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Assessing the Impact of Communication Channel on Behavior Changes in Energy Efficiency

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ABSTRACT

With the increase in government and commissions incentivizing electric utilities to get consumers to save energy, there has been a large increase in the number of energy saving programs. Some are structural, incentivizing consumers to make improvements to their home that result in energy savings. Some, called behavioral programs, are designed to get consumers to change their behavior to save energy. Within behavioral programs, Home Energy Reports are a good method to achieve behavioral savings as well as to educate consumers on structural energy savings. This paper examines the different Home Energy Report communication channels (direct mail and e-mail) and the marketing channel effect on energy savings, using SAS® for linear models. For consumer behavioral change, we often hear the questions: 1) Are the people that responded via direct mail solicitation saving at a higher rate than people who responded via an e-mail solicitation? 1a) Hypothesis: Because e-mail is easy to respond to, the type of customers that enroll through this channel will exert less effort for the behavior changes that require more time and investment toward energy efficiency changes and thus will save less. 2) Does the mode of that ongoing dialog (mail versus e-mail) impact the amount of consumer savings? 2a) Hypothesis: E-mail is more likely to be ignored and thus these recipients will save less. As savings is most often calculated by comparing the treatment group to a control group (to account for weather and economic impact over time), and by definition you cannot have a dialog with a control group, the answers are not a simple PROC FREQ away.

This study used clustering (PROC FASTCLUS) to segment the consumers by mail versus e-mail and append cluster assignments to the respective control group. This study also used DID (Difference-in-Differences) and PROC GLM to calculate the statistical savings differences of these groups.

INTRODUCTION

SUMMARY: Electric and natural gas utilities have many bottom-line reasons to help customers use less energy—from regulatory compliance and avoiding costly new generation plants to simple public relations. Utilities spend millions of dollars each year trying to persuade hard-to-reach residential and commercial customers to change their behaviors and make facility improvements for greater energy efficiency. What if the secret to success was as simple as choosing the right communication channel?

One tool used by many utilities to generate residential energy savings is Home Energy Reports. This paper examines whether communicating information about Home Energy Reports by e-mail or through direct mail solicitation impacts the measurable energy savings that customers achieve.

We hypothesized that direct mail would be a more effective communication channel in terms of real, measurable energy savings over the long run. This was based on a premise that people who enrolled through the easiest communication channel (e-mail) would exert less effort toward behavioral changes that required time and energy on their part—thus resulting in lower energy savings. In addition, we hypothesized that the relative ease of ignoring e-mails would make ongoing dialog through this communication channel less effective than direct mail.

APPROACH AND RESULTS: The study employed SAS and statistical techniques to cluster consumers into treatment and multiple matched control groups and compare actual electric usage (kWh) for each cluster pre- and post-treatment called “difference in differences”. While all of the customers in treatment groups (those who enrolled in Home Energy Reports) saved more energy than those who were not, the group that was solicited by direct mail and received ongoing mailed reports saved energy at a much higher rate than the other groups.

WORTHINESS: There is a lot on the line for utilities when it comes to energy conservation programs. The time and money being invested needs to deliver quantifiable and predictable results. This paper provides data-driven insights that empower utilities (both electric and natural gas) to better communicate with customers for heightened program effectiveness, improved customer responses and greater energy efficiency. This translates into regulatory compliance, customer satisfaction, and, ultimately, a stronger bottom line.

DIFFERENCE IN DIFFERENCES: To calculate energy savings – look at the difference in electric usage of our treatment group from the pre-treatment period to the post-treatment period, and compare that to the difference in electric usage of the control group from the equivalent pre-treatment period to the post treatment period, and assume the control represents what would have happened without treatment. See Figure 0.

