Evaluating the Energy-Saving Effects of a Utility Demand-Side Management Program: A Difference-in-Difference Coarsened Exact Matching Approach

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ABSTRACT

This paper seeks to estimate the energy-saving effect of a Demand-Side Management 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. We use a difference-in-difference coarsened exact matching approach to reduce the imbalance of pre-treatment characteristics between treated and control households. We find substantial annual energy savings of the high-efficiency AC program. We disaggregate the energy-saving effects into summer peak effects, winter peak effects, and non-peak effects. The results indicate that the summer peak effects are substantial and statistically significant while there are little or no statistically significant effects of the program on winter peak demand. Also, by following program participants over a three-year period, we find that there is no statistically significant rebound effect of the high-efficiency AC rebate program.

Keywords: Demand-side management, Energy savings, High-efficiency AC, Rebate, Coarsened exact matching, Treatment effects, Gainesville Regional Utility, Rebound

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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 consumers to participate in an automated demand-response programs. 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" (Ryan and

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Gamtessa, 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,[1] 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.[2]) to engineering simulation models,[3] 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 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 misrepresent 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 consumers 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 their 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 paper, we evaluate the energy-saving effects of a residential retrofitting program, GRU's high-efficiency AC rebate program. We combine a difference-in-difference (DD) methodology with a Coarsened Exact Matching (CEM) approach[4] described in Iacus et al. (2012) 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 appropriate for dealing with selection bias[5] when there are no valid instruments to allow for an instrumental variable approach. This method is also 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. 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 our

1. Loughran and Kulick (2004) estimate that between 1989 and 1999, U.S. electric utilities spent $14.7 billion on DSM programs.

2. See Ito (2012) for a background of the program.

3. See Jacobs et al. (1992) for a review of various engineering simulation programs for estimating energy savings from DSM programs.

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

5. 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.

matching methodology controls for the effects of building characteristics and materials on electricity 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-saving estimate because the treatment group does not include all sections of the population.

We use data on household electricity and natural gas consumption and retrofit program participation from Gainesville Regional Utilities from 2008 to 2012. Specifically, we evaluate the energy-saving effects of the 2009 high-efficiency AC rebate program. First, we estimate the energy-saving effect on annual energy consumption. Next, since the main aim of a DSM or energy efficiency programs is to reduce peak period consumption, we 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, particularly summer peak consumption. The results indicate that while the program led to substantial energy consumption reductions in the summer peak, winter peak reductions are small or non-existent. Also, by following the group of households that participated in the program for another year, we found no statistically significant rebound effects. This implies that the supply resources that the DSM program is designed to displace will indeed be avoided over the long run. The remainder of this chapter is as follows: Section 2 gives a brief background of GRU's rebate programs, Section 3 describes the empirical strategy, Section 4 gives a brief description of the data, and Section 5 investigates selection into treatment based on pre-treatment characteristics. Section 6 presents the results of the program on annual energy consumption and summer peak consumption while Section 7 gives an estimate of the rebound effect. Section 8 concludes.

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 paper, we evaluate the energy-saving effect of the high-efficiency central air conditioner rebate program. The high-efficiency central air conditioner program encourages homeowners to replace their 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 lists the relevant financial incentives in GRU's 2009 rebate programs.[6]

6. We provide information for the 2009 rebate program since we specifically evaluate the 2009 program.

Table 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

†One duct leak repair per HVAC system, three per location.
Source: Database of State Incentives for Renewables and Efficiency, http://www.dsireusa.org.

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 electricity consumption when there is no proxy for household-specific weather. We use a difference-in-difference (DD) strategy in combination with the Coarsened Exact Matching (CEM) methodology described in Iacus et al. (2012).

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

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

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:

$$E(y^1_{it+s} - y^0_{it+s} \mid treat_{it} = 1, X) = E(y^1_{it+s} \mid treat_{it} = 1, X) - E(y^0_{it+s} \mid treat_{it} = 1, X), \tag{2}$$

where X is a vector of control variables. Since $E(y^0_{it+s} \mid treat_{it} = 1, X)$ 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, $E(y^0_{it+s} \mid treat_{it} = 0, X)$, 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, as is the case in the high-efficiency rebate program, 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 also plagued with endogeneity.

