, using the price elasticity to estimate the response to energy efficiency for just one appliance may overstate the response to energy efficiency. While the theoretical literature models household demand as a sum of electricity demand for electricity consuming appliances (e.g., (Reiss and White, 2005)), one problem with empirical estimation is how to separate the total household demand into its parts without smart meters that can measure energy consumption at the appliance level. Some empirical studies measure changes in thermostat setting and use this change to estimate the energy required to maintain the new setting. For example, Dubin et al. (1986) approximated daily heating load as a quadratic function of the difference between outdoor and indoor temperature and estimated the price of

[1] There is also an indirect rebound effect which measures the impact of the energy efficiency improvement on the consumption of other energy-consuming appliances or all other products.

comfort as the change in billing period utilization associated with a degree change in household thermostat setting.

There is also the problem of which price consumers respond to when utility companies use the complex increasing-block pricing schedule that has become very common among utilities. Price elasticities calculated using marginal prices implicitly make the assumption that consumers, at any point in time, know their level of consumption, and therefore, their marginal price. This reasoning seems unrealistic as this would mean consumers visit their electricity meter on a daily or hourly basis. Price elasticities estimated with these assumptions either overstates or understates the true price elasticity and thus the responsiveness to energy efficiency. Dubin et al. (1986) estimated the price elasticities of space heating in January, February, and March to be -0.52, -0.81, and -0.73 respectively for Florida Power and Light Customers. Using these elasticities, the authors estimated the responsiveness of space heating and cooling to declining unit energy consumption of appliances and concluded that the rebound effect is about 8-12% below engineering estimates for those months.

An important element of the Florida Power and Light study is that space heating was metered separately which allowed for an accurate estimation of the direct rebound effect. However, it ignores the impact of the low energy consumption of one appliance on the energy consumption of other energy-consuming appliances. Some of the rebound may be desirable for overall energy usage. For example, the analysis in section 6 of this paper suggests that there is fuel switching in the winter months so that electricity consumption in the winter months is low for households with both electricity and natural gas. An increase in AC efficiency means electricity becomes competitive or even better than natural gas as the primary heating fuel. Thus, while we might observe an increased AC usage in the winter, natural gas usage and the use of other stand-alone room heaters may have reduced so that the overall energy consumption for the household is lower. In such a case, we might have a significant direct rebound effect of the AC program but the total rebound effect (sum of direct and indirect rebound) may be small or nonexistent.

2.2 Conceptual Framework

As stated earlier, the main reason for using price variation to estimate rebound of energy efficiency improvements is the endogeneity of efficiency improvements (West et al., 2015). That is, while prices are taken exogenously by consumers, households that participate in retrofitting programs are not selected randomly from the set of all households. In this part of the analysis, we make a selection-on-observables assumption. We assume that participation in the energy efficiency improvement depends on households pre-treatment characteristics. Hence, by selecting a control group that has similar characteristics as program participants, we are able to minimize the bias from the endogenous selection into treatment. We used the coarsened exact matching methodology to select a reasonable control group that has similar pre-treatment characteristics as the treated households so that in the absence of the program, the trajectory of average electricity consumption of the program participants would be similar to that of the control households. If the selection-on-observables assumption holds, then the control group would have the similar likelihood of participating in the program as the treated households but rather chose not to participate.

Again, in contrast to estimating rebound in the fuel economy of new cars in which consumers can easily compare the fuel cost per mile traveled given the fuel economy of a car, the exact cost savings of efficient electric appliances are not readily known to the consumer. The complex price schedules used by utility companies further muddle the calculation of the cost savings. We, therefore, posit that even though consumers expect a reduction in their bill after installing a new efficient AC, the exact effect on their bill is not known. It is only after observing the impact of participating in the program on their total energy bill that consumers infer their energy cost savings. Thus, we assume that in the period that consumers undertake the energy efficiency improvements, there is no behavioral change in anticipation of the money savings from participating in the retrofitting program. Changes in energy consumption above the counterfactual consumption in the first period of the program can, therefore, be considered as "pure" program effects. However, after consumers learn of their energy cost savings through their energy usage bill, they make changes to their behavior or lifestyle which might reduce their energy savings or increase energy consumption. In this case, the rebound may occur on a month-on-month basis as consumers learn their electricity cost savings from the previous month's bill or can occur in the next winter or summer after observing their cost savings in the previous winter or summer. For example, households that participate in a weatherization assistance program might change their thermostat setting in the second winter after observing their energy cost reduction in the first winter after the program. In this paper, we consider the whole year, or the winter peak, summer peak, or the non-peak months as our period. Thus, participants, after observing their energy cost decrease in the first period are more likely to engage in activities that lead to energy savings rebound in the second year. This framework is similar to the research design of Fowler et al. (2015) in estimating temperature take back effects. The authors surveyed households' indoor air temperature at least one year after the households have received efficiency improvements to "allow plenty of time for residents to observe how the retrofit affected winter heating cost"(Fowler et al., 2015). We follow the participants of the 2009 program for another year to observe the changes in their energy savings in the second year after the program. This allowed participants to see their summer and winter energy cost for at least one year.

2.3 Graphical Analysis of The Rebound Effect

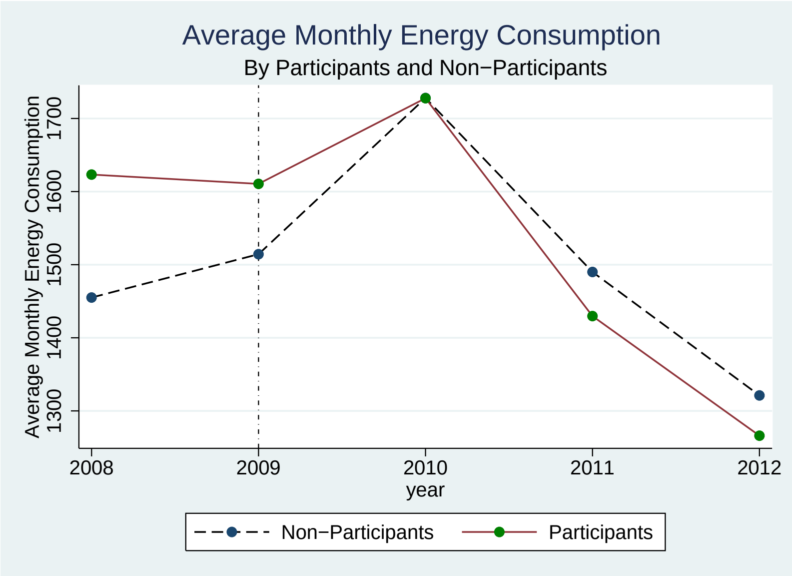
Using the control group and the treatment group obtained using the CEM methodology (with census tracts as neighborhoods), we graph the average monthly consumption of both groups before treatment (2008), in the treatment year (2009), and three years after treatment (2010, 2011, 2012). This gives a rough estimate of the rebound effect. Figure 2-1 shows the graph of average monthly energy consumption of participants and non-participants. The chart shows that before treatment, i.e. in 2008, the participants had a higher energy consumption than the non-participants with a significant (t-statistic=9.86) difference of about 168 kWh and with the program participants being the high energy users. However in the year of the treatment, this difference diminishes to 96.2 kWh. Thus, there was immediate effect of the program even in the year of treatment. The year 2010 is the first full year of participating in the program, and while the energy consumption of both groups increased, the energy consumption of the control group increased sharply compared to that of the treated households so that average monthly energy consumption is almost the same for both groups with no statistically significant difference. Again while the monthly average energy consumption of both groups decreased in 2011 and 2012, the program participants had a sharp decline of about 17.3% compared to the non-participants who had a reduction of 13.8%. The average energy consumption of the treatment group is below that of the control group in 2011 with a statistically significant difference of 60.3 kWh. The average consumption of both groups decreased by the same percentage (11%) in the year 2012.

The graph, therefore, suggest that even after consumers learn of their energy cost savings in the year of program participation and after the first full year of program participation, their energy savings in the subsequent years is even much higher. The graph thus suggests no rebound effect of the AC rebate program but rather a continued increase in energy savings in the subsequent years. Figures B-1 and B-2 in the appendix shows the graph of average energy consumption of the treated and control consumers who were matched in the CEM methodology when zip codes were used as neighborhoods and when no matching methodology were used. While the two figures differ slightly from Figure 2-1 and from each other, the main observation from Figure 2-1 that the program participants even increased their energy savings much higher in the subsequent years after the program is present in all three figures.

2.4 Estimation and Results

Our estimation of the rebound effects follows the same procedure as the evaluation of the energy savings effects. We estimate whether compared to the control group, the treatment group increased consumption in the year 2011 after their first full year (2010) of program participation and observing their energy cost savings. Any rebound after observing their usage cost will lead to a reduction of energy savings or an increase in energy consumption by the treatment group compared to the control group. We, therefore, compared the energy

Figure 2-1. Average Energy Consumption by Participants and Non-Participants



consumption of the treatment group to the control group across the years 2010 and 2011. We used Equations 1–5 and 1–6 with and without the CEM methodology. I repeat these equations below for easy reference. Equation 1–5 models the log of total energy usage of the form:

$$y_{it} = \beta_0 + \delta_0.\ d2 + \delta_1 treat_{it} + \delta_2 treat_{it} \cdot X_i + \beta_1 X_i + \beta_2\ d2 \cdot X_i + \gamma_i + u_{it}, \quad t = 1, 2 \quad (2\text{–}1)$$

where y_{it} is the log of total energy consumption for household i in period t. Total energy consumption for household i is defined as the sum of electricity consumption measured in kilowatt hours (kWh) and natural gas consumption converted to equivalent kilowatt hours (ekWh).[2] $d2$ is a dummy variable for the second time period, γ_i is the individual heterogeneity that is constant across time, and u_{it} is the idiosyncratic error that varies with time. X_i is a vector of household characteristics. First differencing the two equations across the two time

[2] Natural gas consumption is originally measured in therms. In order to combine electricity consumption to natural gas consumption, natural gas consumption were converted to equivalent kWh using the conversion rate 1 therm = 29.300111 ekWh.

periods (2010 and 2011) removes the individual heterogeneity as well as all the time constant explanatory variables so we obtain the estimation equation:

$$\Delta y_i = \delta_0 + \delta_1.treat_i + \delta_2 treat_i \cdot X_i + \beta_2 X_i + \Delta u_{it} \tag{2–2}$$

Table 2-1 shows the result of the estimation using Equation 1–6. Column I of the table gives the results of the DD CEM with census tracts as neighborhoods, Column II gives the results of the DD CEM with zip codes as neighborhoods, and Column III gives the results of the regular DD methodology with only the matched sample from the CEM (with census tracts as neighborhoods). All three regressions give a negative sign on the treatment group which implies that the treatment group further decreased energy consumption in 2011 above the 2010 consumption (as observed in Figure 2-1). However, the effect is not statistically significant in the DD CEM with census tracts as neighborhoods and in the regular DD but significant at the 5% level in the DID CEM with zip codes as neighborhoods. All three results, therefore, show there is no rebound effect of the high-efficiency AC rebate program, rather program participants further increased their energy savings in the subsequent year after the program.

Rebound in Peak and Non-peak Periods

The results above concludes that there are no substantial annual rebound effects. We investigate if there are rebound effects in some periods than in some other periods. The results in Table 2-2 show that there is no statistically significant rebound effect in all periods.[3] The coefficients in both regressions for all periods have negative signs implying that energy savings were even more pronounced in 2011, but the estimates are not statistically significant. This result is however in contrast to the result by Dubin et al. (1986). Dubin et al. (1986) conducted an analysis of the effects of high-efficiency AC or a high-efficiency heat pump

[3] Columns I, III, V shows the results using the DD CEM with census tracts as neighborhoods, while Columns II, IV, and VI shows the results using the regular DD on the matched CEM sample.

Table 2-1. Effect of The 2009 High-Efficient Rebate Program on 2011 Energy Savings

Δlog(Energy Usage)	CEM DD (Census Tracts)	CEM DD (Zip Codes)	Regular DD (with CEM)
Treatment group	-0.0261	-0.0300*	-0.0166
	(-1.74)	(-2.30)	(-0.64)
Bedrooms	-0.0044	0.0005	-0.0034
	(-0.17)	(0.03)	(-0.14)
Stories	-0.0217	-0.0143	0.0060
	(-0.96)	(-0.57)	(0.15)
Heated Area (1000 square feet)	-0.0158	-0.0037	-0.0121
	(-0.60)	(-0.21)	(-0.52)
Age	-0.0032**	-0.0014*	-0.0023*
	(-3.01)	(-2.25)	(-2.34)
Pool	0.0359	-0.0036	-0.0046
	(1.20)	(-0.20)	(-0.17)
Electric and Gas	-0.0759**	-0.0674***	-0.0612**
	(-3.26)	(-6.15)	(-3.06)
Mean Income ($1000)	0.0003	0.0004	-0.0002
	(0.59)	(1.58)	(-0.71)
Mean Household Size	-0.0327	-0.0599	0.0169
	(-0.68)	(-1.76)	(0.38)
Hot Tub	-0.0785*	-0.0666	-0.0478
	(-2.17)	(-1.88)	(-0.98)
cons	0.0882	0.0543	-0.0618
	(0.74)	(0.53)	(-0.49)
N	1552	7843	1552

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

program operated by Florida Power and Light in 1981. The authors combined statistical analysis to engineering study in their model and concluded that little rebound takes place in the summer (about 1-2% below engineering estimates) but a significant rebound in the spring and fall (about 13% below engineering estimates). In the DD CEM regression with zip codes as neighborhoods, the results show that there were rather increased energy savings of about 3% in the summer and non-peak periods.[4]

[4] See Table B-4 in the appendix.

