EnergyScoreCards Minnesota Impact Evaluation

A Pilot Program to Study Energy and Water Benchmarking in Multifamily Buildings

Conservation Applied Research & Development (CARD) Impact Evaluation

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Executive Summary

EnergyScoreCards Minnesota is a pilot program to study the impact of an energy and water benchmarking service in 500+ Minnesota multifamily buildings. The effort is funded by a Minnesota Department of Energy Resources (DER) Conservation Applied Research Program (CARD) grant, the Xcel Energy Emerging Technologies Grant Program, and a Multifamily Rental Energy Efficiency grant from Minnesota Housing. The program was led by Bright Power, Inc. with several partner organizations.

The EnergyScoreCards Minnesota pilot was designed as a two year experiment of the EnergyScoreCards service, a benchmarking service including online software and hands-on account management support. A treatment group received two years of free access to the service, and a control group was tracked for the same time period, but did not have access to the service until after the second year, allowing a comparison of outcomes between the two groups.

This impact evaluation seeks to quantify the measurable impact of the EnergyScoreCards tool and service on participating buildings over two years in terms of:

- Energy and water savings
- Energy- and water-conservation actions taken
- Participation in Conservation Improvement Programs (CIP)

A separate Process Evaluation and Final Program Report contain additional results not included in this Impact Evaluation.

Primary results are:

- Master-metered buildings, where the owner pays for all utilities in the building, experienced a significant decrease in their Owner Energy Index of 4.5 ± 1.6 kBTU/sqft/year by the second year, relative to the control group, about a 5% reduction for a typical master-metered building. This result is measured at the 95% confidence level, and represents a total savings of 7,242 mmBTU/year. Master-metered buildings accounted for 17% of the analyzed buildings.
    - The primary area where master-metered buildings found savings was heating, where treatment group participants decreased their Heating Index by 0.48 ± 0.17 BTU/sqft/HDD, about a 9% reduction in heating for a typical Minnesota building. Heating savings represented 82% of the overall observed savings in master-metered buildings.
    - Energy savings in master-metered buildings amounted to 443,780 kWh/year in electricity and 57,289 therms/year in natural gas.
- Master-metered buildings in the treatment group decreased their water usage by 24 ± 9 gallons/bedroom/day in the second year compared to the control group, roughly a 30% reduction in water for a typical Minnesota building. This is a total savings of 18,820 kGal/year.

- Master-metered buildings showed only marginally significant energy and water savings after the first year.
- Non-master-metered buildings in the treatment group did not show statistically significant energy or water savings. One possible explanation for the difference in results is that owners of may put greater focus on energy and water savings at master-metered properties where they know they pay all utilities. Analysis of the data set also suggests that a building population of roughly twice as large would have been needed to detect significance in the smaller changes observed in non-master-metered buildings.
- Conservation Improvement Program (CIP) participation records showed that 19% of treatment group properties participated in at least one electricity rebate program over the two year period, while only 10% of control group properties participated. For gas rebate programs, there was no statistically significant difference between treatment and control group participation. Data received from the utilities did not allow a complete analysis of building level participation (only treatment and control group total participation). However, applying the overall average increase in rebate uptake to the master-metered buildings, we estimate that
    - 16% of observed electric savings, 72,419 kWh, is jointly attributable to the EnergyScoreCards service and the increased participation in rebate programs. Annual electric savings attributable only to the pilot (total savings minus jointly attributable savings) is 371,361 kWh.
- Survey data on conservation actions taken showed no differences between control and treatment groups, but the data quality was poor, in terms of the level of detail received and the apparent reliability of information. Because of difficulty in attaining high-quality data on actions from the approaches taken, it was concluded that a different study design would have been needed to accurately assess conservation actions taken by members of both groups.
- Cost-effectiveness of the program in producing energy and water savings was estimated in two scenarios. Each scenario uses the same savings – those observed for master-metered buildings (net of joint rebate savings) but different costs:
    - First, the full cost of the EnergyScoreCards Minnesota program ($728,940) was 2.7 times greater than the year-two savings in master-metered buildings ($269,380), which are the only statistically significant savings observed during the pilot.
    - Second, the pro-rated cost of the EnergyScoreCards Minnesota pilot for master-metered buildings only is $125,435. For this group the $269,380 of savings over the two year pilot are 2.15 times the cost. Furthermore, in a long-term program targeting master-metered buildings, service costs per year would be reduced since a large portion of program costs were associated with program design and launch. Energy and water savings, however, would be expected to persist or deepen over time. In a 10 year program, for instance, $7.79 of savings could potentially be produced for every $1 spent on master-metered buildings,

assuming savings continue at the levels observed here. Although cost-effective in this scenario, we do not recommend that a program exclude other metering types, as savings may well occur in these buildings in later years or with other changes in program design.

Further studies might investigate different service levels, seek to understand the difference in results observed among different metering types and across fuels, test the applicability to other geographic regions, and pilot a more direct integration of benchmarking with other multifamily energy and water programs. These results suggest that multifamily energy and water benchmarking services hold significant potential as a component to increase participation in programs, increase the proportion of customers experiencing savings, and improve the magnitude and persistence of those savings over time.

Introduction

EnergyScoreCards Minnesota is a pilot program to study the impact of an energy and water benchmarking service in 500+ Minnesota multifamily properties. The effort is funded by a Minnesota Department of Energy Resources (DER) Conservation Applied Research Program (CARD) grant, the Xcel Energy Emerging Technologies Grant Program, and a Multifamily Rental Energy Efficiency grant from Minnesota Housing.

The EnergyScoreCards Minnesota pilot was designed as a two year experiment: a treatment group received two years of free access to the EnergyScoreCards service, and a control group was tracked in EnergyScoreCards, but did not have access to the service until after the second year, allowing a comparison of outcomes between the two groups.

The EnergyScoreCards service includes an online benchmarking tool, automated utility data retrieval, training materials, and support and outreach from assigned Account Managers who guide participants in learning about the energy and water consumption in their buildings.

This Impact Evaluation quantifies the impact of the EnergyScoreCards service by comparing outcomes of the treatment group to those of the control group. Pilot deliverables also include a Process Evaluation and Final Report which include additional findings, description, context and implications of the pilot.

Objective

The goal of the study was to determine how the EnergyScoreCards service impacted buildings using the service. The main hypothesis was that providing participating building owners or managers with feedback about energy and water efficiency and support and guidance on how to use this information at their properties would lead to changes in behavior (building operation) or capital upgrades that produce measurable energy and water savings. Specifically, the study sought to determine if two years of access to the EnergyScoreCards service led to differences in:

- Energy and water consumption in the buildings
- Number and type of conservation actions taken
- Participation in utility rebate programs (i.e. conservation improvement programs [CIP])

A detailed methodology describing how these three measures of impact were evaluated is presented in the next section.

Methodology

The hypotheses were tested by splitting the pilot participants into a treatment group, which received the EnergyScoreCards service for 2 years, and a control group, which signed up to participate in the pilot, but did not receive access to the EnergyScoreCards service until after 2 years. Key elements of the methodology, described below, are: participant recruitment, the EnergyScoreCards service, data collection, group assignment (to treatment or control), analysis of energy and water usage change in EnergyScoreCards, and statistical tests to analyze the changes.

Recruitment

EnergyScoreCards Minnesota was offered as a free pilot program to interested multifamily building owners or managers who opted to sign up. Initial outreach and recruitment was necessary for both treatment and control group buildings, because critical building and utility access information could only be collected directly from building owners or managers. Eligibility was as follows:

- Open to market rate and affordable rental properties
- Open to buildings with ten or more units
- Open to properties in the service area of Xcel Energy, CenterPoint Energy, and/or Rochester, Austin, Owatonna, St. Cloud and Mankato utilities
- Open to buildings with at least ten months of existing operating history as of pilot launch in early 2012
- Townhomes, condominiums, and cooperatives were NOT eligible
- To be considered for participation all buildings were required to:
    - Complete a brief property survey
    - Authorize EnergyScoreCards Minnesota to collect owner-paid utility data for the duration of the pilot
    - Enroll a maximum of 25 participating buildings per owner/manager[1]
- Properties with ongoing performance contracts were NOT eligible

Outreach was conducted through several methods:

- Creation of a public website
- Multiple open webinars
- Email blasts from Minnesota Housing and the Minnesota Multi-Housing Association (MHA)
- A phone and email campaign to contact eligible owners based on lists from Minnesota Housing

[1] Originally the maximum eligible buildings per portfolio was set at 10, but was later expanded due to strong interest from several larger portfolios.

The EnergyScoreCards Service

EnergyScoreCards is a benchmarking service offered to multifamily buildings across the country by Bright Power as a subscription service which includes access to an online software tool and hands-on guidance and support from Bright Power staff. Typically, the service is offered to owners and property managers of multifamily portfolios. Over 18,000 properties (600,000+ units of housing) are currently tracked in EnergyScoreCards. Participants in the EnergyScoreCards Minnesota pilot had free access to the EnergyScoreCards service, including the software, training materials, and assigned Account Managers who help guide participants in learning about their buildings and energy and water consumption and making use of that information.

Tool

EnergyScoreCards is an online energy benchmarking software tailored to multifamily buildings. The tool uses utility bills and basic property information to generate scorecards, which allow users to quickly see how their building's consumption compares to others, identify the most promising areas for upgrades, and watch trends. Figure 1 shows a sample property scorecard for one of the buildings in the pilot. The letter grades for energy and water efficiency metrics indicate how the property compares to other Minnesota buildings in EnergyScoreCards. Grades are assigned for owner energy (i.e., all energy paid for by the owner), cooling, heating, electric baseload, fossil fuel baseload and water metrics. Efficiency grades are shown alongside spending to help guide the user to target areas for improvement.

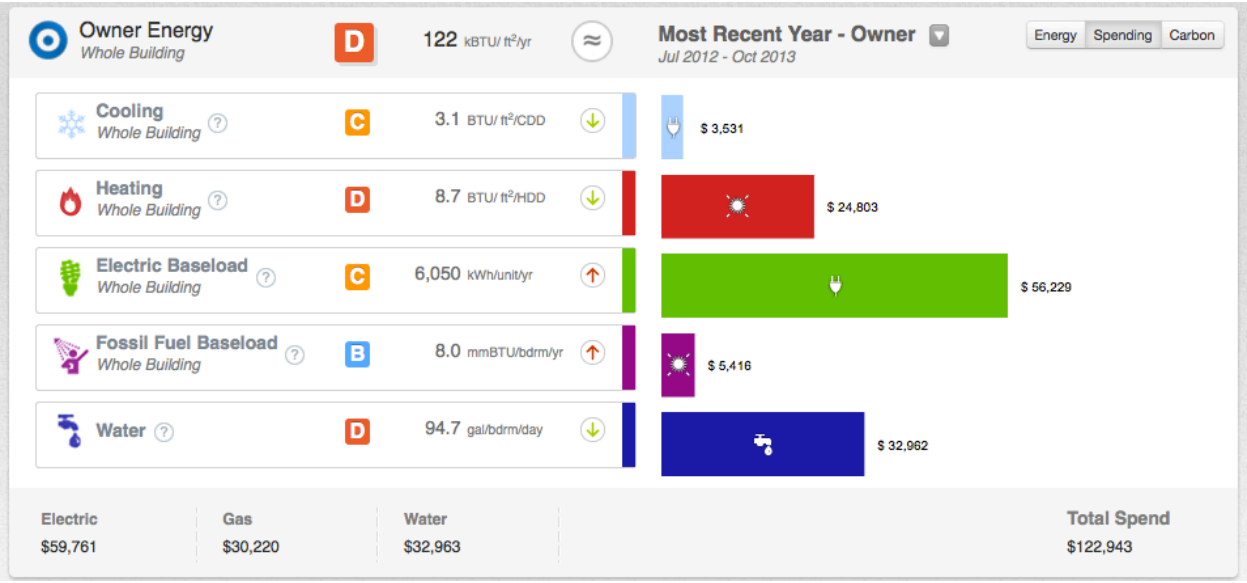


Figure 1: Sample Property ScoreCard

Additional features of the tool include:

- optional owner tracking of energy events (e.g. energy retrofits or other upgrades)
- monthly reporting

- year on year comparisons
- portfolio reporting
- automatically generated alerts.

Utility Data Collection

Collecting and storing utility bill information is a critical piece of the EnergyScoreCards service. A majority of EnergyScoreCards customers and all pilot participants use the tool's Automatic Bill Retrieval feature. Utility data is automatically loaded into EnergyScoreCards and stored in the tool for each utility account. The dates, consumption and cost for each bill are stored in the system. Utility accounts are identified by fuel and labeled as 'owner' or 'tenant' (if the latter are available) based on who pays the bill.

Support

In addition to the online tool, the EnergyScoreCards service includes support and training from an assigned Account Manager, as well as access to resources and events provided to all EnergyScoreCards subscribers.

Account Managers

Each treatment group member was assigned an Account Manager to help them utilize the EnergyScoreCards tool and resources. Account Managers served as primary contacts for technical questions, helped with reporting and interpreting, and were a resource for information about opportunities. Account Managers for the pilot were Janne Flisrand of Minnesota Green Communities (MNGC) and Billy Weber and Patrick Smith from the Center for Sustainable Building Research (CSBR) at the University of Minnesota. Account Managers provided each participant with an orientation to the tool and their initial benchmark at the launch of the pilot, regularly performed check-in calls with the participants, and helped direct participants to applicable resources, including available utility rebate programs. Whether over email, phone or in-person, these points of communication may have included:

- Answering specific questions from the participant.
- Training on how to use various features of the tool.
- Troubleshooting issues or questions around data or analysis in the tool.
- Sharing sample reports or opportunities identified in the tool.
- Sharing tips or resources around best practices for energy and water management.
- Discussing possible next steps to act on information received (e.g. pointing toward a utility program that might assist with an area of high consumption).
- Brainstorming ways to use the information for portfolio planning.
- Helping track savings from upgrades undertaken during or before the pilot.

Regular EnergyScoreCards clients, outside of the pilot, receive similar support from Bright Power Energy Analysts.

Resources

A series of quick guides, tips, and worksheets were developed for the Minnesota participants. Participants could access these resources on the EnergyScoreCards Minnesota website (http://energyscorecardsmn.com/tools), and Account Managers provided resources to participants, as applicable. Additional resources are also available on the help site accessible through the EnergyScoreCards tool.

Newsletters

Newsletters were sent via email to all treatment group members throughout the pilot. Some newsletters were Minnesota specific, while others are general EnergyScoreCards and Bright Power newsletters. Seven newsletters were sent in the treatment phase of the pilot, and featured announcements about upcoming webinars, case studies, energy tips, pilot updates, and information about relevant energy or water programs.

Webinars

Treatment group members were invited to participate in Bright Power and EnergyScoreCards webinars, which were offered on various topics throughout the treatment phase; seven webinars in total were provided. Webinars included presentations, screen-sharing within EnergyScoreCards, and interactive question and answer with attendees.

The analysis presented in this report attempted to include all buildings accepted into the pilot, only excluding buildings for which data access was lost during the two year pilot, making the full analysis of changes impossible. While the level of engagement with the service (e.g. logging into the online tool, participating in email, phone, and in-person discussions with account managers) varied considerably between participants, there was no exclusion of data for less-engaged participants.

Data Collection

To sign up to be part of the pilot, all candidates submitted information about their buildings, allowing their buildings to be benchmarked throughout the pilot, regardless of whether they were assigned to the treatment or control group. This resulted in the collection of several types of data that are used in this evaluation and described below.

Property Information

Organizations voluntarily signed up for the pilot at no charge and were asked to submit an Agreement and Property Survey, including information about their buildings.[2] Information submitted included:

[2] A public website with information for potential participants was created at www.energyscorecardsmn.com

- Property name
- Address
- Square footages (total multifamily and common-area)[3]
- Metering configuration (i.e., whether the owner or the tenant pays for electricity, cooling, heating and/or hot water used in the apartments)
- Fuels used for heating, cooling, domestic hot water
- Number of units
- Number of bedrooms
- Occupancy type (e.g., family vs. senior properties)
- Hi/mid/low-rise building configuration
- Subsidy types

Utility Information

The Pilot Program Agreement provided authorization for Bright Power to access the relevant utility information on owner-paid utility accounts and the following utility information:

- Utility providers
- Account numbers
- Meter numbers
- Utility website login information

In order to be eligible for the pilot, all buildings were required to provide utility information and data release authorization for all *owner-paid energy accounts.* Water information was requested but not required. An example of the Property Survey file sent to applicants to be completed for consideration in the pilot is in Appendix A.

With this authorization and utility information provided in the property survey, Bright Power was able to collect utility data on both treatment and control group properties in a variety of ways:

- Through the utility provider's website
- By sending a request to the utility provider
- For Xcel Energy, through an automated data feed

At least one year of historical data was collected in EnergyScoreCards to provide an initial benchmark year of performance. Data was kept up-to-date on a regular basis (typically monthly) throughout the two year pilot, primarily through EnergyScoreCards' automated bill retrieval, which leverages the providers' websites. A direct electronic data feed was established with Xcel Energy. Consumption data was used throughout the pilot to provide feedback to

[3] *Common area square footage* (e.g. halls, lobby, community rooms) is a subset of total multifamily square footage. Some properties also submitted *commercial square footage* (e.g. ground-floor retail in a downtown apartment building), which is not included in multifamily square footage, though this was uncommon among pilot buildings.

treatment group members on their buildings' energy and water consumption, and is used in this evaluation to assess differences in the energy performance trends between treatment and control groups.

Information on Conservation Actions Taken

Information on number and type of conservative actions taken was more difficult to collect than initially anticipated. Two methods of collecting this information were attempted.

First, treatment group members were asked to enter conservation actions into the Energy Events feature of the EnergyScoreCards tool. Some participants used this feature extensively; some did not use it at all. After the pilot, control group members were engaged to access a free year of EnergyScoreCards, but emphasis on engaging the organizations and collecting any changed utility data was the priority in these conversations, rather than collection of conservation actions taken.

A second attempt to collect information on conservation actions was made through the Process Evaluation survey conducted by CEE in October and November 2014, at the conclusion of the two years of service and before the control group members were offered their complimentary year of access. This survey, conducted by phone, included questions on the number and type of conservation actions taken by both groups, although all data is self-reported and no verification (e.g. contractor invoices or details on actions) were requested. Furthermore, the person surveyed may or may not have had full information about specific actions taken at the property in question; i.e., for most properties there are multiple people involved with identifying and implementing conservation actions, but only one person was surveyed.

Additional information was collected from utilities on building participation in rebate programs, as described later, in the section on Conservation Improvement Program (CIP) Participation.

Group Assignment

After thoroughly reviewing all submissions, the pilot accepted 564 properties[4] from 93 organizations, excluding only those buildings with incomplete information or which did not meet an eligibility requirement. All organizations accepted into the pilot were randomly assigned to the treatment or control group. The treatment group received access to the EnergyScoreCards service beginning in Fall 2012 for two years. The control group was tracked in the tool, but did not receive access until late 2014.

The organizations were randomized between treatment and control status in order to allow a comparison of energy and water use trends in buildings which received access against those which did not, to test whether receiving the EnergyScoreCards service has a measurable impact on consumption. An evaluation partner, CEE, used a stratified, group-randomized approach to

[4] The total number of properties at the time of analysis differs from original number of properties assigned because some properties were sold in the course of the two years, and some properties were split up by building into multiple "properties" in the EnergyScoreCards tool.

split the pilot group into participants and controls and balance the groups across many factors, so that the characteristics of the two groups were largely similar in terms of building age and size, the parties responsible for various utilities, and starting energy efficiency. For organizations with multiple buildings in the pilot, all buildings were placed in the same group to avoid potential cross-contamination if the organization had buildings in both the control and treatment groups.[5] Basic information on the treatment and control groups at the time of analysis is shown in Table 1.

	All	Treatment	Control
Organizations	93	46	47
Properties	561	286	275
Sq ft	31,246,310	16,013,082	15,221,258
Units	29,075	14,393	14,682

Table 1: Group Breakdown in Numbers

For more details on the assignment of applicants to participant or control status, see Appendix B: Participant Assignment.

Analysis of Energy and Water Consumption in EnergyScoreCards

The EnergyScoreCards tool was used as the primary platform for analyzing building energy and water consumption before and after treatment. To analyze changes in utility consumption, EnergyScoreCards adjusts for the impact of the weather – critical to allow a building to be compared to itself over time, as well as for it to be compared to other buildings. Additionally, analysis in EnergyScoreCards allows for different end-uses to be identified; each utility account may supply energy for heating, cooling, and/or baseload usage. In order to account for the weather, multiple end-uses, and varying utility billing periods, EnergyScoreCards generates models to analyze utility data, as described below. The outputs of this analysis were used as the inputs for statistical tests described in the following section.

Account Analysis

Two primary challenges in using utility bill data to assess changes in building energy and water consumption are normalizing for changes in weather and dealing with utility bills with different start and end dates. For instance, comparing gas consumption on utility bills received in February 2012 and February 2014 is problematic, both because the required heating in each month would have varied depending on outdoor temperatures, and because the number of days reflected in each bill period may have been different depending on the exact start and end dates of each bill. Weather-normalization is not simple, because, for example, while some gas is associated with heating, often another portion is used for domestic hot water and does not vary

[5] If an owner/manager had some buildings in the treatment group and some in the control group, s/he might apply some of the knowledge gained from the program to the control buildings as well as the treatment buildings, which would make the measured savings (treatment-control) look smaller than they actually are.

with outdoor temperature. Similarly, adding up all utility bills at a building received in one month or a year is problematic because multifamily buildings typically have multiple meters or accounts, and bill dates are often misaligned between meters at the same building in the same year, and between years.

EnergyScoreCards uses a utility account modeling approach to solve both of these problems, as described below.[6]

For each analyzed year for each utility account, EnergyScoreCards fits a model of energy consumption to weather and time using an ordinary least squares linear regression. The fit outputs values for the three coefficients: A, B, C and their uncertainties for each utility account in a particular time period. This model takes the form of Energy consumption = A*CDD + B*HDD + C*Days, in which:

- A = cooling coefficient
- B = heating coefficient
- C = baseload (non-seasonal) coefficient
- CDD = Cooling Degree Days, base 65°F
- HDD = Heating Degree Days, base 65°F
- Days = # of days in billing period

In order to reduce the impact of incorrect billing data, there are two types of "toggling" that occur during the fit.

a. First, a series of F-tests are run to check whether the inclusion of each component (heating, cooling and baseload) in explaining the variance of the data justifies the increase in degrees of freedom. In all cases the simplest model that can explain the variance is selected. This step is important because some accounts have no association with one or more component, and attempting to fit to these components could produce misleading results.

b. Second, each bill is evaluated to see if it strays too far from the fit. If the bill exceeds a set threshold[7] from the fit, the bill is toggled off, i.e. excluded from the analysis. This step is important to reduce the impact of outlier bills produced by utility company estimates or other errors that do not reflect actual changes in consumption.

Water is modeled in the same way, but the heating and cooling components are always automatically toggled off, so a much simpler equation fits the water data.

[6] This approach to utility bill analysis is in line with ASHRAE Guideline 14-2002 and International Performance Measurement and Verification Protocol (IPMVP) Option C.

[7] The threshold was chosen through a tuning process on the much larger EnergyScoreCards dataset and was found empirically to exclude a high proportion of bad bills without being overly punitive. Across all properties, this process excluded 1.6% of all bills in the pilot. The exact threshold was provided to CEE for an audit of the methods used here.

Calculating Building Consumption

All account-level models are then summed to create a building-level model, reflecting the energy and water usage for all owner-paid accounts, or for the whole building (in the case of master-metered buildings).[8] In order to calculate building energy consumption in a particular time period, this building model can be applied to the weather data (HDD and CDD) and the number of days in the time period. For this evaluation, building-level consumption models were created for the baseline year (2012), the first year (2013), and the post-treatment year (2014), and these models were applied to typical year weather (HDD and CDD) and 365 days in order to create weather-normalized annual before and after consumption values for each building.