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 electricity 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.

In this study, we employ the Coarsened Exact Matching (CEM) methodology described in Iacus et al. (2012) 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 has similar pre-treatment characteristics as the treated households with whom they are paired. We 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.[7] The original (uncoarsened) variables are however retained for analysis.

The Coarsened Exact Matching algorithm as described in Blackwell et al. (2008) is as follows:

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

We then perform exact matching on the matched strata. Let T and C be the set of treated and control units in the sample. Also denote the total number of treated and control observation as N_T and N_C respectively. Let S be a set of matched strata with coarsened exact matching methodology. For each $s \in S$, let T^s and C^s denote the treated units and the control units in stratum s respectively. Let N_T^s and N_C^s be the number of treated and control observations in stratum s. Let y_{is} be the post-treatment electricity consumption of household i in stratum s. A standard matching estimator for the Average Treatment effect on the Treated (ATT) of a DSM program is:

$$ATT = \sum_{\substack{i \in T \\ s \in S}} \left\{ y_{is} - \sum_{j \in C^s} w_s \ y_{js} \right\}, \tag{3}$$

7. Not all variables need to be coarsened, some variables can be restricted from coarsening.

where w_s is the weight that CEM assigns to each control unit in stratum s. w_s is defined as:

$$w_s = \frac{N_C}{N_T}\frac{N_T^s}{N_C^s}. \tag{4}$$

Treated households are assigned a weight of one while unmatched households are assigned a weight of zero. Equation 3 uses only the post-treatment electricity consumption to estimate the program effects. However, since we have panel data, we follow Girma and Görg (2009) and 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 time-invariant differences in electricity consumption between treated and control households that standard matching estimators fail to eliminate (Girma and Görg, 2009; Smith and Todd, 2005). Let Δy_{is} be the difference in electricity consumption between the post- and pre-treatment periods of household i in stratum s. Then the difference-in-difference coarsened exact estimator is defined as:

$$\delta = \sum_{\substack{i \in T \\ s \in S}} \left\{ \Delta y_{is} - \sum_{j \in C^S} w_s \ \Delta y_{js} \right\}. \tag{5}$$

If we had performed exact matching, then there would be no imbalance left and Equation 5 perfectly estimates the energy savings effects of the demand-side management program. However since we used coarsened variables, we used a variant of Equation 5 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. We start with an initial equation of the form:

$$logy_{it} = \beta_0 + \delta_0 . d2 + \delta_1 treat_{it} + \delta_2 treat_{it} \cdot X_i + \beta_1 X_i + \beta_2 \ d2 \cdot X_i + \gamma_i + u_{it}, \quad t = 1,2 \tag{6}$$

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 measured in kilowatt-hours (kWh) and natural gas consumption converted to equivalent kilowatt-hours (ekWh).[8] $d2$ is a dummy variable for the second period (post-treatment 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, we 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.[9] We 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.

8. Natural gas consumption is originally measured in therms. In order to combine electricity consumption with natural gas consumption, natural gas consumption was converted to equivalent kWh (ekWh) using the conversion rate 1 therm = 29.300111 ekWh.

9. The 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. However, the National Oceanic and Atmospheric Administration website collects daily maximum and minimum temperature only for one weather station. Hence the total degree days, using information from only one weather station, would be constant for all households in the dataset.

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:

$$\Delta y_i = \delta_0 + \delta_1.treat_i + \delta_2 treat_i \cdot X_i + \beta_2 X_i + \Delta u_{it} \tag{7}$$

It should, however, be noted that Equation 7 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 this equation should, therefore, be interpreted in the context of the original level equation (Equation 6).[10] 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.

4. DATA

We 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 of the University of Florida, 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. We extracted the ACPA data from the ACPA website, and it contains information on the physical characteristics and location of all buildings in Alachua County. We geocode the location address of each house using ArcGIS and map the geocoded addresses into the census tract to which they belong.[11] The census tracts and zip codes serve as neighborhoods for each property so that by matching on the census tracts or zip codes we can control for the effects of weather on energy consumption without actually having weather data.[12] Since Ryan and Gamtessa (2007) found demographic information such as income and household characteristics to play a role in the decision to undertake rebate programs, we extracted the mean income and mean household size for each census tract and imputed those values to all households in a census tract or zip code.