Table 2-2. Summer Peak, Winter Peak, and Non-peak Rebound Effects of The AC Rebate Program

ΔΔlog(Energy Usage)	SUMMER		WINTER		NON-PEAK	
	DD CEM	regular DD	DD CEM	regular DD	DD CEM	regular DD
Treat	-0.0154	-0.0089	-0.0059	-0.0001	-0.0328	-0.0235
	(-0.69)	(-0.50)	(-0.30)	(-0.00)	(-1.87)	(-1.53)
Bedrooms	-0.0219	-0.0162	0.0123	-0.0076	0.0133	0.0359
	(-0.60)	(-0.51)	(0.32)	(-0.41)	(0.44)	(1.56)
Stories	-0.0373	0.0031	-0.0231	-0.0152	-0.0133	0.0166
	(-1.05)	(0.14)	(-0.63)	(-0.75)	(-0.49)	(0.86)
Heated Area (1000 square feet)	0.0039	-0.0101	-0.0029	0.0148	-0.0461	-0.0470*
	(0.07)	(-0.37)	(-0.11)	(0.82)	(-1.62)	(-2.16)
Age	-0.0045**	-0.0012	-0.0033*	-0.0043***	-0.0019	-0.0012
	(-2.72)	(-0.86)	(-2.49)	(-4.96)	(-1.34)	(-0.98)
Pool	0.0445	-0.0035	0.0283	0.0077	0.0410	0.0119
	(1.01)	(-0.11)	(1.07)	(0.41)	(1.21)	(0.57)
Electric and Gas	-0.0001	0.0201	-0.1084***	-0.0877***	-0.1005***	-0.0821***
	(-0.00)	(0.74)	(-3.46)	(-5.28)	(-3.92)	(-4.03)
Mean Income ($1000)	0.0006	-0.0002	0.0014	0.0011***	-0.0008	-0.0014**
	(0.92)	(-0.36)	(1.93)	(3.41)	(-1.29)	(-3.13)
Mean Household Size	0.0311	0.1149	-0.1819	-0.1392**	0.0523	0.0617
	(0.40)	(1.80)	(-1.36)	(-3.20)	(0.95)	(1.37)
Hot Tub	-0.1100	-0.0075	-0.0150	-0.0654	-0.0990	-0.0799*
	(-1.55)	(-0.17)	(-0.26)	(-1.84)	(-1.94)	(-2.23)
cons	0.0393	-0.2303	0.1868	0.1408	-0.0484	-0.1620
	(0.20)	(-1.54)	(0.70)	(1.14)	(-0.35)	(-1.28)
N	1552	1552	1552	1552	1552	1552

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

2.5 Conclusion

The section contributes significantly to the growing literature on rebound effects of energy efficiency policies. It shows that in the case of the high-efficient AC rebate program, there is no rebound effect. In fact the program had incremental energy savings two years after the program participation. The additional energy savings is however not statistically significant. Rebound effects are important to the utility and regulators to determine if the first year energy savings would persist or whether the supply resources that the DSM program was designed to displace will indeed be avoided over the long run. An accurate measurement of the rebound effect therefore helps in estimating the avoided cost of DSM programs in order to garner more stakeholder support for these programs.

CHAPTER 3
EFFECTS OF AUTOPAY PROGRAM ON PRICE SENSITIVITY

3.1 Introduction

Economic theory is built on the assumption that rational agents make consumption decisions by choosing a bundle of goods to maximize utility given the prices of each good. It further assumes that the price of the good, as well as its observable attributes, is perfectly known to consumers when making consumption decisions. Also, the method of payment does not affect a consumer's evaluation of product characteristics. The optimization decision of a consumer who faces a constant marginal price for a good is straightforward. Nonlinear pricing, however, complicates the optimization decision by creating multiple marginal prices for the same good based on the level of consumption. Nonetheless, a perfectly-optimizing, perfectly informed consumer would still make the optimization decision by consuming up to the point where the marginal price of the good equals the consumer's marginal value for the last unit of the good.

However, empirical evidence shows that in a nonlinear pricing schedule, consumers make the optimization decision with limited information, attention, and cognitive ability. For example, subjects in an experiment respond to average tax rates but respond to the true marginal tax rate if the tax table is redesigned to stress the marginal rates (De Bartolome, 1995). Taxpayers have low awareness of their marginal tax rates (Gensemer et al., 1965). Liebman and Zeckhauser (2014) suggest that when people are faced with the complex price schedule, instead of responding to the discrete jumps in the pricing schedule with discrete jumps in consumption, they smooth their consumption over the entire range of the schedule. Another set of empirical evidence further suggests that the use of credit cards as a payment mechanism, for example, increases the propensity to spend more as compared to cash in otherwise identical purchase situations (Prelec and Simester, 2001; Soman, 2001). Also, consumers' perception and evaluation of the products differ across payment mechanisms (Chatterjee and Rose, 2012).

The contribution of this paper is two-fold. First, we discuss what price consumers respond to in a nonlinear pricing of electricity. Second, we analyze whether automatic bill payments in which a consumer's electricity bill is taken directly from his bank accounts increases his inattention and make him less price sensitive.

Many utilities use the increasing-block pricing, an example of nonlinear pricing in which the price of the utility service follows a step-function with the marginal price increasing at specified levels of consumption.[1] See Figure 3-1 for Gainesville Regional Utilities (GRU)'s increasing block pricing schedule. Normally, there is also a constant upfront fee or customer charge that does not depend on the level of consumption and a constant per-unit fuel charge. The complexity of this pricing schedule makes the prices less salient to consumers. The consumption decision of most electricity consumers, thus, tends to deviate systematically from that of a perfectly optimizing consumer. An electric consumer's electricity usage does not exhibit discrete jumps in consumption in response to the discrete jumps in the marginal prices (Borenstein, 2009). Furthermore, household electricity consumption does not bunch around the cut-off points of the increasing block pricing schedule as would be expected if consumers respond to the true marginal price (Ito, 2014).

The complex price schedule, as well as the fact that consumers do not know their electricity consumption at any point in their billing cycle, combine to make the prevailing marginal price of electricity less transparent to the consumer. Empirical evidence shows that consumers respond to the average price of the increasing-block pricing schedule (Ito, 2014), or an expected marginal price (Borenstein, 2009) instead of the marginal price. One reason often cited for why consumers respond to the (current) average price of the increasing-block pricing instead of the marginal prices, as theory predicts, is that the expected cost of learning

[1] Declining-block pricing whereby the marginal price of electricity is lower for higher levels of consumption had been common in the 1970s. However, since the 1980s, utilities have been switching to increasing-block pricing because the declining block pricing was seen as promoting wastefulness.

the prevailing marginal price exceeds the corresponding expected benefit (Foster and Beattie, 1979). However, consumers responding to current average prices[2] still requires lots of effort on the part of consumers. It requires them to know the price schedule or the start and end dates of their billing period. It further requires consumers to be able to anticipate all demand shocks within the billing period or have knowledge of their total consumption at the end of the period. These assumptions seem at odds with reality. "It seems safe to say that not only do most consumers not know how much power or water they have used since their billing period began, but most consumers also don't know when their current billing period began" (Borenstein, 2009).

I, therefore, propose a conceptual model in which consumers make behavioral rules about consumption only after observing their previous bill. If their electricity bill in the past month is high, consumers make rules aimed at reducing electricity consumption in the current month. On the other hand, if their bill is low, consumers makes rules to ease on their conservation practices. This model suggests that a consumer's current demand for electricity responds to the average price he paid for electricity in the preceding month. I empirically test this model to determine whether the proposed conceptual model is an adequate description of reality. I use the encompassing test of non-nested models to show that consumers respond to their one-month lagged average price instead of the current average price, consistent with the conceptual model. The result has implications for utility rate design, as the empirical price elasticity plays a role in utility's rate design and the choice of price and non-price conservation strategies. It also has implications for energy efficiency policies because in a full information world in which consumers respond to marginal prices, increasing the marginal prices especially the top tier marginal prices would encourage consumption reduction. However, if consumers instead respond to their average or lagged average prices, then mean-preserving changes to the

[2] current average price in calculated as the total bill in a billing period divided by the total usage in that billing period

price schedule would not affect electricity consumption. It is important to know the actual price consumers respond to if changes to the price schedule are expected to influence consumers behavior in a predictable and consistent way.

An implication of the conceptual model is that consumers who inspect their bill carefully will respond more to prices than consumers who only take a cursory look at their bill or fail to examine their bill. The electricity bill of autopay users is deducted from their bank account after their bill is sent to them, so most autopay users do not bother to review the charges since they do not have to write a check. Hence, automatic bill payments increase the probability that users will forgo bill inspections, which increases inattention to the lagged average price, and make consumers respond less to prices. Furthermore, utility companies encourage autopay users to participate in online billing[3] to complement their enrollment in autopay. Participating in both programs increases further the probability that consumers will ignore their bill and thus respond less to prices than non-autopay users.

My second empirical methodology test this concept by allowing the price elasticity of electricity consumption to differ between autopay users and non-autopay users in an Instrumental Variable (IV) estimation of household electricity demand. The results show that automatic bill payment users have an elasticity of electricity demand that is 10% lower (in absolute value) than non-autopay users. Also, using a difference-in-difference framework, I show that enrolling in automatic bill payments reduces consumers' elasticity of electricity demand by 5% . While Sexton (2015) suggests that an autopay program may reduce price sensitivity, to the best of my knowledge this paper is the first to estimate the impact of enrolling in automatic bill payments on price elasticity. We also find (contrary to Sexton's (2015) findings) that the lower price elasticity for autopay users does not necessary lead to

[3] Online billing implies that consumers do not receive their bill in the mail. They receive a notification in their e-mail that their bill is ready, and they can securely view their complete bill details online.

increased electricity consumption. We show that non-autopay users reduce their consumption in months following the receipt of a high electricity bill. However, autopay users had lower consumption in months following the receipt of a lower electricity bill. The net effect can be ambiguous.

These findings also have implications for energy consumption policies. The price salience effects of autopay programs interfere with the electricity utility's effort of using price signals to steer energy consumption (Sexton, 2015). It further makes a strong point for the need to increase information provision or use advanced technology to help consumers perceive their actual marginal price of electricity.

I use a large panel of monthly electricity billing data from Gainesville Regional Utilities (GRU) 's single family residential households from 2009 to 2014. I also use GRU's automatic bill payment enrollment information from 2007 through 2014. I matched each house's parcel number to housing information data from the Alachua County Property Appraiser (ACPA) website. I also use weather information from the National Oceanic and Atmospheric Administration website which we used to calculate the Heating Degree Days (HDD) and Cooling Degree Days (CDD) for each billing period for each household.

The remainder of the paper is as follows: Section 3.2 gives a brief history of automatic bill payment programs and a background of GRU's autopay program. Section 3.3 provides a theory of household electricity demand and describes the conceptual framework. Section 3.4 describes the datasets. The empirical analysis and results are presented in Section 3.5. Section 3.6 concludes.

3.2 A Brief on Automatic Bill Payment and A Background to GRU's Autopay Program

Automatic Bill Payment, a convenient method of payment in which a customer's bill is taken directly from their bank account has become a popular payment system for the payment of almost all monthly recurring bills since the last decade. According to the 2010 Fiserv Consumer Billing and Payments trends survey, the number of households that uses online bill payment in the US increased about eight-fold between 2000 and 2010 (Fiserv, 2010). According to the survey, as of 2010, 80 percent of all households with Internet access use online banking while 40 percent of all households with Internet access use online bill payment (Fiserv, 2010). Automatic bill payments have become particularly popular in the payment of cell phone bills, cable or satellite bills, major credit cards, insurance, electricity, natural gas, water, and almost every recurring monthly bill or transaction. One primary importance of automatic bill payment is that it saves consumers the hassle of having to schedule payment every month for such recurring payments such as car payments or utility bills. They can also help customers avoid late fees due to forgetfulness. Further, it gives consumers a choice of a variety of payment channels. It also saves the consumer time of going through a cluster of paper bills and writing checks every month. Vendors or retailers and service providers also enjoy benefits of autopay such as reduced billing transaction cost and greater certainty of timely payment (Sexton, 2015).

In the US, almost all electric utility companies now allow and encourage their customers to pay their bill through automatic bill payment methods. Some further incentivize their customers to use automatic bill payments. For example, Gainesville Regional Utilities waives the initial deposit for new residential customers who sign up for autopay. Often, the major downsides for automatic bill payments are that the customer might incur a returned fee payment if there were insufficient funds in the account or an overdraft fee from the bank. The vendors, on the other hand, do not face any downside. However, in the utility sector, automatic bill payment makes consumers less price sensitive, which acts against the utility's ability to use price signals to steer energy conservation.