Data Excluded from the Final Analysis

Buildings were only excluded from the final analysis if deemed 'invalid' due to incomplete data. Typically the full 12 months of data were available for analysis in this pilot, but in some cases data was missing because it had not been received from the utility, wasn't available in the utility's online interface, or because account numbers or login credentials changed and we were unable to obtain updated utility information.

EnergyScoreCards considers a utility *account* 'valid' if it has a minimum of 235 days of bills (about 8 months), which allows an analysis of consumption across weather conditions. This rule does exclude bills that have been toggled off, as described above. To illustrate, in a case where an account has 240 days of bills for 2014, but one 30-day bill was toggled off, the account would not meet the 235-day minimum, disallowing analysis of that account, and that property, for 2014, and making it invalid for this evaluation. A *building* is considered 'valid' for analysis in a particular year if all owner-paid energy accounts are valid (i.e. have at least 235 days of data for analysis). Energy validity and water validity are calculated separately – many buildings in the pilot had complete analyzed energy data, but no water data (water data was not required as part of the pilot).

Buildings were removed from final analysis only if they were deemed invalid, meaning there were less than 235 days of bills for years 2012 or 2014 on any owner-paid energy account.

As an overview of data completeness, Table 2 and Table 3, below, show the number of buildings by number of months of complete data (i.e. months not missing any days of bills for any owner-paid accounts) for electricity and gas. Note that eight buildings in the pilot are all-electric, and have no gas service, which represents the difference in totals between the electric and gas tables.

[8] EnergyScoreCards can also calculate full building consumption for non-master-metered properties by combining analysis of owner and tenant accounts, though this evaluation is focused solely on owner-paid data since very little tenant data was obtained.

Buildings with complete owner electric data			
	In Calendar Year		
Months of Complete Data	2012	2013	2014
12	532	517	397
11	9	11	68
10	3	4	18
9	3	1	8
8	0	2	26
7 or fewer	14	26	44
Total	561	561	561

Table 2: Data Completeness for Owner Electric Accounts

Buildings with complete owner gas data			
	In Calendar Year		
Months of Complete Data	2012	2013	2014
12	534	510	386
11	9	6	74
10	4	5	25
9	0	1	14
8	1	2	3
7 or fewer	5	29	51
Total	553	553	553

Table 3: Data Completeness for Owner Gas Account

As illustrated here, about 70% of buildings have 12 complete months of data for both electricity and gas for all three years, and over 80% have at least 11 months of complete data for both utilities for all three years.

No outlier properties were removed from the analysis based on observed consumption, or any other reasons aside from the test of 'validity' (i.e. data completeness) described here.

In total, sixty-seven buildings (11.9%) did not have valid data for both 2012 and 2014 calendar years, thirty-six in the Control group and thirty-one in the Treatment group. These, and only these, were removed from analysis, leaving 494 properties for the evaluation as shown in Table 4.[9]

[9] The set of 67 buildings invalid for analysis includes any buildings with fewer than 235 days of bills for any account. This is approximated by those buildings with 7 or fewer months of data in 2012 or 2014 in Table 2 and Table 3, but the numbers can't be simply added due to incomplete overlap between the years and missing gas or electric data.

Group	Total Properties	Invalid for Analysis	Valid for Analysis
Control	275	36	239
Treatment	286	31	255
Total	561	67	494

Table 4: Property Validity in Both Groups

Building Indices

EnergyScoreCards uses these building-level consumption models to calculate performance indices that can be compared to peer buildings, and used to track changes over time at the same building. Five building consumption indices are used in this evaluation:

- **Owner Energy Index** (kBTU/Sq ft/year) which represents the total annual weather-normalized energy consumption on all owner-paid energy accounts divided by the total multifamily square footage (which includes common area and residential space).
- **Owner Heating Index** (BTU/Sq Ft/HDD) which represents the total weather-normalized heating consumption on all owner-paid accounts divided by the square footage of space being heated by owner-paid accounts and the HDD in a typical year. Note that heating index may contain both electricity and gas if both fuels are found to have some association with HDD.
- **Owner Electric Baseload Index** (kWh/unit/year) which represents the baseload (non-seasonal) electricity use (e.g. excluding any heating or cooling consumption) on all owner-paid accounts divided by the number of residential units.
- **Owner Fossil Fuel Baseload Index** (mmBTU/bedroom/year) which represents the baseload (non-seasonal) gas consumption (excluding heating and in rare cases cooling gas use) on all owner-paid accounts divided by the number of bedrooms.
- **Owner Water Index** (kGal/bedroom/day) which represents the daily average water consumption on all owner-paid accounts divided by the number of bedrooms.

All energy indices show *site* energy consumption.[10] Each index is calculated on an annual basis. The pilot was launched in October 2012 with outreach to the treatment group. Activity in October 2012 – January 2013 primarily included notifying applicants whether they would receive access immediately (treatment group), or after a 2 year waiting period (control group), and, for the treatment group, some early orientation activities. Access to the EnergyScoreCards tool and service for the treatment group started on October 19, 2012 and ended on October 31, 2014. During November 2014, control group members were contacted to begin access to the service. For the purposes of the evaluation, full calendar years were used (January 1 – December 31), with 2012 considered the baseline year, 2013 is Year 1, and 2014 is Year 2.

[10] Site energy and source energy are the two common ways of displaying energy consumption. Site energy represents the amount of energy consumed at a building, while source energy incorporates all raw fuel required to generate and deliver the energy required at a building; source energy factors in transmission, delivery, and production losses.

Fuel Indices

In addition to the indices calculated in EnergyScoreCards, this evaluation also used fuel indices, calculated by dividing total weather-normalized owner-paid fuel usage by the multifamily building square footage. This was performed for electricity and natural gas.

Statistical Analysis

In order to determine the impact of the pilot on energy and water consumption, building indices from EnergyScoreCards were exported from the tool for both the baseline year (2012) and Year 2 (2014), allowing a comparison of the changes over this time period across the control and treatment groups. Some additional analysis was performed comparing the baseline year (2012) to Year 1 of the pilot (2013), as will be discussed later.

As a first step in the statistical analysis, the final analyzable set of buildings in the control and treatment groups were compared to assess whether they were balanced on factors that might affect changes in consumption. Then, tests were run to determine differences between the change in energy and water use in the treatment and control groups. Analyses were conducted for the entire pilot group and for subgroups by metering configuration (who pays which end-uses in the building). Secondary analyses were performed on the energy end-uses (heating, electric baseload, fossil fuel baseload)[11], fuel indices, and other variables.

All statistical tests described below were run using Stata® IC Version 13, an industry-standard statistical software package. A complete set of tests and results from the Stata® analysis is available in Appendix C: Complete Statistical Analysis Results. The basic statistical tests used for the analysis are:

- Student's t test: this determines if two groups of data are significantly different from each other.
- Pearson's Chi-squared test: this, much like the t test, determines if groups are significantly different, and is used when variables are discrete, rather than continuous (a variable is grouped by buckets of values, rather than any value).
- Linear regression: this determines if one or more variables significantly contribute to an outcome.

Confirming Balanced Treatment and Control Groups

To confirm that the resulting groups were not biased with respect to any important variables, a series of Student's t tests for continuous variables and Pearson's Chi-squared tests for discrete variables were performed to test that the control and treatment groups remain balanced with respect to these characteristics after loss of some properties.

[11] Cooling was not analyzed as a separate end-use, as it was generally a very small portion of owner-paid energy usage at the properties in the pilot.

Student's t-tests (2-tailed) were performed on the building size, number of residential units, apartment size, year built, and initial Owner Energy Index (OEI). All of these tests returned a probability greater than 0.05, indicating that the final groups remain reasonably balanced on these characteristics. Of all of the above, the initial OEI was the closest to being significant, with the treatment group showing a mean starting OEI almost 5 kBTU/sqft/lower ($p = 0.08$). OEI is included as a covariate in the final regression analysis to account for this starting difference.

Pearson's Chi-squared test was performed on building height category, payment code (a code showing the building's metering configuration, i.e., whether the tenant or owner pays for energy for different end-uses), fuel code (a code showing what fuel is used for different end-uses), and whether the property received subsidies. Here the results were mixed. Payment code and fuel code are well distributed between control and treatment groups. However, the subsidized housing flag showed imbalance that was statistically significant, with the control group being more likely to contain subsidized housing. Subsidized housing was also included in the final regression analysis to account for this.

Finally, the Spearman Rank Correlation Coefficients for all of the above variables were calculated to determine which of the above potential covariates are correlated. The only strong correlation found was that Building Size (in square feet) was correlated with Number of Units, as would be expected. As a result, Number of Units is excluded from the final analysis.

Analyzing Changes in Energy and Water Consumption

To test the null hypothesis, and determine whether changes in energy and water usage were different for the treatment and control groups, the following tests were run on the change in energy performance indices between the two years:

- Initially, a simple t test was run on change in OEI across all buildings in the data set. This test does not give the correct p-value or confidence interval because it does not take into account the fact that the sample was randomized at a group or cluster level. It was run only to give a quick check of the differences.
- Multivariable linear regressions were run to determine the effect of treatment (included as a binary dummy variable), while controlling for differences in starting Owner Energy Index, building height category, building size, and the presence of subsidies. The regression model was beneficial for two main reasons:
    - This test could be used with a cluster-robust standard error calculation to account for the fact that the properties were randomized in groups (portfolios) and that there may be intra-group correlations. This way, 5 properties in the same portfolio aren't assumed to be completely independent of each other; the error calculation accounts for their being related.
    - This analysis also allowed the ability to add in control variables (to separate out non-program effects due to differences between the participant and control groups and provide more precise estimates of the treatment effect) and to examine some interaction effects in the secondary analysis.

Analysis by Metering Configuration Type

An important distinction to make in evaluating this dataset is that the energy change evaluated is based on the Owner Energy Index (OEI). Owner Energy Index is a metric used in EnergyScoreCards to provide owners and managers feedback on the parts of their buildings for which they pay utilities. This index can be calculated in the absence of tenant utility data, but of course only reflects a portion of the building's energy use for non-master-metered buildings.

When buildings have different metering configurations, the Owner Energy Indices are essentially different values from each other. Because the Owner Energy Index is the owner-paid portion of the building's energy use divided by square footage, the owner-paid portion of a master-metered building (the whole building) is fundamentally different from the owner-paid portion of an all tenant-paid-utilities building (where the OEI only includes utilities for the common area only). The values of the Owner Energy Indices, therefore, cannot be meaningfully compared across different metering configurations. For this reason, EnergyScoreCards keeps these peer groups separate for analytics, grading, and reporting, and the evaluation of impacts in EnergyScoreCards Minnesota is also broken out by metering types.

EnegyScoreCards uses a Payment Code[12] as a shorthand way to represent the metering configuration of the building, and metering structure is denoted by Payment Code in the EnergyScoreCards output, as well as the statistical analysis in Appendix C: Complete Statistical Analysis Results. Table 5 shows a breakdown of payment codes and the number of buildings included in the analysis for each type.

Payment code	Metering configuration	Number of Buildings
(O)OOO	Master-metered (fully owner-paid utilities)	85
(T)OOO	Tenant-paid in-unit electricity, Owner-paid cooling, heating, and hot water	9
(T)TOO	Tenant-paid in-unit electricity and cooling, owner-paid heat and hot water	348
(T)TTO	Tenant-paid in-unit electricity, cooling, and heating, owner-paid hot water	39
(T)TTT	Tenant-paid utilities, owner-paid common areas only	10
Other (e.g. (T)OTO)	Other metering configurations	3
	Total	494

Table 5: Buildings analyzed by metering configuration (payment code)

For each Payment Code, then, the null hypothesis was tested with a multivariable linear regression.

[12] The Payment Code uses T to denote tenant-paid utilities and O to denote owner-paid, in the following order: (in-unit electricity), cooling, heating, hot water.

Changes in water usage were also analyzed by Payment Code, using the same methods. While the water use index does in all cases represent whole building water consumption regardless of the Payment Code for energy utilities, differences in energy savings observed across Payment Code groups suggested that separating by Payment Code was warranted for water use comparisons as well, as described below.

Secondary Analyses

Multiple secondary analyses were also performed. Effects of the pilot on individual end-uses were analyzed (heating, baseload electricity, and baseload fossil fuel) in order to understand which parts of building energy use were impacted. This was performed with a multivariable linear regression for each end-use change (i.e. the end-use index in 2014 minus the end-use index in 2012) to determine the impact of the treatment.

Similarly, the fuel indices (electricity and natural gas) were analyzed to determine total savings for each type of utility. A multivariable linear regression was used to analyze change in fuel index (i.e. the fuel index in 2014 minus the fuel index in 2012) to determine the impact of the treatment.

Analysis of Year 1 Changes

Statistical tests resulting in significant findings for Year 2 of the pilot (comparing 2012 to 2014) were also run comparing the baseline year (2012) to Year 1 of the pilot (2013). The same methodology described in the previous sections was employed, with a goal of determining when changes took place – during the first or second year of the pilot period.

Conservation Improvement Program (CIP) Participation

Bright Power and program partners collected data on pilot group members' participation in utility rebate programs directly from the utilities for the years of the pilot, 2013 and 2014. Requests were made to Xcel Energy, CenterPoint Energy, Minnesota Energy Resources, Dakota Electric, Rochester Public Utilities, Owatonna Public Utilities, and Austin Utilities. Bright Power and partners sent the utilities requests, which included lists of account information gathered from all participants, so that utilities could share information on which of those participants obtained rebates during the pilot period.

Data received from the utilities included number of buildings in each group (treatment and control) that participated in a rebate program, deemed energy savings, and rebate amounts. Breakdowns showing which measures took place in which year and breakdowns of measure types by buildings were not provided by all utilities. Rebate data were not obtained for the baseline year.[13] Based on the buildings eligible for rebates (determined by which buildings had utility accounts in each region), the percentage of eligible buildings that participated was calculated separately for electric rebates and gas rebates.

[13] Because 2012 CIP program information was not collected, we cannot control for possible differences in program participation before the start of the program.

Electric and gas rebates were considered separately, and the following were calculated from the rebate data provided, for treatment group and control group each:

- Number of buildings eligible for rebates
- Number of buildings obtaining rebates
- Percent of eligible buildings that participated
- Average deemed savings per property

Known in-unit electric rebates received for properties where the owner does not pay for in-unit electricity were removed for the calculation of electric savings, so as to only look at savings on the meters for which savings were calculated.

From the remaining rebates, the percent of eligible treatment and control buildings that obtained rebates was compared. Where the difference in the percentages was significant (i.e. where the EnergyScoreCards service increased participation), the incremental treatment group savings was calculated as follows:

> Incremental Treatment Group Savings from rebates =
>
> ([% eligible treatment buildings receiving rebates] – [% eligible control buildings receiving rebates]) x (Number of buildings in treatment group) x (Average treatment group savings/building)

These savings due to the incremental increase in rebate program participation were achieved jointly by the EnergyScoreCards pilot and the rebate program. However, to avoid double-counting, such savings cannot be counted by both programs. Overall savings are shown both including and excluding these joint savings in the Results section below.

Analysis of Cost-Effectiveness

Two scenarios were used to estimate the cost-effectiveness of the EnergyScoreCards service as an approach to achieving energy and water savings based on these results. The scenarios each use the total cost savings from the pilot, after deducting savings jointly attributable to increased rebate program participation. Cost savings were calculated using the average rates for electricity, gas and water among pilot buildings. The cost of the service used in the two scenarios differs significantly:

- Scenario 1 uses the full costs of the EnergyScoreCards Minnesota pilot and compares this to the savings achieved during the two year pilot.
- Scenario 2 compares the costs and savings of the two-year EnergyScoreCards Minnesota pilot only for master-metered buildings and also extrapolates estimated costs and savings to a 10-year, master-metered-only program.

Results

Energy and Water Savings

The results of tests to quantify the effect of the EnergyScoreCards service (the treatment) on energy and water consumption are described below. Except where specifically discussing Year 1 Results, the results described in this section represent the annual savings level reached in the second year of the service as compared to the year prior to participants using the EnergyScoreCards service, i.e., the difference between 2014 and 2012 consumption.

Overall Energy and Water Savings

Across the entire population of buildings, the EnergyScoreCards service (the treatment) did not produce statistically significant savings over the two years compared to the control group. Figure 2 shows the overall change in Owner Energy Index for the treatment and control groups.

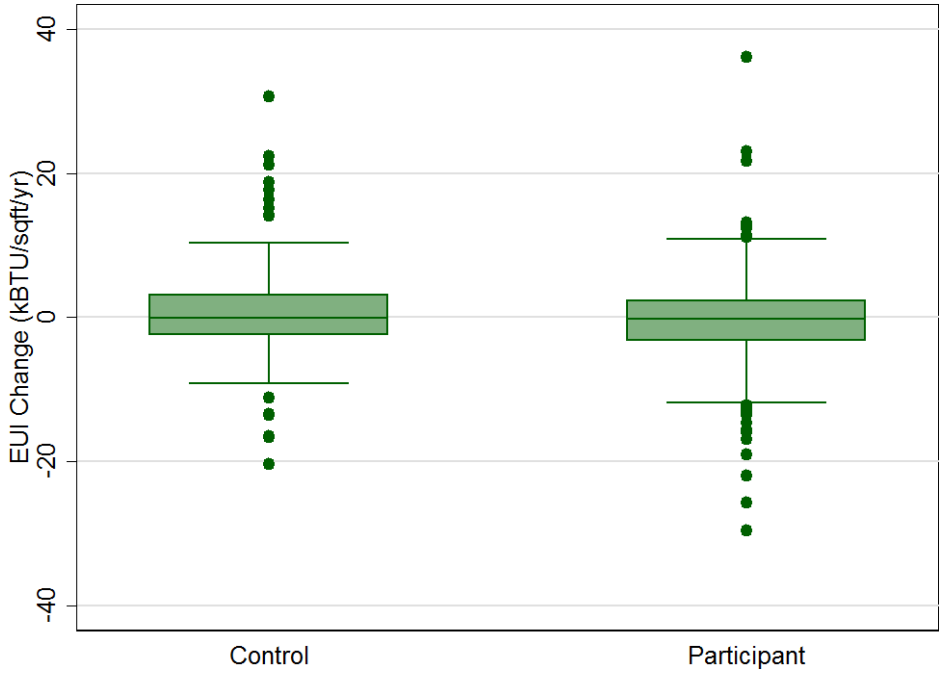


Figure 2: Overall change in Owner Energy Index

When buildings were analyzed separately based on metering configuration, however, master-metered treatment group buildings showed a statistically significant savings over master-metered control group buildings in change in the Owner Energy Index from prior to the project to the second year. The savings (4.49 kBTU/sqft/yr) represents roughly a 5% energy use

reduction for a typical master-metered multifamily building in Minnesota.[14] Master-metered buildings represent 17% of analyzed buildings, and other metering types, when analyzed separately, did not show significant changes. A summary of these findings is shown in Table 6 below.

Metering Configuration	**Number of buildings** (treatment/ control)	**Savings Impact** (kBTU/sqft/yr)	**P value**
Master-metered	85 (45/40)	4.49	0.007
Central heat and hot water	347 (177/170)	0.38	0.715
Central hot water only	39 (19/20)	0.06	0.978

Table 6: Owner Energy Change for the Three Most Common Metering Configurations

Figure 3 shows a box and whisker plot[15] with a much more visible change on the master-metered properties – designated (O)OOO. The (T)TOO designation is for properties with central heat and hot water and tenant paid cooling and apartment electricity, which has no statistically significant change.

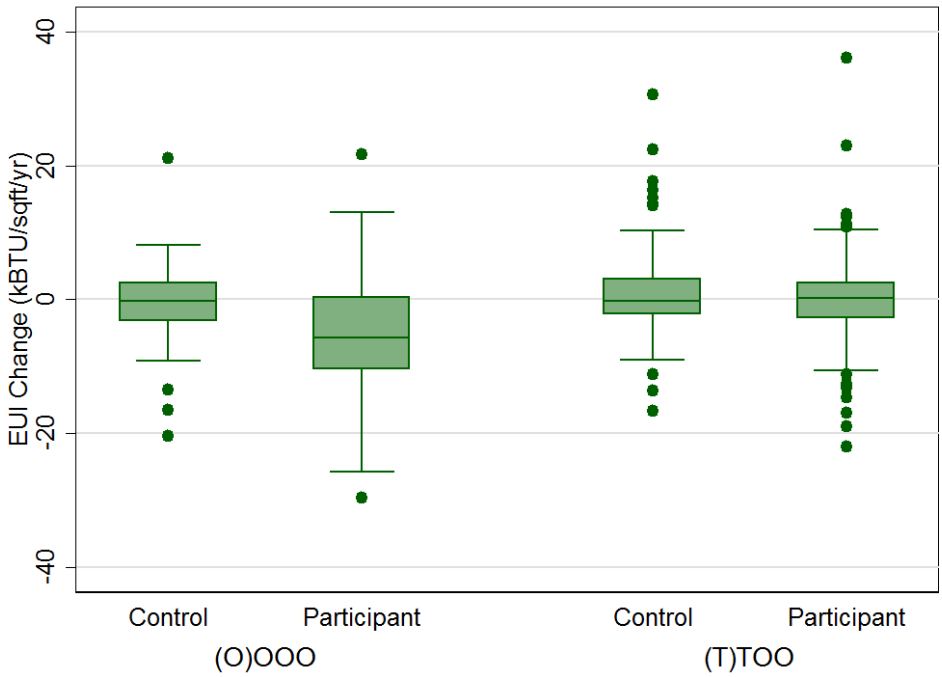


Figure 3: Owner Energy Index Change by Payment Code

When all participant properties are analyzed together, there is no significant reduction in water consumption; Figure 4 shows the Water Index Change for the control and treatment groups.

[14] 5% energy savings for a typical Minnesota multifamily building is estimated by dividing the EUI savings (4.49 kBTU/sqft/year) by the median EUI for master-metered Minnesota buildings in EnergyScoreCards (81 kBTU/sqft/year).

[15] Each box plotted shows the first and third quartile values (top and bottom of the box), with the median line marked. Dots above and below the 'whiskers' show outliers falling outside the adjacent value, which is the last point within 1.5 times the interquartile range.

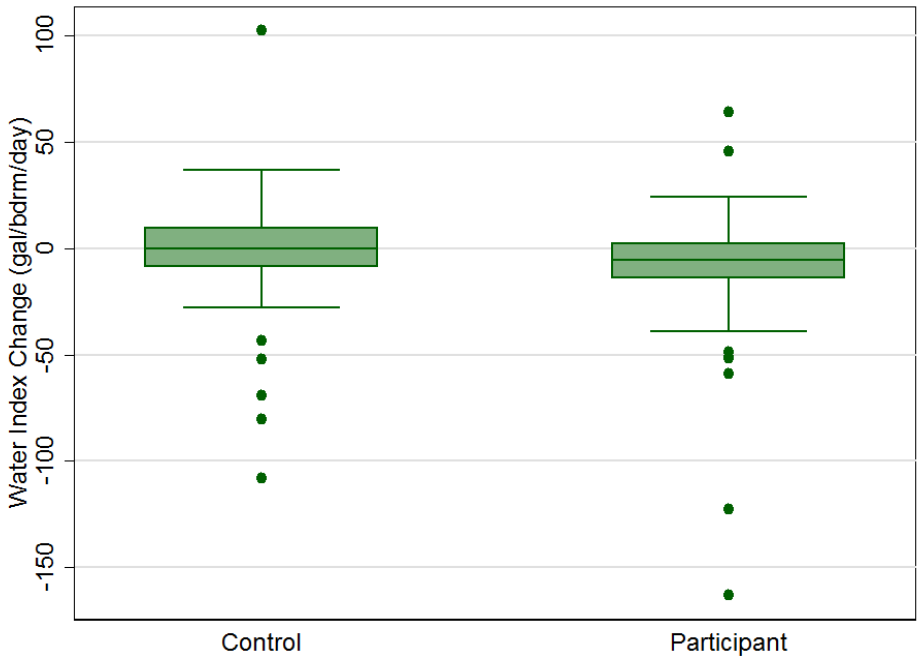


Figure 4: Overall Water Index Change

However, when analyzing the 50 master-metered properties with complete water data, the treatment group has significant savings of 24 ± 9 gallons per bedroom per day compared with the control group (P=0.013), roughly 30% savings for a typical Minnesota multifamily building.[16] Non-master-metered properties do not show a significant difference. Figure 5 shows the Water Index change for master-metered buildings, (O)OOO and central heat and hot water buildings, (T)TOO.