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. Our base dataset with the geocoded addresses contains approximately 28000 single family households. Because the

10. Thus the coefficients on the household characteristics, X_i in Equation 7 do not measure 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 6. For example, the coefficient on the number of bedrooms in Equation 7 measures differences in the effects of bedrooms on energy consumption across the two years.

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, we searched for the parcel number in Google Earth to find the address and census tract.

12. The best way of controlling for weather is to include household-specific weather information. However, since household-specific weather information is not available, an approximation to controlling for weather information is to map each house location to 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 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.

purpose of this research is to evaluate the energy-saving effect 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 that made home improvements over the period that are likely to affect their energy consumption significantly 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 in one program only 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 50% of all residential households in Gainesville according to the 2010 census). Table 2 gives a summary statistics of the data.

Table 2: 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

4.1 Billing Timing and Standardization of Monthly Energy Consumption

Different households usually have different billing periods based on when their electricity and natural gas 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 of households 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 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 energy consumption of households within the same cohort. In our data, the billing cohort that a household belongs to sometimes changes across years so that we are not able to follow the same household in a particular billing cohort for two or more years. Also, since we have only a few program participants, comparing across billing cohorts will lead to more strata with only treated or non-treated observations. We might lose a significant percentage of our already limited treated group. The approach we took in this paper is to standardize electricity and natural gas consumption by calculating the average consumption for each calendar month. We achieve this by dividing each household's billing period's consumption by the total number of days of consumption to find a daily average electricity and natural gas consumption. If consumption in a calendar month spans two billing periods, the number of days in the month that are in each billing period is multiplied by the average daily consumption in each period and summed together to calculate the electricity (or natural gas) 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.

5. SELF-SELECTION BASED ON 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 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.

5.1 Pre-treatment Usage Pattern

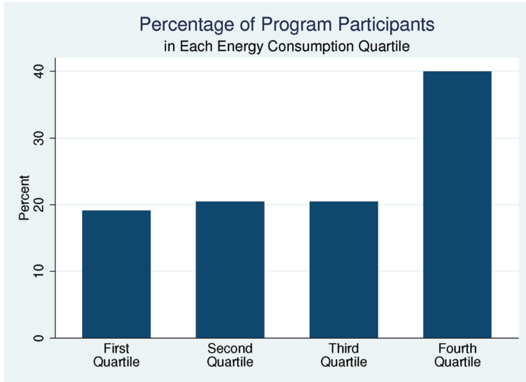
We expect that high energy consumers will be the ones more willing to save energy by switching to more energy efficient appliances. This is the case in Figure 1. The figure shows the percentage of program participants in each energy consumption quartile.[15] It shows that majority of

13. This method was particularly useful when estimating the summer peak and winter peak effects. We 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.

15. 2008 annual Energy Usage for all households in the dataset was divided into quartiles as follows: First Quartile (less than 12360.23 ekWh); Second Quartile (between 12360.23 ekWh and 17000.65 ekWh); Third Quartile (between 17000.56 ekWh and 22613.54 ekWh); Fourth Quartile (greater than 22613.54 ekWh).

Figure 1: Percentage of Program Participants within Each Energy Consumption Quartile



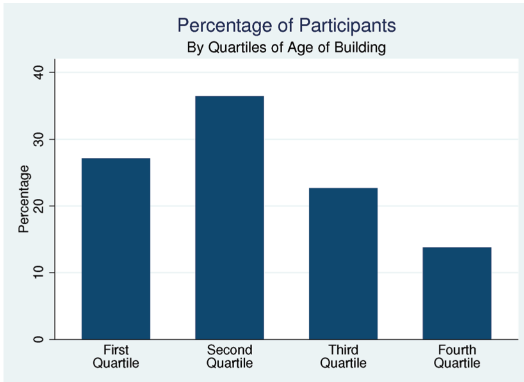
the treatment group (about 40%) are in the fourth quartile. The fourth quartile contains about twice the number of treated observation as the other quartiles. Thus, consumers with high energy usage are more likely to participate in the rebate program than consumers with low usage. The figure also shows that the number of treated observations is nondecreasing (or increasing) as we move from the lower quartile to the upper quartile.