In Gainesville, enrollment in the autopay program is open to all GRU customers with satisfactory payment history and all new GRU customers. GRU still sends customers bill directly to them through the traditional mail or e-billing. To increase participation, GRU offers to waive the initial deposit fee of about \$270[4] for all new customers who enroll in automatic bill payments. Enrollment was initially slow with only 10% of customers participating in the program. However, because of the financial incentive, about 80% of all new customers enroll in automatic bill payments. Currently, more than half of GRU's customers use automatic bill payments

3.3 Electricity Demand and Conceptual Framework

Many utility companies use an increasing-block pricing schedule for electricity demand. Under the increasing-block pricing schedule, electricity price follows a step function with the marginal price increasing at specified levels of consumption. Normally, there is also a constant upfront fee or customer charge that does not depend on the level of consumption and a constant per-unit fuel charge. For example, consider a three-tiered increasing block pricing schedule where consumers pay marginal per unit charges of p_1, p_2, p_3 per kilowatt-hour for consumption in the intervals $[0, x_1], (x_1, x_2], (x_2, \infty)$ respectively. Assume a per-unit fuel charge of f per kWh and a constant customer charge C per bill. Assume further that a consumer used x units of electricity during the period. Then the consumer's total electricity bill is given by:

$$B = \begin{cases} C + p_1 x + fx, & \text{if } 0 \leq x \leq x_1 \\ C + p_1 x_1 + p_2(x - x_1) + fx, & \text{if } x_1 < x \leq x_2 \\ C + p_1 x + p_2(x_2 - x_1) + p_3(x - x_2) + fx, & \text{if } x > x_2 \end{cases}$$

Figure 1 shows the graph a Gainesville Regional Utilities' increasing block pricing schedule.

The nonlinear pricing implies that consumers face a nonlinear budget constraint (Gabor, 1955; Reiss and White, 2005; Acton et al., 1980; Herriges and King, 1994). While economic theory assumes that households optimize based on marginal prices [5] , Reiss and White (2005)

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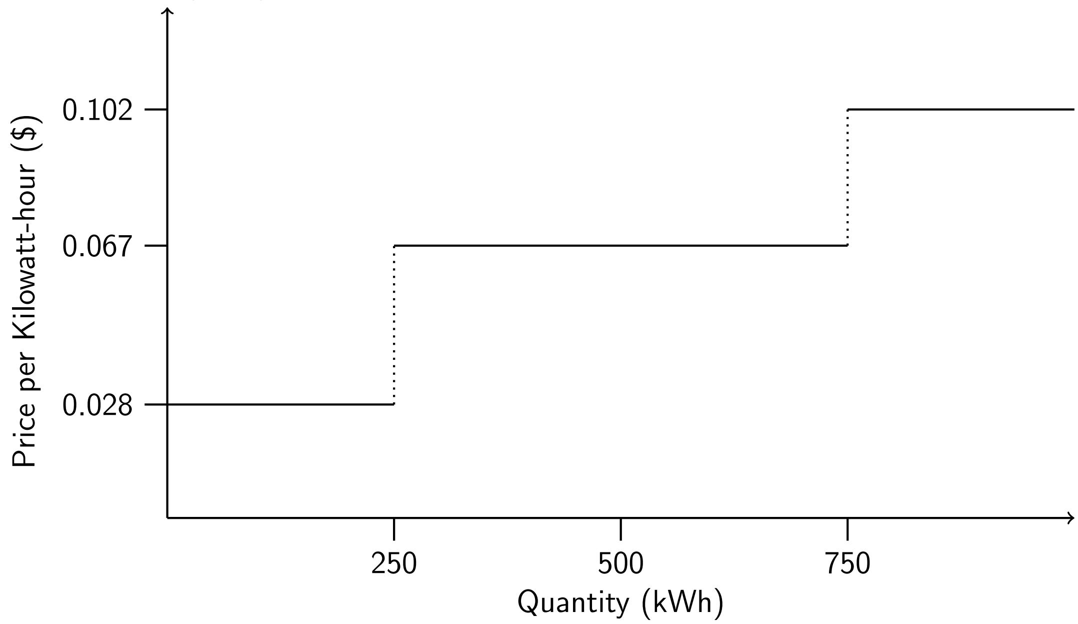
[4] This amount is the total fee for all GRU services. The breakdown of the fee among GRU's services are as follows: electricity- \$ 145, gas- \$50, water- \$35, and wastewater - \$40.

[5] Diamond (1998) and Mirrlees (1971) both assume that people respond the marginal tax rate of a non-linear tax schedule.

Figure 3-1. Increasing-Block Residential Electricity Pricing Schedule of Gainesville Regional Utilities (GRU), 2009



notes that, "The demand behavior of a utility-maximizing consumer thus depends not on the average price, nor any single marginal price, but on the entire price schedule" (Reiss and White, 2005). Nonetheless, Reiss and White (2005) still used marginal prices in estimating price elasticities of electricity demand under nonlinear prices. Other empirical studies such as Huang (2008) in estimating demand for cellular phone service under nonlinear pricing and Hausman (1985) in applying choice under uncertainty with a nonlinear budget set to a model of disability insurance still use marginal prices or assumed consumers respond to marginal prices.

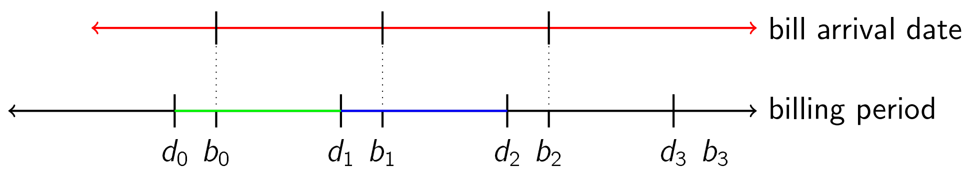
This oversimplification on the use of the marginal price as the price to which consumers respond in estimating demand with nonlinear prices is because there has not been any econometric technique to incorporate the whole nonlinear price schedule that consumers respond to into a demand specification (Reiss and White, 2005). In contrast to the assumption that consumers respond to marginal prices used in some of the studies, recent empirical evidence, however, shows that consumers respond to the average price of a nonlinear pricing schedule. For example subjects in an experiment respond to average tax rate instead of the marginal rate (De Bartolome, 1995). Ito (2014) shows that consumers respond to the average price of the nonlinear pricing of electricity while Borenstein (2009) suggest that electricity consumers are probably responding to the expected marginal price under increasing-block pricing.

Because the data consist of electricity consumption and pricing information from only one utility company and only one utility service area, there is not enough variation in the marginal prices to allow for a consistent estimation of demand elasticities. I, therefore, follow the predictions of the recent empirical studies that consumers may be responding to average prices. However, consumers responding to current average pricing still seems at odds with how consumers behave in reality.

The average price of an increasing-block pricing changes with respect to the level of consumption. Consumers responding to their current average prices imply that consumers know their exact level of consumption, are fully aware of the marginal prices, and know the cutoff points in the pricing schedule. "It seems safe to say that not only do most consumers not know how much power or water they have used since their billing period began, but most consumers also don't know when their current billing period began" (Borenstein, 2009). Consumers responding to the current average price further assumes that consumers have a perfect or near perfect idea about their total consumption at the end of the billing period or can anticipate any demand shock they might face in the billing period. Such an assumption again seems to be at odds with reality.

We propose a behavioral or constrained optimization model of how electricity consumers respond to nonlinear pricing in which households do not know the start or end of their billing period or the amount of usage at the end of the period or at any point in time during the billing period. We propose that after consumers receive their bill, depending on the total amount of their bill, they make behavioral adjustments to their lifestyle that affect their electricity consumption in the days following their bill arrival. These behavioral adjustments or rules remain in place until consumers receive their next bill, after which they update their behavioral rules. If consumers receive their bill at the end of each billing period, then the behavioral rules based on the previous month's bill will affect the electricity consumption of only the current month so that consumers respond to their previous month's bill or the average price of their previous month bill. However, consumers normally receive their previous month's bill mid-way in their current billing period. Thus, the behavioral rules that consumers make based on the previous bill, only affect a portion of their current billing period and a portion of the next billing period. This implies consumers respond to their two-month lagged average price until they receive their previous month's bill. After the receipt of their previous month's bill, they switch to responding to the average price of that bill. Figure 3-2 gives an illustration of what lagged average price consumers might respond in the current billing period.

Figure 3-2. Billing Periods and Bill Arrival Times: An Illustration of What Lagged Average Price Consumers Respond During The Bill Period



d_0, d_1, d_2, d_3 represents the start or end of billing periods. Billing period i extends from date d_i to date d_{i+1}. Bill for billing period i arrives on date b_i in billing period $i+1$.

The conceptual model suggests that consumers might respond to an expected value of their previous two billing periods' average price instead of the current period's average price. Nevertheless, since the electricity bills arrive quickly enough, consumers respond to their one-month lagged average price for most days in the billing period.[6] We, therefore, use the previous month's average bill as the price to which consumers respond. Under Section 3.5, we test this model by using an encompassing test of non-nested models to investigate whether consumers respond to the current average bill or the one-month lagged average bill.

[6] For example in GRU's service area, customers receive their bill usually between 3 to 5 days after their billing period ends.

3.4 Data

We use the following five datasets for our analysis. Table 3-1 gives a list of some of the variables contained in each dataset.

1. GRU's monthly electricity consumption data for single family households from 2008 to 2014.
2. GRU's historic rates and fuel adjustment data.
3. GRU's automatic payment enrollment data from 2007 to 2014.
4. House Characteristics and information data from the Alachua County Property Appraiser(ACPA).
5. Weather information from the National Oceanic and Atmospheric Administration website.

Table 3-1. Variables from Each Dataset

GRU Consumption and Rates Dataset	ACPA Dataset	GRU's Autopay Dataset	Weather Dataset
Parcel Number	Parcel Number	Parcel Number	Min. Temp.
Month of consumption	Physical Address	Date enrolled	Max. Temp.
Year of consumption	Year built	Date exited	
Monthly consumption	Number of bedrooms		
Service Address	Number of bathrooms		
Start date of billing per	Number of Stories		
Enddate of billing period	Base Area square footage		
Marginal prices	Total Area square footage		
customer charge	Heated Area square footage		
fuel adjustment rate	Subdivision		
Gainesville tax rate	Pool ownership		
County tax rate			

1. Min. Temp. is the minimum average daily temperature
2. max. Temp. is the maximum average daily temperature

GRU provided the monthly billing data for households in Gainesville from 2008 to 2014, which I complement with data already provided by the Program for Energy Efficient Communities at the University of Florida. I merged the two datasets to form a comprehensive dataset that contains more information than the two individual datasets. For example, monthly consumption dataset from GRU didn't have the billing periods while the data from the Program for Energy Efficient Communities didn't have the billing addresses. First, I merged the monthly consumption dataset with the house characteristics data obtained from the Alachua County Property Appraiser website. I selected houses that were designated as single family residential. The initial electricity consumption dataset is a panel of electricity consumption data for 35,248 single family residential households over a period of 84 months from 2008 to 2014. The dataset contains information on household's monthly electricity consumption, billing dates, and service address.

The automatic bill payment enrollment data, also from Gainesville Regional Utility, contains the enrollment and exit dates for GRU's autopay program from 2007 to 2014. The base dataset contained 21,174 different parcels. However, this dataset also contains enrollment and exit dates for multifamily residential households and apartments. We restricted the autopay data to only households in the consumption dataset. The restricted autopay dataset contains 13138 single family residential households that participated in GRU's autopay program from 2007 to 2014. Some households enrolled multiple times during the period. For example, two households enrolled 6 times during the period 2007 to 2014. I deleted households that enrolled multiple times from the dataset and also from the electricity consumption dataset.[7] The final autopay enrollment dataset contained 10,335 single family households that participated in the autopay program only once during the period 2008 through 2013. Also a total of 32,080 households, with 72 months of billing data for each household, remained in the monthly consumption dataset. There were, however, 3,103 missing monthly billing information, so the base dataset used in the analysis contains 2,926,565 observations.

The GRU's historic rate data, extracted from the GRU's website, contains information about GRU's pricing schedule, marginal prices for the different consumption levels, fuel adjustment rate for each month, the constant customer charge, Gainesville tax rate, and the Alachua County tax rate. The information also included a summary of how to calculate the

[7] Multiple enrollment dates suggests that the building changed hands several times during the period.

electricity bill for each house. Using the information, I calculated each consumer's bill for each billing period and compared it to the billing data already obtained from GRU.