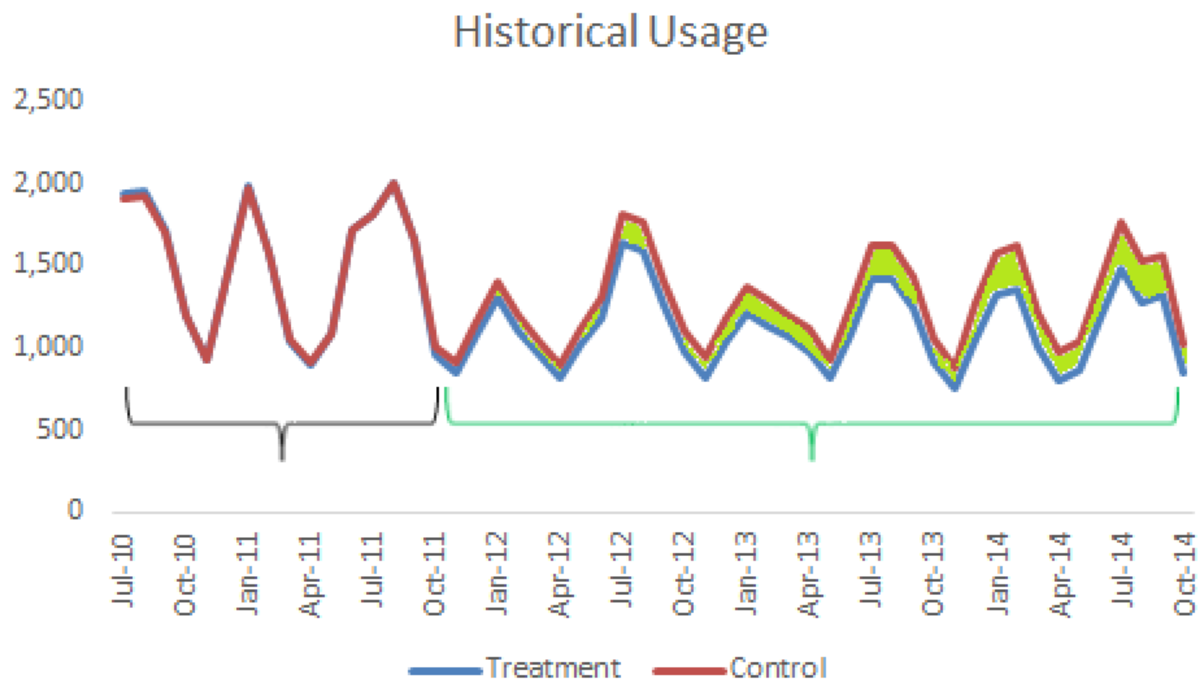


Figure 0. Usage Comparison of Treatment group to control group during Pre-Treatment Period and Treatment periods

USING CLUSTERING TO SEGMENT THE CONTROL GROUP BY A MISSING "TREATMENT" VARIABLE

OPT-IN/ENGAGEMENT FACTOR: Previous to solicitation/treatment, a randomized number of people should be held out for the broad\unmatched control group. As people opt-in to the program (the treatment group) and become engaged in the program, the demographics will change. Select people from the broad\unmatched group to be part of the matched group. See Figure 1.

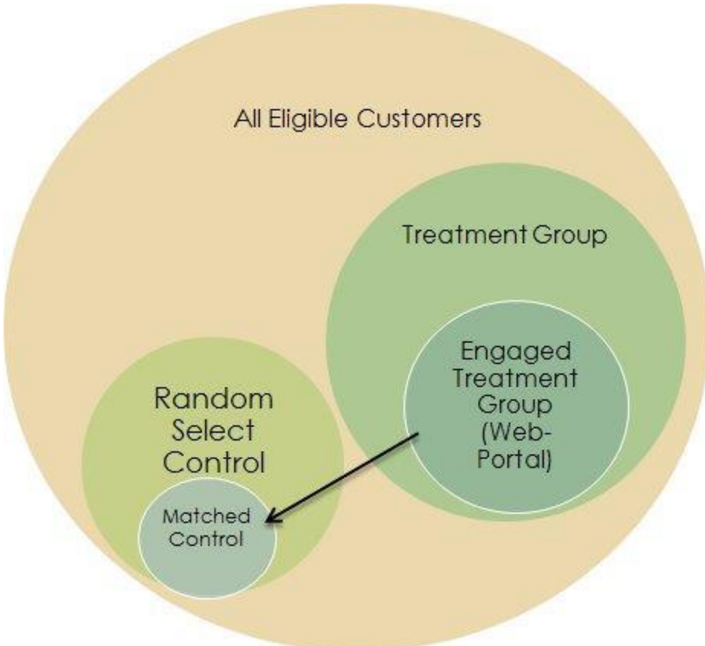


Figure 1. Broad Treatment w\ Opt-in Subset: Random Control with Matched Subset:

MARKETING CHANNEL: In trying to look at Marketing Channel effect on energy savings for the treatment group, there is the added problem that the control group has not been marketed to, thus does not have marketing channels to segment by.

This treatment group has 2 types of marketing channels.

