MyMeter Multi-Utility Impact Findings

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Accelerated Innovations

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Table of Contents

1. EXECUTIVE SUMMARY

Illume Advising, LLC (ILLUME) and Klos Energy Consulting (Klos) (hereinafter, the ILLUME team) were commissioned to conduct an impact evaluation of Accelerated Innovations' (AI) MyMeter program. The goal of this report is two-fold: (1) to document a preferred methodology used to estimate savings associated with the MyMeter program, and (2) to provide impact savings values for select Minnesota utilities currently delivering the MyMeter program.

1.1 Project background

Accelerated Innovations' MyMeter initiative is an opt-in, online feedback program offered to all residential and commercial utility customers. To participate, customers sign-up through their local utility's website. Once enrolled, participants can customize their profile by providing information on their household's or business's characteristics, such as size of the building, age of the building, equipment owned, and occupation. Once registered, consumers are incentivized to engage with the program through a number of features, including comparative usage, energy challenges, bill threshold alerts, peak time alerts, energy markers, and outage alerts.

For several years, the MyMeter programs have remained actively in-field, beginning in 2007 for Wright-Hennepin and as recently as 2010 for Lake Region.

1.2 Key findings

The MyMeter program demonstrated savings reductions for residential customers, ranging from 1.8% to 2.8%. Table 1 summarizes the impact results.

Table 1. Summary of Electric Savings by Utility

Utility	Total Participants	Evaluation Period	Avg. Annual Residential Savings (% Reduction and Total kWh)	
Beltrami	2,540	05/10-05/13	2.8%	705,344 kWh
Lake Region	3,287	01/10-04/13	2.6%	857,849 kWh
Stearns	2,141	05/10-04/13	1.8%	463,783 kWh
Wright-Hennepin	6,188	04/07-06/13	2.2%	844,030 kWh

In addition to measuring unique savings due to the MyMeter program, we pooled across the four utilities to examine seasonal trends by baseline usage, longevity, and engagement. Savings tended to occur during the spring and fall suggesting that savings are coming from year-round sources such as lighting. Savings persisted at a steady level during the first two years of participation, were higher for participants with higher baseline usage, and in some cases were higher for participants with higher levels of engagement.

We found that MyMeter savings are unique of other programs effects. We introduced participation terms to control for rebate participation and found that the savings effects estimated for MyMeter participation remained the same. Generally, the rebate terms were not statistically significant. In one instance where we accounted for heat pump program participation, we found an increase in MyMeter savings. This indicates that customers who participated in the heat pump program may have increased their usage. While the efficient equipment installed by a homeowner may use less energy than standard equipment, the equipment may be adding load if it represents a new use of electricity for the homeowner.

1.3 Recommendations

As aforementioned, the goal of this report is to outline a methodology to evaluate the MyMeter program and to assess the program impacts.

The primary goal of an impact evaluation is to develop a rigorous counterfactual – what we expect to happen in the absence of program. In behavioral programs, this has meant a strong movement towards Randomized Control Trials (RCTs), largely driven by the home energy report model and protocols that strongly recommend using RCTs to establish a counterfactual.[1] However, pure experimental designs can be impractical in practice for many reasons, and recent evaluations have looked for alternative models for opt-in program designs.

Recent evaluations of opt-in programs have used matching approaches to mimic the effect of a purely randomized control group by using observable characteristics, such as energy use, to match treatment customers to a target comparison group with the theory that such matching accounts for *unobservable* characteristics that might be correlated with both one's likelihood to enroll in the program and one's overall energy consumption during treatment.

For the purposes of the MyMeter program, we recommend drawing on these lessons. Specifically:

[1] State and Local Energy Efficiency Action Network. 2012. *Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-based Energy Efficiency Programs.* Prepared by A. Todd, E. Stuart, S. Schiller, and C. Goldman, Lawrence Berkeley National Laboratory.

- **Future evaluations of the MyMeter should use the Imbens Bias Adjustment Matching Approach.** We recommend using the bias-corrected matching set forth by Abadie and Imbens (2011)[2][3] for the MyMeter program.

- **To refine the Imbens model, we recommend stratifying customers based on the variation of their usage over time prior to matching.** Not all energy use is equal. For this reason, we recommend first stratifying customers based on the range of their energy use (high-to-low) prior to matching customers. This allows for better matching across homes with similar usage profiles.

For the purposes of future MyMeter program, we recommend:

- **Targeting customers with higher usage.** Overall, customers who are consuming more energy save more, on average than their counterparts. These findings are expected. If the AI is interested in garnering greater savings per participants, the team should consider targeting higher users.

- **Customers who engage MyMeter for longer periods of time save at higher rates.** Based on this insight, AI should consider piloting tactics to maintain customer engagement over time to test whether increased engagement drives greater savings.

[2] Abadie, Alberto, and Guido Imbens. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business and Economic Statistics* 29(1): 1-11.

[3] Note this approach was used in the 2013 impact evaluations for the WMECo and CLC efforts.

2. Introduction to the Program

MyMeter's key offerings include:

- Load management and efficiency help
- Energy usage visualizations
- Customer communication platform
- Improved billing options.

Each is reviewed in turn below.

2.1 Load Management and Efficiency Help

MyMeter helps utilities operate programs that manage customer usage loads and achieve energy savings. Capabilities include dynamic pricing programs; air conditioning cycling for residential and small business customers; direct load control programs for large commercial and industrial customers; and behavioral energy efficiency programs. MyMeter can also run contests and challenges that promote energy conservation.