The daily minimum and maximum temperature for each day from January 1, 2008, to December 31, 2014 were obtained from the National Oceanic and Atmospheric Administration (NOAA). For each day, the daily minimum and maximum temperatures were added together and divided by two to find the daily average temperature. I then calculated the Heating Degree Days (HDD) and the Cooling Degree days (CDD) for each billing period for each household.[8]

3.5 Empirical Strategy and Results

Let q_{it}[9] be daily average electricity consumption for household i during billing period t. Let p_{it} be the price that household i respond to during billing period t. This price, p_{it}, can be the current period's marginal price, the current period's average price, the lagged average price, or the lagged marginal price. We assume that consumers respond to price p_{it} with constant elasticity, β_1. We further assume that the constant price elasticity is the same across all households and all billing periods, so that the demand for household i in period t can be described as:

$$\log q_{it} = \alpha + \beta_1 \log p_{it} + \beta_2 w_{it} + \beta_3 X_i + \beta_4 X_i \cdot w_{it} + \tau_t + \gamma_i + u_{it} \tag{3–1}$$

[8] Heating degree-days for a household in a billing period is the number of degrees that the mean temperature for a day falls below 65^0F summed over all days in the billing period. Cooling degree days, on the other hand, is the is the sum over all days in a billing period of the number of degrees that the mean temperature is above65^0F. Thus, a household's cooling degree-days for the billing period beginning at time t_1 and ending at time t_2 is calculated as $\text{CDD} = \sum_{t=t_1}^{t_2} \max\{A(t)-65, 0\}$ where $A(t)$ is the average temperature of the daily maximum and minimum temperatures measured ^{0}F. Heating degree-days are calculated in a similar way as $\text{HDD} = \sum_{t=t_1}^{t_2} \max\{65 - A(t), 0\}$.

[9] The data contains the total household electricity consumption for each billing period. However since the duration of the billing period varies across months and households. We standardize the data by dividing the total consumption over the billing period by the duration of the billing period to find the daily average electricity consumption for each billing period.

Table 3-2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Monthly usage 2008 (Kwh)	374082	1069.45	689.82	1	15120
Monthly usage 2009 (Kwh)	373142	1061.07	690.93	1	19720
Monthly usage 2010 (Kwh)	374396	1107.13	744.57	1	20640
Monthly usage 2011 (Kwh)	376706	1036.44	698.73	1	21680
Monthly usage 2012 (Kwh)	379301	964.95	621.71	1	16280
Monthly usage 2013 (Kwh)	379343	942.88	609.82	1	15360
Marginal Price ($)	2259198	0.08	0.02	0.03	0.102
Average price ($)	2256947	0.15	0.21	0.10	14.92435
HDD (1000)	2309760	0.00	0.00	0	0.0040
CDD (1000)	2309760	0.00	0.00	0	0.0064
Autopay	2309760	0.18	0.38	0	1
Autopayever	32080	0.28	0.45	0	1
Bedrooms	32075	3.17	0.66	1	5
Bathrooms	32075	2.05	0.67	1	10
Stories	32080	1.12	0.41	0	3
Total Area (1000 square feet)	32080	2.39	1.06	0.40	22.685
Heated Area (1000 square feet)	32080	1.81	0.77	0.37	14.844
Pool Ownership	32080	0.10	0.30	0	1
Age of Building (as of 2013)	32080	28.69	11.42	0	113

Autopayever is a dummy variable equal to 1 if a household ever participated in the Automatic bill payment program between 2008 and 2013.

where w_{it} is a vector of weather information for household i in period period t. w_{it} includes the cooling degree days (CDD) and heating degree days (HDD) for household i in billing period t.[10] γ_i is the subdivision of household i's building.[11] τ_t represents year fixed-effects and controls for unobservable differences in electricity consumption across years. The demand function in Equation (3–1) can be obtained from a quasilinear utility function so there are no income effects of price changes.

[10] Since households have different billing periods, the CDD and HDD varies for each household for each month.

[11] The Alachua County Property Appraiser defines subdivision as the legally recorded name of a developed area. It includes parcels or building that are close to each other and have similar characteristics. There are over a 1,500 subdivisions in Gainesville. Adding subdivision as a control in the regression further controls for the effects of weather on electricity consumption since weather can differ substantially from one neighborhood to another even in the same city.

From a standard demand equation, p_{it} is endogenous because of the simultaneity between price p_{it} and quantity q_{it}. Another source of endogeneity is from the fact that the marginal price depends on the level of consumption. The average price is also obtained by dividing the total bill amount by the total quantity on the left-hand-side of Equation 3–1 and that presents another source of endogeneity. Ordinary Least Square (OLS) estimation, therefore, leads to inconsistent estimates of the price elasticity of demand. Hence, we estimate Equation (3–1) using instrumental variable estimation. We use the two-stage least square estimation method. Valid instruments should be correlated with the price p_{it} but uncorrelated with the error term of Equation (3–1).

We follow Ito (2014) in our choice of instruments. We use a policy-induced price $p_{it}(\tilde{q}_{it})$, also called simulated instrument as our instrumental variable for p_{it}. This instrument, $p_{it}(\tilde{q}_{it})$, computes the predicted price in period t for a consumption level $\tilde{q}_{it}$. To be a valid instrument, $\tilde{q}_{it}$ should not be correlated with u_{it}. We could use the consumption of household i in the same period in the previous year q_{it-12} for $\tilde{q}_{it}$. Hence, our simulated instrument for p_{it} is the predicted price, using the current year's price schedule on the consumption of the same billing period in the previous year. That is, our simulated instrument for p_{it} is what the price would have been had consumers used the same amount of electricity as they did in the same billing period of the previous year. Since GRU changes its price schedule in October of every year, such an instrument would ensure that the instrument and the current period's average price are different even when consumption in the two periods is the same. In the case when consumption in the same month of the previous year is the same as the consumption in the current billing period, the difference between the current period's average price and the instrument is induced by the policy of price schedule change.

But, as noted by (Ito, 2014), q_{it-12} is likely to be correlated with u_{it} because of mean reversion of consumption. We therefore used a quantity level q_{it-13} for $\tilde{q}_{it}$ so that the policy-induced price for period t, $p_{it}(q_{it-13})$ is one instrument for p_{it}. Since the two periods t, and $t-13$ are only one month apart, they are likely to belong to the same season and have similar electricity usage for each household. Under stable weather conditions the differences in consumption between the two periods is induced by the policy change. We add another instruments by choosing q_{it-6} for $\tilde{q}_{it}$. t and $t-6$ are likely to have the same price schedule but are from different seasons. Hence, $p_{it}(q_{it-6})$ is the price (current) for the weather induced consumption in period $t-6$. Using these two instruments imply that our model is over-identified.

Encompassing Test of Current Average Price versus Lagged Average Price

While our conceptual framework in Section 3.3 predicts that consumers respond to lagged average price instead of the current average price, under the empirical section we allowed for the possibility that consumers might respond to the current average price or both the current and the one-month lagged average price. We estimate Equation (3–1) using the current period's average price as the price consumers respond. Next, we estimate the same equation using the previous month's average price as the price consumers respond. Thus we estimate the following two models:

$$\log q_{it} = \beta_0 + \theta \log AP_{it} + \beta_2 w_{it} + \beta_3 X_i + \beta_4 X_i \cdot w_{it} + \tau_t + \gamma_i + u_{it} \tag{3–2}$$

and

$$\log q_{it} = \beta_0 + \alpha \log AP_{it-1} + \beta_2 w_{it} + \beta_3 X_i + \beta_4 X_i \cdot w_{it} + \tau_t + \gamma_i + u_{it} \tag{3–3}$$

where θ and α are the elasticities with respect to the current average price and the one-month lagged average price respectively. Next, using the encompassing test for nonnested models suggested by Mizon and Richard (1986), we test the two nonnested models against each other by constructing a comprehensive model that contains each model as a special case and testing the restrictions that would lead us to each model (Wooldridge, 2012) and (Ito, 2014)). Our comprehensive model is given by:

$$\log q_{it} = \alpha + \theta \log AP_{it} + \alpha \log AP_{it-1} + \beta_2 w_t + \beta_3 X_i + \beta_4 X_i \cdot w_{it} + \tau_t + \gamma_i + u_{it} \qquad (3\text{–}4)$$

In estimating the comprehensive Equation 3–4, we add another policy-induced instrument by choosing another consumption level, q_{it-11} for $\tilde{q}_{it}$. The results of the estimation using Equations 3–2, 3–3, and Equation 3–4 are represented in Table 3-3. Column I of the table shows the results of the estimation from Equation 3–2 when the current average price is used as the price consumers respond while Column II shows the results when lagged average price is used. Column III shows the encompassing test results using the comprehensive Equation 3–4. In all three regressions, standard errors were clustered at the household level to correct for serial correlation. The first two columns show that consumers respond to both the current and the one-month lagged average price with price elasticities of -0.65 and -0.56 respectively. These elasticities are statistically significant even at the 1% level. The encompassing test result in Column III shows that the coefficient on lagged average price is still significant at the 1% level, but the coefficient on current average price becomes positive and statistically insignificant. That is, the coefficient of current average price becomes statistically insignificant once the lagged average price is controlled. Hence conditional on the lagged average price, the current average price do not affect current electricity consumption.

Self-Selection Into Autopay?

The autopay program is voluntary hence participation in the program may be based on the physical characteristics of the household and the house. Households with higher incomes, for example, are more likely to participate in the autopay program than lower income households. This is because lower income households are more likely to have insufficient balance in their bank account, so are more susceptible to fees on returned checks. While household income is not present in the data, household income is known to be correlated with the size and subdivision of the building. Hence I expect number of bedrooms and total area square footage to have a positive effects of autopay participation. Also since GRU offers to waive the initial

Table 3-3. Encompassing Test: Current Vs. One-Month Lagged Average Price

log(daily usage)	I	II	III
log(AP)	-0.6443***		0.1506
	(-7.64)		(1.39)
log(AP_{-1})		-0.5526***	-0.5975***
		(-6.29)	(-7.66)
CDD	1359.0720***	1369.4750***	1373.7198***
	(44.74)	(47.97)	(47.87)
HDD	84.8559	111.5930*	120.6977**
	(1.71)	(2.41)	(2.59)
Heated Area	0.2369***	0.2407***	0.2398***
	(24.74)	(25.22)	(25.30)
Stories	0.0130	0.0155	0.0158*
	(1.61)	(1.94)	(1.98)
Bedrooms	0.0292***	0.0312***	0.0322***
	(4.35)	(4.65)	(4.75)
Bathrooms	0.0453***	0.0408***	0.0402***
	(5.37)	(4.90)	(4.81)
age	-0.0008	-0.0009	-0.0010
	(-1.35)	(-1.60)	(-1.81)
pool	0.2917***	0.2931***	0.2919***
	(27.77)	(28.23)	(28.30)
cons	1.0380***	1.2049***	1.4100***
N	1817360	1812922	1805575
R^2	0.3399	0.3126	0.3029

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.
The coefficients on the subdivision dummies, the year effects, and the interaction term between CDD, HDD, and the household characteristics are left out from the table.

deposit fee for all new services, households in newer buildings are expected to participate in the autopay program more than households in older building.

Different households participated in the autopay program on different dates. Thus, there is no particular date of autopay program participation. I therefore created a new dummy variable, autopayever, equal to 1, if a household participated in the autopay program irrespective of date of participation. Autoypayever equals zero for households that never participated in the autopay program between the January 2007 through December 2008. This variable in used as the dependent variable in estimating the probability of autopay program participation. The probability of participating the the autopay program is assumed to depend on age of the building, total area square footage, number of stories, number of Bedrooms and pool ownership. Since total annual electricity usage is correlated with income, I included total annual usage in 2010. The probit regression equation for the estimation is given by:

$$\text{Autopayever}_i = \alpha_0 + \alpha_1 X + \gamma_j + u_i \tag{3–5}$$

where X_i is a vector of house characteristics while γ_j is a subdivision dummy to control for the subdivision of the house. u_i is the idiosyncratic error term that is assumed to have a normal distribution with mean zero. The results of the probit regression in given in Table 3-4.

Table 3-4. What Affects Participation in Autopay

autopayever	I	II
Annual Electricity Usage in 2010 (Kwh)	-0.0211***	-0.0241***
	(-14.73)	(-18.71)
Total Area Square feet (1000 sq. feet)	0.1382***	0.2648***
	(8.98)	(24.42)
Stories	-0.0328	-0.0128
	(-1.59)	(-0.67)
Bedrooms	-0.0230	-0.0896***
	(-1.37)	(-6.12)
Age of Building	-0.0075***	-0.0041***
	(-5.13)	(-5.68)
Pool	0.0167	0.0498
	(0.59)	(1.85)
Cons	-0.3281	-0.5102***
	(-1.41)	(-10.77)
N	31432	32075
Pseudo R^2	0.0775	0.0271

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis
The coefficients on subdivisions in Column I have been left out from the table.