[16] 30% water savings for a typical Minnesota multifamily building is estimated by dividing the water index savings (24 gal/bedroom/day) by the median water index for Minnesota buildings in EnergyScoreCards with family occupancy (74 gal/bedroom/day).

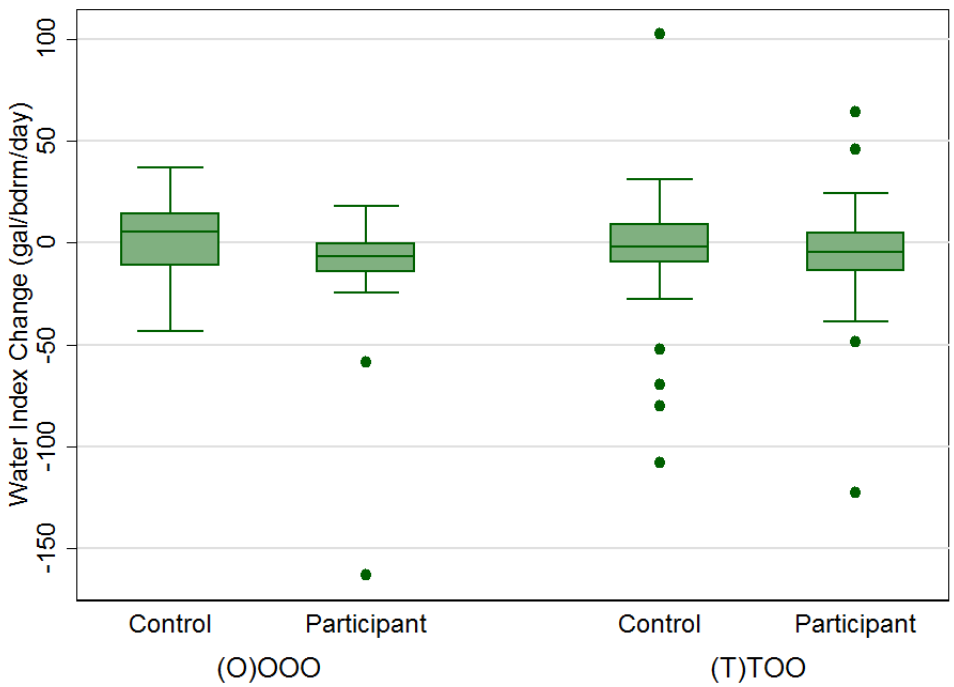


Figure 5: Water Index Change for Master-Metered and Central Heat and Hot Water Buildings

Table 7 shows the water savings impact of the treatment (the EnergyScoreCards service) for the three most common metering configurations in the data set. As shown in this Table, only master-metered buildings have a statistically significant water change ($p<0.05$), and a large savings.

Metering Configuration	**Number of buildings** (treatment/ control)	**Savings Impact** (gal/bdrm/day)	**P value**
Master-metered	50 (30/20)	23.9	0.013
Central heat and hot water	121 (74/47)	4.5	0.432
Central hot water	12 (4/8)	0.7	0.918

Table 7: Water Change for the Three Most Common Metering Configurations

Energy Savings by End-Use and Fuel

Master-metered buildings showed statistically significant heating savings of 0.48 ± 0.17 BTU/sqft/HDD from prior to the project to the second year, roughly a 9% reduction in heating for a typical Minnesota multifamily building.[17] This represents 82% of the overall observed energy savings, 3.7 kBTU/sqft out of a total observed savings of 4.5 kBTU/sqft. Non-master-metered buildings did not show significant heating savings, even though in the largest of these groups ((T)TOO) the owner does pay for heat. Figure 6 shows the change in Heating Index of

[17] 9% heating savings for a typical Minnesota building is estimated by dividing the heating savings (0.48 BTU/sqft/HDD) by the median heating index for Minnesota buildings in EnergyScoreCards (5.1 BTU/sqft/HDD).

control and treatment groups for master-metered properties and properties with central heat and hot water but tenant paid cooling and apartment electricity ((T)TOO).

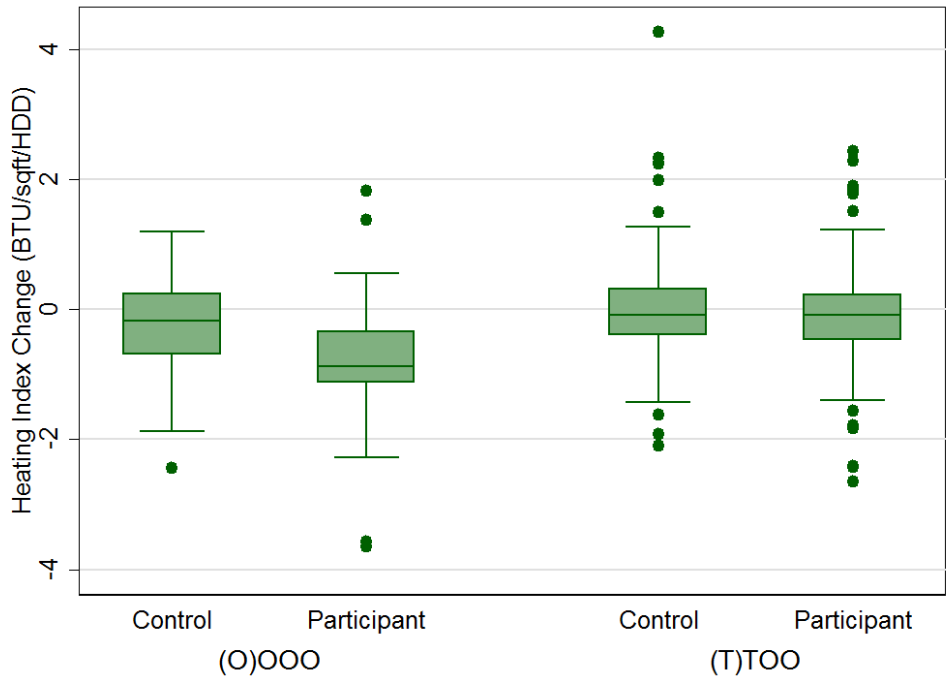


Figure 6: Heating Index Change by Payment Code

Table 8 shows the change on heating for the most common metering configurations, with only master-metered buildings showing a statistically significant change.

Metering Type	**Number of properties** (treatment/ control)	**Savings Impact (BTU/sqft/HDD)**	**P value**
Master-metered	85 (45/40)	0.48	0.006
Central heat and hot water	347 (177/170)	0.14	0.246
Central hot water	39 (19/20)	-1.21	0.622

Table 8: Heat Index Change for Three Most Common Metering Types

Neither baseload electricity nor baseload fossil fuel showed a significant difference between treatment and control groups, whether analyzed across the entire data set or separately by metering group. Figure 7 shows change in Electric Baseload Index between control and treatment groups for the two most common metering configurations – master-metered and central heat and hot water. Figure 8 shows the same for change in Fossil Fuel Baseload Index.

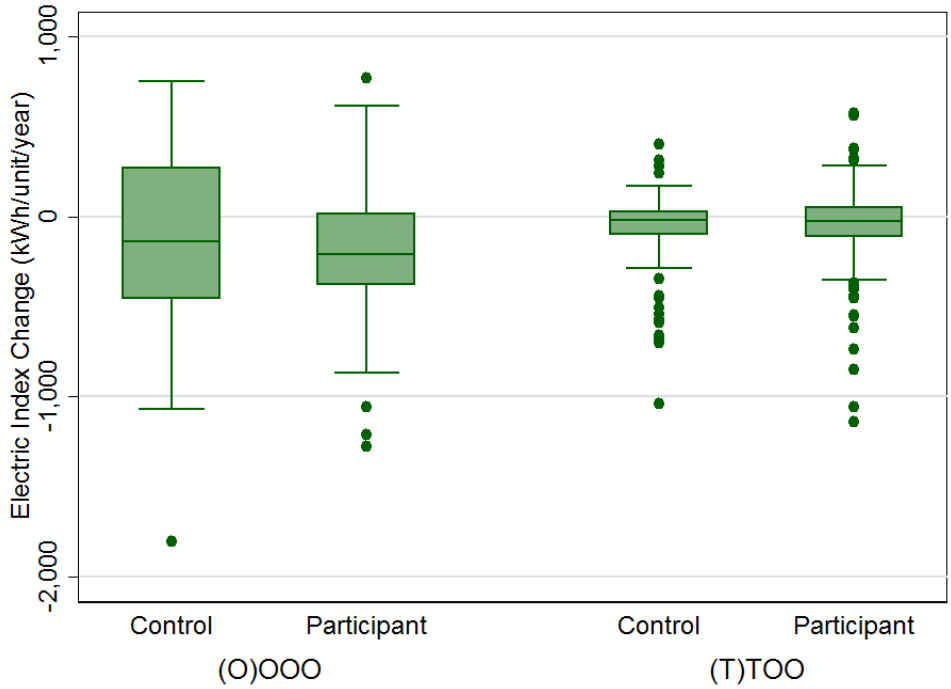


Figure 7: Electric Baseload Index Change by Payment Code

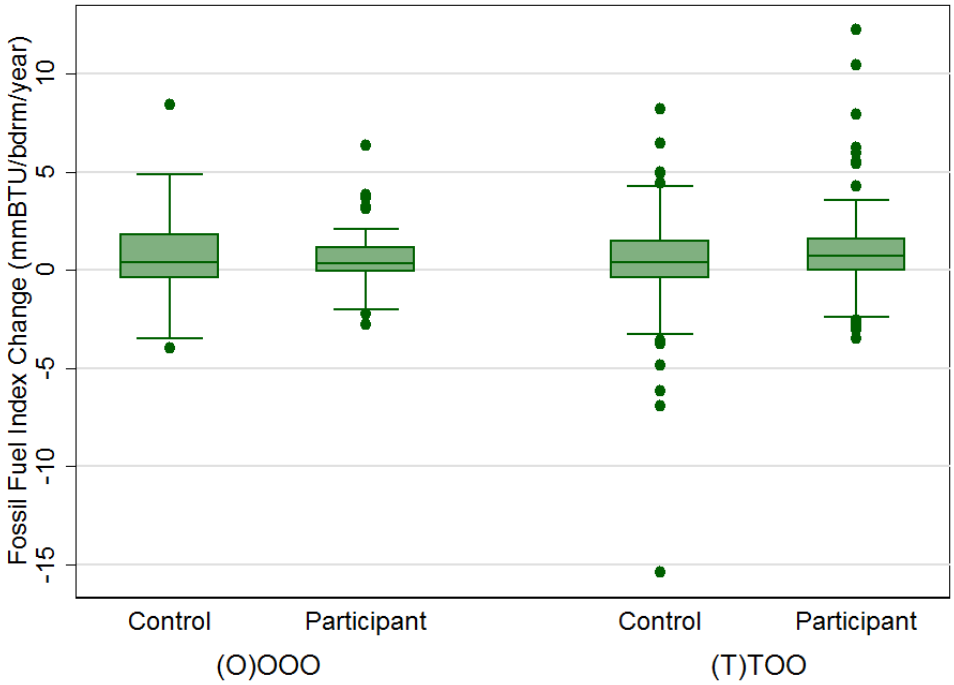


Figure 8: Fossil Fuel Baseload Index Change by Payment Code

Additional regressions were run to calculate the savings by fuel for electricity and gas in the master-metered buildings only. Results from the regressions of the calculated electricity and natural gas indices (per square foot) are shown in Table 9.

Fuel Index	Savings Impact	P Value
Electricity/sqft	0.27 kWh/sqft	0.028
Natural gas/sqft	0.035 therm/sqft	0.018

Table 9: Fuel Index Savings for Master-Metered Buildings

Calculating Total Energy and Water Savings

Electricity and gas savings were derived for master-metered buildings by applying the fuel index savings reported in Table 9 to the total square footage of the master-metered buildings in the treatment group. Water savings was calculated by applying the Water Index savings (see Table 7 above) to the total number of bedrooms in the master-metered buildings in the treatment group. Costs savings are calculated using average utility rates of pilot participants ($0.13/kWh for electricity, $0.87/therm for natural gas, and $9.10/kGal for combined water and sewer charges). Although 45 master-metered buildings in the treatment group were analyzed, only 30 of those buildings tracked water usage during the pilot.

Fuel	Number of buildings	Total Year 2 Savings	Total Year 2 Cost Savings
Electricity	45	443,780 kWh	$57,691
Natural Gas	45	57,289 therms	$49,841
Water	30	18,820 kGal	$171,262

Table 10: Total Year 2 Fuel Savings

Table 11 shows the average cost savings achieved per building for master-metered buildings, over $8,000 in average annual savings per building.

Fuel	Year 2 Savings per Building	Year 2 Cost Savings per Building
Electricity	9,862 kWh	$1,282
Natural Gas	1,273 therms	$1,108
Water	627 kGal	$5,708
Total		$8,098

Table 11: Total per Building Savings for Master-Metered Buildings

Year 1 Results

The results described above represent the annual savings level reached in the second year of the service, i.e., the difference between 2014 and 2012 consumption. At the end of Year 1 (2013), the magnitude of the difference between treatment and control group was similar to that after Year 2 (2014), but the variability across buildings was much larger, so the results were only marginally significant for change in Owner Energy Index and heating for master-metered buildings; change in water index was not significant in the first year. By the second year (2014) the effect was more consistent across the master-metered treatment group, and pilot results for that group become statistically significant. Year 1 results for the master-metered buildings are shown in Table 12, along with results after Year 2, for comparison.

Index	Timeframe	Savings Impact	P Value
Owner Energy Index	2012 vs. 2013	4.13 kBTU/sqft/yr	0.072
	2012 vs. 2014	4.49 kBTU/sqft/yr	0.007
Heating Index	2012 vs. 2013	0.35 BTU/HDD/sqft	0.078
	2012 vs. 2014	0.48 BTU/HDD/sqft	0.006
Water Index	2012 vs. 2013	8.4 gal/bdrm/day	0.172
	2012 vs. 2014	23.9 gal/bdrm/day	0.013

Table 12: Year 1 and Year 2 Results for Master-Metered ((O)OOO) Buildings

Conservation Improvement Program Participation by Treatment and Control Group

Xcel Energy, Dakota Electric, Minnesota Energy Resources, and CenterPoint Energy provided data about participation in utility programs during the 2-year pilot period for buildings in their respective service territories that were in the pilot.[18] Analysis of this data shows that 10% of eligible properties in the control group participated in electric rebate programs during the pilot period, while 19% of treatment group properties participated. This is a statistically significant difference, indicating that the EnergyScoreCards service nearly doubled participation in those programs. For gas rebate programs, no statistically significant difference was found between participation by the treatment and control groups, with both groups showing participation rates of 29%.[19]

Overall, these results suggest that the EnergyScoreCards service can be viewed as a tool to increase program participation – at least for electric measures. Because all utilities did not provide participation data at the building level, we were not able to look at differences in participation rates by metering type.

Table 13, below, shows the number of participant and control group buildings receiving rebates for gas and electricity measures during the program period based on records received, and the gross and per building annual deemed savings from these measures.

[18] Data from the Triad utilities (Rochester, Austin and Owatonna utilities) were requested by not received in time for this evaluation.

[19] An additional analysis could have gathered rebate information for the year before the pilot as well, to compute and compare the change in participation over time for the two groups, analogous to the change in energy use over time. Data on rebates for the year before the program was not collected.

Fuel	Group	Buildings Eligible	Buildings Participated	Percent Participated	Deemed Savings	Average Deemed Savings per Building	Units
Electricity	Treatment	262	50	19.1%	914,803	18,296	kWh
	Control	243	25	10.3%	475,476	19,019	
Gas	Treatment	271	81	29.9%	112,066	1,384	therms
	Control	260	74	28.5%	182,695	2,469	

Table 13: Rebate Program Participation and Savings

Accounting for Rebates in Savings Estimates

In order to estimate the energy savings due solely to the EnergyScoreCards service we discounted the derived energy savings to account for savings associated with participation in utility rebate programs. Three assumptions led to a conservative estimate of savings due to the EnergyScoreCards service:

- The annual deemed savings provided to us by utilities was assumed to be actually experienced by the buildings during the second year of the pilot.
- The deemed savings from rebates information available reflected aggregate energy savings for all treatment group participants. Since not enough information was provided to tally building specific rebate participation, it was assumed that master-metered buildings received rebates at the save rate seen across the whole treatment group (e.g. 19% in the second year of the pilot program).
- 100% of the joint rebate/EnergyScoreCards savings was subtracted, giving the rebate programs full credit although EnergyScoreCards appears to have played a role in driving increased rebate participation.

Table 14 shows the calculated incremental electricity savings (72,419 kWh/yr) due to increased uptake of rebates by the master-metered treatment group, based on the increased participation and the average deemed savings from the programs. This amount reflects 16% of the total observed Year 2 electricity savings of 443,780 kWh reported in Table 10.

Master-metered buildings in Treatment Group	45
Incremental increase in participation (# bldgs)	4
Average deemed savings per building (kWh)	18,296
Incremental savings (kWh)[20]	72,419

Table 14: Electric Rebate Incremental Savings

After calculating the incremental savings attributable to the utility rebate programs, the EnergyScoreCards-only savings were calculated by subtracting the incremental deemed savings

[20] Numbers in the table are rounded to the nearest whole number, which is why the multiplication of numbers shown will not result in the exact incremental savings shown.

(Table 14) from the savings due to the treatment (Table 13), as shown in Table 15 below. Because there was no statistically significant increase in participation in gas rebate programs for the treatment group, no gas savings were deducted.

Fuel	Total Year 2 Savings	Estimated Year 2 Savings from increased rebate participation	Year 2 Savings due to EnergyScoreCards Only
Electricity	443,780 kWh	72,419 kWh	371,361 kWh
Natural Gas	57,289 therms	0 therms	57,289 therms

Table 15: Savings on Master-Metered Buildings after Deducting Joint ESC-CIP Rebate Savings

This results in a new per building cost savings for the EnergyScoreCards service alone, net of any rebate programs, shown in Table 16. These savings, net of rebate deemed savings, are used in the cost-effectiveness section below.

Fuel	Year 2 Savings per Building	Year 2 Cost Savings per Building
Electricity	8,252 kWh	$1,073
Gas	1,273 therms	$1,108
Water[21]	627 kGal	$5,708
Total		$7,889

Table 16: Savings per Master-Metered Buildings after Deducting Joint ESC-CIP Rebate Savings

Actions Taken by Treatment and Control Group

Building owners may take actions to save energy and water independent of rebates, either for measures not covered by rebates, or because they did not know or take the time to access rebates. Data on actions taken by the treatment and control groups were collected in two ways, but proved difficult to attain. The data collected do not show any clear overall differences between treatment and control groups. However, we believe these data are insufficient to draw a firm conclusion on possible impacts in this area, both because limited data was collected from the control group, and because treatment group data appears inconsistent and likely incomplete.

In this pilot, Account Managers worked with treatment group participants and asked about projects completed and work performed, on multiple occasions. Participants were encouraged to enter this information into the "Energy Events" feature of the tool, or provide it over the phone or by email to Account Managers. Providing this information, however, was not a requirement, and information and details were never provided throughout the duration of the pilot for many participants. In total, among the 286 buildings in the treatment group, only 71 tracked any activities using this feature. In many cases properties saw significant usage changes

[21] There are not water utility rebate programs for the City of Minneapolis or Saint Paul water, which represents the vast majority of water data available in the pilot, so the observed water savings are not discounted by any rebates.

most likely associated with energy upgrades, but did not provide information on what actions were taken.

As an example, two graphs from EnergyScoreCards are shown below – both are from treatment group buildings, both showing gas accounts with a significant reduction in consumption. In these graphs, the black line shows actual usage, and the green line shows modeled usage based on the consumption in 2012 adjusted to historical weather in each month. When the black line is below the green line after 2012, this shows that actual usage was less than historical usage, based on 2012 consumption levels adjusted to current weather. Both graphs show similar reduction in consumption, but in one case the participant entered an Energy Event into EnergyScoreCards (marked by a red dot in Figure 9), and in the other case, they did not (Figure 10 shows no Energy Event dot).

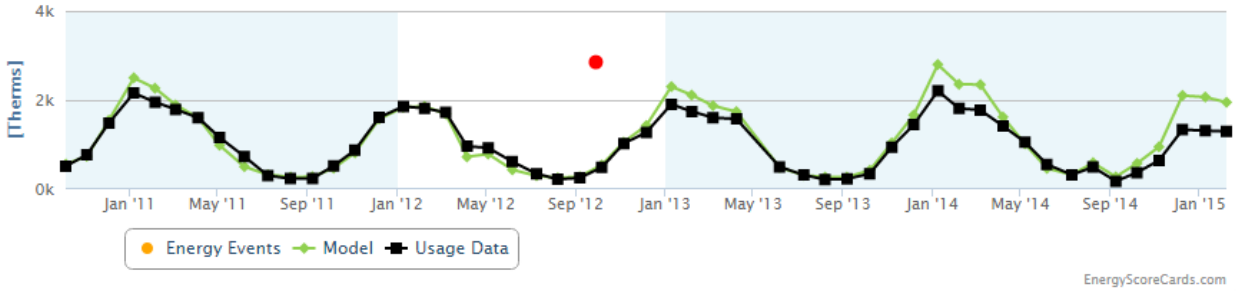


Figure 9: Gas consumption history showing savings and Energy Event tracked (red dot)

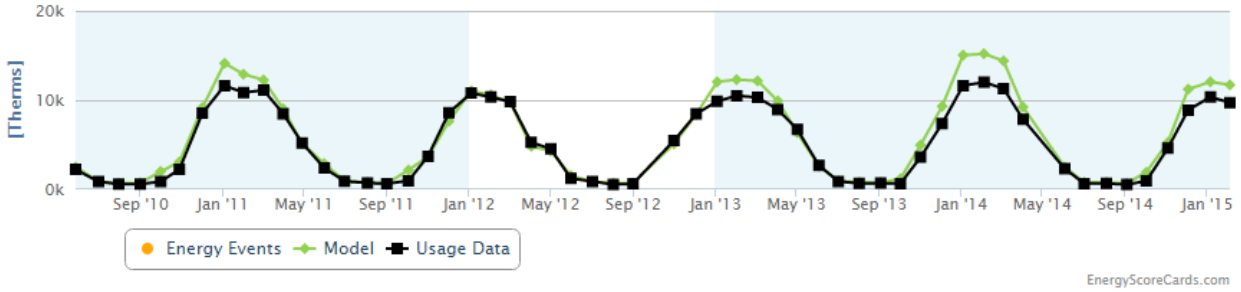


Figure 10: Gas consumption history showing savings with no Energy Event tracked

Information on conservation actions proved even more difficult to retrieve from the control group members, who received communication from Bright Power staff in November 2014 and were given access to the tool after the pilot period concluded, after two years of no contact. The priority at the time was to re-engage these organizations and fill in gaps in utility data for use in the impact evaluation, rather than to concentrate on data associated with conservation actions. No usable information on conservation actions was received from control group contacts at this time.