1) How they were initially solicited
2) How they receive ongoing treatment (“Reports”)

This resulted in four treatment segments. See Figure 2.

		Solicitation Type	
	Savings (kWh)	Direct Mail	Email
Ongoing (“Report”)	Direct Mail	A	B
	Email	C	D

Figure 2. The Experimental Design

For clustering, based on prior results and trial and error, there were 9 clusters (K=9). Additionally, there were 9 for each report/solicitation type, resulting in 36 sub-segments.

4 variables were the most important in determining the clusters:

- Age
- Income
- Length of Residence
- Electrical Usage

PROCESS:

- Randomly assign broad\unmatched control group to each A/B/C/D treatment according to size of treatment group. See Figures 3a & 3b.
- For each A/B/C/D:
    - Use K-Means cluster (Proc FASTCLUS), cluster each group including both treatment and random control.
        - This likely will result in an uneven split of the random control group to each individual cluster (k). Some clusters are over represented, others under represented. See Figure 4.
    - Find the size of each resulting K for the treatment group.
    - Multiply by 33.33% to get the X number of people in the random control group that should be selected for each "K" and associated matched control group.
        - The control group size as a % of the treatment group was determined outside of this study.
    - Randomly choose every nth record of the random control group to be assigned to the matched control group until X is reached.
        - Each individual cluster thus has the same representation\proportion within both the treatment and the matched control group. See Figure 5.
    - Compare summary of A/B/C/D treatment demographics to demographics of matched A/B/C/D control groups. See Figures 6 and 7.
        - Looking at both univariate distributions of demographics by treatment and matched control as well as the interaction effect concludes that the matched control is a good representation of those customers in the treatment groups.

Savings (kWh)	Direct Mail	Email
Direct Mail	42%	2%
Email	21%	35%

Figure 3a. Proportion of each treatment subset to whole.

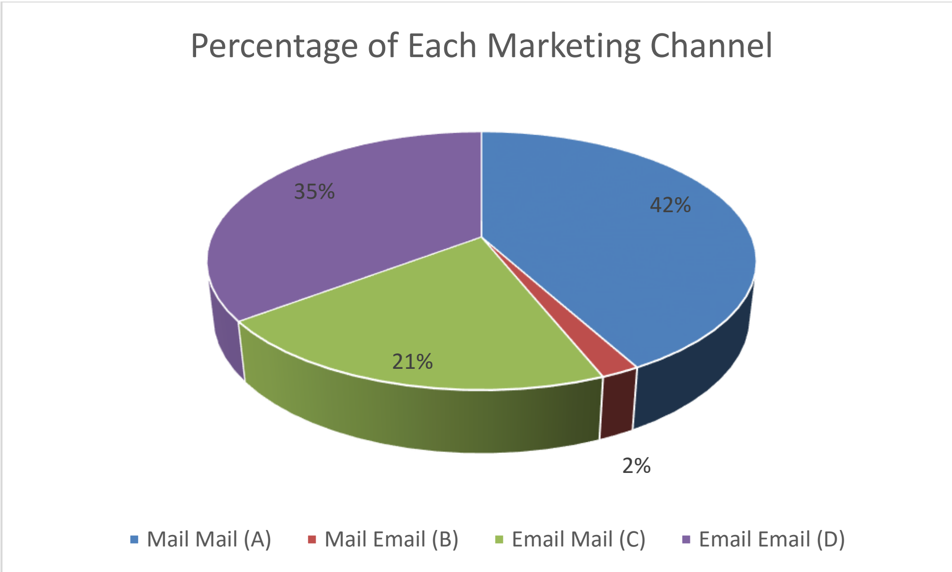


Figure 3b. Proportion of each treatment subset to whole.