2.2 Energy Usage Visualizations

MyMeter provides visualization tools that enable customers to easily track energy usage and billing information. Utility support can also access these features, which helps to more easily resolve customer complaints and reduce support costs. These tools include:

- Comparative usage: a feature that benchmarks customer usage against their own usage history and others in the territory.
- Energy challenges: customers set their own conservation goals and track their progress.
- Property profile: customers fill out detailed information on their homes and businesses.
- Bill threshold alerts: notifies customers when they hit pre-set usage thresholds.
- Peak time alerts: notifies customers when peak demand hours are

occurring.

- Energy markers: tracks major changes in the home that may impact usage.
- Outage alerts: notifies customers about power outages in their region.

These features, available on desktop and mobile devices, allow customers to see how their usage changes over time; how weather, occupancy, and appliance use affect their usage patterns; and how they compare to their neighbors. Overall, these tools provide consumers with valuable insights on how to conserve energy.

Additionally, these visualizations are filterable by time intervals, from hourly to monthly. MyMeter's Energy Markers™ allow customers to track time-based efficiency events to better understand how changing usage behavior impacts consumption. Using these same features, utilities can also track the effectiveness of their efficiency programs.

2.3 Customer Communication Platform

MyMeter developed a platform that facilitates effective communication with energy end-users. The platform includes automated real-time notifications and alerts via email and text messaging, which notifies customers of significant changes in energy usage, possible issues at second homes, or potential power outages. Using its consumers' demographic and behavioral information, MyMeter also sends customized messages regarding useful rebates or programs that can help them lower their bill.

2.4 Improved Billing

To further improve customer satisfaction, MyMeter offers several options to streamline payment including online, mobile and pre-paid billing. The program also offers real-time projected bill calculation so customers are up-to-date on billing amounts.

The MyMeter features used by each utility are summarized in Table 2 below.

Table 2: Summary of MyMeter Utility Programs Evaluated in this Report

Utility	Total Participants	Number of Years Implemented	Feedback Level (Hourly, Daily)	MyMeter Features Delivered (Opt-In)		
Beltrami Electric Cooperative	2,522 Res 13% of Population	3+ years 5/2010-Present	Up to daily	▪ Comparative usage ▪ Energy challenge	▪ Threshold alerts ▪ Property profile	▪ Energy markers
Lake Region Electric Cooperative	3,569 Res 15% of Population	~4 years 1/2010-Present	Up to hourly	▪ Comparative usage ▪ Energy challenge	▪ Threshold alerts ▪ Property profile	▪ Energy markers
Stearns Electric Association	2,169 Res 9% of Population	3+ years 5/2010-Present	Up to hourly	▪ Comparative usage ▪ Energy challenge	▪ Threshold alerts ▪ Energy markers	
Wright Hennepin Electric Cooperative	6,718 Res 16% of Population	6+ years 7/2007-Present	Up to daily	▪ Comparative usage ▪ Energy challenge ▪ Property profile	▪ Threshold alerts ▪ Peak alerts	▪ Energy markers ▪ Outage alerts

3. Methodology

3.1 Discussion of opt-in methods

Behavioral programs are changing. With increasing demand for mass market rollouts and more engaging features (i.e. online platforms, text messaging, email communications, and online advertising) opt-in program models are growing. When considering opt-in programs, evaluator's primary concerns are around self-selection bias. Specifically, how are we certain that the effects we are seeing are due to the program and not participants' natural inclination to save energy?

It is necessary to consider this question when designing the evaluation and in selecting the comparison group, in particular. In recent years, econometric approaches used in energy efficiency to address opt-in bias have evolved, expanding both pure experimental[4] and quasi-experimental[5][6] methodologies to develop rigorous designs that address selection bias. However, not all methods are appropriate for a given program, and evaluators must consider the program design and stage of the programs' implementation. It is thus vital that the evaluation team's members have in-house expertise in experimental and quasi-experimental program designs *and* evaluation in order to make the necessary methodological trade-offs when developing evaluation frameworks for opt-in programs.

3.1.1 SEE Action recommendations

Notably, there is a strong movement in energy program evaluation toward Randomized Control Trials (RCTs) or other purely experimental evaluation techniques for feedback programs. The SEE Action Network's recent protocol, "Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations" strongly recommends using purely experimental methods to establish a counterfactual.[7] Pure experimental design is an appropriate choice, in our opinion, if and when the evaluation circumstances allow for integrated evaluation in the *design phase* of the program, and when the treatment and control groups are identifiable in advance. Under

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4 Cappers, P., Todd, A., Perry, M., Neenan, B., and Boisvert, R.. 2013. "Quantifying the Impacts of Time-based Rates, Enabling Technology, and other Treatments in Consumer Behavior Studies: Guidelines and Protocols." Lawrence Berkeley National Labs and Electric Power Research Institute.

5 A quasi-experiment is an empirical approached that is used to estimate the causal impact of an intervention on participants. Quasi-experimental research designs have the same goals as randomized control trials, but do not utilize random assignment to create a counterfactual.

6 Harding, M., and A. Hsiaw. 2011. "Goal Setting and Energy Efficiency." Working paper; Abadie, Alberto, and Guido Imbens. 2011. Bias-corrected matching estimators for average treatment effects. Journal of Business and Economic Statistics 29(1): 1-11.