Column I of Table 3-4 shows the results from Equation 3–5 while Column II shows the results from the same equation but without the subdivision fixed effects. While I expect subdivisions to affect autopay participation because the subdivisions of one's house is related to his income, Column II was added to show that the results of the estimation is not primarily driven by the inclusion by the subdivision fixed effects. The main different between the two columns is the higher pseudo R^2 in Column I. The coefficients and their signs are similar in the two columns. The only exception is the coefficient on Bedrooms which is not statistically significant in Column I but statistically significant in Column II. The results from Column I show that a 1000 square feet increase in the total area increases the probability of program participation by 0.1 points. The coefficient on bedrooms is, however, not statistically significant. As expected, the age of the house reduces the probability of autopay participation. A 10 year increase in the age of the house increases the probability of program participation by 0.08 points. GRU waives the initial deposit fee for new customers who opt to participate in autopay. Since new homes requires new service, households in new homes are more likely to participate in the autopay program than households in older houses. Surprisingly, annual electricity usage is negatively related to the probability of autopay program participation. A 1000 kwh increase in annual electricity usage decreases probability of participating by 0.1 points. Thus, large residential energy consumers are less likely to participate in the autopay program. This result in robust irrespective of the year used for calculating the annual electricity usage.

Automatic Bill Payment Effects on Price Salience - Theoretical Motivation

Let $\log q = \alpha + \log p + y$ be the demand function electricity or any good when consumers perfectly perceive the price. q is the quantity of the good consumed, p is the price and y in income. We assume a quasilinear demand function of the good only for simplicity. Let θ be an inattention parameter, so that instead of consumers observing price, p, they perceive price $(1+\theta)p$, where $\theta \in [-1, 1]$. This imply that consumers perceive a higher than actual price for $\theta \in (0, 1]$, and a price lower than actual price for $\theta \in [-1, 0)$. The demand equation with inattention is therefore given by:

$$\log q = \alpha + \log(1+\theta)p + y \tag{3–6}$$

The price elasticity of demand under full attention ($\theta = 0$) is β. while the price elasticity of demand under inattention is given by:

$$\epsilon_\theta = \frac{\partial \text{log} q}{\partial \text{log}(1+\theta)p} \times \frac{\partial(1+\theta)p}{\partial p} = \beta(1+\theta) \tag{3–7}$$

Thus, the price elasticity under inattention could be greater or less than the price elasticity under full attention depending on the inattention parameter. However since prices have a tendency to be adjusted upward, the inattention normally imply that consumers perceive a lower price than it actually is so that $\theta < 0$. In such a case, the price elasticity of the inattentive consumer would be lower (in absolute terms) than that of the attentive consumer. Our empirical analysis considers automatic bill payment as a proxy of inattention. It therefore assumes that non-autopay users have full attention while autopay users make their consumption decision with some degree of inattention. Thus we assume, with respect to Equation 3–7, that non-autopay users have price elasticity β while non-autopay users have price elasticity $\beta(1+\theta)$. In the case that automatic bill payment does not cause inattention, the two elasticities would be the same, that is $\theta = 0$. Thus, our null hypothesis of no price salience effects of automatic bill payment is $\theta = 0$.

Automatic Bill Payment Effects on Price Salience

The previous subsection suggest that consumers respond to their lagged average price instead of their current average price. The reasoning behind this is that consumers have less information or are inattentive to their level of consumption in each period. Moreover, most consumers do not know the cut-off points of the price schedule or the start or end of their billing period. Thus, consumers do not respond to their marginal price or their current average price but make behavioral rules about consumption only after receiving and observing their bill so that they respond to their one-month lagged average price. An implication of this result is that consumers who inspect their bill carefully will respond more to prices than consumers who only take a cursory look at their bill or fail to examine their bill. The electricity bill of autopay users is deducted from their bank account even before they receive their bill, so most autopay users do not bother to review the charges since they do not have to write a check. Hence, automatic bill payments increase the probability that users will forgo bill inspections, which increases inattention to the lagged average price, and make consumers respond less to prices. Utility companies further encourages autopay users to participate in online billing to complement their enrollment in autopay. Participating in both programs increases further the probability that consumers will ignore their bill and thus respond less to prices than non-autopay users.

We now investigate whether autopay users are less price elastic than non-autopay users. While (Sexton, 2015) suggests that an autopay program may reduce price sensitivity, to the best of our knowledge our paper is the first to estimate the impact of enrolling in automatic bill payments on price elasticity. Using the demand Equation (3–3) we estimate the elasticity of demand for electricity consumers. We allowed the price elasticity of demand to be different for the group with autopay and the group without autopay. We added a dummy variable autopay defined as:

$$\text{autopay}_{it} = \begin{cases} = 1, & \text{if household } i \text{ is enrolled in autopay in time period } t \\ = 0, & \text{otherwise} \end{cases} \tag{3–8}$$

We modify Equation (3–3) to obtain the equation,

$$\log q_{it} = \beta_0 + \alpha \log AP_{it-1} + \theta \text{autopay}_{it} * \log AP_{it-1} + \beta_2 w_t + \beta_3 X_i + u_{it} \tag{3–9}$$

The results of the estimation using Equation (3–9) is presented in Table 3-5. In all columns of the table, I used the lagged average price as the price consumers use. The coefficient of interest is the coefficient on $\log \text{AP}_{-1} \times$ autopay. The coefficient is positive and statistically significant across all the columns. In Columns I and II, only the price in assumed to be endogenous. Autopay assignment is assumed to be random. Column I further assumes that after controlling for the effects of autopay on price, the autopay assignment does not affect electricity consumption. That is, autopay only affects electricity consumption through it's effects on the price elasticity so that after controlling for the effects of autopay on price elasticity, the autopay assignment itself does not affect electricity consumption. Equation 3–9, therefore, does not explicitly include autopay as an independent variable except the interaction term between autopay and the price. This assumption is however relaxed in Column II. We allowed autopay to have a direct effect on electricity consumption even after controlling for its effects on the price elasticity. We added autopay as an independent variable in Equation 3–9 to obtain Equation 3–10:

$$\log q_{it} = \beta_0 + \alpha \log AP_{it-1} + \gamma \text{autopay}_{it} + \theta \text{autopay}_{it} * \log AP_{it-1} + \beta_2 w_t + \beta_3 X_i + u_{it} \quad (3\text{–}10)$$

Column I, thus, shows the results of the regression form Equation 3–9 while Column II shows the regression from Equation 3–10.

The results from Column I shows that while the price elasticity on non-autopay users is about -0.58, the price elasticity of demand for the autopay users is -0.53. That is, the price elasticity of demand for the autopay users is about 10% lower than that of the non-autopay users. Column II shows a more pronounced difference in price elasticities between autopay and non-autopay users. While the price elasticity of non-autopay users is -0.65, autopay users have a price elasticity of -0.13[12] . That is, the price elasticity of the autopay users is about 78% lower (in absolute terms) than that of the non-autopay users. The coefficient on autopay in Column II, however, shows that an autopay user consumes about 88% more electricity than a comparable non-autopay user. This result is likely to be over estimated since the autopay assignment is not random. High income earners, for example, who have higher electricity consumption than low income earners, are more likely to participate in an autopay program than low income earners. One drawback to automatic bill payment enrollment is that it requires consumers to have some minimum amount of money in their bank account

[12] The price elasticity of autopay users is the sum of the coefficients on $\log\text{AP}_{-1}$ and $\log\text{AP}_{-1} \times$ autopay

every month. While automatic bill payment saves customers from late payment fees, overdraft fees from banks, when customers have insufficient funds can be more costly than the savings on late fees. This is particularly true for poor customers who are more likely to occasionally have insufficient funds to cover their bills. The fear of overdraft fees means low income people (who are usually low electricity usage), are less likely to use autopay than high income earners. Autopay is, therefore, likely to be endogenous since the missing variable in the regression, income, is correlated with autopay.

In Boampong (2014), I mapped each household to the census tract to which they belonged and used the average income of the census tract as an imputed income for each household. This approach, however, did not give a consistent estimate of the coefficient of the income variable because the census tracts were large and did not allow enough variation in the income variable. The subdivision/neighborhood variable in Equations 3–9 and 3–10 while controlling for the differences in energy consumption as a result of the slight differences in weather across neighborhoods, also serve as a proxy variable for income. The neighborhood variable used in Equations 3–9 and 3–10 is the refined definition of neighborhoods/subdivisions used by the Alachua County property Appraiser. According to the Alachua county property Appraiser website, subdivisions are the most common way of describing a property location and contains household based on proximity. The subdivisions are usually not different from the area designation also used by the Alachua County Property Appraiser (ACPA). The ACPA defines area as a group of parcels having similarly characteristics concerning assessment, one of which may not be the physical location or subdivision. However, in most cases the area and the subdivision are almost the same or that houses in the same subdivisions are normally in the same area. These houses not only have similar characteristics concerning assessment, but also are inhabited by people of similar incomes. Thus controlling for subdivisions effectively controls for income levels.

Also, different households usually have different billing periods based on when their electricity meter is read. When a household's billing meter is read, their billing period closes and a new billing period starts. Since the billing meter is read on different days for different households, the "monthly" electricity consumption of households have different dates of consumption. In the dataset, households in the same subdivision had the same billing period. Adding a subdivisions dummy further controls for cohorts effects on electricity consumption.

In Column (III) of the Table 3-5, I combined the analysis in Columns I with a Coarsened Exact Matching Approach in order to solve any possible endogeneity resulting from autopay participation even after controlling for subdivisions. [13] . The purpose of the matching is to pair autopay households with non-autopay households based on characteristics that affect autopay adoption. First, I grouped households into participants and non-participants. All households that participated in the autopay program at least once in the period were considered as autopay participants and those that never participated in the autopay program were considered as non participants. I then perform a coarsened exact matching based on the participants/non-participants assignment. The idea of the Coarsened Exact Matching is to temporarily group each variable into meaningful strata and pair program participants to non-participants who belong to the same strata on all coarsened variables.[14] The original(uncoarsened) variables are however retained for analysis.

I choose characteristics that are more likely to affect a household's participation in automatic bill payment. Thus we performed the exact matching on subdivisions (controls for income and neighborhood effects), number of bedrooms (controls for the size of the size), and the age group of the house.[15]

[13] See Boampong (2014) or Iacus et al. (2008) for a description of Coarsened Exact Matching

[14] Not all variables need to be coarsened, some variables can be restricted from coarsening.

[15] We divided all houses in the data based on whether they were build before 2002 or after 2002. This is because Florida increased the stringency of its building codes in 2002 which have been shown to reduce energy consumption by 4% (Jacobsen and Kotchen, 2013).

Households in the same group (both participants and non-participants) have similar characteristics on the factors that affect autopay participation. The effects of the autopay program is then estimated using only the matched sample from the CEM methodology. Such an estimation approach is "arguably more appropriate compared to a simple instrumental variable approach (for dealing with the selection bias [16]) as no strong exclusion restrictions are needed"(Girma and Görg, 2007). The results in Column (III) includes autopay as an independent variable, but it is statistically insignificant. This is expected as the matching pairs participants and non-participants with similar characteristics so that any imbalance between the two groups in the same matched cell is small or negligible. The results from Column (III) shows that while the price elasticity of demand is -0.5 for non-autopay households, the price elasticity of demand for the autopay household is -0.07. That is, the price elasticity of the autopay households is about 86% lower (in absolute terms) than that of the non-autopay households.

Does Enrolling in Automatic Bill Payment Make Consumers Less Price Sensitive?

The previous subsection reveals that autopay users are less price elastic than non-autopay users. In this subsection, we further investigate whether enrolling in automatic bill payments makes consumers less price sensitive by comparing the price elasticity of autopay users before and after enrolling in automatic bill payments. The difference in the pre-enrollment elasticity of demand and the post-enrollment elasticity of the autopay users is compared to that of a control group in a difference-in-difference estimation. Treatment in this case is enrolling in an automatic bill payment. Households in the data enrolled in the autopay program at different times from 2007 to 2014. To use the difference-in-difference methodology we defined new time variables $\tilde{t}_i$ and $\tilde{\tau}_i$. Let $\bar{t}_i$ be the time that household i enrolled in the autopay program then, $\tilde{t}_i$ is the number of billing periods or months elapsed since household i enrolled in the autopay program, defined as $\tilde{t}_i = t - \bar{t}_i$. $\tilde{\tau}_i$ is a dummy variable equal to one for the first twelve months

[16] Selection bias occurs when participation is a program is not random and depends on some observable or unobservable characteristics that are correlated with the outcome of interest.