5.2 Self-selection Based on Age of The Building

Recent houses are more energy efficient and normally contain more energy efficient appliances than older homes. A change in an appliance in an older home is thus expected to have a higher energy-saving effect (since older AC units consume more energy than modern AC units). We expect households in older buildings to participate more in energy efficiency programs to take advantage of the high energy savings associated with older houses 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 usage 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 lead to only a fraction of the energy savings expected from replacing a very old AC unit in an old building.

In Figure 2, we divided the age of the building into age of building quartiles. These divisions were based on all the households in the dataset even though the figure shows only the treated households. The first quartile contains building aged less than 16 years; the second contains buildings between the ages of 16 years and 28 years; the third contains buildings aged between 28 years and 33 years while the fourth quartile is made up of buildings aged more than 33 years. The Figure shows that households in old houses over 33 years are less likely to participate in the program. Program participation was rather high among households in houses with 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. The low participation among households in the fourth quartile is, however, expected if households in the fourth quartile had already participated in a similar program in the past. Also, households in the first quartile may already have a high-efficiency AC units already installed in their homes. Households in the second quartile are more likely to be those with old AC units who have not participated in an AC rebate program in the past.

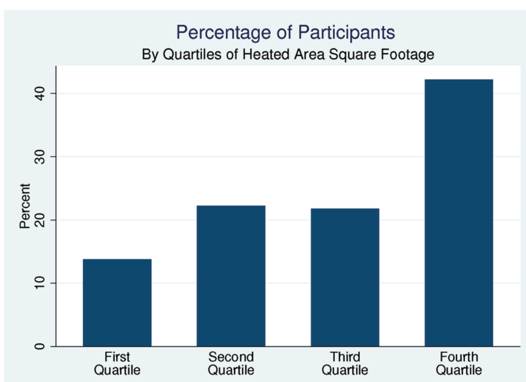
Figure 2: Distribution of Age of Building of Program Participants



5.3 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 3 shows the distribution of the treatment group by 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. From the figure, a large percentage of the treated households (42 %) are in the fourth quartile while the second and third quartile each contains about 22% of the treated households. The first quartile contains the least number of treated observations (13%). The figure, therefore, supports the argument that larger houses are the ones more eager to reduce energy since they consume more.

Figure 3: Distribution of Heated Area Square Footage of Building of Program Participants



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 bedrooms, number of bathrooms, the number of stories, heated area square footage, and type of heating fuel.[16] 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 re-coded 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.[17] Program participants entered the program at different months in the year 2009. In analyzing the 2009 rebate program, we do not use 2009 as the post-treatment year. Instead, we use 2010 as the post-treatment year and 2008 as the pretreatment year.

6.1 Annual Effects of The High-Efficiency AC Rebate Program

Table 3 shows the total number of observations and the number of treated and untreated observations 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 the census tracts is expected to provide an accurate match, because census tracts are smaller, it produces fewer matched cells than matching on zip codes. We also lose a significant number of the already limited treated observations when matching on census tracts. The matching on the zip codes as neighborhoods, on the other hand, produces more matched cells. However, houses within a matched cell or the demographics of the households within the matched cells are more likely to deviate significantly from each other. They may also experience different weather conditions which might bias the results.

Table 3: Matching Summary–High Efficiency AC

Census Tracts Number of strata: 9771 Number of matched strata: 135			**Zip Codes** Number of strata: 3653 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

Columns I to III of Table 4 shows the results of the DD CEM methodology (with census tracts as neighborhoods), while Columns IV to VI shows the results of the regular DD methodology.[18] The results in columns I and IV of Table 4 show that the high-efficiency AC rebate program

16. 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.

17. These divisions are arbitrary and did not affect the results. For example dividing the heated area square footage by the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles of the distribution of heated area did not affect the result.