7 State and Local Energy Efficiency Action Network. 2012. *Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-based Energy Efficiency Programs.* Prepared by A. Todd, E. Stuart, S. Schiller, and C. Goldman, Lawrence Berkeley National Laboratory.

these circumstances, there are additional experimental models to implement as well, such as "recruit-and-delay" and "recruit-and-deny."[8]

While these three evaluation approaches are ideal for determining rigorous savings estimates, they are difficult to implement in utility settings. First, sample sizes in small jurisdictions limit the ability to retain control groups and meet savings goals. Second, the program may utilize mass media and marketing approaches that are not conducive to pure experimental models. Finally, if the evaluation is conducted after the program is implemented in-field, the ability to establish an experimental design is negated.

3.2 Imbens bias adjustment approach

To estimate savings for opt-in energy feedback initiatives, we employed a "matching method" suited to utility programs. This method was approved by the Massachusetts Energy Efficiency Advisory Council and outlined originally by Imbens and Woolridge (2009) and Abadie and Imbens (2011).[9] Using this approach, a comparison cohort was made up of a counterfactual consumption group. To create this group, program participants' pre-period usage was matched to households with similar patterns. Counterfactual households were then given a "bias adjustment" to account for remaining differences between themselves and participants during the matching pre-period. Provencher et al, describes this method in greater detail in his white paper shared in the 2013 International Energy Program Evaluation Conference's proceedings.

This approach is illustrated below using the Beltrami evaluation example.

[8] Dougherty, A., Randazzo, K. 2013. "Impacts of Feedback Programs: Generating Comparable Impacts across Varying Program Design Models." International Energy Program Evaluation. And State and Local Energy Efficiency Action Network. 2012. *Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-based Energy Efficiency Programs.* Prepared by A. Todd, E. Stuart, S. Schiller, and C. Goldman, Lawrence Berkeley National Laboratory.

[9] Imbens, G.W. and Woolridge, J.M. "Recent Developments in the Econometrics of Program Evaluation", Journal of Economic Literature 47(2009), 5-86. And Abadie, A. and Imbens, G.W. "Bias-corrected matching estimators for average treatment effects." Journal of Business & Economic Statistics 29.1 (2011): 1-11, as cited in the Opinion Dynamics Evaluation of the Massachusetts Cross-Cutting Behavioral Program Evaluation Integrated Report delivered in June 2013 to the Massachusetts Energy Efficiency Advisory Council.

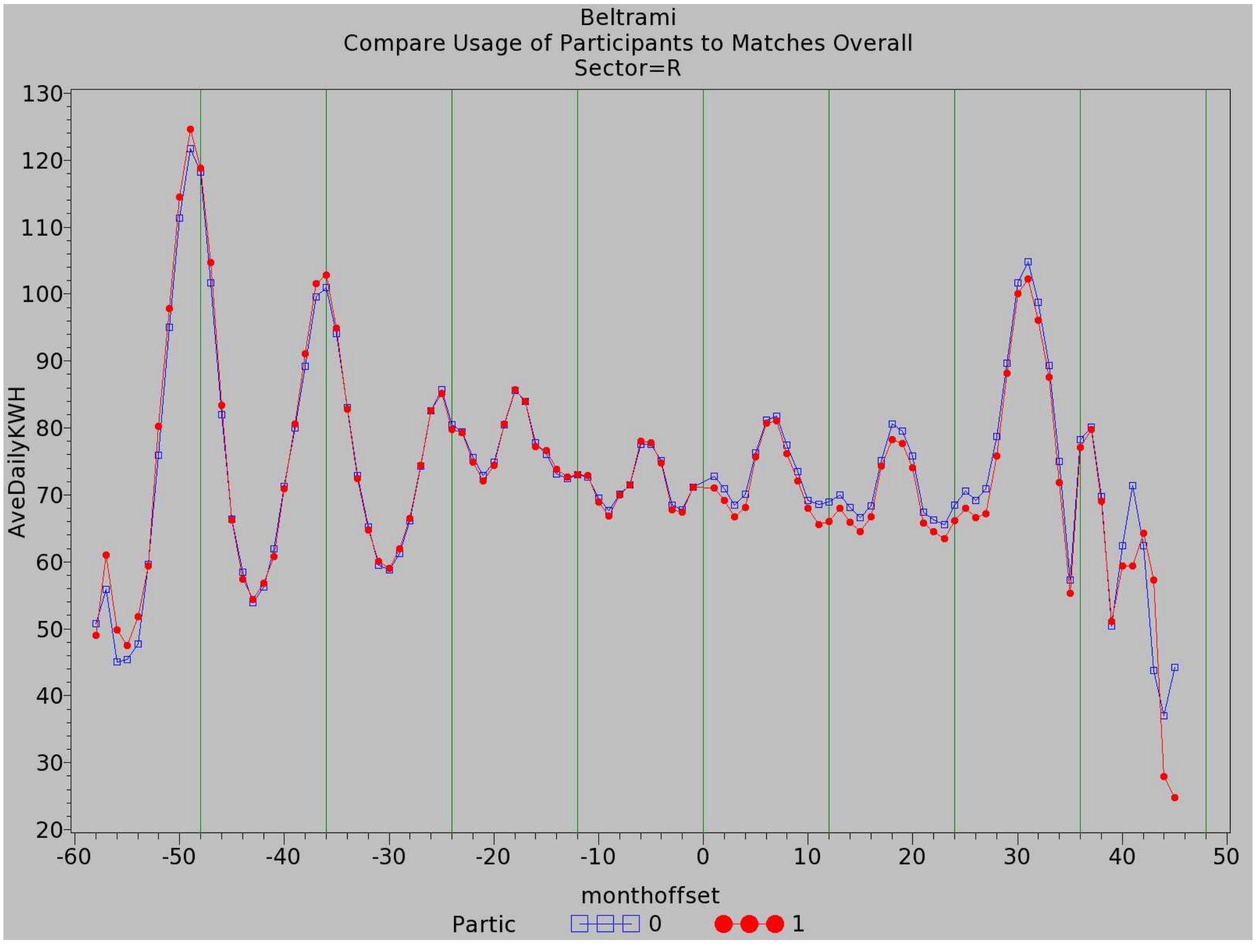

Figure 1. Graphic Depiction of Pre-period Usage Matches (-60-0 months) and Post Period Changes (0-50 months) in Consumption Between Participants (1) and Comparison Group Matches (0) for Beltrami Customers.