Table 3-5. Automatic Bill Payment Effects on Price Elasticity

log(daily usage)	I	II	III
$\log AP_{-1}$	-0.5787***	-0.6441***	-0.5047***
	(-6.66)	(-7.28)	(-5.06)
$\log AP_{-1}$ ×	0.0563***	0.5073*	0.4297*
	(17.97)	(2.45)	(1.96)
Autopay		0.8760*	0.7296
		(2.17)	(1.71)
CDD	1370.6753***	1375.9023***	1398.8295***
	(48.02)	(48.00)	(46.54)
HDD	108.8295*	111.8534*	40.3222
	(2.35)	(2.41)	(0.81)
Heated Area	0.2444***	0.2447***	0.2426***
	(25.58)	(25.68)	(27.17)
Stories	0.0144	0.0140	0.0202**
	(1.81)	(1.77)	(2.62)
Bedrooms	0.0299***	0.0300***	0.0254***
	(4.47)	(4.48)	(3.38)
Bathrooms	0.0423***	0.0424***	0.0426***
	(5.11)	(5.11)	(5.01)
Age	-0.0010	-0.0010	-0.0000
	(-1.83)	(-1.83)	(-0.03)
Pool	0.2906***	0.2899***	0.3020***
	(28.03)	(28.03)	(31.42)
cons	1.1774***	1.0491***	1.2949***
	(6.28)	(5.52)	(6.11)
N	1812922	1812922	1653691
R^2	0.3160	0.3161	0.3153

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.
The coefficients on the subdivision dummies, the year effects, and the interaction term between CDD, HDD, and the household characteristics are left out from the table.

after household i enrolled in autopay and equal to zero for the 12 months before household i enrolled in autopay. That is

$$\tilde{\tau}_i = \begin{cases} = 1, & \text{if } 0 \leq \tilde{t}_i < 12 \\ = 0, & \text{if } -12 \leq \tilde{t}_i < 0 \end{cases} \tag{3–11}$$

Thus for each autopay user, we used the 12 months before they enrolled in autopay as the pre-treatment years and the 12 months after enrollment in the program as the post-treatment years. For autopay users who were in the program for less than 12 months, we choose the pre-treatment periods to correspond to the same months as the treatment periods but in a the previous year. Next we assigned the billing periods of the control group (households who never enrolled in autopay programs during the period 2008 - 2013) to pre-treatment and post-treatment times. We used the median date of enrollment in the program for the treated group to divide the billing periods of the control group. Thus for each non-treated household, all billing periods before the median enrollment date was assigned to pre-treatment while all billing periods after the median enrollment date was assigned to post-treatment.

We modify Equation (3–9) to obtain the difference-in-difference estimation Equation (3–12).

$$
\begin{aligned}
\log q_{it} = {} & \beta_0 + \alpha_0 \log p_{it} + \alpha_1 \text{autopay}_{it} * \log(p_{it}) + \alpha_2 \tilde{\tau}_i * \log(p_{it}) + \alpha_3 \tilde{\tau}_i * \text{autopay}_{it} * \log(p_{it}) + \\
& \beta_2 w_{it} + \beta_3 X_i + \beta_4 X_i \cdot w_{it} + \tau_t + \gamma_i + u_{it}
\end{aligned}
\tag{3–12}
$$

The coefficient on $\log p_{it}$, α_0 measures the pre-treatment price elasticity of demand for the non-autopay while the coefficient on $\text{autopay}_{it} * \log(p_{it})$, α_1, measures the difference in price elasticity between non-autopay users and the autopay users before treatment. Thus, the price elasticity of the autopay users before they enrolled in the autopay program is $\alpha_0 + \alpha_1$. The coefficient on $\tilde{\tau}_i * \log(p_{it})$, α_2, measures the change in price elasticity between the pre- and post-treatment years that is common to both the treated group and the control group. Our coefficient of interest is α_3, the coefficient on $\tilde{\tau}_i * \text{autopay}_{it} * \log(p_{it})$, which is the difference-in-difference estimate. It measures the additional change in elasticity for the autopay users after enrolling in the autopay program.

Table 3-6. Summary of Difference-in-Difference Estimates

Price Elasticities	Before	After	After-Before
Control (Non-autopay users)	α_0	$\alpha_0 + \alpha_2$	α_2
Treated(Autopay users)	$\alpha_0 + \alpha_1$	$\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$	$\alpha_2 + \alpha_3$
Treated-Control	α_1	$\alpha_1 + \alpha_3$	α_3

Table 3-7 gives the results of the difference-in-difference estimation. The table shows only the difference-in-difference estimates presented in Table 3-6. The results using the one-month lagged average price (Column I) and the current average price (Column II) are very similar. Column I of the table shows that before treatment, the price elasticity of demand for the non-autopay users was about -0.96 while the price elasticity of demand for the treatment group was -0.92. After treatment, the price elasticity of the control group increased by 0.084 points to -1.04, while that of the treated group increased by 0.034 points to -0.96. The counterfactual price elasticity for the treatment group is in the absence of treatment is -0.96-0.0834+0.049=**-1.01**. Enrolling in automatic payment, therefore, reduced price elasticity by approximately 5%.

Table 3-7. Effects of Enrolling in Automatic Bill Payment on Price Elasticity

log(daily usage)	I	II
$\log AP_{-1}$	-0.9636***	
	(-13.31)	
$\log AP_{-1} \times \tilde{\tau}$	-0.0837***	
	(-7.49)	
$\log AP_{-1} \times$ autopaygroup	0.0350***	
	(4.55)	
$\log AP_{-1} \times \tilde{\tau} \times$ autopaygroup	0.0491***	
	(4.85)	
logAP		-0.9439***
		(-14.11)
$\log AP \times \tilde{\tau}$		-0.0815***
		(-7.21)
$\log AP \times$ autopaygroup		0.0366***
		(4.73)
$\log AP \times \tilde{\tau} \times$ autopaygroup		0.0502***
		(4.90)
N	311463	312576
R^2	0.3110	0.3665

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

3.6 Conclusion

In this paper, we analyzed whether consumer respond to the current price or the one-month lagged average price when they face an increasing-block price schedule used by many utility companies. Using the encompassing test, we found support for the idea that consumers respond to the one-month lagged average price instead of the current average price. This has policy implications for utility rate design as the empirical price elasticity plays a role in utility's rate design and the choice of price and non-price demand strategies. It also helps to inform price specification debate as to which price of the nonlinear pricing schedule consumers respond.

Current empirical research shows that consumers respond to the average prices of the increasing block pricing schedule, rather than to the marginal price as theory predicts. The main reasons usually cited for why consumers respond to the marginal prices are that marginal prices are not worth the trouble to learn the rate schedule and track consumption levels. However, responding to the current average prices also require great deal of effort from consumers: it still requires consumers to know the price schedule or at the least know exactly when their bill period starts and ends. Again since average prices is calculated from the total bill, it requires consumers to know their total consumption at the end of the billing period, or that consumers be able to anticipate all demand shocks within the billing period.

We proposed a conceptual model in which consumers makes behavioral rules about consumption only after observing their previous month's bill. The first empirical analysis shows that consumers respond to their one-month lagged prices instead of the current average price. This is because the lagged average price requires the least calculation and effort from consumers. Thus in the absence of technological developments to provide information to consumers about their true marginal price, energy policy on price elasticity should be based on the assumption of consumers responding to the lagged average price.

Consumers responding to lagged average prices also suggest that automatic bill payments which increase the likelihood that a consumer will forgo inspection decreases price salience and hence price responsiveness. The analysis shows that automatic payment users are 10% less elastic than non-automatic payment users and that enrolling in autopay makes consumers 5% less price sensitive. These results imply that automatic bill payments may act against the utility's conservation effort of using price signals to steer energy conservation. Thus, the paper suggests that while automatic bill payment is a convenient method of payment for both consumers and the utility, there is the need for more information provision to help consumers respond to prices. Advances in technology that helps consumers perceive their actual marginal cost should be a complement to automatic bill payment methods. For example, Wolak (2011) shows that smart metering with dynamic pricing provides a stable and sizable demand reductions in response to critical peak pricing (CPP) and hourly pricing (HP) warnings.

APPENDIX A

APPENDIX TO ACCOMPANY EVALUATING THE ENERGY SAVINGS EFFECTS OF A UTILITY DEMAND-SIDE MANAGEMENT PROGRAM USING A DIFFERENCE -IN-DIFFERENCE COARSENED EXACT MATCHING APPROACH

Table A-1. DID CEM Estimate of The Effects of The 2009 High Efficiency AC Program

Δlog(Energy Usage)	I	II	III
Treat	-0.0858***	-0.1382**	-0.1048
	(-5.15)	(-2.83)	(-1.59)
Treat*Heated Area(1000 square feet)		0.0262	0.0240
		(1.32)	(1.22)
Treat*Age			-0.0012
			(-0.63)
Bedrooms	0.0100	0.0100	0.0100
	(0.69)	(0.69)	(0.69)
Stories	-0.0007	-0.0007	-0.0007
	(-0.04)	(-0.04)	(-0.04)
Heated Area (1000 square feet)	-0.0049	-0.0056	-0.0055
	(-0.32)	(-0.37)	(-0.36)
Age	0.0003	0.0003	0.0003
	(0.35)	(0.35)	(0.38)
Pool	-0.0279	-0.0278	-0.0278
	(-1.83)	(-1.83)	(-1.83)
Electric and Gas	0.0991***	0.0991***	0.0990***
	(7.80)	(7.81)	(7.80)
Mean Income ($1000)	-0.0006*	-0.0006*	-0.0006*
	(-2.36)	(-2.35)	(-2.36)
Mean Household Size	0.0276	0.0275	0.0275
	(0.92)	(0.92)	(0.92)
Hot Tub	0.0327	0.0331	0.0331
	(0.83)	(0.84)	(0.84)
cons	0.0311	0.0325	0.0318
	(0.38)	(0.39)	(0.38)
N	7843	7843	7843

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-2. Annual Energy Savings Effect Of The 2010 High Efficiency AC Rebate Program

Δlog(Energy Usage)	CEM DID (Census Tract)			Regular DID		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treat	-0.0817***	-0.1463*	-0.2742**	-0.0981***	-0.1463**	-0.2860***
	(-4.00)	(-2.12)	(-3.19)	(-6.91)	(-3.19)	(-4.75)
Treat*Heated Area		0.0350	0.0578		0.0231	0.0366
		(1.01)	(1.74)		(1.20)	(1.87)
Treat*Age			0.0036			0.0046**
			(1.67)			(3.04)
Bedrooms	-0.0341	-0.0340	-0.0341	-0.0054	-0.0054	-0.0053
	(-1.13)	(-1.13)	(-1.13)	(-1.16)	(-1.15)	(-1.14)
Stories	0.0382	0.0383	0.0386	0.0038	0.0037	0.0036
	(0.64)	(0.64)	(0.65)	(0.73)	(0.73)	(0.71)
Heated Area	0.0157	0.0129	0.0117	-0.0061	-0.0065	-0.0067
(1000 square feet)	(0.55)	(0.44)	(0.39)	(-1.27)	(-1.34)	(-1.38)
Age	-0.0002	-0.0002	-0.0005	-0.0015***	-0.0015***	-0.0015***
	(-0.18)	(-0.17)	(-0.36)	(-6.50)	(-6.51)	(-6.63)
Pool	-0.0218	-0.0217	-0.0220	-0.0139*	-0.0139*	-0.0139*
	(-0.67)	(-0.67)	(-0.68)	(-2.34)	(-2.34)	(-2.34)
Electric and Gas	0.0209	0.0212	0.0211	-0.0084	-0.0084	-0.0084
	(0.67)	(0.67)	(0.67)	(-1.68)	(-1.68)	(-1.66)
Mean Income ($1000)	0.0006	0.0006	0.0006	0.0001	0.0001	0.0001
	(1.42)	(1.43)	(1.43)	(1.72)	(1.74)	(1.76)
Mean Household Size	-0.1557	-0.1558	-0.1557	-0.0210*	-0.0211*	-0.0209*
	(-1.57)	(-1.57)	(-1.57)	(-2.01)	(-2.02)	(-2.00)
Hot Tub	0.0168	0.0177	0.0173	-0.0086	-0.0088	-0.0086
	(0.37)	(0.39)	(0.38)	(-0.96)	(-1.00)	(-0.97)
cons	0.2784	0.2826	0.2911	0.0538	0.0544	0.0550
	(1.00)	(1.01)	(1.04)	(1.81)	(1.83)	(1.85)
N	2504	2504	2504	24057	24057	24057

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-3. CEM DID Estimate of The Effects of The 2010 High Efficiency AC Program

Δlog(Energy Usage)	I	II	III
Treat	-0.0890***	-0.1681**	-0.2846***
	(-5.68)	(-2.92)	(-4.20)
Treat*Heated Area(1000 square feet)		0.0401	0.0553*
		(1.54)	(2.23)
Treat*Age			0.0036*
			(2.11)
cons	0.1103	0.1115	0.1136
Bedrooms	-0.0236	-0.0237	-0.0237
	(-1.91)	(-1.92)	(-1.92)
Stories	-0.0075	-0.0074	-0.0074
	(-0.33)	(-0.33)	(-0.33)
Heated Area (1000 square feet)	0.0013	0.0005	0.0002
	(0.09)	(0.03)	(0.01)
Age	-0.0003	-0.0003	-0.0004
	(-0.58)	(-0.57)	(-0.71)
Pool	0.0036	0.0036	0.0034
	(0.22)	(0.22)	(0.21)
Electric and Gas	-0.0210	-0.0209	-0.0210
	(-1.66)	(-1.65)	(-1.65)
Mean Income ($1000)	0.0000	0.0000	0.0000
	(0.04)	(0.05)	(0.05)
Mean Household Size	-0.0305	-0.0303	-0.0300
	(-1.13)	(-1.12)	(-1.11)
Hot Tub	0.0362	0.0363	0.0362
	(1.43)	(1.43)	(1.43)
	(1.26)	(1.27)	(1.30)
N	9616	9616	9616

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-4. Non-Peak Months Effects Of The 2009 AC Rebate Program using CEM DID with Zip Codes as Neighborhoods