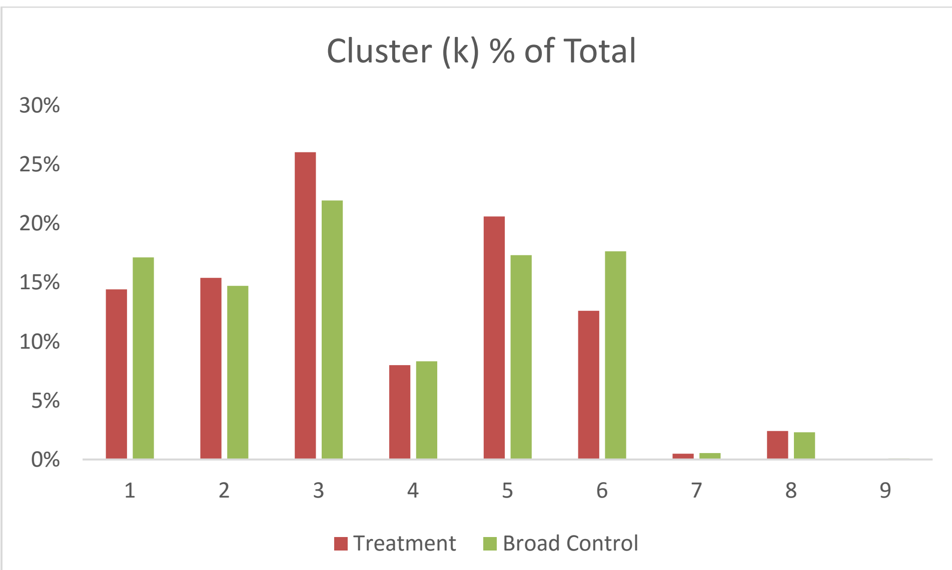


Figure 4: Random control was over represented in some clusters, underrepresented in others.

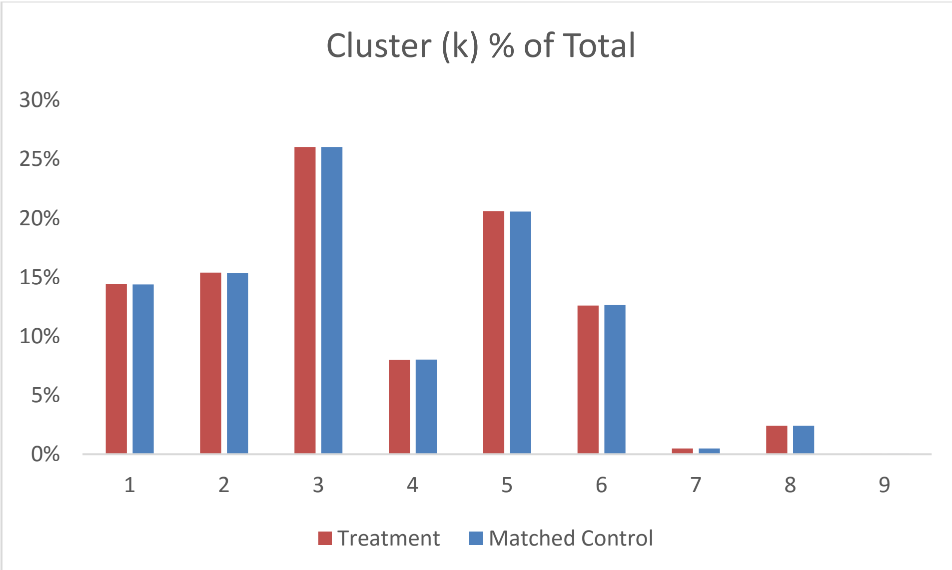


Figure 5: Matched control has the same cluster representation as the treatment group.