Finally, the Process Evaluation survey conducted by Center for Energy and Environment included a survey portion for both groups. The survey included questions about actions taken. However, it's unknown how aware survey respondents were of conservation actions taken. Multifamily building are managed and operated by teams of people including maintenance staff, property managers, asset managers, directors, etc., and the level of record-keeping and internal communication of building issues and activities varies significantly between

organizations. That is, it would be a mistake to assume that the survey respondent (which included all of the roles listed above) was fully aware of all activities taking place at the property. Additionally, multiple contacts at some organizations were surveyed, meaning that there is not a one-to-one correspondence between 'participants' as defined throughout the impact evaluation and survey *respondents*.

The data that was collected through this survey does not show many clear differences[22] between the treatment and control group, as shown in Figure 11 below.

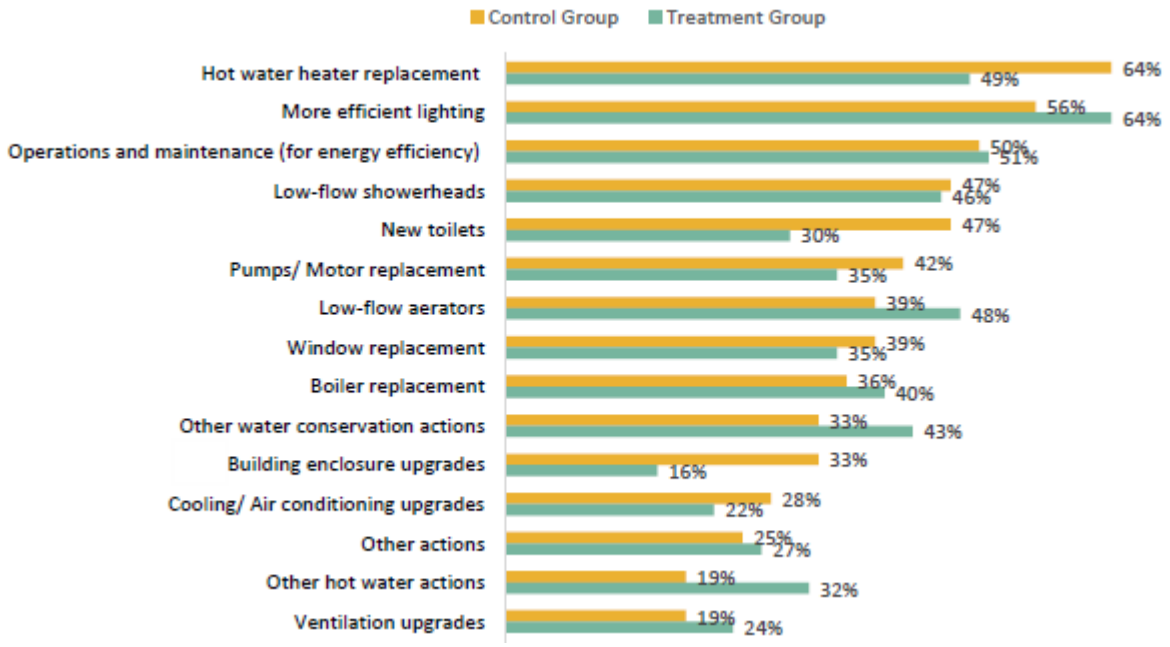


Figure 11: Percent of respondents reporting actions taken by building system in the Process Evaluation Survey

(See the Process Evaluation report for a full description of other information collected in the survey).

The challenges faced here in collecting data on actions taken echo Bright Power's experience with EnergyScoreCards clients outside of the pilot. Many organizations lack good records of building improvements, even significant equipment changes. When they do exist, records can still be difficult to acquire. From many building owners' perspective, compiling this information is not a priority.

In order to better analyze differences in conservation actions taken, a concerted effort would be needed to identify key personnel with information about actions taken, and have scheduled, thorough interviews to review and discuss actions taken at their buildings, and potentially verify changes through collection of contracts or other documentation.

[22] The difference between treatment and control group for building enclosure upgrades is the only statistically significant difference represented.

Cost-Effectiveness

For this impact evaluation, we assess cost-effectiveness of the EnergyScoreCards service as a strategy to drive energy and water savings under two scenarios, described below. Each scenario uses the same savings observed here in the pilot, but with varying costs, depending on the intent of the scenario.

Scenario 1: Gross costs and savings from EnergyScoreCards Minnesota program

The simplest way to assess the cost-effectiveness of energy and water savings from the EnergyScoreCards Minnesota program is to compare the total budget for the project to the value of achieved energy and water savings documented over the course of the program. Because statistically significant savings were only observed in master-metered properties, only these savings are used in this calculation, although costs reflect the entire program. Table 17 shows the total budget for the project alongside the total second year savings (because statistical significance was only reached in the second year) for the treatment group, after deducting savings jointly attributable to rebate programs.

Fuel	Total Year 2 Savings	Total Year 2 Cost Savings	Total program costs
Electricity	371,361 kWh	$48,277	
Natural Gas	57,289 therms	$49,841	
Water	18,820 kGal	$171,262	
Total		$269,380	$728,940

Table 17: Gross Program Costs and Savings

As shown here, the cost of the program exceeded the value of these savings by a factor of 2.7, not surprising given that savings are only claimed of a subset (17%) of buildings and that many additional costs not directly related to services for these buildings are included.

Scenario 2: Costs and savings for master-metered buildings only

The second scenario compares the actual program savings (only observed for master-metered buildings) to the pilot costs for master-meter buildings only. This is done by simply multiplying the total program costs, $728,940, by the portion of the buildings that were master-metered (in both treatment and control groups), approximately 17%. In this scenario, the cost for the master-metered buildings is $125,425, and the savings is $269,380, yielding $2.15/year of average savings from each $1/year spent on the service. This shows the potential cost-effectiveness of a similar two-year program targeted only at master-metered buildings.

To extrapolate this scenario a step further, the following illustrates a long-term program targeting master-metered buildings. It's important to point out that some program costs are one-time, while others are annual recurring costs. Table 18 divides the budget for the EnergyScoreCards Minnesota program between one-time and recurring.

Type	Task	Total Cost	Cost per Building
One-time	Recruitment, start-up, and launch	$215,160	$436
	Evaluation, final reports	$133,080	$270
Annual recurring[23]	Service for treatment and control groups[24]	$174,950	$354[25]
	Program reporting	$15,400	$31

Table 18: One-time and Ongoing Pilot Costs

In the case of a long-term, ten year program, one-time costs will occur once, and recurring costs will occur for each of the ten years. In this hypothetical all participants are master-metered buildings and savings are assumed to start in the second year at the level observed in the pilot and then continue in each remaining year at the same level. Over a ten year program for master-metered buildings, overall costs are estimated at $2,251,652, while savings would be $17,537,247 – a savings of $7.79 for every $1 spent.

[23] These costs are actual 2-year pilot costs divided by two to get annual costs

[24] Along with service costs for buildings receiving the service, these costs include ongoing data collection for a control group of equal size to allow an ongoing comparison set. In designing a long-term program, other approaches to reporting might be considered, but the approach used here is extrapolated without modification.

[25] $354/building/year represents the actual service costs in this program, but costs for EnergyScoreCards or similar benchmarking services may vary depending on the context. For instance, the cost for the EnergyScoreCards service when offered to individual buildings outside of a program is generally closer to $500/building/year. Per building service costs might be substantially *lower* in a large utility scale deployment of EnergyScoreCards.

Discussion

The observed impacts of the EnergyScoreCards service in this pilot provide some support for the notion that feedback on energy and water consumption – benchmarking – combined with account manager services can spur energy and water savings for multifamily buildings, an effect that has only been documented previously in other building types. These results also raise questions and suggest areas for further research.

The Impact of Metering Configuration on Results

Why did master-metered properties save more than properties with other metering configurations (including those with master-metered heat and hot water)? Although this study was not designed to answer this question, possible mechanisms can be explored to explain the apparent difference in the effectiveness of the treatment across buildings with different metering arrangements.

Because this study only looked at owner-paid energy and water consumption, the lack of direct financial incentive for owners of non-master-metered properties to reduce apartment energy usage cannot explain the result in a straightforward way. (If this study looked at full building consumption, master-metered building owners would be expected to have a much greater incentive to save, given that other owners do not pay for apartment energy use.)

It is reasonable to assume, however, that energy and water costs represent a *higher percent of overall building operating expenses at master-metered buildings*. Owners of master-metered properties thus may have a stronger motivation to focus on controlling utility costs as opposed to other areas of cost management. For organizations with limited staff time, this may have led to an increased focus on energy and water improvements at master-metered properties. Future studies could seek to study this hypothesis directly by tracking overall operating expenses at buildings.

The psychological impact on owners of non-master-metered properties of knowing that tenants are responsible for a portion of utilities may also play a role. Some owners may feel that they have little control, responsibility, or potential impact on building energy use because tenants pay their own bills. In fact, the difference between per unit owner energy spending between master-metered and other building types in this study suggests that tenants pay only 30-40% of energy costs at buildings with central heat and hot water but tenant paid in-unit electricity. This ratio is likely not known by most owners, however. Owners of master-metered properties may have a greater sense of responsibility and agency to manage energy and water because they know they are responsible for full building consumption.

Other possible explanations might include greater staff capacity at organizations with master-metered properties, or an association of metering configuration with other building characteristics not tracked in this study, but related to increased responsiveness to the benchmarking service. Future studies might focus solely on certain metering groups (e.g. only those with owner paid heat and hot water) in order to optimize the service for that type.

Sample Size and Study Duration

Through the analysis of Owner Energy Index change in the pilot, it is now possible to calculate the sample size needed to detect the level of savings observed across the entire population of buildings. A savings of 1.3 kBTU/sqft/year was observed across the entire treatment group in comparison to the control group, though this was not found to be statistically significant in the two year pilot ($p = 0.127$). Given the level of variance in the data set, observing a statistically significant change of this magnitude would require 359 buildings in a data set randomized at the building level. If the data set was clustered in portfolios, as it was for this pilot, 790 buildings, in at least 158 portfolios, would be required to detect the 1.3 kBTU/sqft/year shift at a significant level – more than 100% larger than our data set. Future studies should use a sample of at least this size to increase the chances that a small effect would be measurable.

The issue of sample size could also explain the lack of observable effect on baseload electricity in any group. Because electricity is used in buildings for many different purposes (where gas is typically used primarily for heat and hot water), electric data tends to be noisier, and the correlation with weather weaker. The types of measures which are typically spurred by receiving a high electricity index in a multifamily building also tend to produce modest savings (e.g. common area lighting retrofits), whereas some low-cost heating controls measures could produce significant heating savings in an overheated building.

It may also take more time (e.g. three or more years of benchmarking) to produce consistent savings in other metering groups. Even in the master-metered set, the variance in results was too high after one year of service for the savings to show statistical significance. In the case of water, it appears significant action was taken late in the first year or early in the second, as the vast majority of water savings only appeared in the second year. Owners of non-master-metered properties might take longer to respond to feedback, or prioritize master-metered properties first before addressing others. The process of making upgrades often includes budgeting for improvements, engaging staff across an organization, engaging with a program or third-party contractor, etc. Anecdotal reports from some participants suggest that feedback was incorporated into longer-term plans for portfolio upgrades, even if actions were not taken during the two year pilot.

A future study that focused on understanding the timeline for owners in taking energy savings activities based on benchmarking feedback might provide insight into how savings would change in a larger program, or how to accelerate results.

How Does Benchmarking Service Save Energy and Water?

Exposure to feedback on building performance and the associated support services produces energy and water savings indirectly. It depends on a building owner first receiving feedback or advice and then making a physical change to the building. This change may be capital or operational, but often involves several steps that require time, knowledge, and often, money on the part of the owner.

Achieving measurable savings through a program like EnergyScoreCards Minnesota thus depends on a number of factors, including:

- Correctly identifying specific energy- or water-saving measures. EnergyScoreCards' feedback is generally at the system level (e.g. high heating consumption) but does not pinpoint specific pieces of equipment that need an upgrade.
- The time it takes to implement energy and water savings measures after receiving feedback.
- The technical capabilities of building owner (or vendors and programs available to the owner) to complete energy and water savings actions.
- The available budget or incentives to fund energy and water savings actions on the part of owners.
- The quality of the feedback provided, both in terms of the tool and account management support.

None of the factors listed above were tested by the EnergyScoreCards Minnesota pilot. That is, we had only one treatment group, with equal access to the service, programs, and time. Further studies would be needed to see, for instance, if results might change over a 3 year engagement, with a different set of online tools and information, through different types of human support for participants, or through pairing with other financial incentives or technical assistance.

How Does the Benchmarking Service Compare to Other Energy- and Water-Savings Activities?

Benchmarking with engagement and account manager assistance services are fundamentally different from other energy and water savings activities (e.g. upgrading equipment) in that it is a recurring, ongoing practice that drives changes through greater attention to consumption and spending. Bright Power's experience tracking multifamily portfolios over more than 5 years suggests that the long-term benefits of benchmarking require long-term tracking. That is, maintaining (and possibly increasing) the savings achieved during the first two years of a benchmarking engagement requires that buildings continue to benchmark forever. In fact, Bright Power's experience has shown that savings from capital improvements also do not persist in the long-run without ongoing tracking. Building energy and water use, if unwatched, tends to gradually creep up over time as systems age and fall out of optimal operation.

Owners and property managers generally choose to adopt benchmarking (and pay for services such as EnergyScoreCards) for reasons other than direct energy and water savings. These include organizational planning, centralizing information, simplifying internal and external reporting, identifying energy and water problems, tracking project success and as a tool to guide long-term energy and water strategy.

For these reasons, Bright Power recommends that a multifamily energy benchmarking service be viewed as a critical best practice in building energy and water management *alongside* rebates, direct install, and one-stop-shop programs, independently pursued upgrades, or other activities. Long-term tracking supports and strengthens other approaches to energy and water savings, and utilities and governments can see long-term benefits in encouraging and supporting this practice throughout the building sector. The uptick in electric rebate participation seen in this study hints at the potential to use benchmarking and engagement and assistance services as a way to increase demand for other energy programs, as well as to deepen savings

Appendix A: Property Survey

EnergyScoreCards Minnesota

Property Survey

Please complete one survey file for each property - be sure to complete both "**Start**" and "**Accounts**" tabs. Once completed, email the Excel-format file to minnesota@energyscorecards.com with a completed "EnergyScoreCards Minnesota Participant Agreement" form. Survey and agreement are available for download at www.energyscorecardsmn.com.

Green fields are required

Yellow fields are optional

Property Name	
Property ID (e.g. MyPortfolio-016)	
Property Owner Name	
Address	
City	
State	
Zip Code	
Primary Contact	
Phone	
Email	
Building Type	
# of Floors	
# of Buildings	
Total Square Feet	
Non-Residential Square Feet	
Year Built	
Occupancy Type	
Primary Rent Category	
--What percentage of units are affordable?	

# of Residents	
# of Units	
# of Bedrooms	
# of Units with in-unit laundry	
# of Common Area Laundry Hook-ups	
# of Units with a Dishwasher	
% of Area Heated	
% of Area Cooled	
Tenant Cooling Fuel	
Tenant Heating Fuel	
Tenant Hot Water Fuel	
Who Pays Tenant Electricity?	
Who Pays Tenant Cooling?	
Who Pays Tenant Heating?	
Who Pays Tenant Hot Water?	
Custom Fields	
Property Manager Name/ Contact	
# of Occupied Units	
Primary Housing Subsidy Type	
Secondary Housing Subsidy Type	
Does property have project-based rent assistance or use utility allowances in rent calculations?	

Notes:

Residential Units *(will autofill cells F6, F7)*	
studio/eff	
1BR	
2BR	
3BR	
4BR	
5BR	
Non-Residential Space Information *Please select any that apply*	
Hallways/lobbies/stairwells	
Elevator	
Community room(s)	
Basement	
Laundry room(s)	
Office(s)	
Commercial kitchen	
Exercise room	
Swimming pool	
Parking garage (indoor)	
Parking lot (outdoor)	
Irrigated Lawn/Landscaping	
Retail Space(s)	

Accounts

Utility	Account Name	Account Number	Meter ID	Who pays this bill?	Utility Company	3rd Party Supplier	Units	Login	Password

Appendix B: Participant Assignment

Assignment of Applicants to Treatment and Control Groups

This document was produced at the beginning of the EnergyScoreCards Minnesota project to determine the assignment of each building to a group (treatment or control).

Conceptual Discussion

We believe that there is likely to be spillover/contamination from one property to another within an applicant's portfolio (i.e., that things they learn in one building will be applied to other buildings). If a participant's properties were divided between treatment and control and the things they learned in treatment buildings were applied to control buildings, it would artificially lower the measurable effect of the treatment. Therefore all properties associated with one applicant are kept together. Analytically, we are treating each participating organization as a "cluster." This results in a "group-randomized" or "cluster-randomized" design.

In addition it was decided that organizations that already have experience with EnergyScoreCards (and are already using EnergyScoreCards independently) would be "forced" into the treatment group.

Nineteen organizations have owner-manager relationships or other close relationships and so were treated as seven difference "super-clusters" and "forced" to be in same group (either treatment or control), again to reduce the potential for contamination of the samples due to spillover.

In general there are two options to improve precision in group-randomized experiments – blocking, in which groups are subdivided on key characteristics and participants and controls assigned within blocks, and covariance adjustment, in which adjustments are made during analysis by treating the outcome as a linear function of treatment group and the covariate(s). Blocking causes a greater loss in degrees of freedom and can actually produce worse precision than completely random assignment if the effect size is small, or if the effect size variance is large, or the number of groups is small. So in general covariance adjustment is preferable. However it can be useful to do some blocking in order to improve the face validity of the sample and to avoid having completely disparate treatment and control samples when the groups (in this case organizations) are highly heterogeneous, as here.

In this case we are guessing that the outcome will be most closely related to the following:

- What parts of the energy use the owner pays for ("payment code" in EnergyScoreCards parlance)
- Annual energy use intensity, Btu/ft^2
- Subsidies received (project-based rent assistance, utility support, both, neither) – somewhat hard to evaluate at this time as about 7% of properties are currently missing this information
- Availability of utility rebates
- Owner size or number of buildings submitted
- Possibly organization type
- Possibly fuel type by end use
- Possibly building type

- Possibly building age
- Possibly the relationship with MHFA

Therefore we would like to have reasonable balance of these things between treatment and control. Yet we want to avoid creating numerous blocks and doing random assignment within blocks, in order to preserve degrees of freedom and the statistical precision of outcome measurement.

One of the difficulties in achieving this is that applicants are to be assigned at the organization level but many of the above characteristics vary at the property level within a given applicant's portfolio. This is exacerbated by the fact that some applicants are to be grouped together into "mega-clusters." So it would impossible to obtain perfect matching no matter how many blocks you used.

After some experimentation it appears that a reasonable strategy is to block applicants by predominant payment code (predominant since portfolios can be mixed on this attribute). One block is primarily (86%) (T)TOO (tenant pays for apartment electricity and cooling, owner pays for heating and hot water), another is primarily (74%) (O)OOO (owner pays for everything), and the third, smallest, block is 50% (T)TTO and 9% (T)TTT (in both of these payment types the tenant pays for apartment electricity, cooling and heating).

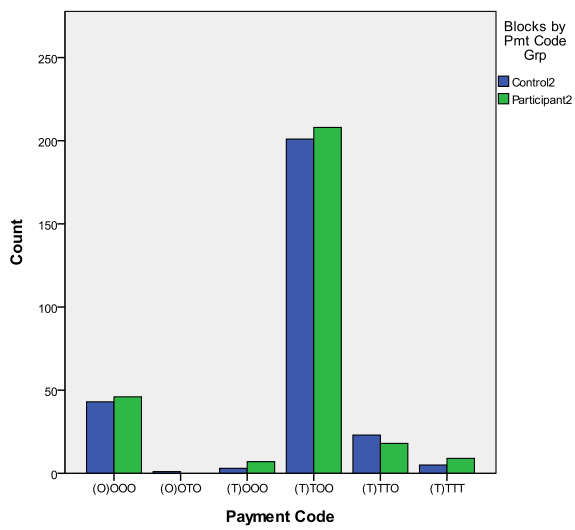
The graphs and analyses below examine the balance on this and other variables resulting from this blocking, both on factors that we think may affect the outcome (reduction in energy use) and on factors we think may be important to the face validity or acceptability of the study to stakeholders.

Note: In the graphs, "Blocks by Pmt Code Grp" is rather poorly named – what it really means is participant and control groups when divided using those blocks.

Properties by Payment Code

The differences between treatment and control properties by payment code are not significant (probability of achieving the observed chi square statistic by chance > 0.05).

Note: In the graphs, "Blocks by Pmt Code Grp" is rather poorly named – what it really means is participant and control groups when divided using those blocks.



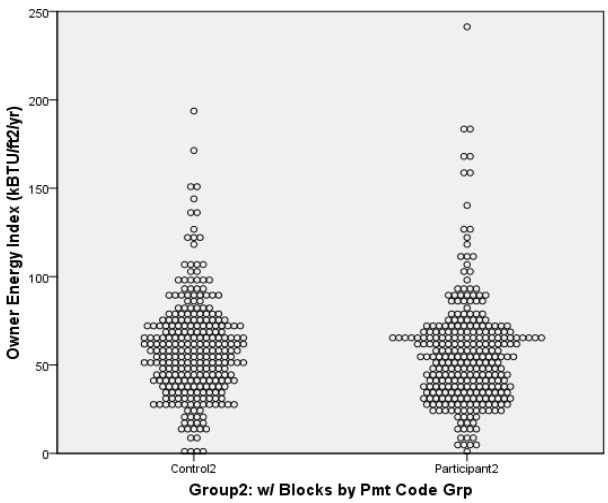
Payment Code * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Payment Code	(O)OOO	Count	43	46	89
		% within Group2: w/ Blocks by Pmt Code Grp	15.6%	16.0%	15.8%
	(O)OTO	Count	1	0	1
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.0%	.2%
	(T)OOO	Count	3	7	10
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	2.4%	1.8%
	(T)TOO	Count	201	208	409
		% within Group2: w/ Blocks by Pmt Code Grp	72.8%	72.2%	72.5%
	(T)TTO	Count	23	18	41
		% within Group2: w/ Blocks by Pmt Code Grp	8.3%	6.3%	7.3%
	(T)TTT	Count	5	9	14
		% within Group2: w/ Blocks by Pmt Code Grp	1.8%	3.1%	2.5%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.504$ ns

Properties by Owner Energy Index (Annual Energy Use Intensity for Owner-Paid Energy)

Differences between treatment and control properties not significant in terms of rank (Mann-Whtiney U test), shape (Kolmogorov Smirnov test) or median (median test). (Probabilities for all three tests > 0.05, though U test is marginally significant (between 0.05 and 0.10).