18. We relegate the results of the DD CEM methodology with zip codes as neighborhoods to the online appendix. See Table A1 in the online appendix.

led to statistically significant energy savings under both the DD CEM regression and the regular DD regression. The regular difference-in-difference regression (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.[19] The treatment effects from both the regular DD and DD CEM are not very different from each other. Both lead to a savings of about 2000 kWh per year (or 167 kWh per month). Using GRU's increasing-block pricing scheme for 2009 and a median electricity consumption per month of a 1000 kWh leads to a monetary saving of $ 40 per month per treated household ($480 saved per year).[20] We believe that matching on a refined neighborhood variable such as the actual neighborhoods or subdivisions used by the Alachua County property appraiser would 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. Thus, matching on the subdivisions would further reduce the imbalance between treated and non-treated households. Houses in the same subdivision are also likely to have similar weather conditions than houses far apart. Hence, by matching on subdivisions, we can control for the marginal differences in weather across subdivisions.

Table 4: Annual Energy Savings Effect Of The 2009 High Efficiency AC Program

	DD CEM (Census Tract)			**Regular DD**		
Δlog(Energy)-Usage)	(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 (1000 sq. ft)		0.0748*	0.0766**		0.0060	0.0036
		(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 (1000 sq. ft.)	–0.0475	–0.0546	–0.0547	0.0143***	0.0141***	0.0142***
	(–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 House-hold 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

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

19. Table A1 in the online appendix also shows that when using zip codes as neighborhoods, the AC rebate program led to savings of 8.6% per year.

20. This calculation assumes all the energy savings comes from electricity usage.

In columns II, III, V, and VI, we allowed the treatment effect 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 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.[21] More importantly, when a house has a heated area of about 1.614 thousand square feet (the median heated area square footage in the data), the energy savings is about 10.9%. On the other hand, a house that has a heated area of about 2.120 thousand square feet (the 75th percentile of the distribution of heated area in the data) has an energy savings of 6.5%. The energy-saving effect of the program becomes non-existent for a house with a heated area square footage of about 3080 square feet (about the 94th percentile of the distribution of heated area in the sample). These 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 2. The difference between the DD estimate and the DD CEM estimates can be attributed to the reduction in the imbalance between the treated households and the non-treated households by the CEM methodology.

6.2 Summer Peak Effects

The main reason for demand-side management programs is to "allow a utility to control the balanFce 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). Utilities are, therefore, particularly interested in how demand-side management programs affect peak-period demands. Florida has two peak periods: the summer peak and the winter peak. The AC rebate program is, however, expected to have high effects in the summer months with little or no effects in the winter months and the non-peak months. Florida's hot, humid summer begins in mid-May or later with average maximum temperatures reaching about 90°F during the day, but with high humidity, the real feel of the temperature is about 108°F. Air conditioning thus becomes the primary 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 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). In this part of our analysis, we analyze the impact of the AC rebate program on summer peak energy consumption. We consider June, July, August, and September as summer months.[22]

The results of the summer peak effects of the program are shown in Table 5. As expected, the AC rebate program led to substantial energy savings of about 20% in the summer months using the DD CEM with census tracts as neighborhoods (Column (I) of Table 5). The regular DD without matching also produced statistically significant but relatively lower energy-saving estimates of 16.77% (Column II of Table 5). These higher estimates in the summer months are expected since air conditioning accounts for a higher percentage of the energy usage during the summer months.[23]

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

22. December, January, and February were considered as the winter 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.

23. The DD CEM with zip codes as neighborhoods also led to a statistically significant energy savings of 17%. We also estimated the effects of the AC rebate program in the winter peak and the non-peak months. The result for the winter peak

Table 5: Summer Peak Effects of the 2009 AC rebate program

Δlog(Energy Usage)	DD CEM (Census Tract) (I)	Regular DD (II)
Treat	–0.2063***	–0.1677***
	(–6.77)	(–8.68)
Bedrooms	0.0490	–0.0020
	(1.45)	(–0.35)
Stories	0.0203	0.0002
	(0.69)	(0.04)
Heated Area (1000 square feet)	–0.0565	0.0021
	(–1.36)	(0.38)
Age	0.0040	0.0000
	(1.95)	(0.02)
Pool	0.0200	–0.0271***
	(0.42)	(–3.79)
Electric and Gas	0.0185	0.0197**
	(0.43)	(3.16)
Mean Income ($1000)	–0.0000	–0.0003**
	(–0.04)	(–2.66)
Mean Household Size	0.0452	0.0007
	(0.75)	(0.06)
Hot Tub	–0.1084*	–0.0140
	(–2.25)	(–1.30)
cons	–0.2178	0.0655
	(–1.38)	(1.87)
N	1552	24008