3.2.1 Stratified matching approach

To clean the data, duplicate records and any observations with insufficient identifiers for analysis were removed. Required identifiers included account number, service location, sector, and date of initial participation in MyMeter.

Next, participants without twelve contiguous during the pre-period months of usage data were also removed. As savings vary seasonally, a full year of data ensured coverage during all periods.

Following this process, the fifteen best non-participant matches were selected for each participant. Matches were identified based on the amount of pre-period data available for the same months as non-participants. Matches were made within sector and variability range.[10] For utilities with a significant portion of seasonal use customers, matching by variability range was particularly important. Seasonality creates exceptionally large use variability, and the matching algorithm performed better when employed among customers with similar variability levels (i.e. seasonal customers compared to other seasonal customers).

3.3 Data cleaning

After the best matches were identified, additional data cleaning checks were performed, which subsequently removed some participants. The first check focused on the availability of post-period data. Normally, twelve months of post-period data is needed. However, as this study examined savings across several years, the twelve-month requirement was not necessary. Instead, the objective here was to acquire as much analyzable data as possible in order to improve the chances of finding statistically significant savings for each utility. This was essential given that the participant pool for each utility is relatively small compared to opt-out behavioral programs.

A second check was made to remove all customers whose usage was always zero in either the pre- or post- period. This indicates potential data issues, or that the building was not in use. In either case, it was appropriate to remove observations from the analysis.

From this point onward, if a participant was removed, so too were their matches. Once data cleaning was completed, at least five good matches for every participant remained.

3.4 Removing usage outliers

Results from initial model runs were closely examined. Graphs were evaluated to identify where individual customers' usage patterns had unreasonable differences from their matched control. It became clear that some customers' usage patterns changed dramatically between the pre- and post- periods. This could reflect a real change or indicate a data problem. If it was a real change, there was likely an unusual shift in the how the customer used energy. For instance, perhaps they put an addition onto their home, added a new family member, left home for an extended period, or did any number of things that dramatically changed usage. It is unlikely that MyMeter caused very large changes in use, yet these results were having a significant impact on the average measured savings from the program.

Although both dramatic increases and dramatic decreases occurred, decreases were bound to -100% since no usage could go lower than zero. This was not true for increases, however, where several hundred percent changes for individual customers were found. These extremely significant increases had an overpowering effect on savings estimates, often wiping out the small average savings that most participants experienced.

[10] Variability range is a measure of each customer's usage data variability.

It is reasonable to assume that MyMeter attracts customers who are considering increases in their energy use. If this is true, the participant population is likely to include a greater than normal share of customers with large usage increases. Therefore, to identify the actual program savings that most customers experienced, participants with unusually large changes in usage were removed from the analysis.

Since the goal was to measure changes in usage after participation the challenge was to not impose findings by setting standards into pre-supposed assumptions too tightly. From previous work evaluating energy efficiency programs, we know it is unusual to find energy efficiency measures or behaviors that reduce overall electric usage by more than 10%. We also know from working with weather-normalized electric consumption data that it is unusual to see a change of more than 50% from one year to the next owing to weather alone. Based on this experience, customers whose base month usage (April, May, September, October) usage dropped or increased by more than 50% between the pre- and post- periods were removed. It is highly unlikely that participation in MyMeter was responsible for usage changes at those levels in the baseline months. This also preserved a broad spectrum of changes and was an equal cut-off in both directions, so as to not pre-impose estimated savings results. For all utilities, this -50%/+50% cut-off was consistently used.

After applying this cut-off to the data, additional participants and non-participants were dropped from the analysis. All participant counts related to data cleaning steps are outlined in the Disposition Reports in Appendix A.

Table 3: Summary of Final Participant Count When Removing Usage Outliers

Outlier Level	Beltrami	Lake Region	Stearns	Wright-Hennepin
-10%-+10%	813	454	331	1,313
-25%-+25%	1,545	882	596	2,463
-50%-+50%	1,953	1,155	715	3,097

3.5 Models

3.5.1 Core Model

To estimate the impacts of MyMeter participation on energy use for each utility, we used an approach first described by Stewart[11] and later implemented in the Massachusetts behavioral program evaluation.[12] We estimated separate models for each utility. The regression models are applied only to the post-treatment periods:

$$kWH_{kt} = \alpha_{0t} + \alpha_1 Partic_{kt} + \alpha_2 PrekWh_{kt} + \varepsilon_{kt}$$

Where:

kWH_{kt} is the average daily electricity use by household k in month t

α_{0t} is a monthly fixed effect

$Partic_{kt}$ is an indicator variable with a value of 1 for participants and 0 for matched non-participants

$PrekWh_{kt}$ is the average daily pre-participation electricity use by household k that is also the same calendar month as month t

ε_{kt} is the error term

3.5.2 Model accounting for other Programs

We also analyzed MyMeter program impact by including terms in the regression model to account for participation in other downstream rebated programs.[13] The updated model controls for participation in rebate programs among both the MyMeter participants and the matched controls. Rather than just dropping rebate participants and losing their data, the model estimates the impact of rebate programs and the impact of MyMeter net of rebate program participation. The new model is shown below:

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[11] Stuart, E.A. 2010. Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1), February 2010, 1-21.
[12] Opinion Dynamics. June 2013. *Massachusetts Cross-Cutting Behavioral Program Evaluation Integrated Report.* Delivered to Massachusetts Energy Efficiency Advisory Council & Behavioral Research Team.
[13] We note here that our analysis did not account for participation in upstream lighting program implemented by Great River Energy's members (Lake Region, Stearns, and Wright-Hennepin). The program is called "A Brighter Idea" and Provide support for its retail distribution cooperatives to promote Energy Star qualified lighting through training, marketing, and financial incentives. Note Beltrami does not have an upstream program.

$$kWH_{kt} = \alpha_{0t} + \alpha_1 Partic_{kt} + \alpha_2 PrekWh_{kt+} + \alpha_3 Rebate_{kt} + \alpha_4 HP_{kt} + \varepsilon_{kt}$$

Where:

kWH_{kt} is the average daily electricity use by household k in month t of the treatment period

α_{0t} is a monthly fixed effect

$Partic_{kt}$ is an indicator variable with a value of 1 for participants and 0 for matched non-participants

$PrekWh_{kt}$ is the average daily pre-participation electricity use by household k that is also the same calendar month as month t

$Rebate_{kt}$ is an indicator variable taking a value 1 for all months t after customer k received a rebate for any energy saving device except heat pumps and 0 otherwise.

HP_{kt} is an indicator variable taking a value 1 for all months t after customer k received a rebate for a heat pump and 0 otherwise.

ε_{kt} is the error term

4. DETAILED FINDINGS BY UTILITY

Detailed findings for each utility evaluated in this report are outlined here. The savings estimates reflect the total savings associated with the program over the duration of its time in-field, which varies by as much as three years across each utility. The average annual savings values represents the average daily reduction in usage per participant across the entire treatment period applied to the number of participants in each treatment year. As a result, these values do not represent savings growth and/or decay as a consequence of the *duration* of treatment, which will be examined as a key next step in our research.

4.1 Beltrami

Beltrami's program implementation ran from May 2010 to May 2013 and consisted of 2,540 participants. The program resulted in an average usage reduction of 2.8%. This translated to a total savings of 2,997,712 kWh, or an average savings of 705,344 kWh per year.

4.2 Lake Region

Lake Region's program implementation ran from January 2010 to April 2013 and consisted of 3,287 participants. The program resulted in an average usage reduction of 2.6%. This translated to a total savings of 2,859,495 kWh, or an average savings of 857,849 kWh per year.

4.3 Stearns

Stearns' program implementation ran from May 2010 to April 2013 and consisted of 2,141 participants. The program resulted in an average usage reduction of 1.8%. This translated to a total savings of 1,391,349 kWh, or an average savings of 463,783 kWh per year.

4.4 Wright-Hennepin

Wright-Hennepin's program implementation ran from April 2007 to June 2013 and consisted of 6,188 participants. The program resulted in an average usage reduction of 2.2%. This translated to a total savings of 5,275,191 kWh, or an average savings of 844,030 kWh per year.