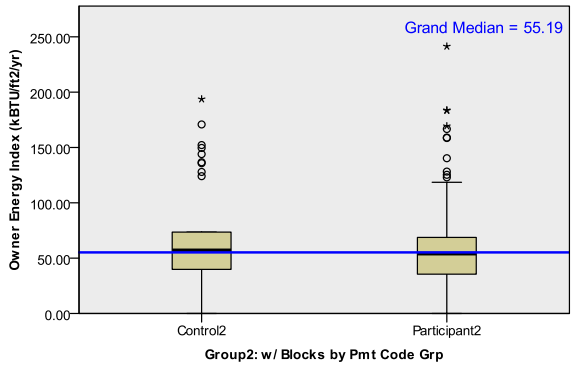


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.099	Retain the null hypothesis.
2	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.240	Retain the null hypothesis.
3	The medians of Owner Energy Index (kBTU/ft2/yr) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.222	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

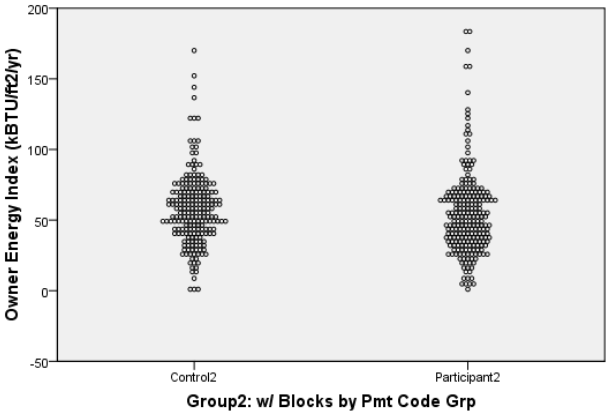
Independent-Samples Median Test



Properties by Payment Code Block by Owner Energy Index

Within randomized blocks, some differences are significant. Likely unavoidable given the factors discussed previously and the relatively small number of groups in each block).

Primarily (T)TOO

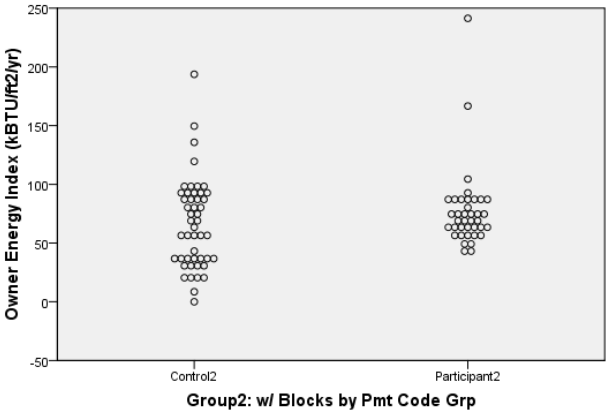


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.021	Reject the null hypothesis.
2	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.014	Reject the null hypothesis.
3	The medians of Owner Energy Index (kBTU/ft2/yr) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.080	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Primarily (O)OOO

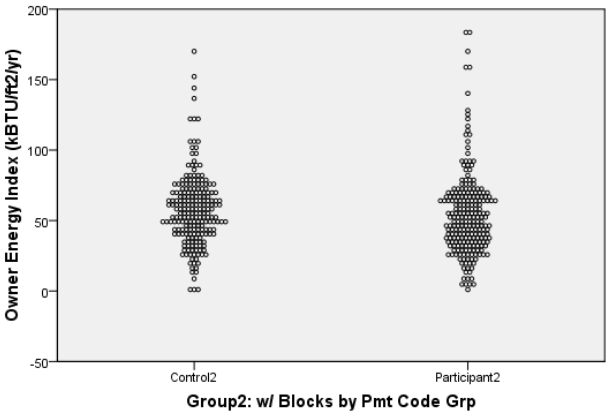


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.301	Retain the null hypothesis.
2	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.005	Reject the null hypothesis.
3	The medians of Owner Energy Index (kBTU/ft2/yr) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	1.000	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Primarily (T)TOO



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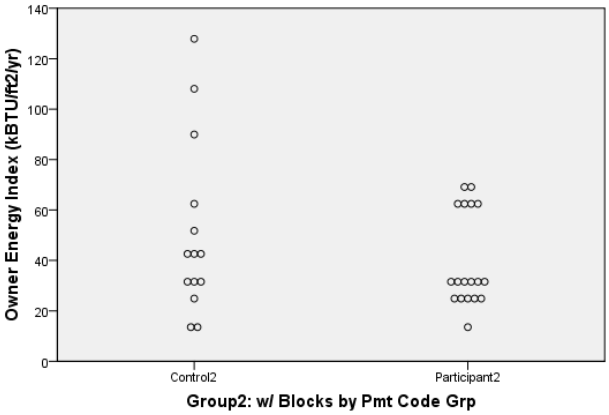
2	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.014	Reject the null hypothesis.
3	The medians of Owner Energy Index (kBTU/ft2/yr) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.080	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

50% (T)TTO and 9% (T)TTT



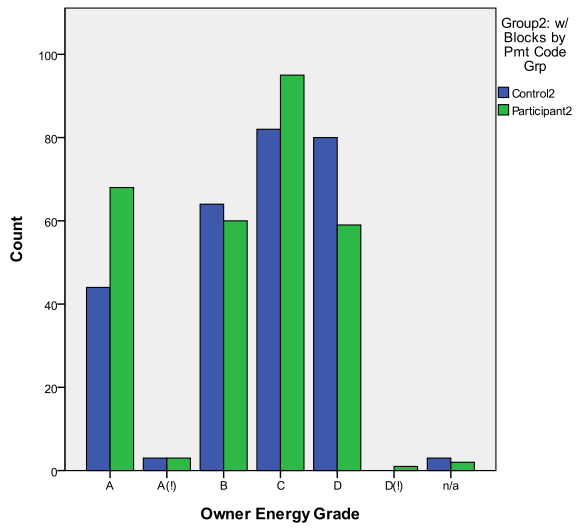
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.287	Retain the null hypothesis.
2	The distribution of Owner Energy Index (kBTU/ft2/yr) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.438	Retain the null hypothesis.
3	The medians of Owner Energy Index (kBTU/ft2/yr) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.154	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Properties by Owner Energy Grade and Related Variables

Differences between treatment and control properties on ESC's Owner Energy Grade are not significant. One reason that the apparent (though non-significant) differences are not too concerning is that, per ESC, the cut-points between are currently is based on the properties previously in ESC (excluding New York and the West Coast). Grades are expected to be revised based on the large number of Minnesota buildings newly in the system.

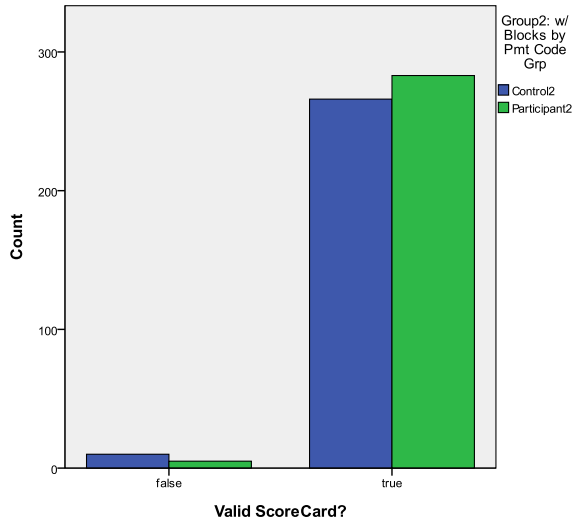


Owner Energy Grade * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Owner Energy Grade	A	Count	44	68	112
		% within Group2: w/ Blocks by Pmt Code Grp	15.9%	23.6%	19.9%
	A(!)	Count	3	3	6
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	1.0%	1.1%
	B	Count	64	60	124
		% within Group2: w/ Blocks by Pmt Code Grp	23.2%	20.8%	22.0%
	C	Count	82	95	177
		% within Group2: w/ Blocks by Pmt Code Grp	29.7%	33.0%	31.4%
	D	Count	80	59	139
		% within Group2: w/ Blocks by Pmt Code Grp	29.0%	20.5%	24.6%
	D(!)	Count	0	1	1
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	.3%	.2%
	n/a	Count	3	2	5
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	.7%	.9%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.111$ ns

The difference between treatment and controls in the proportion of the properties that do not yet have a valid scorecard is not significant.

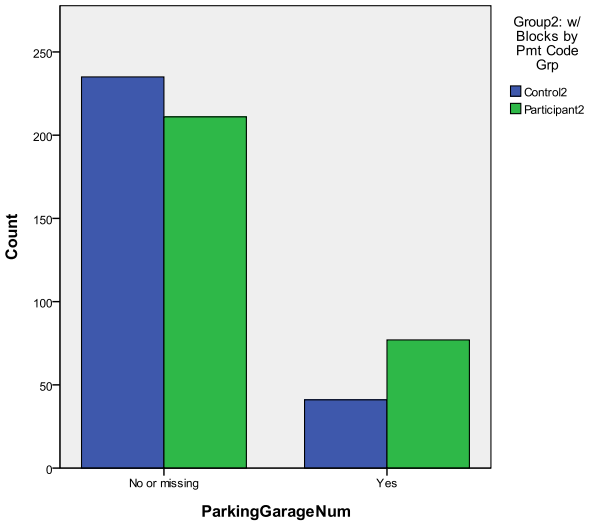


Valid ScoreCard? * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Valid ScoreCard?	false	Count	10	5	15
		% within Group2: w/ Blocks by Pmt Code Grp	3.6%	1.7%	2.7%
	true	Count	266	283	549
		% within Group2: w/ Blocks by Pmt Code Grp	96.4%	98.3%	97.3%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.164$ ns

A larger fraction of the Minnesota properties have parking garages than has been the case in previous ESC datasets and this may be affecting the energy indices and grades, but this cannot be evaluated fully until the project starts working with participants. The difference between treatment and control properties on presence of parking garages is highly significant, but it is unlikely that this could be rebalanced without throwing other variables out of balance for the reasons discussed earlier.

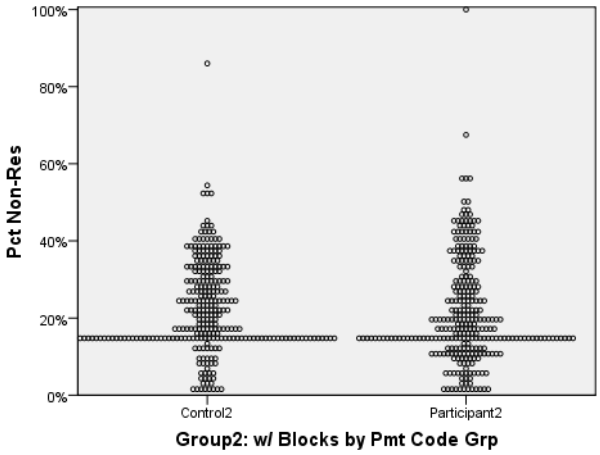


ParkingGarageNum * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
ParkingGarageNum	No or missing	Count	235	211	446
		% within Group2: w/ Blocks by Pmt Code Grp	85.1%	73.3%	79.1%
	Yes	Count	41	77	118
		% within Group2: w/ Blocks by Pmt Code Grp	14.9%	26.7%	20.9%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.001$***

Related to this, the treatment and control properties do not differ on ranks or medians of percent non-residential square footage, though they do differ on the shape of the distribution. Note that the large number of properties with 15% non-residential area is due to the fact that ESC assigns this percentage in the absence of other information (this will presumably get refined as the project proceeds).

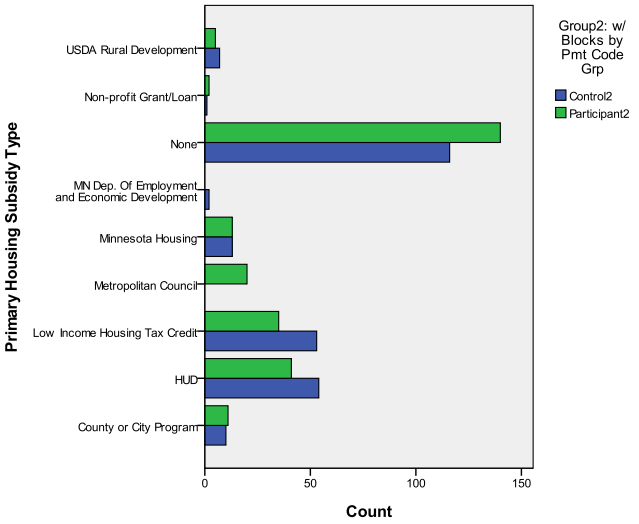


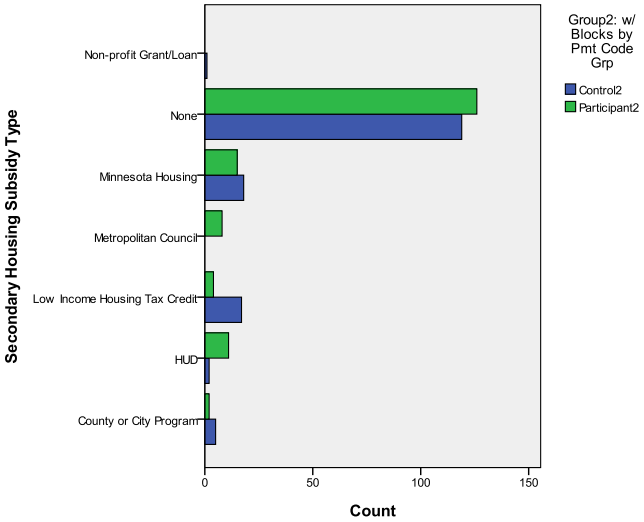
Hypothesis Test Summary

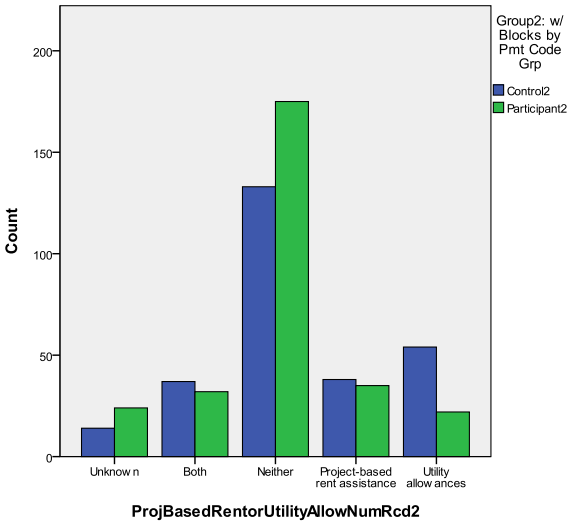
	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Pct Non-Res is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.065	Retain the null hypothesis.
2	The distribution of Pct Non-Res is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.033	Reject the null hypothesis.
3	The medians of Pct Non-Res are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.222	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Properties by Subsidies Received


Primary Housing Subsidy Type
USDA Rural Development
Non-profit Grant/Loan
None
MN Dep. Of Employment and Economic Development
Minnesota Housing
Metropolitan Council
Low Income Housing Tax Credit
HUD
County or City Program
0
50
100
150
Count
Group2: w/ Blocks by Pmt Code Grp
Control2
Participant2


Secondary Housing Subsidy Type
Non-profit Grant/Loan
None
Minnesota Housing
Metropolitan Council
Low Income Housing Tax Credit
HUD
County or City Program
0
50
100
150
Count
Group2: w/ Blocks by Pmt Code Grp
Control2
Participant2



ProjBasedRentorUtilityAllowNumRcd2 * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
ProjBasedRentorUtility AllowNumRcd2	Unknown	Count	14	24	38
		% within Group2: w/ Blocks by Pmt Code Grp	5.1%	8.3%	6.7%
	Both	Count	37	32	69
		% within Group2: w/ Blocks by Pmt Code Grp	13.4%	11.1%	12.2%
	Neither	Count	133	175	308
		% within Group2: w/ Blocks by Pmt Code Grp	48.2%	60.8%	54.6%
	Project-based rent assistance	Count	38	35	73
		% within Group2: w/ Blocks by Pmt Code Grp	13.8%	12.2%	12.9%
	Utility allowances	Count	54	22	76
		% within Group2: w/ Blocks by Pmt Code Grp	19.6%	7.6%	13.5%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

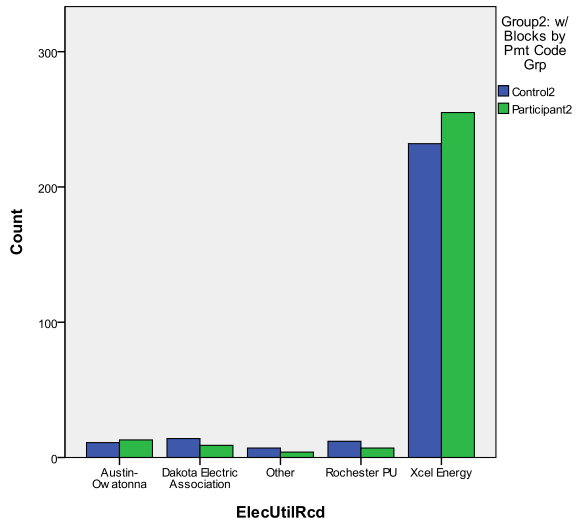
$P(X^2)=0.000$***

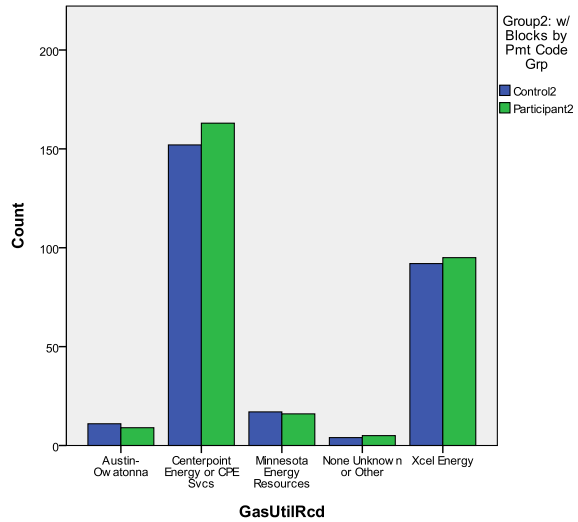
The above graph lumps on "no" response with "neither" and on "yes" response with "both"

There appear to be more treatment properties than control properties that do not get either type of subsidy, and more control properties than treatment properties that get utility allowances. However it would be risky and difficult to attempt to balance the two groups on this characteristic since there are still 38 properties with this information missing. (MHFA staff indicated that they are not concerned that differences in subsidies received would affect owners' energy use incentives.)

Properties by Utility

The utility is a proxy for rebates available. Differences between the treatment and control properties are not significant.





ElecUtilRcd * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
ElecUtilRcd	Austin-Owatonna	Count	11	13	24
		% within Group2: w/ Blocks by Pmt Code Grp	4.0%	4.5%	4.3%
	Dakota Electric Association	Count	14	9	23
		% within Group2: w/ Blocks by Pmt Code Grp	5.1%	3.1%	4.1%
	Other	Count	7	4	11
		% within Group2: w/ Blocks by Pmt Code Grp	2.5%	1.4%	2.0%
	Rochester PU	Count	12	7	19
		% within Group2: w/ Blocks by Pmt Code Grp	4.3%	2.4%	3.4%
	Xcel Energy	Count	232	255	487
		% within Group2: w/ Blocks by Pmt Code Grp	84.1%	88.5%	86.3%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

GasUtilRcd * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
GasUtilRcd	Austin-Owatonna	Count	11	9	20
		% within Group2: w/ Blocks by Pmt Code Grp	4.0%	3.1%	3.5%
	Centerpoint Energy or CPE Svcs	Count	152	163	315
		% within Group2: w/ Blocks by Pmt Code Grp	55.1%	56.6%	55.9%
	Minnesota Energy Resources	Count	17	16	33
		% within Group2: w/ Blocks by Pmt Code Grp	6.2%	5.6%	5.9%
	None Unknown or Other	Count	4	5	9
		% within Group2: w/ Blocks by Pmt Code Grp	1.4%	1.7%	1.6%
	Xcel Energy	Count	92	95	187
		% within Group2: w/ Blocks by Pmt Code Grp	33.3%	33.0%	33.2%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

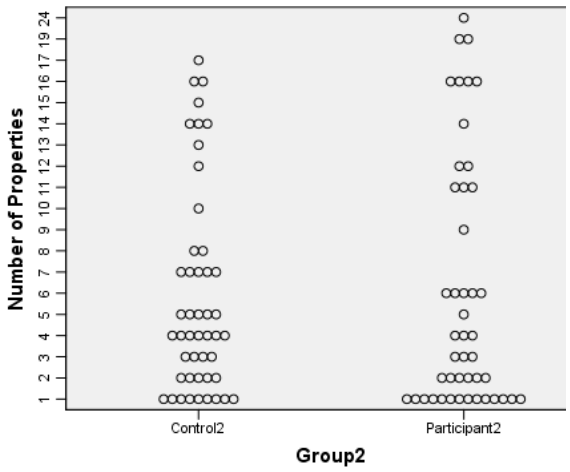
$p(X^2)=0.382$ ns

$p(X^2)=0.972$ ns

Applicants by Number of Properties Submitted and by Applicant Size

Differences between treatment and control properties are not significant.

Properties submitted:

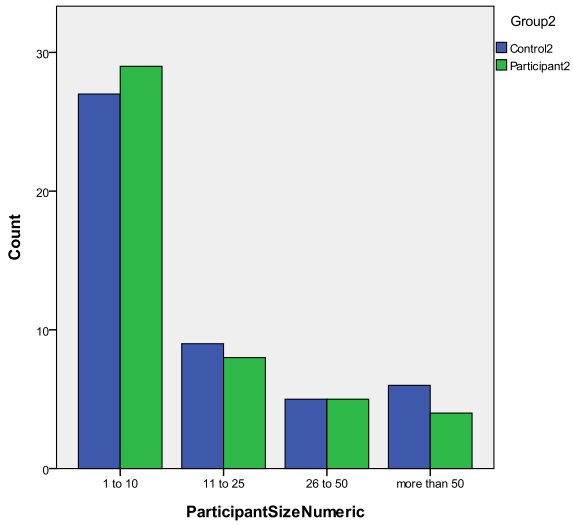


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Number of Properties is the same across categories of Group2.	Independent-Samples Mann-Whitney U Test	.595	Retain the null hypothesis.
2	The distribution of Number of Properties is the same across categories of Group2.	Independent-Samples Kolmogorov-Smirnov Test	.776	Retain the null hypothesis.
3	The medians of Number of Properties are the same across categories of Group2.	Independent-Samples Median Test	.747	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Participant size:



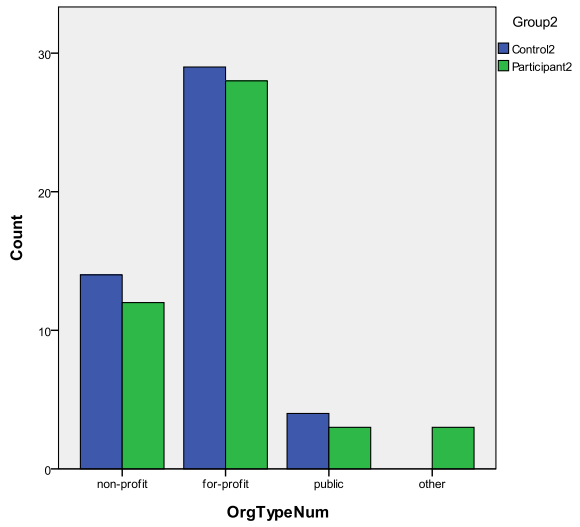
ParticipantSizeNumeric * Group2 Crosstabulation

			Group2		
			Control2	Participant2	Total
ParticipantSizeNumeric	1 to 10	Count	27	29	56
		% within Group2	57.4%	63.0%	60.2%
	11 to 25	Count	9	8	17
		% within Group2	19.1%	17.4%	18.3%
	26 to 50	Count	5	5	10
		% within Group2	10.6%	10.9%	10.8%
	more than 50	Count	6	4	10
		% within Group2	12.8%	8.7%	10.8%
Total		Count	47	46	93
		% within Group2	100.0%	100.0%	100.0%

$p(X^2)=0.915$ ns

Applicants and Properties by Organization Type

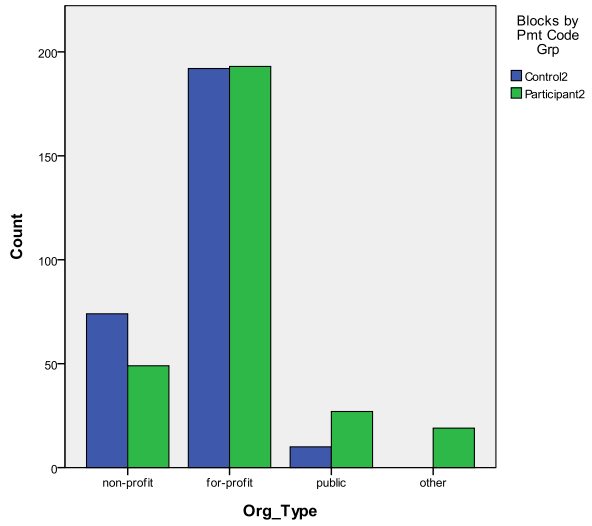
Differences between applicants by organization type are not significant. However, differences at the property level are highly significant, with more non-profit properties in the control group and more public and "other" properties in the participant group. Again it would probably be difficult to balance this without unbalancing other characteristics.