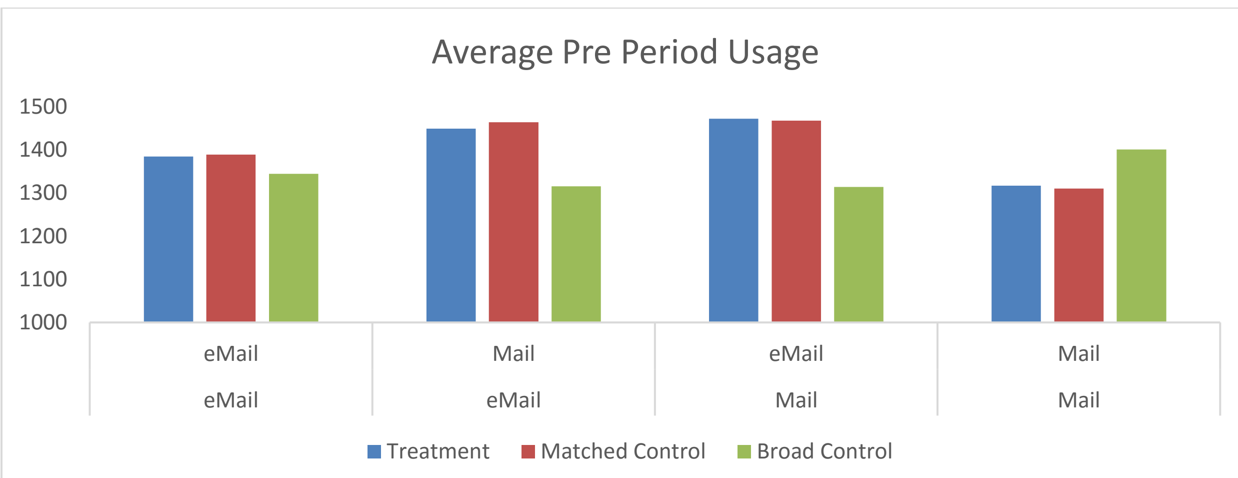


Figure 6: Average Usage by Channel, Treatment vs. Random Control and Matched Control.