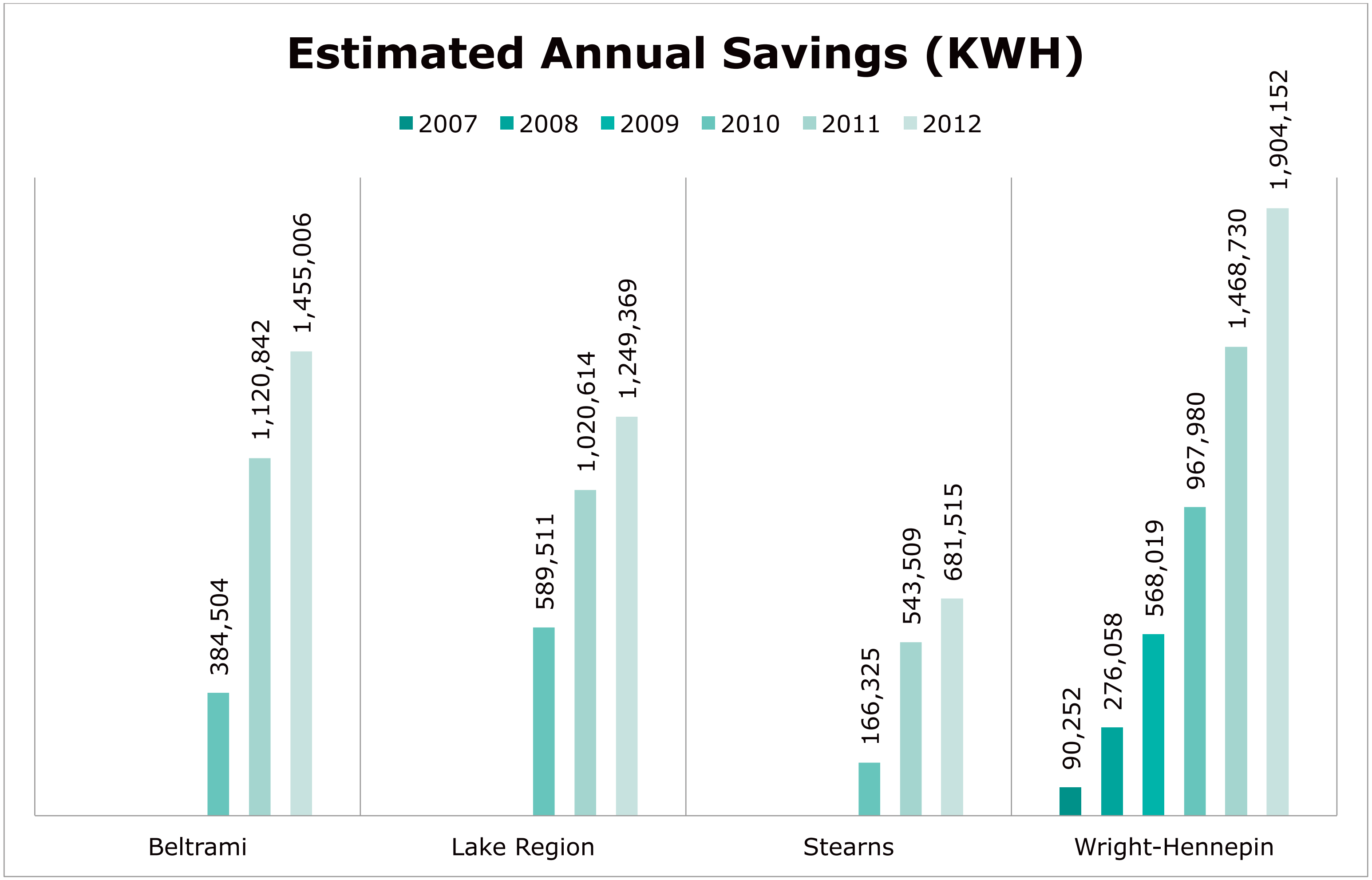

Figure 2: Estimated Annual Kilowatt Hour Savings by Utility by Participants per Year

Table 4. Summary of Total Electric Savings by Utility

Utility	Total Participants	Evaluation Period	Program Years Evaluated	Total Number of Months Evaluated	Total Savings (% Reduction and Total kWh)		P-Value	Standard Deviation
Beltrami	2,540	05/10-05/13	4.25 years	51	2.8%	2,997,712 kWh	0.00	0.2%
Lake Region	3,287	01/10-04/13	3.33 years	40	2.6%	2,859,495 kWh	0.00	0.8%
Stearns	2,141	05/10-04/13	3 years	36	1.8%	1,391,349 kWh	0.00	0.5%
Wright-Hennepin	6,188	04/07-06/13	6.25 years	75	2.2%	5,275,191 kWh	0.00	0.4%

5. POOLED EVALUATION RESULTS

To examine how savings vary by baseline usage and program engagement and how savings persist over time, the data across all four utilities were pooled and then segmented into relevant categories and analyzed by season and overall. The seasonal definitions for this analysis are:

- Summer - June, July, and August
- Winter – December, January, February
- Base Months – March, April, May, September, October, November

5.1 Baseline Usage

We divided customers into four categories based on their baseline average monthly electricity use. All customers except those with the lowest pre-program usage (<1000 kWh/mo) saved energy over the program period. The largest customers (>3000 kWh/mo) experienced the greatest percentage savings. All of the groups showed savings in the base months and none of the groups showed savings in the summer. The largest energy users experienced savings in winter. These seasonal patterns suggest that most customers are reducing energy use from year-round sources such as lighting. Year-round sources like lighting comprise a larger share of energy use during the base months so changes in use are most likely to show up then. The largest customers, who likely use electric space heating, also reduced energy use in winter.

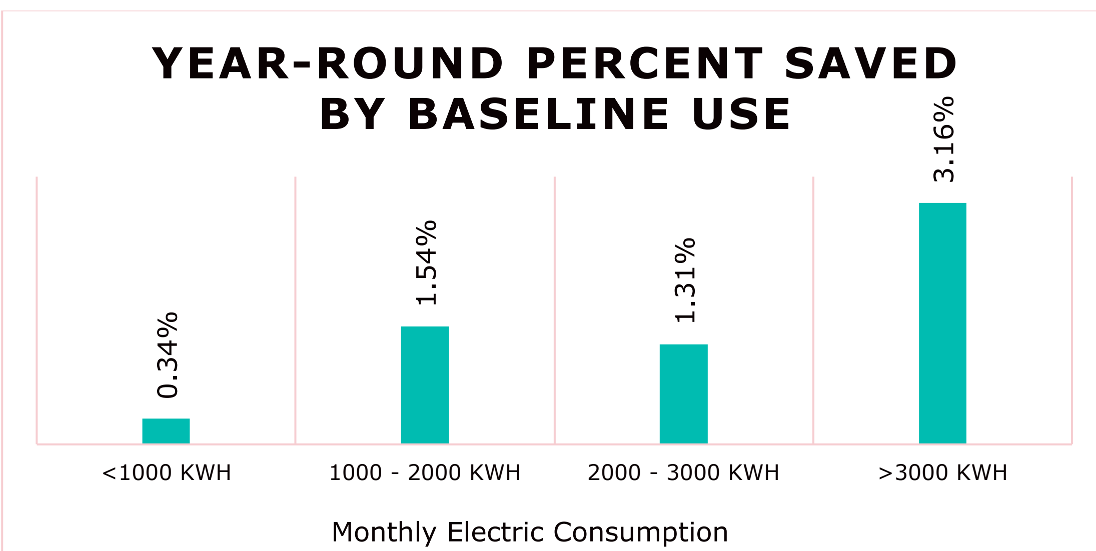

Figure 3: Average Savings by Electricity Consumption Range

5.2 Persistence

To examine persistence, customers were group based on the number of years they participated in the program. The results show that savings persist at the same level over the first two years of the program and drop only slightly (not statistically significant) in the third year.