OrgTypeNum * Group2 Crosstabulation

			Group2		
			Control2	Participant2	Total
OrgTypeNum	non-profit	Count	14	12	26
		% within Group2	29.8%	26.1%	28.0%
	for-profit	Count	29	28	57
		% within Group2	61.7%	60.9%	61.3%
	public	Count	4	3	7
		% within Group2	8.5%	6.5%	7.5%
	other	Count	0	3	3
		% within Group2	.0%	6.5%	3.2%
Total		Count	47	46	93
		% within Group2	100.0%	100.0%	100.0%

p(Fisher's exact test) = 0.432



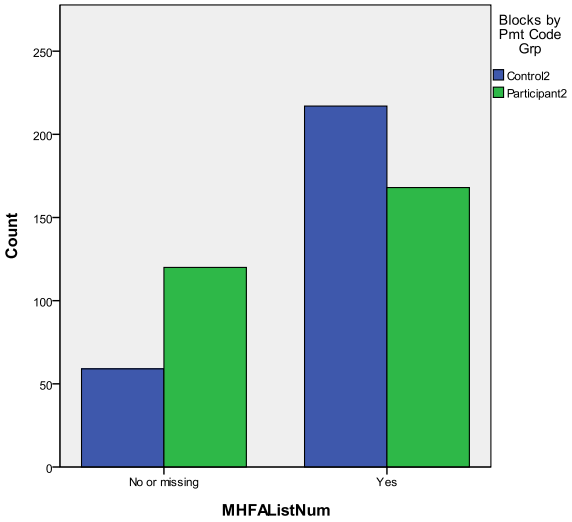
Org_Type * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Org_Type	non-profit	Count	74	49	123
		% within Group2: w/ Blocks by Pmt Code Grp	26.8%	17.0%	21.8%
	for-profit	Count	192	193	385
		% within Group2: w/ Blocks by Pmt Code Grp	69.6%	67.0%	68.3%
	public	Count	10	27	37
		% within Group2: w/ Blocks by Pmt Code Grp	3.6%	9.4%	6.6%
	other	Count	0	19	19
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	6.6%	3.4%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.000$***

Properties by MHFA Relationship

Treatment and control properties are significantly different in terms of having a relationship with MHFA (being on the MHFA list provided to ESC). MHFA staff suggested that this may not be a major concern since MHFA does not currently focus on energy management in its interactions with multi-housing clients.



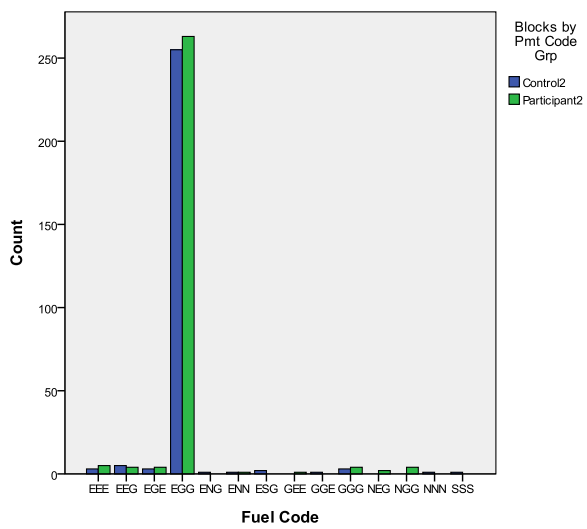
MHFAListNum * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
MHFAListNum	No or missing	Count	59	120	179
		% within Group2: w/ Blocks by Pmt Code Grp	21.4%	41.7%	31.7%
	Yes	Count	217	168	385
		% within Group2: w/ Blocks by Pmt Code Grp	78.6%	58.3%	68.3%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.000$***

Properties by Fuel Type

The treatment and control properties are not significantly different by fuel type used for each end use, with EGG (electric cooling, gas heating and gas hot water) being by far the predominant fuel type.



Fuel Code * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

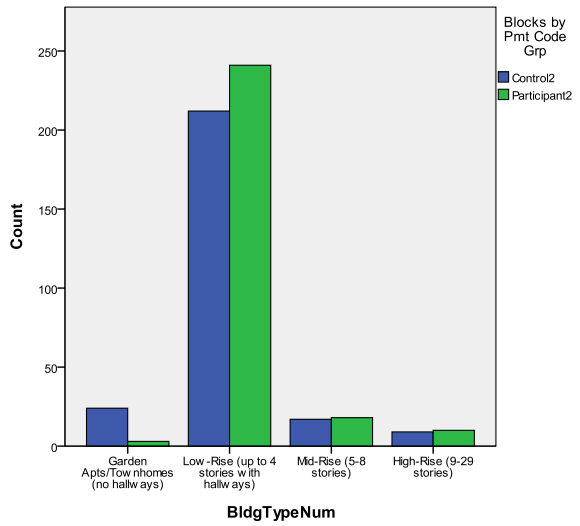
			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Fuel Code	EEE	Count	3	5	8
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	1.7%	1.4%
	EEG	Count	5	4	9
		% within Group2: w/ Blocks by Pmt Code Grp	1.8%	1.4%	1.6%
	EGE	Count	3	4	7
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	1.4%	1.2%
	EGG	Count	255	263	518
		% within Group2: w/ Blocks by Pmt Code Grp	92.4%	91.3%	91.8%
	ENG	Count	1	0	1
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.0%	.2%
	ENN	Count	1	1	2
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.3%	.4%
	ESG	Count	2	0	2
		% within Group2: w/ Blocks by Pmt Code Grp	.7%	.0%	.4%
	GEE	Count	0	1	1
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	.3%	.2%
	GGE	Count	1	0	1
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.0%	.2%
	GGG	Count	3	4	7
		% within Group2: w/ Blocks by Pmt Code Grp	1.1%	1.4%	1.2%
	NEG	Count	0	2	2
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	.7%	.4%
	NGG	Count	0	4	4
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	1.4%	.7%
	NNN	Count	1	0	1
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.0%	.2%
	SSS	Count	1	0	1
		% within Group2: w/ Blocks by Pmt Code Grp	.4%	.0%	.2%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

p(Fisher's exact test)=0.398

Properties by Building Type, Number of Bldgs on Property, Number of Units, Total Area, Area per Unit

The treatment and control properties are significantly different by type of building, with the treatment group having more low-rise buildings with hallways and the control group having more garden apartment/townhouse style buildings with no hallways. This comes about again because of the heterogeneity of the groups (organizations) and the impossibility of achieving complete balance on all characteristics.

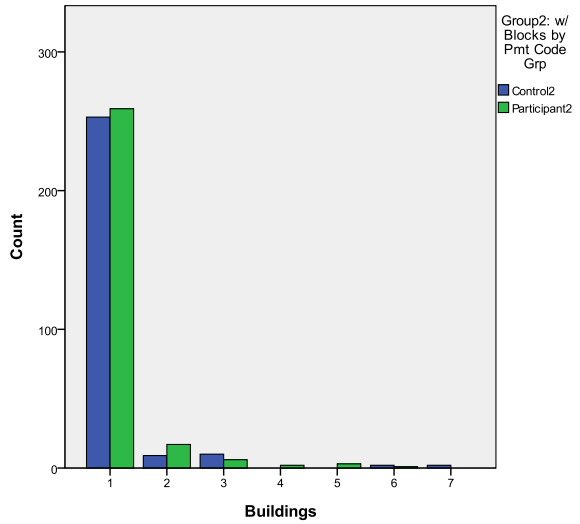
The treatment and control properties are marginally different in terms of number of buildings on each property.



BldgTypeNum * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
BldgTypeNum	Garden Apts/Townhomes (no hallways)	Count	24	3	27
		% within Group2: w/ Blocks by Pmt Code Grp	9.2%	1.1%	5.1%
	Low-Rise (up to 4 stories with hallways)	Count	212	241	453
		% within Group2: w/ Blocks by Pmt Code Grp	80.9%	88.6%	84.8%
	Mid-Rise (5-8 stories)	Count	17	18	35
		% within Group2: w/ Blocks by Pmt Code Grp	6.5%	6.6%	6.6%
	High-Rise (9-29 stories)	Count	9	10	19
		% within Group2: w/ Blocks by Pmt Code Grp	3.4%	3.7%	3.6%
Total		Count	262	272	534
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.000$***

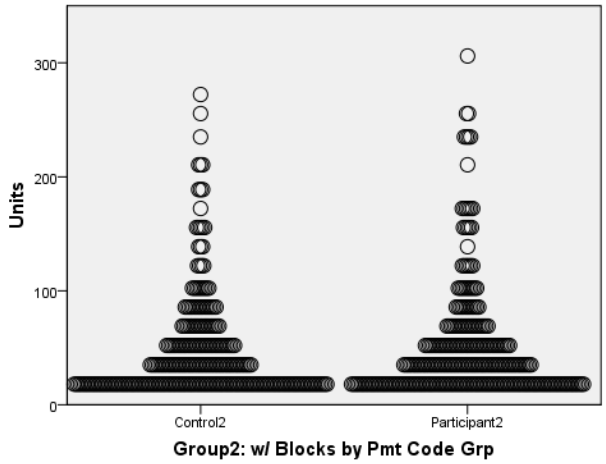


Buildings * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Buildings	1	Count	253	259	512
		% within Group2: w/ Blocks by Pmt Code Grp	91.7%	89.9%	90.8%
	2	Count	9	17	26
		% within Group2: w/ Blocks by Pmt Code Grp	3.3%	5.9%	4.6%
	3	Count	10	6	16
		% within Group2: w/ Blocks by Pmt Code Grp	3.6%	2.1%	2.8%
	4	Count	0	2	2
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	.7%	.4%
	5	Count	0	3	3
		% within Group2: w/ Blocks by Pmt Code Grp	.0%	1.0%	.5%
	6	Count	2	1	3
		% within Group2: w/ Blocks by Pmt Code Grp	.7%	.3%	.5%
	7	Count	2	0	2
		% within Group2: w/ Blocks by Pmt Code Grp	.7%	.0%	.4%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

p(Fisher's exact test)=0.082 m

The treatment and control properties do not differ on the number of units or number of sq.ft. on each property.

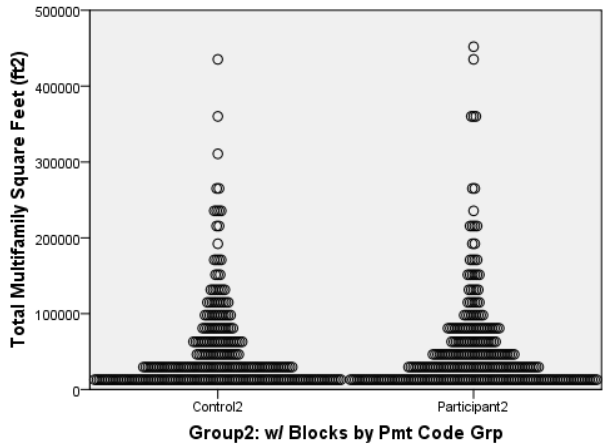


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Units is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.299	Retain the null hypothesis.
2	The distribution of Units is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.276	Retain the null hypothesis.
3	The medians of Units are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.601	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Note: The graph of # of units excludes two extreme values in the control group. The graph of total sq ft. excludes one extreme value in the control group. These extreme values are not excluded from the statistical tests.

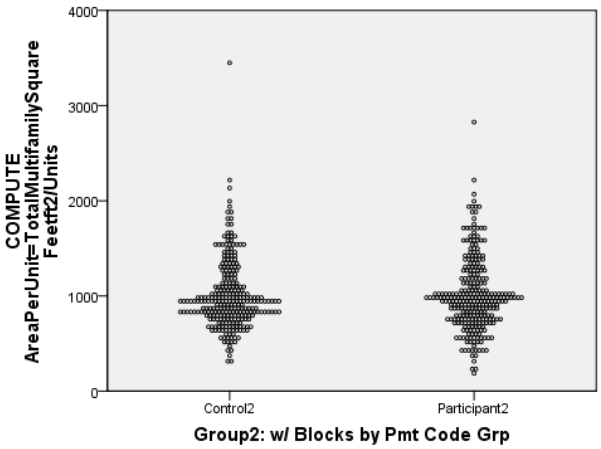


Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Total Multifamily Square Feet (ft2) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.497	Retain the null hypothesis.
2	The distribution of Total Multifamily Square Feet (ft2) is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.144	Retain the null hypothesis.
3	The medians of Total Multifamily Square Feet (ft2) are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.162	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Treatment and control properties do not differ significantly on gross area per unit, although the medians are marginally different.



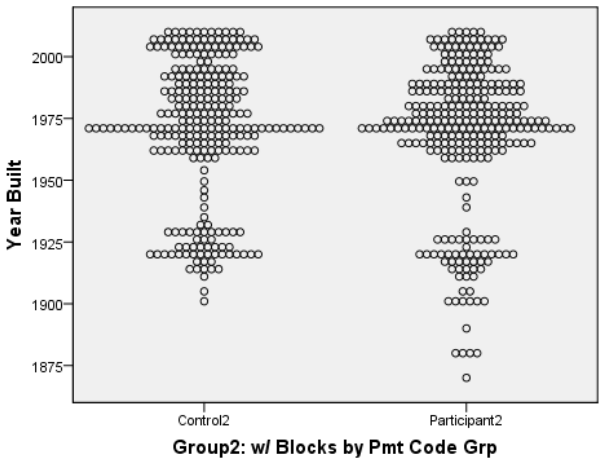
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of COMPUTE AreaPerUnit=TotalMultifamily SquareFeetft2/Units is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.536	Retain the null hypothesis.
2	The distribution of COMPUTE AreaPerUnit=TotalMultifamily SquareFeetft2/Units is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.150	Retain the null hypothesis.
3	The medians of COMPUTE AreaPerUnit=TotalMultifamily SquareFeetft2/Units are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.099	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Properties by Year Built

The treatment and control properties do not differ by year built.



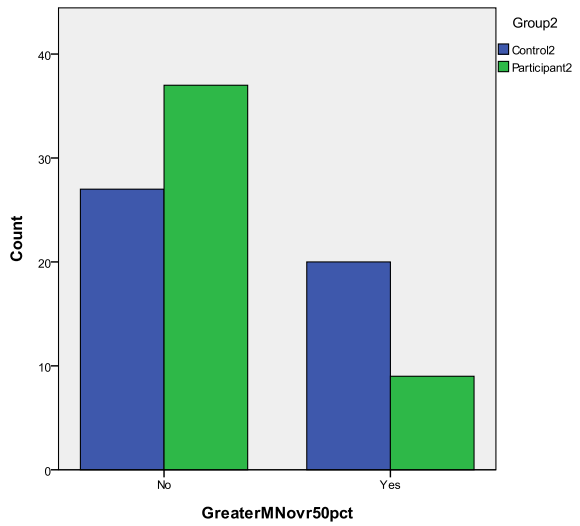
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of Year Built is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Mann-Whitney U Test	.211	Retain the null hypothesis.
2	The distribution of Year Built is the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Kolmogorov-Smirnov Test	.304	Retain the null hypothesis.
3	The medians of Year Built are the same across categories of Group2: w/ Blocks by Pmt Code Grp.	Independent-Samples Median Test	.653	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Applicants and Properties by Geography

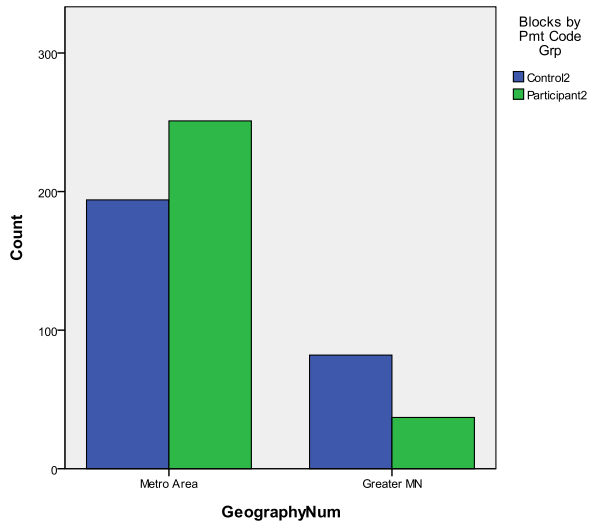
The treatment and control organizations and properties differ significantly in the portion located in the metro area versus in greater Minnesota, with more metro-located organizations and properties in the treatment group and more organizations located in greater Minnesota in the control group. Again this likely could not be rebalanced without unbalancing other characteristics. This characteristic is not expected to be as important a factor in savings as other characteristics that are well balanced.



GreaterMNovr50pct * Group2 Crosstabulation

			Group2		Total
			Control2	Participant2	
GreaterMNovr50pct	No	Count	27	37	64
		% within Group2	57.4%	80.4%	68.8%
	Yes	Count	20	9	29
		% within Group2	42.6%	19.6%	31.2%
Total		Count	47	46	93
		% within Group2	100.0%	100.0%	100.0%

$p(X^2)=0.017$*



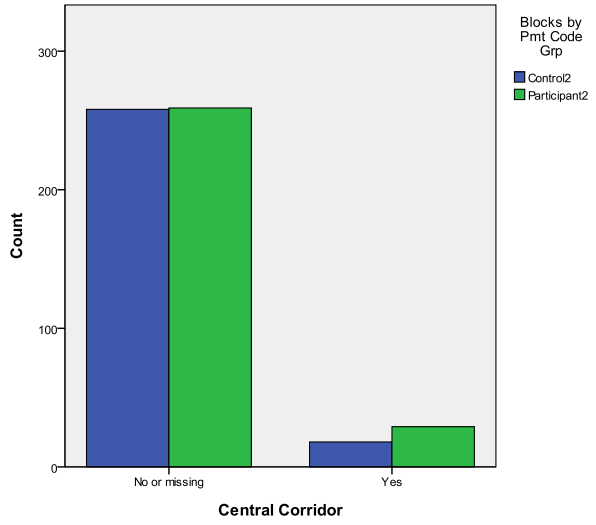
GeographyNum * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		Total
			Control2	Participant2	
GeographyNum	Metro Area	Count	194	251	445
		% within Group2: w/ Blocks by Pmt Code Grp	70.3%	87.2%	78.9%
	Greater MN	Count	82	37	119
		% within Group2: w/ Blocks by Pmt Code Grp	29.7%	12.8%	21.1%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.000$***

Properties by Location in Central Corridor

Properties in the Central Corridor, the vicinity of a major new light rail development project, are of particular interest to MHFA. Forty-seven such properties have been recruited and 29 of these are in the treatment group. The treatment and control groups do not differ in the proportion of properties located in the Central Corridor.



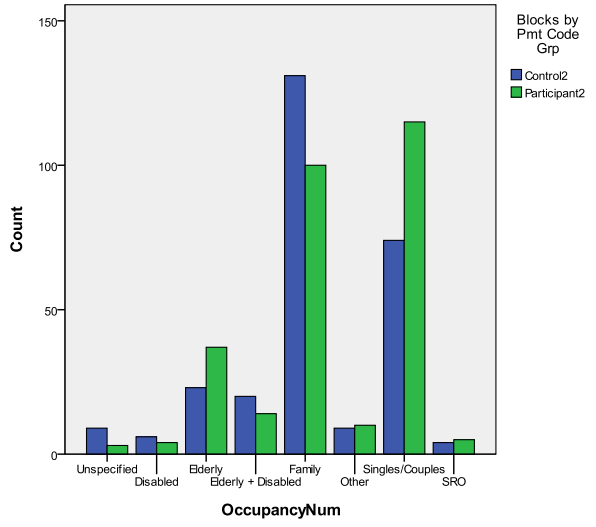
Central Corridor * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
Central Corridor	No or missing	Count	258	259	517
		% within Group2: w/ Blocks by Pmt Code Grp	93.5%	89.9%	91.7%
	Yes	Count	18	29	47
		% within Group2: w/ Blocks by Pmt Code Grp	6.5%	10.1%	8.3%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.128$ ns

Properties by Type of Occupants

The treatment and control properties differ significantly by type of occupants, with the treatment group having more singles/couples and the control group having more families.