Δlog(Energy Usage)	I	II	III
Treat	-0.0461**	-0.0964*	-0.0948
	(-2.69)	(-2.03)	(-1.31)
Treat*Heated Area		0.0252	0.0251
		(1.31)	(1.31)
Treat*Age			-0.0001
			(-0.03)
Bedrooms	0.0211	0.0211	0.0211
	(1.41)	(1.41)	(1.41)
Stories	0.0134	0.0135	0.0135
	(0.86)	(0.87)	(0.87)
Heated Area	-0.0251	-0.0258	-0.0258
(1000 square feet)	(-1.71)	(-1.73)	(-1.73)
Age	-0.0006	-0.0006	-0.0006
	(-0.73)	(-0.73)	(-0.71)
Pool	-0.0153	-0.0152	-0.0152
	(-0.91)	(-0.90)	(-0.90)
Electric and Gas	0.0572***	0.0572***	0.0572***
	(4.11)	(4.11)	(4.11)
Mean Income ($1000)	0.0003	0.0003	0.0003
	(1.21)	(1.21)	(1.21)
Mean Household Size	0.0529	0.0528	0.0528
	(1.73)	(1.72)	(1.72)
Hot Tub	0.0131	0.0135	0.0135
	(0.43)	(0.44)	(0.44)
cons	-0.1896*	-0.1882*	-0.1882*
	(-2.19)	(-2.18)	(-2.17)
N	7843	7843	7843

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-5. DID CEM Estimate of The Effect of The High Efficiency AC Rebate on Summer Peak Energy Consumption

Δlog(Energy Usage)	I	II	III
Treat	-0.1710***	-0.2754***	-0.2447***
	(-8.09)	(-4.38)	(-3.83)
Bedrooms	0.0245	0.0245	-0.0017
	(1.25)	(1.25)	(-0.31)
Stories	0.0252	0.0253	0.0004
	(1.22)	(1.22)	(0.06)
Heated Area	-0.0380	-0.0394	0.0012
(1000 square feet)	(-1.87)	(-1.92)	(0.21)
Age	-0.0002	-0.0002	-0.0000
	(-0.20)	(-0.20)	(-0.01)
Pool	0.0168	0.0169	-0.0269***
	(0.93)	(0.94)	(-3.76)
Electric and Gas	0.0199	0.0199	0.0197**
	(1.26)	(1.26)	(3.16)
Mean Income	-0.0009**	-0.0009**	-0.0003**
($1000)	(-2.68)	(-2.67)	(-2.62)
Mean Household Size	0.0495	0.0492	0.0004
	(1.18)	(1.17)	(0.03)
Hot Tub	0.0320	0.0327	-0.0142
	(0.58)	(0.60)	(-1.32)
Treat*Heated Area		0.0524	0.0315*
		(1.85)	(2.05)
treatage			0.0003
			(0.16)
cons	-0.0435	-0.0406	0.0669
	(-0.41)	(-0.38)	(1.91)
N	7843	7843	24008

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-6. DID CEM Estimate of The Effect of The High Efficiency AC Rebate on Winter Peak Energy Consumption

Δlog(Energy Usage)	I	II	III
Treat	-0.0432*	-0.0756	-0.0096
	(-2.14)	(-1.32)	(-0.13)
Bedrooms	0.0054	0.0054	0.0053
	(0.37)	(0.37)	(0.37)
Stories	-0.0198	-0.0198	-0.0198
	(-0.87)	(-0.87)	(-0.87)
Heated Area	0.0098	0.0094	0.0095
(1000 square feet)	(0.61)	(0.58)	(0.59)
Age	0.0007	0.0007	0.0008
	(0.88)	(0.88)	(0.93)
Pool	-0.0589**	-0.0588**	-0.0587**
	(-2.97)	(-2.97)	(-2.97)
Electric and Gas	0.1590***	0.1590***	0.1589***
	(10.72)	(10.72)	(10.71)
Mean Income	-0.0009***	-0.0009***	-0.0009***
($1000)	(-3.81)	(-3.80)	(-3.81)
Mean Household Size	-0.0273	-0.0274	-0.0273
	(-0.83)	(-0.83)	(-0.83)
Hot Tub	-0.0085	-0.0083	-0.0082
	(-0.23)	(-0.23)	(-0.22)
Treat*Heated Area		0.0162	0.0119
(1000 square feet)		(0.66)	(0.49)
treatage			-0.0024
			(-1.16)
cons	0.3675***	0.3684***	0.3671***
	(3.64)	(3.64)	(3.62)
N	7843	7843	7843

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-7. Summer, Winter, and Non-Peak Months Effects of the High Efficiency AC program for Households with Electricity but No Natural Gas Using The DID CEM with Zip Codes as Neighborhoods

Δlog(Energy Usage)	Summer	Winter	Non-Peak Months
Treat	-0.1307***	-0.0753**	-0.0524*
	(-3.72)	(-2.85)	(-2.23)
Bedrooms	-0.0003	0.0188	0.0154
	(-0.02)	(1.05)	(1.03)
Stories	0.0032	-0.0220	-0.0057
	(0.19)	(-1.06)	(-0.36)
Heated Area (1000 square feet)	0.0283	0.0005	0.0106
	(0.91)	(0.03)	(0.78)
Age	0.0011	0.0018*	0.0003
	(0.90)	(1.96)	(0.39)
Pool	-0.0466	-0.0613**	-0.0493*
	(-1.45)	(-2.68)	(-2.33)
Mean Income $1000)	-0.0002	-0.0009***	0.0002
	(-0.63)	(-3.43)	(0.81)
Mean Household Size	0.0150	0.0366	0.0127
	(0.38)	(1.16)	(0.45)
Hot Tub	-0.0282	0.0201	-0.0127
	(-0.68)	(0.46)	(-0.30)
cons	-0.0454	0.1639	-0.1280
	(-0.37)	(1.69)	(-1.48)
N	3407	3407	3407

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table A-8. Summer, Winter, and Non-Peak Months Effects of the High Efficiency AC program for Households with Electricity and Natural Gas Using The DID CEM with Zip Codes as Neighborhoods

Δlog(Energy Usage)	Summer	Winter	Non-Peak Months
Treat	-0.2015***	0.0596	-0.0689**
	(-6.11)	(1.81)	(-3.03)
Bedrooms	0.0537	-0.0492	-0.0127
	(1.45)	(-1.47)	(-0.50)
Stories	-0.0477	0.1007	0.0214
	(-0.64)	(1.91)	(0.66)
Heated Area	-0.0630*	0.0375	0.0203
(1000 square feet)	(-2.35)	(1.55)	(0.86)
Age	0.0001	0.0030*	-0.0004
	(0.04)	(2.16)	(-0.37)
Pool	-0.0032	-0.0960**	-0.0687**
	(-0.10)	(-2.98)	(-2.65)
Mean Income ($1000)	-0.0000	-0.0007	-0.0003
	(-0.05)	(-1.28)	(-0.84)
Mean Household Size	0.0981	0.0028	-0.0346
	(1.08)	(0.04)	(-0.65)
Hot Tub	-0.0086	0.0182	-0.0026
	(-0.24)	(0.42)	(-0.09)
cons	-0.1708	0.0088	0.0913
	(-0.76)	(0.05)	(0.69)
N	3477	3479	3479

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

APPENDIX B
APPENDIX TO ACCOMPANY THE "REBOUND" EFFECT

Figure B-1. Average Energy Consumption by Participants and Non-Participants

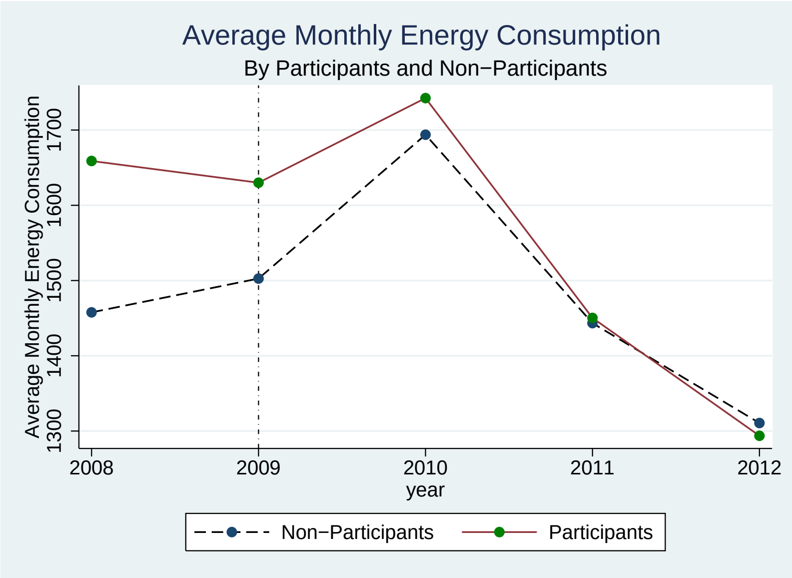


Figure B-2. Average Energy Consumption by Participants and Non-Participants

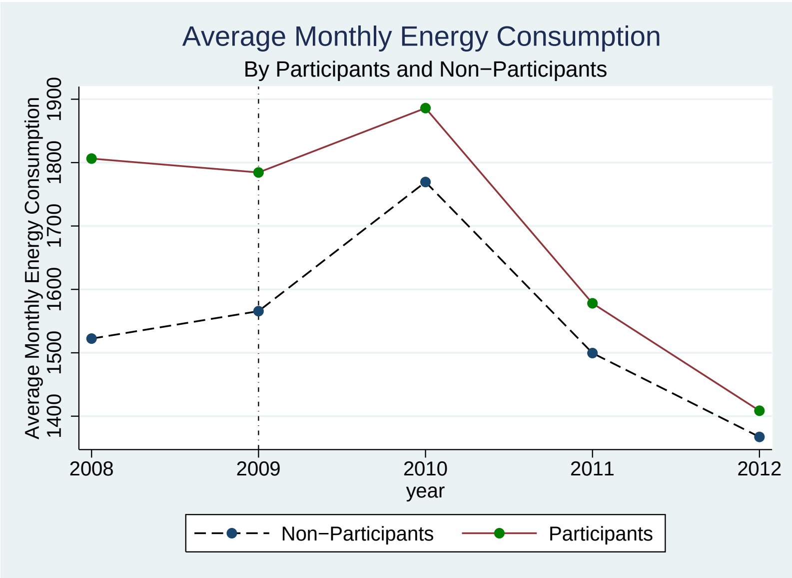


Table B-1. Summer Peak Rebound Effects by Fuel Mix Using CEM DD with Zip Codes as Neighborhoods

ΔΔlog(Energy Usage)	Electricity-only Households	Electric and Gas Households
Treat	0.0251	0.0735*
	(0.57)	(2.38)
Bedrooms	-0.0168	-0.0412
	(-0.47)	(-1.23)
Stories	-0.0351	-0.0961
	(-1.08)	(-1.66)
Heated Area (1000 square feet)	0.0158	0.0193
	(0.57)	(0.53)
Age	0.0004	0.0001
	(0.14)	(0.05)
Pool	-0.0833*	-0.0204
	(-1.96)	(-0.66)
Mean Income ($1000)	0.0009	0.0014*
	(1.67)	(2.37)
Mean Household Size	-0.0706	-0.1328
	(-0.88)	(-1.72)
Hot Tub	-0.0554	-0.1002
	(-1.25)	(-1.33)
cons	0.1157	0.3650
	(0.55)	(1.75)
N	2231.0000	5611.0000

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table B-2. Winter Peak Rebound Effects by Fuel Mix

ΔΔlog(Energy Usage)	Electricity-only Households			Electric and Gas Households		
	CEM DDD (census tracks)	CEM DDD zip codes	regular DDD (with CEM)	CEM DDD (census tracks)	CEM DDD zip codes	regular DDD (with CEM)
Treat	-0.000	0.020	0.028	0.026	0.011	0.016
	(-0.00)	(0.56)	(0.71)	(0.74)	(0.39)	(0.50)
Bedrooms	-0.171	-0.020	-0.065	-0.021	-0.006	-0.058*
	(-1.45)	(-0.50)	(-0.96)	(-0.56)	(-0.26)	(-2.19)
Stories	-0.063	0.046	-0.013	0.032	-0.016	0.036
	(-0.85)	(0.87)	(-0.29)	(0.60)	(-0.34)	(0.81)
Heated Area (1000 square feet)	0.138	0.073	-0.035	-0.003	-0.026	0.003
	(1.18)	(1.30)	(-0.52)	(-0.08)	(-1.40)	(0.09)
Age	-0.009**	-0.000	-0.003	-0.003	-0.004**	-0.004*
	(-2.81)	(-0.24)	(-1.41)	(-1.44)	(-2.81)	(-2.44)
Pool	-0.024	0.005	-0.019	0.081*	0.064**	0.057
	(-0.36)	(0.09)	(-0.43)	(2.36)	(2.66)	(1.88)
Mean Income ($1000)	-0.000	0.001	0.001	0.003***	0.002***	0.002***
	(-0.26)	(1.01)	(1.30)	(3.58)	(4.55)	(4.09)
Mean Household Size	-0.124	0.125	-0.025	-0.381*	-0.055	-0.123
	(-0.69)	(1.62)	(-0.27)	(-2.37)	(-0.99)	(-1.50)
Hot Tub	0.579***	0.008	0.268	-0.050	0.031	-0.039
	(3.98)	(0.11)	(1.53)	(-1.13)	(0.76)	(-0.94)
cons	0.563	-0.820**	-0.067	0.235	-0.382*	-0.175
	(1.11)	(-3.21)	(-0.23)	(0.68)	(-2.53)	(-0.79)
N	296.000	2232.000	296.000	1256.000	5611.000	1256.000