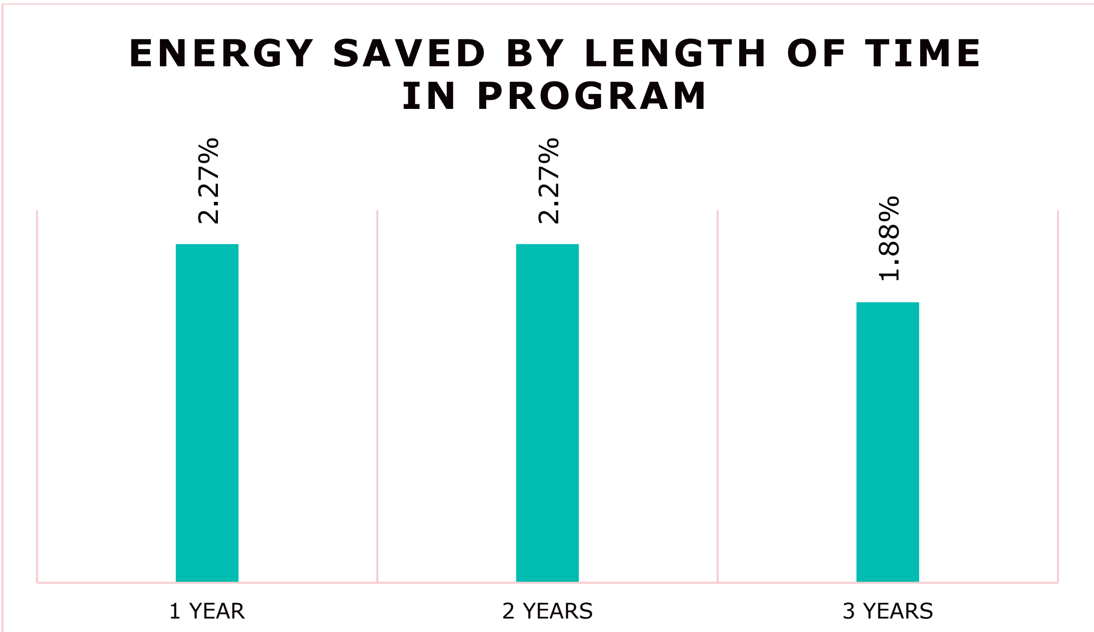

Figure 4: Savings by Length of Participant Tenure

5.3 Engagement

We used two approaches to model customer engagement. First, we divided customers into groups based on the number times customers logged into MyMeter (one time, two times, three to nine times, 10 to 50 times and more than 50 times). Customers at all engagement levels saved energy with customers at the highest levels of engagement saving the most. These savings occurred during the spring and fall base months, again indicating that savings are coming from year-round sources such as lighting. Note that large energy users were spread across the engagement categories and were slightly over-represented in the highest engagement category. More analysis is needed to determine the relationship between engagement and savings independent of baseline usage.

A second indicator of engagement that we examined is the length of time between first and last login, which suggests how long customers were engaged with the program. Savings increased as length of time increased from one login to 12 months between first and last login.

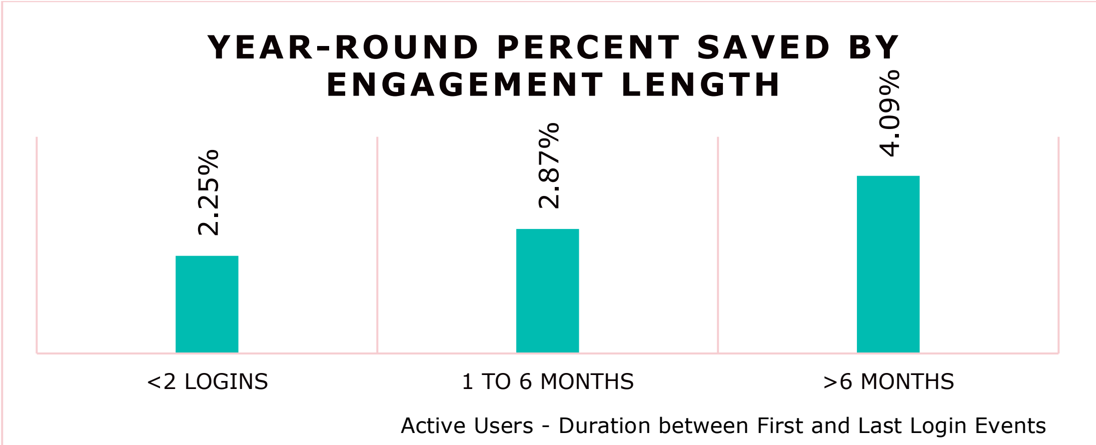

Figure 5: Savings by Length of Active Engagement in the Program

6. Comparison to Similar Programs

Based on our research, the MyMeter program savings were within the expected range for similar online feedback programs. Here, we compare the MyMeter savings values derived from this analysis against similarly evaluated programs, namely online feedback offerings of C3 Energy and Tendril for WMECo's Western Mass Saves Program and the Cape Light Compact's Energize program, which were both evaluated using the matched-comparison approach.

Notably, our comparisons with other online and meter-based feedback programs indicated that the MyMeter program savings were not only within range of the expected savings for direct feedback programs, but also that the Imbens Bias Adjustment method produces reliable savings values across program models and regions.