OccupancyNum * Group2: w/ Blocks by Pmt Code Grp Crosstabulation

			Group2: w/ Blocks by Pmt Code Grp		
			Control2	Participant2	Total
OccupancyNum	Unspecified	Count	9	3	12
		% within Group2: w/ Blocks by Pmt Code Grp	3.3%	1.0%	2.1%
	Disabled	Count	6	4	10
		% within Group2: w/ Blocks by Pmt Code Grp	2.2%	1.4%	1.8%
	Elderly	Count	23	37	60
		% within Group2: w/ Blocks by Pmt Code Grp	8.3%	12.8%	10.6%
	Elderly + Disabled	Count	20	14	34
		% within Group2: w/ Blocks by Pmt Code Grp	7.2%	4.9%	6.0%
	Family	Count	131	100	231
		% within Group2: w/ Blocks by Pmt Code Grp	47.5%	34.7%	41.0%
	Other	Count	9	10	19
		% within Group2: w/ Blocks by Pmt Code Grp	3.3%	3.5%	3.4%
	Singles/Couples	Count	74	115	189
		% within Group2: w/ Blocks by Pmt Code Grp	26.8%	39.9%	33.5%
	SRO	Count	4	5	9
		% within Group2: w/ Blocks by Pmt Code Grp	1.4%	1.7%	1.6%
Total		Count	276	288	564
		% within Group2: w/ Blocks by Pmt Code Grp	100.0%	100.0%	100.0%

$p(X^2)=0.004$**

Appendix C: Complete Statistical Analysis Results

```
*********** Summary Statistics section (see later for analysis) ****************

ttest squareFeet, by (partCtrl)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 Control |     239    56649.38    6360.346    98328.57    44119.62    69179.15
Particip |     255    57163.61    4339.044    69288.98    48618.53     65708.7
---------+--------------------------------------------------------------------
combined |     494    56914.82    3802.072    84505.26    49444.56    64385.09
---------+--------------------------------------------------------------------
    diff |            -514.231    7615.827               -15477.79    14449.33
------------------------------------------------------------------------------
    diff = mean(Control) - mean(Particip)                         t =  -0.0675
Ho: diff = 0                                     degrees of freedom =      492

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.4731         Pr(|T| > |t|) = 0.9462          Pr(T > t) = 0.5269


ttest units, by (partCtrl)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 Control |     239    54.51046    6.341025    98.02987    42.01876    67.00216
Particip |     255    51.16471    3.039666    48.53958    45.17855    57.15087
---------+--------------------------------------------------------------------
combined |     494     52.7834     3.44298    76.52405    46.01868    59.54812
---------+--------------------------------------------------------------------
    diff |            3.345754    6.894923               -10.20137    16.89288
------------------------------------------------------------------------------
    diff = mean(Control) - mean(Particip)                         t =   0.4852
Ho: diff = 0                                     degrees of freedom =      492

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.6861         Pr(|T| > |t|) = 0.6277          Pr(T > t) = 0.3139


ttest unitSize, by (partCtrl)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 Control |     239    999.8827    23.83342    368.4557    952.9313    1046.834
Particip |     255    1032.476     23.5679    376.3492    986.0625    1078.889
---------+--------------------------------------------------------------------
combined |     494    1016.707    16.76094    372.5306    983.7755    1049.639
---------+--------------------------------------------------------------------
    diff |           -32.59317    33.54138               -98.49519    33.30884
------------------------------------------------------------------------------
    diff = mean(Control) - mean(Particip)                         t =  -0.9717
Ho: diff = 0                                     degrees of freedom =      492

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.1658         Pr(|T| > |t|) = 0.3317          Pr(T > t) = 0.8342
```

```
ttest yearBuilt, by (partCtrl)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 Control |     230    1971.687    1.881093    28.52819     1967.98    1975.393
Particip |     254    1968.713     1.83875    29.30486    1965.091    1972.334
---------+--------------------------------------------------------------------
combined |     484    1970.126    1.315759     28.9467    1967.541    1972.711
---------+--------------------------------------------------------------------
    diff |            2.974358     2.63401               -2.201202    8.149918
------------------------------------------------------------------------------
    diff = mean(Control) - mean(Particip)                         t =   1.1292
Ho: diff = 0                                     degrees of freedom =      482

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.8703         Pr(|T| > |t|) = 0.2594          Pr(T > t) = 0.1297


ttest eui2012, by (partCtrl)

Two-sample t test with equal variances
------------------------------------------------------------------------------
   Group |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
 Control |     239    59.62771    1.817512    28.09805    56.04725    63.20818
Particip |     255    55.03805    1.879759    30.01734    51.33616    58.73995
---------+--------------------------------------------------------------------
combined |     494    57.25856    1.312227    29.16569    54.68031     59.8368
---------+--------------------------------------------------------------------
    diff |            4.589659    2.620341               -.5587799    9.738098
------------------------------------------------------------------------------
    diff = mean(Control) - mean(Particip)                         t =   1.7516
Ho: diff = 0                                     degrees of freedom =      492

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9598         Pr(|T| > |t|) = 0.0805          Pr(T > t) = 0.0402

* None of these show a significant split between Control and Participants


tabulate partCtrl paymentCode, chi2

             |                                  paymentCode
    partCtrl |    (O)OOO     (O)OTO     (T)OOO     (T)TOO     (T)TOT     (T)TTO     (T)TTT |     Total
-------------+-----------------------------------------------------------------------------+----------
     Control |        40          1          3        171          0         20          4 |       239
 Participant |        45          1          6        177          1         19          6 |       255
-------------+-----------------------------------------------------------------------------+----------
       Total |        85          2          9        348          1         39         10 |       494

           Pearson chi2(6) =   2.3074   Pr = 0.889

* Shows good randomization of the payment codes
```

```
tabulate partCtrl fuelCode, chi2

             |                                        fuelCode
    partCtrl |       EEE        EEG        EGE        EGG        ESG        GGE        GGG        SSS
|     Total
-------------+-------------------------------------------------------------------------------------------
+----------
     Control |         3          5          3        223          1          1          2          1
|       239
Participant |         5          6          5        238          1          0          0          0
|       255
-------------+-------------------------------------------------------------------------------------------
+----------
       Total |         8         11          8        461          2          1          2          1
|       494

          Pearson chi2(7) =   5.0661   Pr = 0.652
```

* Shows good randomization of the fuel codes

```
tabulate partCtrl height_category, chi2

             |         height_category
    partCtrl |       Hig        Low        Mid |     Total
-------------+---------------------------------+----------
     Control |         8        216         15 |       239
Participant |        10        228         17 |       255
-------------+---------------------------------+----------
       Total |        18        444         32 |       494

          Pearson chi2(2) =   0.1535   Pr = 0.926
```

```
tabulate partCtrl subsidy, chi2

             |        subsidy
    partCtrl |         0          1 |     Total
-------------+----------------------+----------
     Control |        98        140 |       238
Participant |       133        122 |       255
-------------+----------------------+----------
       Total |       231        262 |       493

          Pearson chi2(1) =   5.9606   Pr = 0.015
```