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

6.3 Effects on Electric-Only Households

In the above analysis, we added both electricity consumption and natural gas consumption even though the high-efficiency AC is expected to have substantial effects on electricity consumption with little or no impact on natural gas consumption. In warm areas like Gainesville where households require minimal heating in the winter, some households (especially those with a packaged AC) still depend on their AC to heat their homes during the winter. Only a small fraction of households use natural gas furnace for heating in the winter. We anticipate that if the high-efficiency AC (packaged AC) becomes economically more efficient for heating than the natural gas furnace, consumers using the high-efficiency (packaged) AC might switch to their AC for heating in the winter months. While such a substitution might reduce natural gas consumption, it might lead to increased electricity consumption. The ideal way of calculation savings, in this case, is to combine electricity and natural gas consumption in the calculation of the energy savings as is done in the previous sections. However, for households with a split AC (with no heating capabilities), the high-efficiency AC might have no effect on natural gas consumption, and adding natural gas in the analysis is redundant and minimally affects the results of the analysis. In this subsection however, we estimate the effects of the high-Efficiency AC on the Electric-only Households (Households with no natural gas usage) to investigate the impact of the high-efficiency AC on summer peak electricity consumption. We also estimate the treatment effect in the winter peak and non-peak months. The estimated effects are shown in Table 6.

months and non-peak months are shown in Table A3 and Table A4 respectively in the online appendix. As expected, there are no statistically significant winter peak effects of the program under the DD CEM with census tracts as neighborhoods. The regular DD and the DD CEM (with zipcodes as neighborhoods) produced statistically significant but relatively lower winter peak effects of 4%. The effect of the program in the non-peak months is also about 4.88%.

Table 6: Summer, Winter, and Non-Peak Months Effects of the High Efficiency AC program for the Electric-Only Households

	DD CEM (Census Tract)			Regular DD		
Δlog(Electricity Usage)	Summer	Winter	Non–Peak	Summer	Winter	Non–Peak
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 (1000 sq. ft.)	–0.0090	–0.0523	–0.0272	–0.0033	0.0131	0.0096
	(–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

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

The results in Table 6 show a statistically significant 14% energy savings in the summer using the DD CEM regression (Column I). The regular DD produces an 11% energy savings in the summer. These estimates are quite less when compared to the estimates using all households. These results imply that in the summer months the high-efficiency AC rebate program has greater energy-saving effects on households with both electricity and natural gas than on households with electricity as their only energy source. The electricity-saving 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 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 results indicate that the high-efficiency AC has a large effect on electricity consumption even in the winter months. The estimated effects in the non-peak months are statistically insignificant in both the DD CEM and the regular DD regressions.[24]

7. "REBOUND" EFFECTS

In this section, we 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 the 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

24. It is, however, significant at the 5% level in the DD CEM regression with zip codes as neighborhoods. See Table A5 in the online appendix.

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 (backfire), 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., Fowlie et al., 2018). 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.[25] 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 respond 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 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 assume 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

25. 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.

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 Dubin et al.'s (1986) 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, an increase in central AC efficiency means, households might reduce the use of (inefficient) standalone electric fans, but increase the use of their central AC unit. While usage of their central AC unit may be higher than previously, the reduction in the use of standalone fans may reduce consumers' overall energy consumption. 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.