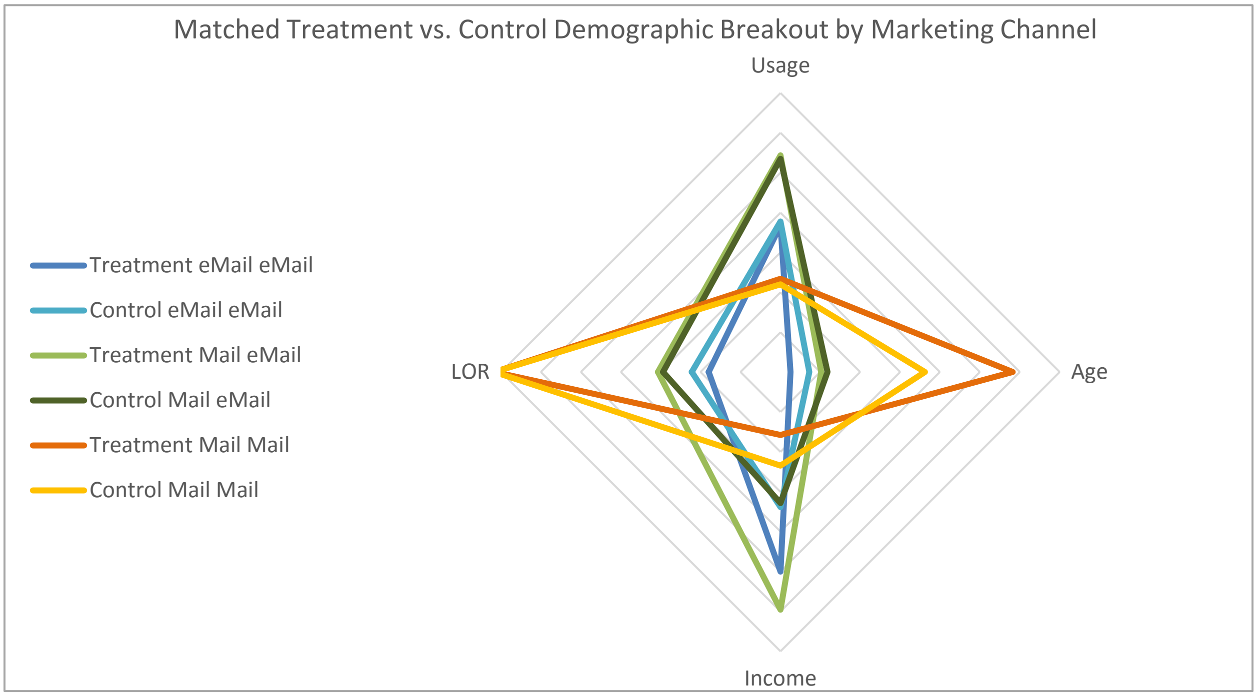


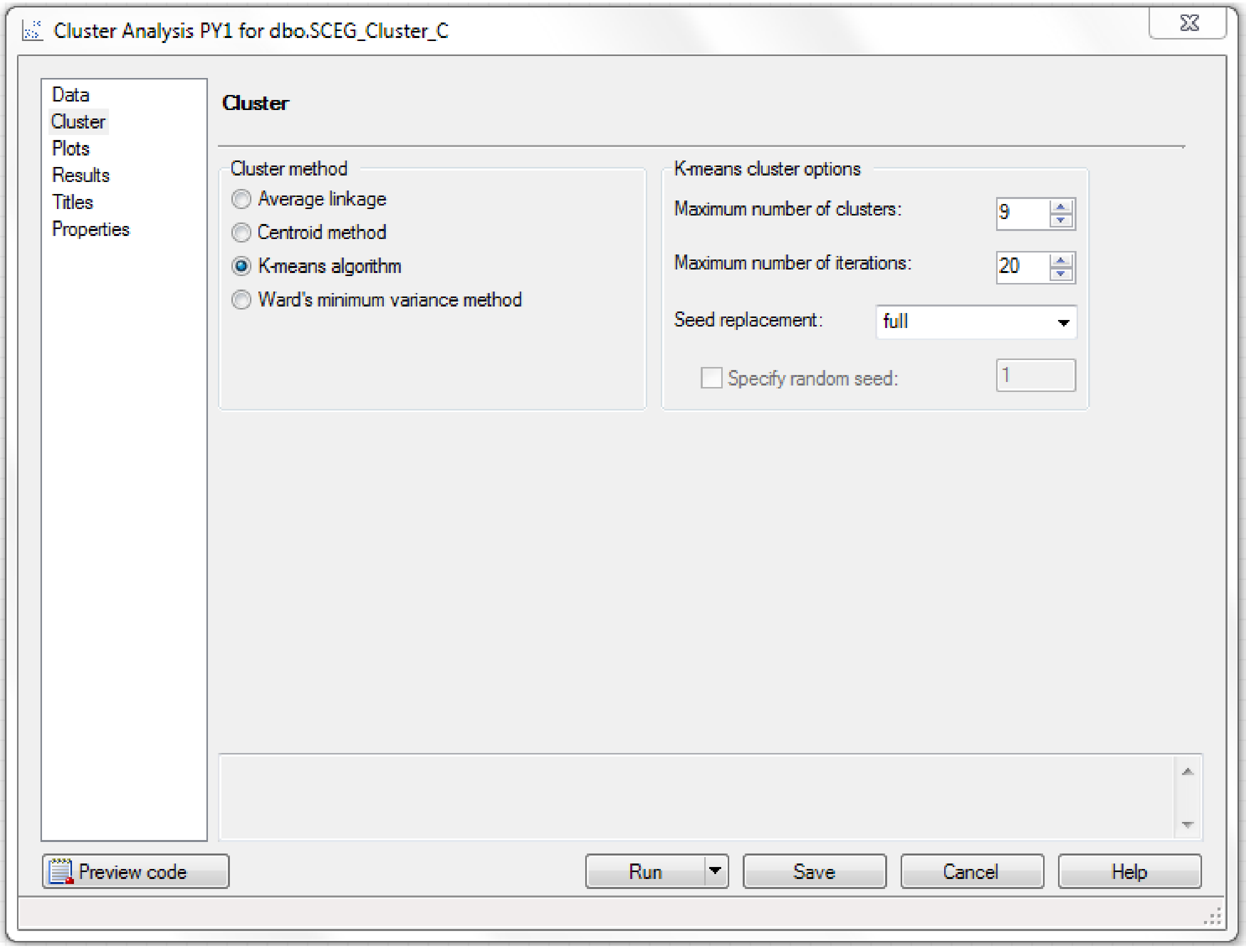
Figure 7: Demographic differences between experimental design groupings.