* Shows fewer Participant properties are on subsidies

** Important to include subsidy and height in the final analysis

```
* Looking at the correlation coefficients

. spearman treated eui2012 height_category yearBuilt squareFeet units unitSize ///

> subsidy payOOOO payTTOO

(obs=483)

             |  treated  eui2012 height~y yearBu~t square~t    units unitSize  subsidy  payOOOO
 payTTOO
-------------+-------------------------------------------------------------------------------------
---
     treated |   1.0000
     eui2012 |  -0.1027   1.0000
height_cat~y |   0.0024  -0.0566   1.0000
   yearBuilt |  -0.0498  -0.5065   0.0229   1.0000
  squareFeet |   0.0545  -0.3608   0.0100   0.4268   1.0000
       units |   0.0511  -0.1977   0.0385   0.3236   0.9255   1.0000
    unitSize |   0.0638  -0.5779   0.0298   0.4294   0.5261   0.2058   1.0000
     subsidy |  -0.1220   0.0840   0.0027   0.1912   0.1260   0.1337  -0.0438   1.0000
     payOOOO |   0.0033   0.3844  -0.0709   0.0150   0.0097   0.0712  -0.1896   0.2245   1.0000
     payTTOO |  -0.0206  -0.0035  -0.0189  -0.2165  -0.0592  -0.0841   0.0302  -0.1641  -0.7091
1.0000

. ** nothing of note, squareFeet and units are strongly correlated (naturally),

. ** we don't use both simultaneously in a model.
```

```
************************ Analysis section ************************************

. regress energyChange i.treated c.eui2012 ib2.height_category c.squareFeet ///

>  i.subsidy, vce(cluster portfolio)

Linear regression                                      Number of obs =     493
                                                       F(  6,    89) =    5.44
                                                       Prob > F      =  0.0001
                                                       R-squared     =  0.1010
                                                       Root MSE      =  6.2422

                                (Std. Err. adjusted for 90 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
   energyChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -1.311704    .852263    -1.54   0.127    -3.005132    .3817245
        eui2012  |  -.0536692   .0208882    -2.57   0.012    -.0951735   -.0121648
                 |
height_category  |
           Hig   |   -5.34126   1.642857    -3.25   0.002    -8.605581   -2.076938
           Mid   |   1.580621   1.589986     0.99   0.323    -1.578647    4.739889
                 |
     squareFeet  |  -2.32e-06   2.36e-06    -0.98   0.329    -7.01e-06    2.37e-06
      1.subsidy  |   -.371353   .8619148    -0.43   0.668    -2.083959    1.341253
           _cons |    3.96942   1.249767     3.18   0.002     1.486159     6.45268
------------------------------------------------------------------------------

. estat summarize
Estimation sample regress
                              Number of obs        =      493

                              Number of clusters   =       90
                              Obs per cluster: min =        1
                                               avg =      5.5
                                               max =       22

-------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+-----------------------------------------------
energyChange |   -.1946609      6.54319   -29.6432    36.1009
             |
     treated |
Participant  |    .5172414     .5002102          0          1
     eui2012 |    57.08302     28.93293    1.99955    239.061
             |
height_cat~y |
        Hig  |    .0365112     .1877487          0          1
        Mid  |    .0649087      .246615          0          1
             |
  squareFeet |    57015.79     84561.27       4536    1.2e+06
   1.subsidy |    .5314402     .4995174          0          1
-------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated

Predictive margins                                     Number of obs   =        493
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |   .4838066   .4238802     1.14   0.257    -.3584343    1.326047
Participant  |  -.8278973   .7497208    -1.10   0.272    -2.317577    .6617819
------------------------------------------------------------------------------
```

```
. ** Running payment codes separately

. regress energyChange i.treated c.eui2012 ib2.height_category c.squareFeet ///

> i.subsidy if payOOOO, vce(cluster portfolio) // Very Significant

Linear regression                                      Number of obs =      85
                                                       F(  6,    36) =    7.12
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1856
                                                       Root MSE      =  7.7946

                                (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
   energyChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -4.486269   1.578996    -2.84   0.007    -7.688621   -1.283918
        eui2012  |  -.0442833   .0488675    -0.91   0.371    -.1433912    .0548246
                 |
height_category  |
           Hig   |  -6.022921   3.685433    -1.63   0.111    -13.49733    1.451484
           Mid   |   1.528865   4.300256     0.36   0.724    -7.192458    10.25019
                 |
     squareFeet  |  -4.49e-06   3.43e-06    -1.31   0.199    -.0000114    2.47e-06
      1.subsidy  |    1.42372   3.457307     0.41   0.683    -5.588024    8.435463
          _cons  |   2.613754    4.87099     0.54   0.595    -7.265071    12.49258
------------------------------------------------------------------------------

. ** Sure enough OOOO buildings are different from the full set, OOOO showing a
. ** large drop which is statistically significant
. estat summarize

Estimation sample regress
                                Number of obs        =       85

                                Number of clusters   =       37
                                Obs per cluster: min =        1
                                                 avg =      2.3
                                                 max =       12

------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+----------------------------------------------
energyChange |   -3.158385     8.322791   -29.6432    21.7253
             |
     treated |
Participant  |    .5294118     .5020964          0          1
     eui2012 |    82.78132      36.1924     28.835    239.061
             |
height_cat~y |
        Hig  |    .1176471     .3241019          0          1
        Mid  |    .0941176     .2937252          0          1
             |
  squareFeet |    60587.56     137534.5       6392    1.2e+06
   1.subsidy |    .7764706     .4190826          0          1
------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated

Predictive margins                                     Number of obs   =         85
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |  -.7833012   .8508276    -0.92   0.363    -2.508859    .9422571
Participant  |   -5.26957   1.640632    -3.21   0.003    -8.596927   -1.942214
```

```
. ** Check TTOOs
. regress energyChange i.treated c.eui2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio) // Not Significant

Linear regression                                      Number of obs =     347
                                                       F(  6,    73) =    1.08
                                                       Prob > F      =  0.3837
                                                       R-squared     =  0.0403
                                                       Root MSE      =  6.1018

                                (Std. Err. adjusted for 74 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
   energyChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -.3826437   1.044736    -0.37   0.715    -2.464799    1.699512
        eui2012  |  -.0467919   .0241981    -1.93   0.057    -.0950186    .0014348
                 |
height_category  |
           Hig   |  -3.952759   3.058528    -1.29   0.200     -10.0484    2.142878
           Mid   |   1.729135   2.087328     0.83   0.410    -2.430904    5.889173
                 |
     squareFeet  |  -1.11e-06   6.72e-06    -0.17   0.869    -.0000145    .0000123
      1.subsidy  |   -.659098   .9268065    -0.71   0.479    -2.506221    1.188025
          _cons  |   3.466126   1.332349     2.60   0.011     .8107579    6.121495
------------------------------------------------------------------------------

. estat summarize

Estimation sample regress
                                Number of obs        =      347

                                Number of clusters   =       74
                                Obs per cluster: min =        1
                                                 avg =      4.7
                                                 max =       22

-------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+-----------------------------------------------
energyChange |    .2882953      6.17431   -21.9789    36.1009
             |
     treated |
Participant  |    .5100865     .5006201          0          1
     eui2012 |    56.01992     22.25904    12.2924    180.357
             |
height_cat~y |
        Hig  |    .0172911     .1305419          0          1
        Mid  |    .0432277     .2036629          0          1
             |
  squareFeet |    47261.06     46990.56       4536     268498
   1.subsidy |    .4783862      .500254          0          1
-------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated

Predictive margins                              Number of obs   =        347
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |   .4834767   .5214123     0.93   0.357    -.5556964     1.52265
Participant  |    .100833   .8475387     0.12   0.906    -1.588309    1.789975
------------------------------------------------------------------------------
```

```
. ** And TTTOs
. regress energyChange i.treated c.eui2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTTO, vce(cluster portfolio) // Not Significant

Linear regression                                      Number of obs =      39
                                                       F(  5,    15) =       .
                                                       Prob > F      =       .
                                                       R-squared     =  0.2342
                                                       Root MSE      =  4.3509

                                (Std. Err. adjusted for 16 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
   energyChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |   .0554502   2.016191     0.03   0.978    -4.241959    4.352859
        eui2012  |  -.0007504   .0747032    -0.01   0.992    -.1599765    .1584756
                 |
height_category  |
            Hig  |    -8.4432   2.030227    -4.16   0.001    -12.77053   -4.115873
            Mid  |   5.955486   5.115333     1.16   0.263    -4.947589    16.85856
                 |
     squareFeet  |  -9.45e-07   8.78e-06    -0.11   0.916    -.0000197    .0000178
      1.subsidy  |   1.927069   1.982451     0.97   0.346    -2.298426    6.152564
           _cons |   .4664629    3.44618     0.14   0.894    -6.878897    7.811822
------------------------------------------------------------------------------

. estat summarize

Estimation sample regress
                                Number of obs        =       39

                                Number of clusters   =       16
                                Obs per cluster: min =        1
                                                 avg =      2.4
                                                 max =       10

-------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+-----------------------------------------------
energyChange |    1.568162     4.562344   -6.22956    18.7778
             |
     treated |
Participant  |    .4871795     .5063697          0          1
     eui2012 |    24.05403      7.88806    6.84184    40.8863
             |
height_cat~y |
        Hig  |     .025641     .1601282          0          1
        Mid  |    .0769231     .2699528          0          1
             |
  squareFeet |    92828.59     109605.2       9754     430472
   1.subsidy |    .4871795     .5063697          0          1
-------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated

Predictive margins                                     Number of obs   =         39
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |   1.541148   1.011054     1.52   0.148    -.6138617    3.696158
Participant  |   1.596598   1.270205     1.26   0.228     -1.11078    4.303977
------------------------------------------------------------------------------
```

```
************************** Secondary Analysis **********************************
. ** First Year Change
. regress firstYearChange i.treated c.eui2012 ib2.height_category c.squareFeet ///
>  i.subsidy, vce(cluster portfolio) // Not Significant

Linear regression                                      Number of obs =     493
                                                       F(  6,    89) =    0.75
                                                       Prob > F      =  0.6147
                                                       R-squared     =  0.0128
                                                       Root MSE      =  8.2509

                                 (Std. Err. adjusted for 90 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
firstYearChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |   .4649155   1.060974     0.44   0.662    -1.643217    2.573047
         eui2012 |  -.0270156   .0202211    -1.34   0.185    -.0671945    .0131632
                 |
height_category  |
            Hig  |  -.1975155   1.037431    -0.19   0.849    -2.258868    1.863837
            Mid  |   .4377753     1.2369     0.35   0.724    -2.019919     2.89547
                 |
      squareFeet |   1.28e-06   3.37e-06     0.38   0.706    -5.42e-06    7.97e-06
       1.subsidy |   .9864814   1.137495     0.87   0.388    -1.273696    3.246659
           _cons |  -.2321786   1.710654    -0.14   0.892    -3.631211    3.166854
------------------------------------------------------------------------------

.
. regress firstYearChange i.treated c.eui2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payOOOO, vce(cluster portfolio) // Not Significant


Linear regression                                      Number of obs =      85
                                                       F(  6,    36) =    1.04
                                                       Prob > F      =  0.4170
                                                       R-squared     =  0.0724
                                                       Root MSE      =  8.2021

                                 (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
firstYearChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |  -4.134729   2.231748    -1.85   0.072    -8.660925    .3914661
         eui2012 |   .0014841   .0431797     0.03   0.973    -.0860884    .0890567
                 |
height_category  |
            Hig  |   2.890966   2.316499     1.25   0.220    -1.807113    7.589044
            Mid  |  -.4624049   3.322393    -0.14   0.890    -7.200531    6.275721
                 |
      squareFeet |  -9.41e-06   4.65e-06    -2.02   0.051    -.0000188    2.26e-08
       1.subsidy |  -2.305088   2.566415    -0.90   0.375    -7.510019    2.899844
           _cons |    2.35938   3.516066     0.67   0.506    -4.771531    9.490292
------------------------------------------------------------------------------

.
. regress firstYearChange i.treated c.eui2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio) // Not Significant
```

```
Linear regression                                      Number of obs =     347
                                                       F(  6,    73) =    0.84
                                                       Prob > F      =  0.5466
                                                       R-squared     =  0.0258
                                                       Root MSE      =  8.7905

                                 (Std. Err. adjusted for 74 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
firstYearChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |   .9124248   1.366797     0.67   0.507    -1.811599    3.636448
        eui2012  |   -.011772    .032103    -0.37   0.715    -.0757531    .0522092
                 |
height_category  |
           Hig   |  -3.831327   2.782118    -1.38   0.173    -9.376081    1.713426
           Mid   |   .6554434   1.345795     0.49   0.628    -2.026722    3.337609
                 |
     squareFeet  |   .0000165   8.51e-06     1.94   0.056    -4.32e-07    .0000335
      1.subsidy  |    1.70783   1.268218     1.35   0.182    -.8197256    4.235385
           _cons |  -2.245058   2.536959    -0.88   0.379    -7.301209    2.811094
------------------------------------------------------------------------------
. ** Overall the first year changes show a similar trend to the 2 year changes
. ** but the scatter in the results renders them as not statistically significant.



. **** Heating Section
. gen heatChange = heat2014-heat2012
. gen firstYearHeatChange = heat2013-heat2012
.
. regress heatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy, vce(cluster portfolio)


Linear regression                                      Number of obs =     493
                                                       F(  6,    89) =  166.91
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0773
                                                       Root MSE      =  2.8665

                                 (Std. Err. adjusted for 90 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     heatChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |  -.1761136   .1792966    -0.98   0.329    -.5323722     .180145
       heat2012  |   -.080518   .0056415   -14.27   0.000    -.0917275   -.0693085
                 |
height_category  |
           Hig   |  -.8293758   .2815339    -2.95   0.004    -1.388778   -.2699739
           Mid   |   .6120019   .6354705     0.96   0.338    -.6506644    1.874668
                 |
     squareFeet  |   1.53e-07   1.05e-06     0.15   0.884    -1.92e-06    2.23e-06
      1.subsidy  |  -.3266059   .1899492    -1.72   0.089     -.704031    .0508192
           _cons |   .6588983   .1813226     3.63   0.000     .2986142    1.019182
------------------------------------------------------------------------------
. ** When look at the individual coefficients there is no evidence when looking at all the
buildings that we
. ** see any of significance, not surprising given their relative errors are larger
. regress heatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy if ownerHeat, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =     442
                                                       F(  6,    85) =    5.82
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1323
                                                       Root MSE      =  .73842

                                (Std. Err. adjusted for 86 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     heatChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -.2076719   .1096444    -1.89   0.062    -.4256745    .0103306
       heat2012  |  -.0826345   .0261004    -3.17   0.002    -.1345291     -.03074
                 |
height_category  |
           Hig   |  -.5360627   .1947205    -2.75   0.007    -.9232192   -.1489062
           Mid   |   .0761027   .1902522     0.40   0.690    -.3021696    .4543749
                 |
     squareFeet  |  -4.48e-07   3.08e-07    -1.46   0.149    -1.06e-06    1.64e-07
      1.subsidy  |  -.1585167   .1122646    -1.41   0.162    -.3817287    .0646954
           _cons |   .5225646   .1526098     3.42   0.001     .2191355    .8259938
------------------------------------------------------------------------------
. ** But when limited to just buildings where the owner controls the tenant heat
. regress heatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payOOOO, vce(cluster portfolio)


Linear regression                                      Number of obs =      85
                                                       F(  6,    36) =   27.47
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.2471
                                                       Root MSE      =  .81957

                                (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     heatChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -.4823104   .1666684    -2.89   0.006    -.8203296   -.1442911
       heat2012  |  -.0753554    .038276    -1.97   0.057    -.1529827    .0022719
                 |
height_category  |
           Hig   |  -.5533647    .442832    -1.25   0.220     -1.45147    .3447402
           Mid   |   .1272899   .4503043     0.28   0.779    -.7859696    1.040549
                 |
     squareFeet  |  -7.57e-07   3.55e-07    -2.13   0.040    -1.48e-06   -3.78e-08
      1.subsidy  |   .0410226   .3594674     0.11   0.910    -.6880111    .7700563
           _cons |   .2883056   .3972843     0.73   0.473    -.5174243    1.094036
------------------------------------------------------------------------------
. ** However if we once again drill into the OOOO subgroup we see a large very significant shift
. regress heatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio)
```

```
Linear regression                               Number of obs =     347
                                                F(  6,    73) =    2.23
                                                Prob > F      =  0.0495
                                                R-squared     =  0.0725
                                                Root MSE      =  .71801

                                (Std. Err. adjusted for 74 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     heatChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |  -.1419637   .1213475    -1.17   0.246     -.383809    .0998816
       heat2012  |  -.0698485   .0299491    -2.33   0.022    -.1295369   -.0101601
                 |
height_category  |
           Hig   |  -.3474544   .3022252    -1.15   0.254    -.9497884    .2548795
           Mid   |   .1695814   .2232427     0.76   0.450    -.2753407    .6145035
                 |
     squareFeet  |   4.92e-08   7.80e-07     0.06   0.950    -1.50e-06    1.60e-06
      1.subsidy  |  -.1576528   .1098947    -1.43   0.156    -.3766726    .0613671
           _cons |   .4397603    .174052     2.53   0.014     .0928753    .7866454
------------------------------------------------------------------------------
. regress heatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTTO, vce(cluster portfolio)


Linear regression                               Number of obs =      39
                                                F(  5,    15) =       .
                                                Prob > F      =       .
                                                R-squared     =  0.1372
                                                Root MSE      =  10.271

                                (Std. Err. adjusted for 16 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     heatChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |   1.205785   2.396098     0.50   0.622    -3.901377    6.312948
       heat2012  |  -.1442849   .1014151    -1.42   0.175    -.3604461    .0718763
                 |
height_category  |
           Hig   |  -2.365824   2.409747    -0.98   0.342    -7.502078    2.770431
           Mid   |   4.101402   8.649792     0.47   0.642    -14.33519      22.538
                 |
     squareFeet  |  -8.34e-06   .0000152    -0.55   0.593    -.0000408    .0000242
      1.subsidy  |  -2.562122   4.487013    -0.57   0.576    -12.12596     7.00172
           _cons |   4.396045   6.317698     0.70   0.497    -9.069808     17.8619
------------------------------------------------------------------------------
.
. ** First Year Heat tests
. regress firstYearHeatChange i.treated c.heat2012 ib2.height_category c.squareFeet ///
>  i.subsidy if ownerHeat, vce(cluster portfolio) // Not significant
```

```
Linear regression                                      Number of obs =     442
                                                       F(  6,    85) =    2.73
                                                       Prob > F      =  0.0179
                                                       R-squared     =  0.0352
                                                       Root MSE      =  .91602

                                (Std. Err. adjusted for 86 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
firstYearHeat~e  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |   .0224103   .1348418     0.17   0.868    -.2456913     .290512
        heat2012 |  -.0611452   .0263787    -2.32   0.023    -.1135931   -.0086973
                 |
height_category  |
             Hig |   .0235222   .1153271     0.20   0.839     -.205779    .2528235
             Mid |   .0889626   .1284922     0.69   0.491    -.1665142    .3444394
                 |
      squareFeet |   2.22e-07   3.79e-07     0.59   0.560    -5.31e-07    9.75e-07
       1.subsidy |   .0344459   .1384528     0.25   0.804    -.2408353    .3097271
           _cons |      .0952    .204822     0.46   0.643     -.312041     .502441
------------------------------------------------------------------------------
.
. **** Electricity Section
. gen elecChange = elec2014-elec2012
(1 missing value generated)

. regress elecChange i.treated c.elec2012 ib2.height_category c.squareFeet ///
>  i.subsidy, vce(cluster portfolio)


Linear regression                                      Number of obs =     492
                                                       F(  6,    89) =    1.86
                                                       Prob > F      =  0.0962
                                                       R-squared     =  0.1563
                                                       Root MSE      =  389.43

                                (Std. Err. adjusted for 90 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     elecChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |  -13.70454   38.29636    -0.36   0.721    -89.79859     62.3895
        elec2012 |  -.0901002   .0385538    -2.34   0.022    -.1667058   -.0134946
                 |
height_category  |
             Hig |   62.46011   105.5677     0.59   0.556    -147.3007    272.2209
             Mid |   64.06609   90.98747     0.70   0.483    -116.7241    244.8563
                 |
      squareFeet |  -.0000892   .0003036    -0.29   0.770    -.0006925    .0005141
       1.subsidy |   76.59837   35.93178     2.13   0.036     5.202684     147.994
           _cons |   32.52236   58.35845     0.56   0.579    -83.43464    148.4794
------------------------------------------------------------------------------
. ** Similarly for electric
. regress elecChange i.treated c.elec2012 ib2.height_category c.squareFeet ///
>  i.subsidy if ownerElec, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =      87
                                                       F(  6,    37) =    0.55
                                                       Prob > F      =  0.7631
                                                       R-squared     =  0.0440
                                                       Root MSE      =  489.03

                                 (Std. Err. adjusted for 38 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     elecChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
         treated |
   Participant   |  -100.7811   139.1503    -0.72   0.473    -382.7264    181.1642
       elec2012  |  -.0435558    .049276    -0.88   0.382    -.1433984    .0562869
                 |
height_category  |
           Hig   |   -87.3243   140.5209    -0.62   0.538    -372.0468    197.3982
           Mid   |   106.7915   136.3539     0.78   0.438    -169.4877    383.0708
                 |
     squareFeet  |   .0002233    .000192     1.16   0.252    -.0001657    .0006122
      1.subsidy  |  -21.34014   90.99788    -0.23   0.816    -205.7194    163.0391
           _cons |   65.05662   274.8028     0.24   0.814    -491.7468    621.8601
------------------------------------------------------------------------------
. ** Similarly for electric
. regress elecChange i.treated c.elec2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payOOOO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =      85
                                                       F(  6,    36) =    0.72
                                                       Prob > F      =  0.6356
                                                       R-squared     =  0.0459
                                                       Root MSE      =  493.66

                                 (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     elecChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
         treated |
   Participant   |  -93.18587   140.6682    -0.66   0.512    -378.4743    192.1025
       elec2012  |  -.0428262   .0514566    -0.83   0.411     -.147185    .0615326
                 |
height_category  |
           Hig   |  -81.31352    142.232    -0.57   0.571    -369.7734    207.1463
           Mid   |   139.5285   149.6661     0.93   0.357    -164.0085    443.0654
                 |
     squareFeet  |   .0002329   .0001798     1.30   0.203    -.0001316    .0005975
      1.subsidy  |  -38.57616   96.84104    -0.40   0.693    -234.9789    157.8266
           _cons |   65.98948   278.2724     0.24   0.814    -498.3732    630.3521
------------------------------------------------------------------------------
. ** Nothing of note
. regress elecChange i.treated c.elec2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =     346
                                                       F(  6,    73) =    4.84
                                                       Prob > F      =  0.0003
                                                       R-squared     =  0.2058
                                                       Root MSE      =  192.06

                                (Std. Err. adjusted for 74 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
     elecChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |    13.3563   19.27935     0.69   0.491    -25.06738    51.77998
       elec2012  |   -.1025613   .0206427    -4.97   0.000    -.1437022   -.0614204
                 |
height_category  |
           Hig   |  -26.14239   134.0582    -0.20   0.846      -293.32    241.0352
           Mid   |   88.17304   73.31963     1.20   0.233    -57.95278    234.2989
                 |
     squareFeet  |   .0006037    .000272     2.22   0.030     .0000616    .0011457
      1.subsidy  |   72.38236   23.02918     3.14   0.002     26.48528    118.2795
           _cons |   2.941684   18.88456     0.16   0.877    -34.69519    40.57856
------------------------------------------------------------------------------
.
. **** Fossil Fuel Section
. gen ffChange = ff2014-ff2012
(8 missing values generated)

. regress ffChange i.treated c.ff2012 ib2.height_category c.squareFeet ///
>  i.subsidy, vce(cluster portfolio)


Linear regression                                      Number of obs =     485
                                                       F(  6,    88) =    2.78
                                                       Prob > F      =  0.0161
                                                       R-squared     =  0.0837
                                                       Root MSE      =  1.9535

                                (Std. Err. adjusted for 89 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
       ffChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
        treated  |
   Participant   |     .20284   .1977993     1.03   0.308    -.1902445    .5959245
         ff2012  |   -.1789842   .0576232    -3.11   0.003    -.2934981   -.0644702
                 |
height_category  |
           Hig   |  -.4741569   .2510933    -1.89   0.062    -.9731522    .0248384
           Mid   |   .1056984     .44026     0.24   0.811    -.7692259    .9806228
                 |
     squareFeet  |   1.14e-07   8.13e-07     0.14   0.889    -1.50e-06    1.73e-06
      1.subsidy  |     .25082   .2245849     1.12   0.267    -.1954952    .6971353
           _cons |   1.759278   .4175436     4.21   0.000      .929498    2.589058
------------------------------------------------------------------------------
. ** No difference overall
. regress ffChange i.treated c.ff2012 ib2.height_category c.squareFeet ///
>  i.subsidy if ownerFF, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =     481
                                                       F(  6,    88) =    2.92
                                                       Prob > F      =  0.0120
                                                       R-squared     =  0.0892
                                                       Root MSE      =  1.9541

                               (Std. Err. adjusted for 89 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
       ffChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |   .2121272   .1985402     1.07   0.288    -.1824297    .6066842
         ff2012  |   -.186748   .0586835    -3.18   0.002    -.3033691   -.0701269
                 |
height_category  |
            Hig  |  -.5188145   .2427337    -2.14   0.035    -1.001197   -.0364322
            Mid  |   .1467796   .4442733     0.33   0.742    -.7361202    1.029679
                 |
     squareFeet  |   3.48e-07   7.71e-07     0.45   0.653    -1.18e-06    1.88e-06
      1.subsidy  |   .2612341   .2265556     1.15   0.252    -.1889975    .7114657
           _cons |   1.803554   .4243598     4.25   0.000     .9602279     2.64688
------------------------------------------------------------------------------
. regress ffChange i.treated c.ff2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payOOOO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =      84
                                                       F(  6,    35) =    1.13
                                                       Prob > F      =  0.3654
                                                       R-squared     =  0.0399
                                                       Root MSE      =  1.9347

                               (Std. Err. adjusted for 36 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
       ffChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |  -.1932373   .3696876    -0.52   0.604    -.9437431    .5572684
         ff2012  |  -.1056384   .0975108    -1.08   0.286    -.3035958     .092319
                 |
height_category  |
            Hig  |  -.7364161   .3569225    -2.06   0.047    -1.461007   -.0118249
            Mid  |  -.4593269   .4270038    -1.08   0.289    -1.326191    .4075368
                 |
     squareFeet  |   7.28e-07   7.25e-07     1.00   0.322    -7.43e-07    2.20e-06
      1.subsidy  |   .6284928   .4944247     1.27   0.212    -.3752426    1.632228
           _cons |   1.221092   .5256534     2.32   0.026     .1539585    2.288225
------------------------------------------------------------------------------
. regress ffChange i.treated c.ff2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =     347
                                                       F(  6,    73) =    2.05
                                                       Prob > F      =  0.0700
                                                       R-squared     =  0.1201
                                                       Root MSE      =  2.0315

                                (Std. Err. adjusted for 74 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
       ffChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
   Participant   |   .4453646   .2819091     1.58   0.118    -.1164795    1.007209
         ff2012  |  -.2401971   .0804413    -2.99   0.004    -.4005163   -.0798778
                 |
height_category  |
            Hig  |  -.7078826   .4489043    -1.58   0.119    -1.602548    .1867824
            Mid  |   .1684175   .7856347     0.21   0.831     -1.39735    1.734185
                 |
     squareFeet  |  -1.32e-06   2.37e-06    -0.56   0.580    -6.04e-06    3.41e-06
      1.subsidy  |    .025666   .2847282     0.09   0.928    -.5417964    .5931285
           _cons |   2.295157   .6089475     3.77   0.000     1.081527    3.508788
------------------------------------------------------------------------------
. ** This time no real difference for OOOOs
.
. *** Water Section
. gen waterChange = water2014-water2012
(300 missing values generated)

. regress waterChange i.treated c.water2012 ib2.height_category c.squareFeet ///
>  i.subsidy, vce(cluster portfolio)


Linear regression                                      Number of obs =     194
                                                       F(  6,    49) =    2.28
                                                       Prob > F      =  0.0512
                                                       R-squared     =  0.3083
                                                       Root MSE      =  21.685

                                (Std. Err. adjusted for 50 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
    waterChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
   Participant   |  -6.817545   4.402689    -1.55   0.128    -15.66508    2.029989
      water2012  |  -.3418286   .1116803    -3.06   0.004    -.5662587   -.1173986
                 |
height_category  |
            Hig  |    3.99663   3.552021     1.13   0.266    -3.141423    11.13468
            Mid  |  -1.998339   3.457202    -0.58   0.566    -8.945846    4.949169
                 |
     squareFeet  |  -7.74e-06   .0000114    -0.68   0.501    -.0000307    .0000152
      1.subsidy  |   7.844762   4.726807     1.66   0.103    -1.654112    17.34364
           _cons |    25.0036   8.495521     2.94   0.005     7.931212    42.07599
------------------------------------------------------------------------------
. ** Water shows a shift of 5% getting close to significance
. regress waterChange i.treated c.water2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payOOOO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =      50
                                                       F(  6,    18) =    5.58
                                                       Prob > F      =  0.0020
                                                       R-squared     =  0.6508
                                                       Root MSE      =  17.685

                                (Std. Err. adjusted for 19 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
    waterChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |  -23.93221   8.678803    -2.76   0.013    -42.16569   -5.698719
       water2012 |  -.4788623   .1212481    -3.95   0.001    -.7335952   -.2241294
                 |
height_category  |
            Hig  |   16.00824   12.23972     1.31   0.207    -9.706453    41.72294
            Mid  |   3.389921   4.721522     0.72   0.482    -6.529628    13.30947
                 |
      squareFeet |   -.000036   .0000137    -2.63   0.017    -.0000648   -7.24e-06
       1.subsidy |    10.2877   4.367576     2.36   0.030     1.111764    19.46364
           _cons |   46.41581   11.85194     3.92   0.001     21.51581    71.31581
------------------------------------------------------------------------------

. ** Sure enough, similar to energy, the OOOOs show a significant improvement
. regress waterChange i.treated c.water2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTOO, vce(cluster portfolio)


Linear regression                                      Number of obs =     121
                                                       F(  6,    36) =    2.75
                                                       Prob > F      =  0.0266
                                                       R-squared     =  0.2774
                                                       Root MSE      =  22.796

                                (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
    waterChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |  -4.495895   5.653701    -0.80   0.432    -15.96213    6.970341
       water2012 |  -.4848355   .1491464    -3.25   0.002    -.7873184   -.1823526
                 |
height_category  |
            Hig  |   4.875239   9.856819     0.49   0.624    -15.11532    24.86579
            Mid  |  -12.59638   5.584535    -2.26   0.030    -23.92234   -1.270417
                 |
      squareFeet |  -.0000319   .0000486    -0.66   0.516    -.0001305    .0000667
       1.subsidy |   8.979329   4.992703     1.80   0.080    -1.146343      19.105
           _cons |   35.66325   10.99183     3.24   0.003     13.37079    57.95571
------------------------------------------------------------------------------
.  regress waterChange i.treated c.water2012 ib2.height_category c.squareFeet ///
>  i.subsidy if payTTTO, vce(cluster portfolio)
```

```
Linear regression                                      Number of obs =      12
                                                       F(  4,     6) =       .
                                                       Prob > F      =       .
                                                       R-squared     =  0.2846
                                                       Root MSE      =  11.879

                                 (Std. Err. adjusted for 7 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
    waterChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
   Participant   |  -.7423007    6.93474    -0.11   0.918      -17.711     16.2264
      water2012  |   -.122541    .221688    -0.55   0.600    -.6649921    .4199101
                 |
height_category  |
            Mid  |   7.172717   4.811016     1.49   0.187    -4.599416    18.94485
     squareFeet  |  -.0000774    .0000713    -1.08   0.320    -.0002519    .0000972
      1.subsidy  |   20.43889   6.739944     3.03   0.023     3.946841    36.93094
           _cons |  -1.531861   12.75414    -0.12   0.908    -32.74011    29.67639
------------------------------------------------------------------------------
. regress waterChange i.treated c.water2012 ib2.height_category c.squareFeet ///
>  i.subsidy if !payOOOO, vce(cluster portfolio)


Linear regression                                      Number of obs =     144
                                                       F(  6,    41) =    2.58
                                                       Prob > F      =  0.0324
                                                       R-squared     =  0.2273
                                                       Root MSE      =  22.345

                                 (Std. Err. adjusted for 42 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
    waterChange  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
   Participant   |  -2.693719   4.860489    -0.55   0.582    -12.50968    7.122237
      water2012  |  -.2932669   .1132548    -2.59   0.013    -.5219895   -.0645442
                 |
height_category  |
            Hig  |  -4.039122   6.375712    -0.63   0.530    -16.91513    8.836889
            Mid  |   -2.86511   3.432221    -0.83   0.409    -9.796621    4.066401
                 |
     squareFeet  |   .0000134   .0000148     0.90   0.373    -.0000166    .0000433
      1.subsidy  |   5.425081   4.928485     1.10   0.277    -4.528196    15.37836
           _cons |   18.88687   8.359299     2.26   0.029     2.004922    35.76882
------------------------------------------------------------------------------
. ** And non OOOOs show nothing of relevance
.
```

```
. *** Fuel Change Section
. ** The following are used to determine the % split of savings between Electricity and Gas
. ** This percentage is then applied to the overall energy savings which is more significant of a
result.
. ** The totals below are close but as expected not exactly the total energy saved.
. ** Number of participants in regression = mean participant value in estat * number of obs
(since participant = 1)
. ** Fuel saved = treated_coeff * mean square footage of participants * number of participants in
regression
. gen elecfuelChangepersqft = (elecfuel2014-elecfuel2012)/squareFeet
(1 missing value generated)

. gen gasfuelChangepersqft = (gasfuel2014-gasfuel2012)/squareFeet
(8 missing values generated)
. gen watertotChangepersqft = (watertot2014-watertot2012)/squareFeet
(300 missing values generated)
. regress elecfuelChangepersqft i.treated c.eui2012 ib2.height_category c.squareFeet i.subsidy if
payOOOO, vce(cluster portfolio)
Linear regression                                      Number of obs =      85
                                                       F(  6,    36) =    3.50
                                                       Prob > F      =  0.0079
                                                       R-squared     =  0.1267
                                                       Root MSE      =  .61917

                                (Std. Err. adjusted for 37 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
elecfuelChang~t  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |  -.2744092   .1195383    -2.30   0.028    -.5168441   -.0319744
        eui2012  |  -.0035206   .0034356    -1.02   0.312    -.0104882     .003447
                 |
height_category  |
           Hig   |  -.0352262   .1461292    -0.24   0.811      -.33159    .2611376
           Mid   |   .5337832   .1459282     3.66   0.001     .2378271    .8297393
                 |
     squareFeet  |   4.44e-08   1.95e-07     0.23   0.821    -3.51e-07    4.40e-07
      1.subsidy  |    .075298   .1619683     0.46   0.645    -.2531889    .4037849
          _cons  |   .2536256   .2758313     0.92   0.364    -.3057862    .8130374
------------------------------------------------------------------------------


. estat summarize

Estimation sample regress
                                Number of obs        =       85

                                Number of clusters   =       37
                                Obs per cluster: min =        1
                                                 avg =      2.3
                                                 max =       12

------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+----------------------------------------------
elecfuelCh~t |   -.0758367     .6384751   -2.23882    1.95138
             |
     treated |
Participant  |    .5294118     .5020964          0          1
     eui2012 |    82.78132      36.1924     28.835    239.061
             |
height_cat~y |
        Hig  |    .1176471     .3241019          0          1
        Mid  |    .0941176     .2937252          0          1
             |
  squareFeet |    60587.56     137534.5       6392    1.2e+06
   1.subsidy |    .7764706     .4190826          0          1
------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated
```

```
Predictive margins                              Number of obs   =         85
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |   .0694387   .0697921     0.99   0.326    -.0721061    .2109836
Participant  |  -.2049705    .091711    -2.23   0.032     -.390969    -.018972
------------------------------------------------------------------------------

. regress gasfuelChangepersqft i.treated c.eui2012 ib2.height_category c.squareFeet i.subsidy if
payOOOO, vce(cluster portfolio)

Linear regression                                      Number of obs =      84
                                                       F(  6,    35) =    8.48
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1384
                                                       Root MSE      =  .08001

                                (Std. Err. adjusted for 36 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
gasfuelChange~t  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
        treated  |
   Participant   |  -.0354244   .0142308    -2.49   0.018    -.0643143   -.0065344
        eui2012  |  -.0003233   .0005032    -0.64   0.525    -.0013448    .0006982
                 |
height_category  |
           Hig   |  -.0589852   .0382578    -1.54   0.132    -.1366526    .0186822
           Mid   |  -.0028634   .0421726    -0.07   0.946    -.0884783    .0827515
                 |
     squareFeet  |  -4.63e-08   3.35e-08    -1.38   0.176    -1.14e-07    2.18e-08
      1.subsidy  |     .01165   .0322577     0.36   0.720    -.0538367    .0771367
           _cons |   .0174559   .0462197     0.38   0.708    -.0763751    .1112869
------------------------------------------------------------------------------

. estat summarize

Estimation sample regress
                                Number of obs        =       84

                                Number of clusters   =       36
                                Obs per cluster: min =        1
                                                 avg =      2.3
                                                 max =       12

-------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+-----------------------------------------------
gasfuelCha~t |   -.0293415     .0830181   -.286909    .287924
             |
     treated |
Participant  |    .5357143     .5017182          0          1
     eui2012 |    82.60772     36.37416     28.835    239.061
             |
height_cat~y |
        Hig  |    .1190476     .3257896          0          1
        Mid  |    .0952381     .2953066          0          1
             |
  squareFeet |     61189.8     138247.8       6392    1.2e+06
   1.subsidy |    .7738095     .4208766          0          1
-------------------------------------------------------------
Std. Dev. not adjusted for clustering

. margins treated
```

```
Predictive margins                              Number of obs   =         84
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |  -.0103642   .0085632    -1.21   0.234    -.0277484    .0070201
Participant  |  -.0457885   .0145862    -3.14   0.003       -.0754    -.016177
------------------------------------------------------------------------------
```

```
. regress watertotChangepersqft i.treated c.eui2012 ib2.height_category c.squareFeet i.subsidy if
payOOOO, vce(cluster portfolio)

Linear regression                                      Number of obs =      50
                                                       F(  6,    18) =   32.43
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1552
                                                       Root MSE      =  .01646

                                 (Std. Err. adjusted for 19 clusters in portfolio)
------------------------------------------------------------------------------
                 |               Robust
watertotChang~t  |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
         treated |
    Participant  |  -.0143127   .0075187    -1.90   0.073    -.0301089    .0014835
         eui2012 |  -.0000758   .0000761    -1.00   0.333    -.0002357    .0000841
                 |
height_category  |
            Hig  |   .0144352   .0068536     2.11   0.049     .0000362    .0288342
            Mid  |    .014405   .0130132     1.11   0.283    -.0129347    .0417447
                 |
      squareFeet |  -2.31e-08   5.27e-09    -4.38   0.000    -3.41e-08   -1.20e-08
       1.subsidy |  -.0058006   .0063111    -0.92   0.370    -.0190598    .0074586
           _cons |   .0127609    .011245     1.13   0.271     -.010864    .0363857
------------------------------------------------------------------------------

. estat summarize

Estimation sample regress
                                 Number of obs        =       50

                                 Number of clusters   =       19
                                 Obs per cluster: min =        1
                                                  avg =      2.6
                                                  max =       12

-------------------------------------------------------------
    Variable |        Mean     Std. Dev.       Min        Max
-------------+-----------------------------------------------
watertotCh~t |   -.0049683     .0167763   -.099198    .015513
             |
     treated |
Participant  |          .6     .4948717          0          1
     eui2012 |    88.03873     39.34668     28.835    239.061
             |
height_cat~y |
        Hig  |         .12     .3282607          0          1
        Mid  |          .1     .3030458          0          1
             |
  squareFeet |    68604.54       175895       6392    1.2e+06
   1.subsidy |          .7       .46291          0          1
-------------------------------------------------------------
Std. Dev. not adjusted for clustering
```

```
. margins treated

Predictive margins                              Number of obs   =         50
Model VCE    : Robust

Expression   : Linear prediction, predict()

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     treated |
    Control  |   .0036193   .0027876     1.30   0.211    -.0022372    .0094757
Participant  |  -.0106934   .0049105    -2.18   0.043      -.02101   -.0003768
------------------------------------------------------------------------------
```

```
.
.
. ** Power calc
```

In order to see the number of observations needed for the overall difference of 1.3 kBTU/sqft we must take into account the intracluster correlation of our properties within portfolios. To get an estimate of that we can use:

```
. loneway energyChange portfolio

                 One-way Analysis of Variance for energyChange:

                                             Number of obs =       494
                                                 R-squared =    0.2993

    Source                SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between portfolio      6311.5184     89    70.915937      1.94     0.0000
Within portfolio       14773.115    404    36.567115
------------------------------------------------------------------------
Total                  21084.633    493    42.768018

         Intraclass        Asy.
         correlation       S.E.       [95% Conf. Interval]
         -----------------------------------------------
            0.14726      0.04610       0.05690     0.23763

         Estimated SD of portfolio effect        2.512944
         Estimated SD within portfolio           6.047075
         Est. reliability of a portfolio mean     0.48436
              (evaluated at n=5.44)
```

This in turn allows us to use the custom user function in Stata clustersampsi where mu1, mu2 are the changes int eh control and participant means respectively, sd1 and sd2 are the standard deviations of the measured variable (energyChange), rho is the Intraclass Coefficient estimated above, size_cv is the coefficient of variation in the size of our clusters and base_correl is the correlation of our measured change with the starting EUI:

```
. clustersampsi, samplesize mu1(0) mu2(-1.3) sd1(6.1) sd2(6.9) m(5) rho(0.14726) size_cv(0.9)
base_correl(0.3)
Sample size calculation determining the number of clusters required,
for a two sample comparison of means (using normal approximations).
```

For the user specified parameters:

mean 1:	0.00
mean 2:	-1.30
standard deviation 1:	6.10
standard deviation 2:	6.90
significance level:	0.05
power:	0.80
baseline measures adjustment (correlation):	0.30
average cluster size:	5
intra cluster correlation (ICC):	0.1473
coefficient of variation (of cluster sizes):	0.90

clustersampsi estimated parameters:

Firstly, assuming individual randomisation:

sample size per arm:	359

Then, allowing for cluster randomisation:

design effect:	2.19
sample size per arm:	790
number clusters per arm (m):	158

Note: sample size per arm required under cluster randomisation is rounded up
to a multiple of average cluster size and includes the addition
of one extra cluster per arm (to allow for t-distribution).
To understand sensitivity to these conservative allowances:

power with m clusters per arm:	0.80
power with m-1 clusters per arm:	0.80

This essentially tells us we need 790 properties if we continue to have an average cluster size of 5 properties to see a difference of 1.3 kBTU per sqft.