7.1 Conceptual Framework

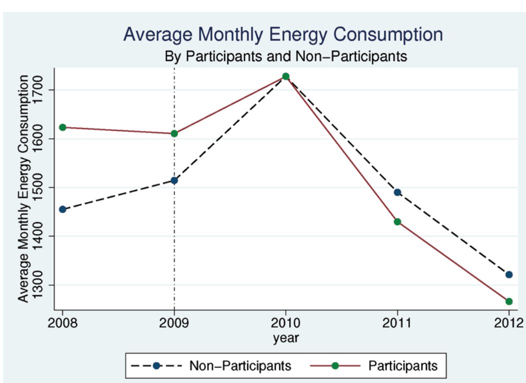
As stated earlier, the main reason for using price variation to estimate rebound of energy efficiency improvements is the endogeneity of efficiency improvements (West et al., 2017). That is, while prices are taken exogenously by consumers, households that participate in retrofitting programs are not 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 use 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 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 summer peak months as the period of learning . Thus, participants, after observing their energy cost decrease in the first year (summer) of the program are more likely to engage in activities that lead to energy savings rebound in the second year (summer). This framework is similar to the research design of Fowlie et al. (2018) 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" (Fowlie et al., 2018). 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 energy cost for at least one year.

7.2 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 4 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.

Figure 4: Average Energy Consumption by Participants and Non-Participants



The graph, therefore, suggests 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.[26]

7.3 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, compare the energy consumption of the treatment group to the control group across the years 2010 and 2011. We use equations 6 and 7 with and without the CEM methodology. We repeat these equations below for easy reference. Equation 6 models the log of total energy usage as:

$$y_{it} = \beta_0 + \delta_0 .\, d2 + \delta_1 treat_{it} + \delta_2 treat_{it} \cdot X_i + \beta_1 X_i + \beta_2\ d2 \cdot X_i + \gamma_i + u_{it}, \quad t = 1,2 \tag{6}$$

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). $d2$ 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 periods (2010 and 2011) removes the individual heterogeneity as well as all the time-constant explanatory variables so we obtain the estimation equation:

$$\Delta y_i = \delta_0 + \delta_1 .treat_i + \delta_2 treat_i \cdot X_i + \beta_2 X_i + \Delta u_{it} \tag{7}$$

Table 7 shows the result of the estimation using equation 7. Column I of the table gives the results of the DD CEM (with census tracts as neighborhoods) and column II gives the results of the regular DD methodology with only the matched sample from the CEM (with census tracts as neighborhoods) method. Both 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 the Figure 4). However, the effect is not statistically significant in both regressions. These results, therefore, show there is no rebound effect of the high-efficiency AC rebate program.[27]

26. Figures A1 and A2 in the online 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 4 and from each other, the main observation from Figure 4 that the program participants even increased their energy savings much higher in the subsequent years after the program is present in all three figures.

27. The DD CEM regression with zip codes as neighborhoods, however, shows a statistically significant negative estimate. This implies increased energy savings or no rebound effects. The estimates using only the summer months also indicates that there are no rebound effects in the summer months.

Table 7: Effect of the 2009 High Efficient Rebate Program on 2011 Energy Savings

Δlog(Energy Usage)	DD CEM (census tracts)	Regular DD (with CEM)
Treatment group	–0.0261	–0.0166
	(–1.74)	(–0.64)
Bedrooms	–0.0044	–0.0034
	(–0.17)	(–0.14)
Stories	–0.0217	0.0060
	(–0.96)	(0.15)
Heated Area (1000 square feet)	–0.0158	–0.0121
	(–0.60)	(–0.52)
Age	–0.0032**	–0.0023*
	(–3.01)	(–2.34)
Pool	0.0359	–0.0046
	(1.20)	(–0.17)
Electric and Gas	–0.0759**	–0.0612**
	(–3.26)	(–3.06)
Mean Income ($1000)	0.0003	–0.0002
	(0.59)	(–0.71)
Mean Household Size	–0.0327	0.0169
	(–0.68)	(0.38)
Hot Tub	–0.0785*	–0.0478
	(–2.17)	(–0.98)
cons	0.0882	–0.0618
	(0.74)	(–0.49)
N	1552	1552

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

8. 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, 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 electricity consumption is one of the contributions of this paper. The results show significant effects of the AC rebate program. This imply that the high DSM effects reported by utilities are more likely to be true as shown by Auffhammer et al. (2008).

The results also contribute 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 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.

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