SAS CODE

```
DATA _NULL_;
      dsid = OPEN("WORK.dbo_SCEG_Cluster_C9498", "I");
      dstype = ATTRC(DSID, "TYPE");
      IF TRIM(dstype) = " " THEN
            DO;
            CALL SYMPUT("_EG_DSTYPE_", "");
            CALL SYMPUT("_DSTYPE_VARS_", "");
            END;
      ELSE
            DO;
            CALL SYMPUT("_EG_DSTYPE_", "(TYPE=""" || TRIM(dstype) || """)");
            IF VARNUM(dsid, "_NAME_") NE 0 AND VARNUM(dsid, "_TYPE_") NE 0
THEN
                  CALL SYMPUT("_DSTYPE_VARS_", "_TYPE_ _NAME_");
            ELSE IF VARNUM(dsid, "_TYPE_") NE 0 THEN
                  CALL SYMPUT("_DSTYPE_VARS_", "_TYPE_");
            ELSE IF VARNUM(dsid, "_NAME_") NE 0 THEN
                  CALL SYMPUT("_DSTYPE_VARS_", "_NAME_");
            ELSE
                  CALL SYMPUT("_DSTYPE_VARS_", "");
            END;
      rc = CLOSE(dsid);
      STOP;
RUN;

/* -------------------------------------------------------------------
   Data set WORK.dbo_SCEG_Cluster_C9498 does not need to be sorted.
   ------------------------------------------------------------------- */
DATA WORK.SORTTempTableSorted &_EG_DSTYPE_ / VIEW=WORK.SORTTempTableSorted;
      SET WORK.dbo_SCEG_Cluster_C9498(WHERE=(PY_Year = 2011 AND IncomeID NOT
= 0 AND LengthOfResidenceID NOT = 396 AND PRE_Usage > 10));
RUN;
TITLE;
TITLE1 "Cluster Analysis Results";
FOOTNOTE;
FOOTNOTE1 "Generated by the SAS System (&_SASSERVERNAME, &SYSSCPL) on
%TRIM(%QSYSFUNC(DATE(), NLDATE20.)) at %TRIM(%SYSFUNC(TIME(), TIMEAMPM12.))";

PROC FASTCLUS DATA=WORK.SORTTempTableSorted
      MAXC=9
      MAXITER=20
      REPLACE=FULL
      OUT=WORK.CLKMKMeansDatadbo_SCEG_Cluster_C(LABEL="K-means cluster data
for WORK.dbo_SCEG_Cluster_C9498")
      ;
      VAR HouseHoldAgeID IncomeID LengthOfResidenceID PRE_Usage;
RUN;
/* -------------------------------------------------------------------
   End of task code.
   ------------------------------------------------------------------- */
RUN; QUIT;
%_eg_conditional_dropds(WORK.SORTTempTableSorted);
TITLE; FOOTNOTE;
ODS GRAPHICS OFF;
```



Statistics for Variables				
Variable	Total STD	Within STD	R-Square	RSQ/(1-RSQ)
HouseHoldAgeID	14.75286	11.43773	0.399035	0.663990
IncomeID	14.25322	13.78288	0.065078	0.069607
LengthOfResidenceID	13.78895	9.80031	0.494945	0.979984
PRE_Usage	34.08018	10.42064	0.906522	9.697756
OVER-ALL	21.04991	11.46108	0.703604	2.373865

Pseudo F Statistic =	13198.69

Approximate Expected Over-All R-Squared =	0.76361

Cubic Clustering Criterion =	-93.113

WARNING: The two values above are invalid for correlated variables.

Cluster Means				
Cluster	HouseHoldAgeID	IncomeID	LengthOfResidenceID	PRE_Usage
1	40.4718565	41.7339025	20.3090725	44.5151208
2	57.3356144	45.9894377	43.4590896	95.8763761
3	59.5100572	45.5181768	43.1592545	65.5725226
4	49.4813484	48.3523073	35.0262503	124.9043935
5	64.2724512	38.0032699	41.4882635	37.4610534
6	40.2438725	43.5344669	21.8370098	80.5621936
7	54.1250000	55.6473214	36.7500000	223.6517857
8	52.6159696	53.0589354	37.4334601	165.9344106
9	60.9375000	61.3125000	37.5000000	327.2187500

Cluster Standard Deviations				
Cluster	HouseHoldAgeID	IncomeID	LengthOfResidenceID	PRE_Usage
1	12.38819916	14.34055328	10.88210617	11.54554418
2	11.50956114	13.28560884	7.53887164	9.02281217
3	11.24011425	12.86811000	7.93934703	8.58759799
4	12.58045958	14.88756283	13.22786339	10.64852469
5	10.24670782	13.76071033	9.84026577	10.52521561
6	11.26868504	14.12187450	10.58371878	11.28139695
7	12.26107992	17.08369511	12.21665407	20.69843686
8	12.35029677	15.52280622	12.24419870	14.10671825
9	12.40691145	12.40301082	12.26587188	47.00359243

Generated by the SAS System ('SASApp', X64_S08R2) on October 16, 2014 at 1:36:18 PM

DIFFERENCE-IN-DIFFERENCES RESULTS

After doing the clustering work above to create the matched control groups for each marketing channel, we were able to do the difference-in-differences calculation and compare the treatment groups to the control groups. We found that while all treatment groups saved energy, the group that was solicited by mail and received ongoing mail reports as their treatment saved energy at a much higher rate than the other groups.

Annual Savings in kWh		Solicitation Type		
		Direct Mail	Email	Total
Report Type	Direct Mail	322	189	317
	Email	218	224	223
	Total	290	221	269

PROC GLM – CALCULATING T-TESTS WITHIN CELLS

The “GLM” in proc glm stands for general linear models which includes multiple linear regression models and many analysis of variance models. After identifying the right control group for the right treatment cell (using the FASCLUS), confirm beyond univariate statistics that the pre period control group usage and pre period treatment group usage in each cell are the same, or not statistically significantly different.