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table B-3. Non-Peak Rebound Effects by Fuel Mix

ΔΔlog(Energy Usage)	Electricity-only Households			Electric and Gas Households		
	CEM DDD (census tracks)	CEM DDD zip codes	regular DDD (with CEM)	CEM DDD (census tracks)	CEM DDD zip codes	regular DDD (with CEM)
Treat	-0.004	-0.008	-0.008	-0.029	-0.012	-0.035
	(-0.11)	(-0.21)	(-0.22)	(-0.91)	(-0.45)	(-1.24)
Bedrooms	-0.013	0.020	0.029	-0.028	-0.050	0.012
	(-0.18)	(0.39)	(0.43)	(-0.63)	(-1.87)	(0.37)
Stories	-0.071	-0.062	-0.032	-0.033	-0.083*	0.014
	(-1.85)	(-1.35)	(-0.92)	(-0.57)	(-1.99)	(0.32)
Heated Area (1000 square feet)	-0.080	0.002	-0.091	0.007	0.003	-0.006
	(-1.14)	(0.05)	(-1.37)	(0.16)	(0.12)	(-0.18)
Age	-0.004	0.001	-0.002	-0.003	-0.000	-0.001
	(-1.17)	(0.40)	(-0.59)	(-1.56)	(-0.18)	(-0.31)
Pool	0.017	-0.022	0.039	0.064	0.028	0.014
	(0.31)	(-0.46)	(0.66)	(1.45)	(1.16)	(0.48)
Mean Income ($1000)	-0.000	0.000	0.000	-0.003**	-0.000	-0.003***
	(-0.15)	(0.18)	(0.26)	(-2.78)	(-0.99)	(-4.82)
Mean Household Size	-0.255*	-0.085	-0.127	0.005	-0.173*	0.044
	(-2.14)	(-1.25)	(-1.22)	(0.06)	(-2.40)	(0.57)
Hot Tub	0.089	0.002	0.016	-0.096	-0.046	-0.066
	(1.36)	(0.05)	(0.21)	(-1.48)	(-1.05)	(-1.32)
cons	0.915*	0.123	0.397	0.299	0.604**	0.034
	(2.55)	(0.51)	(1.26)	(1.24)	(3.09)	(0.17)
N	296.000	2232.000	296.000	1256.000	5611.000	1256.000

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. t-statistics are in parenthesis.

Table B-4. Summer Peak, Winter Peak, and Non-peak Rebound Effects of The AC Rebate Program Using DD CEM with Zip Codes as Neighborhoods

ΔΔlog(Energy Usage)	SUMMER	WINTER	NON-PEAK
Treat	-0.0390*	-0.0026	-0.0319*
	(-2.41)	(-0.17)	(-2.12)
Bedrooms	-0.0079	0.0080	-0.0074
	(-0.38)	(0.61)	(-0.39)
Stories	-0.0450	0.0081	-0.0300
	(-1.85)	(0.25)	(-1.13)
Heated Area (1000 square feet)	0.0006	0.0161	-0.0071
	(0.03)	(0.74)	(-0.42)
Age	-0.0000	-0.0020**	-0.0013
	(-0.04)	(-2.68)	(-1.84)
Pool	-0.0295	0.0016	0.0108
	(-1.41)	(0.07)	(0.56)
Electric and Gas	0.0164	-0.0844***	-0.0904***
	(1.14)	(-6.63)	(-7.35)
Mean Income ($1000)	0.0006	0.0013***	-0.0007**
	(1.76)	(5.49)	(-2.59)
Mean Household Size	-0.0218	-0.0862*	-0.0511
	(-0.68)	(-2.24)	(-1.25)
Hot Tub	-0.0865	-0.0074	-0.0421
	(-1.62)	(-0.31)	(-1.84)
cons	0.0453	-0.1322	0.1782
	(0.54)	(-0.96)	(1.53)
N	7843	7843	7843

* $p<0.05$, ** $p< 0.01$, *** $p<0.001$. t-statistics are in parenthesis.

REFERENCES

Acton, Jan, Mitchell, Bridger, and Mowill, Ragnhild. "Residential Demand For Electricity in Los Angeles: An Econometric Study of Disaggregated Data." 1976.

Acton, Jan Paul, Mitchell, Bridger M, and Sohlberg, Ragnhild. "Estimating residential electricity demand under declining-block tariffs: an econometric study using micro-data." *Applied Economics* 12 (1980).2: 145–161.

Architectural Energy Corporation. "Engineering Methods for Estimating the Impacts of Demand-Side Management Programs. Volume 1: Fundamentals of Engineering Simulations for Residential and Commercial End Uses." 1992.

Blackwell, Matthew, Iacus, Stefano, and King, Gary. "cem: Coarsened Exact Matching in Stata." *The Stata Journal* 9 (2009).4: 524–546.

Boampong, Richard. "Evaluating the Energy Savings Effect of a Utility Demand-Side Management Program using a Difference-in-Difference Coarsened Exact Matching Approach. PURC Working Paper, 2014." Tech. rep., 2014.

Borenstein, Severin. "To what electricity price do consumers respond? Residential demand elasticity under increasing-block pricing.", 2009.

Bushnell, James, Hobbs, Benjamin F., and Wolak, Frank A. "When It Comes to Demand Response, Is FERC Its Own Worst Enemy?" *The Electricity Journal* 22 (2009): 9–18.

Chatterjee, Promothesh and Rose, Randall L. "Do payment mechanisms change the way consumers perceive products?" *Journal of Consumer Research* 38 (2012).6: 1129–1139.

Cohen, Sam, Goldman, Charles, and Harris, Jeff. "Energy Savings and Economics of Retrofitting Single-Family Buildings." *Energy and Buildings* 17 (1991): 297–311.

De Bartolome, Charles AM. "Which tax rate do people use: Average or marginal?" *Journal of public Economics* 56 (1995).1: 79–96.

Diamond, Peter A. "Optimal income taxation: an example with a U-shaped pattern of optimal marginal tax rates." *American Economic Review* (1998): 83–95.

Dubin, Jeffrey A., Miedema, Allen K., and Chandran, Ram V. "Price Effects of Energy-Efficient Technologies: A Study of Residential Demand for Heating and Cooling." *The Rand Journal of Economics* 17 (1986).3: 310–325.

Fels, Margaret F. and Keating, Kenneth M. "Measurement of Energy Savings from Demand Side Management Programs in U.S. Electric Utilities." *Annual Review of Energy and the Environment* 18 (1993): 57–88.

Fiserv. "2010 Annual Billing Household Survey." *Fiserv Research Paper* (2010).

Foster, Henry S and Beattie, Bruce R. "Urban residential demand for water in the United States." *Land Economics* (1979): 43–58.

Fowler, Meredith, Greenstone, Michael, and Wolfram, Catherine. "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program." *NBER Working Paper Series* (2015).

Gabor, Andre. "A note on block tariffs." *The Review of Economic Studies* 23 (1955).1: 32–41.

Gamtessa, Samuel and Ryan, David L. "Utilization of Residential Energy-Saving Retrofit Programs in Canada: Who, What, and Why?" 2007.

Gensemer, Bruce L, Lean, Jane A, and Neenan, William B. "Awareness of marginal income tax rates among high-income taxpayers." *National Tax Journal* (1965): 258–267.

Gillingham, Kenneth. "The Consumer Response to Gasoline Price Changes: Empirical Evidence and Policy Implications." *Stanford University Ph.D Disertation* (2011).

Girma, Sourafel and Görg, Holger. "Evaluating The Foreign ownership Wage Premium Using a Difference-in-Difference Matching Approach." *Journal of International Economics* 72 (2007): 97–112.

Godberg, Miriam L. "A Midwest Low-Income Weatherization Program Seen Through PRISM." *Energy and Buildings* 9 (1986).1-2: 37–44.

Greene, David L. "Rebound 2007: Analysis of US light-duty vehicle travel statistics." *Energy Policy* 41 (2012): 14–28.

Hausman, Jerry A. "The econometrics of nonlinear budget sets." *Econometrica* (1985): 1255–1282.

Herriges, Joseph A and King, Kathleen Kuester. "Residential demand for electricity under inverted block rates: Evidence from a controlled experiment." *Journal of Business & Economic Statistics* 12 (1994).4: 419–430.

Huang, Ching-I. "Estimating demand for cellular phone service under nonlinear pricing." *Quantitative Marketing and Economics* 6 (2008).4: 371–413.

Iacus, Stefano M., king, Gary, and Porro, Giuseppe. "Causal Inference without Balance Checking: Coarsened Exact Matching.", 2008.

URL http://gking.harvard.edu/files/gking/files/political_analysis-2011-iacus-pan_mpr013.pdf

Ito, Koichiro. "Do consumers respond to marginal or average price? Evidence from Nonlinear Electricity Pricing." *American Economic Review* (2014): 537–563.

Jacobsen, Grant D. and Kotchen, Matthew J. "Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida." *The Review of Economics and Statistics* 95 (2013): 34–49.

Jones, Pierce H., Taylor, Nicholas W., Kipp, M. Jennison, and Knowles, Harold S. "Quantifying Household Energy Performance Using Annual Community Baselines." *International Journal of Energy Systems Management* 4 (2010).4: 593–613.

Khazzoom, Daniel. "Economic Implications of Mandated Efficiency in Standards for Household Appliances." *The Energy Journal* Volume 1 (1980): 21–40.

Koichiro, Ito. "Does Conservation Targeting Work? Evidence from a Statewide Electricity Rebate Program in California. Working Paper.", 2012.

Liebman, Jeffrey B. and Zeckhauser, Richard J. "Schmeduling." (2014).

URL http://www.hks.harvard.edu/fs/rzeckhau/Schmeduling_Oct172004.pdf

Mirrlees, James A. "An exploration in the theory of optimum income taxation." *The review of economic studies* (1971): 175–208.

Mizon, Grayham E and Richard, Jean-Francois. "The encompassing principle and its application to testing non-nested hypotheses." *Econometrica* (1986): 657–678.

Parti, Michael and Parti, Cynthia. "The Total and Appliance-Specific Conditional Demand for Electricity in the Household Sector." *The Bell Journal of Economics* 11 (1980).1: 309–321.

Prelec, Drazen and Simester, Duncan. "Always leave home without it: A further investigation of the credit-card effect on willingness to pay." *Marketing letters* 12 (2001).1: 5–12.

Reiss, Peter C. and White, Matthew W. "Demand and Pricing in Electricity markets: Evidence from San Diego During California's Energy Crisis. NBER working paper 9986.", 2003.

Reiss, Peter C and White, Matthew W. "Household electricity demand, revisited." *The Review of Economic Studies* 72 (2005).3: 853–883.

Sexton, Steven. "Automatic bill payment and salience effects: Evidence from electricity consumption." *Review of Economics and Statistics* 97 (2015).2: 229–241.

Smith, Jeffrey A. and Todd, Petra E. "Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics* 125 (2005): 305–352.

Soman, Dilip. "Effects of payment mechanism on spending behavior: The role of rehearsal and immediacy of payments." *Journal of Consumer Research* 27 (2001).4: 460–474.

Violette, Daniel. "Demand Response in Organized Electric Markets." *Federal Energy Regulatory Commission (FERC) Technical Conference* (2008).

West, Jeremy, Hoeskstra, Mark, Meer, Jonathan, and Puller, Steven L. "Vehicle Miles (Not) Traveled: Why Fuel Economy Requirement Don't Increase Household Driving." *NBER Working Paper Series* (2015).

Winsberg, Morton D. and Simmons, Melani. "An Analysis of the Begining, End, Length, and Strength of Florida's Hot Season." (2009).

URL http://coaps.fsu.edu/climate_center/specials/flhotseason.shtml

Wolak, Frank A. "Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment." *The American Economic Review* (2011): 83–87.

Wooldridge, Jeffrey. *Introductory econometrics: A modern approach*. Cengage Learning, 2012.

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Richard Boampong earned his Bachelor of Arts degree in mathematics and economics from the University of Ghana in 2006. He received a Master of Arts degree in business economics from the University of South Florida in 2010. Richard started the Economics Ph.D. degree at the University of Florida in 2011 and specialized in Industrial Organization, Econometrics, and Economic Theory. While pursuing his degree, he served as an instructor of Econometrics and Environmental Economics. He was also a research assistant at the Public Utility Research Center. His research interest includes Industrial Organization, Applied Econometrics, Energy Economics, and Environmental Economics. Richard has accepted a position of post-doctoral scholar for the next academic year at Florida State University.