The hypothesis test is H_0: $\mu_1 = \mu_2$

The usage database is set up as follows:

Obs	CustomerID	group	ControlGroup	PRE_Avg_Monthly_Usage
1	39671	MailMail	0	631
2	49742	MailMail	0	1566
3	39772	MailMail	1	837
4	49785	eMaileMail	0	1749
5	43836	eMaileMail	1	1735
6	43938	eMaileMail	0	1948
7	43984	MaileMail	0	1962
8	43992	MaileMail	1	625
9	40013	MaileMail	0	1780
10	44017	eMailMail	0	860

From proc print procedure option obs=10

The data must be sorted prior to using By group statements in the glm.

```
PROC SORT data=preusage;
by group; /*cells: MailMail, MailEmail, EmailEmail,EmailMail*/
run;

PROC GLM data=preusage;
by group;
class controlgroup;
model pre_avg_monthly_usage=controlgroup;
means controlgroup/t alpha=.05 lines;
run;
```

In all four cells (mail/mail, mail/email, email/email, mail/email) based on the t test result, accept the null hypothesis that the average usage within cells between the control group and the treatment group were not statistically significantly different. Therefore you are confident in the results of the clustering approaches that assign the right person in a control group to the right group in the treatment group within the right cells.

Bonferroni & Duncan produced the same results as the t test. Below are the SAS Output results for the t test for the Mail/Mail Group. Means with the same letter are not statistically significantly different.(Output 1.)

The GLM Procedure

t Tests (LSD) for PRE_Avg_Monthly_Usage

group=MailMail

Note: This test controls the Type I comparisonwise error rate, not the experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	15339
Error Mean Square	440433
Critical Value of t	1.96012
Least Significant Difference	24.375
Harmonic Mean of Cell Sizes	5696.213

Note: Cell sizes are not equal.

Means with the same letter

are not significantly different.

t Grouping	Mean	N	ControlGroup
A	1391.67	11562	0
A			
A	1388.01	3779	1

Output 1. Output from a Proc GLM Statement

CONCLUSION

This paper describes one approach to measuring marketing channel indicators on energy savings through matching control and treatment groups using PROC FASCLUS and PROC GLM for ANOVA. Actual energy savings can be calculated using a variety of statistical and engineering methods other than the difference-in-difference method used here.

The clustering was able to find similarly situated customers in the non-treatment group that looked like the treatment groups that received different communication pieces. The descriptions of the customers in each treatment group allows us to identify the highest savings potential customers for the behavior program campaigns prior to the implementation, and allow us to estimate the cost effectiveness of direct mail compared to the benefit of energy savings.

SAS software procedures provided the necessary tools to conduct the clustering of the treatment populations and finding the matching customers in the control populations.

REFERENCES

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Julie Zenner, Freelance Writer/Editor and Co-host, Almanac North, WDSE/WRPT TV

RECOMMENDED READING

- *SAS® System for Linear Models*
- *SAS® For Dummies®*
- *ACEEE Field Guide to Utility-Run Behavior Programs, December 2013*

CONTACT INFORMATION

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FAQS

Why did you limit clustering to 4 variables?
There was a previous analysis done which identified the matched control group based on those 4 variables. The results were used for EM&V and filed with government regulators. We had to duplicate that process as much as possible, and include the same members that were in the original matched control group. Our process added to the original matched control group while additionally segmenting them into the marketing channels we had identified.

Why k=9?
See response to above question regarding previous analysis. It used 9. Additionally we used trial and error with multiple values of k. Fewer k did not give us the distinction we needed to apply to the control group to get a good match. More k resulted in some segments that were too small to get enough people in our matched control group.

Why is the eMail solicited Mail Report Type so small?
People who were solicited via mail could sign up online or via paper and thus get emailed or mailed reports. People who were solicited via eMail could only sign up online and thus receive emailed reports. The only way they would get mailed reports was if the email they signed up with bounced.

Why 33%?
This gave us enough of an overall matched control to be able to further segment into the four solicitation/report channels. Since solicitations go out for this program every year, there are some years that have fewer participants and thus a much smaller control group. As weather changes daily, the date that someone joins the program can be very important in calculating their 'pre' and 'post' usage.