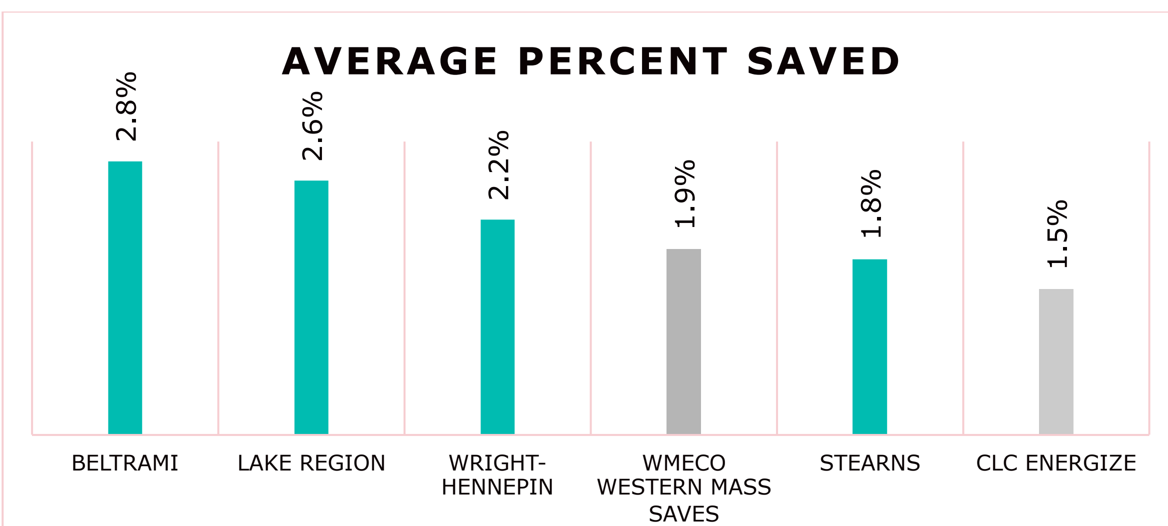

Figure 6: Evaluated Minnesota Utility Program Results vs. Evaluated Opt-In Program Results in Massachusetts

7. ACCOUNTING FOR OTHER PROGRAMS

In this section, we outline the results of our model that accounts for other program effects (outlined in section 3.5.2) compared to the initial models that did not include terms to control for cross-program participation. Generally, the addition of rebate participation has little impact on the overall model, indicating the MyMeter savings were generated without the aid of other programs. For Beltrami and Lake Region, inclusion of terms to control for heat pump and other rebate participation had no impact. Furthermore, the coefficients for heat pump and other rebate participation are not statistically significant.

While the coefficients for heat pump and other rebate participation in the Wright-Hennepin model are statistically significant, the terms explain very little additional variation and the change in the coefficient for MyMeter participation is not statistically significant.

Only the Stearns data show a meaningful change in the coefficient for MyMeter participation after controlling for rebate participation. The impact for heat pumps alone is statistically significant and positive and the coefficient for MyMeter participation becomes larger. This suggests that after controlling for heat pump installation, MyMeter participants actually save more energy than initially estimated.[14]

In the case of Stearns, the expanded models suggest that heat pump installation may lead to greater electricity use. This is likely an artifact of fuel switching. Some customers install heat pumps in order to switch from propane to electricity for heating their homes and water, resulting in higher electricity use. Homeowners may also be misusing the heat pump by erroneously engaging the emergency-heating mode, resulting in much higher electricity use.

We present the results of our models below.

Table 5. Beltrami Parameter Estimates

	Original Model			Revised Model		
Variable	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	**Parameter Estimate**	**Standard Error**	**Pr > |t|**
Intercept	0.0000	0.0782	1	0.0000	0.0781	1
PreAvekWh	0.8706	0.0012	<0.0001	0.8704	0.0012	<0.0001
Partic	-1.7882	0.1563	<0.0001	-1.7786	0.1573	<0.0001
Rebates				-0.0156	0.3052	0.9591
Heat Pumps				0.4011	0.6472	0.5354

Table 6. Lake Region Parameter Estimates

[14] Note that the negative coefficient means participants are using less electricity or saving more. Positive coefficients imply greater electricity use.

	Original Model			Revised Model		
Variable	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	**Parameter Estimate**	**Standard Error**	**Pr > |t|**
Intercept	0.0000	0.1915	1	0.0000	0.1915	1
PreAvekWh	0.7211	0.0023	<0.0001	0.7210	0.0023	<0.0001
Partic	-1.1926	0.3829	0.0018	-1.1136	0.3859	0.0039
Rebates				1.4610	1.0556	0.1664
Heat Pumps				1.3405	1.5868	0.3982

Table 7. Stearns Parameter Estimates

	Original Model			Revised Model		
Variable	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	**Parameter Estimate**	**Standard Error**	**Pr > |t|**
Intercept	0.0000	0.1302	1	0.0000	0.2305	1
PreAvekWh	0.8977	0.0020	<0.0001	0.6546	0.0030	<0.0001
Partic	-0.9562	0.2604	0.0002	-1.5196	0.4654	0.0011
Rebates				0.0249	0.7953	0.9750
Heat Pumps				5.9896	1.8674	0.0013

Table 8. Wright-Hennepin Parameter Estimates

	Original Model			Revised Model		
Variable	**Parameter Estimate**	**Standard Error**	**Pr > |t|**	**Parameter Estimate**	**Standard Error**	**Pr > |t|**
Intercept	0.0000	0.0885	1	0.0000	0.0884	1
PreAvekWh	0.8048	0.0014	<0.0001	0.8044	0.0014	<0.0001
Partic	-1.0598	0.1769	<0.0001	-0.9856	0.1778	0.0000
Rebates				0.8004	0.4100	0.0509
Heat Pumps				5.1844	0.8457	0.0000

Given these findings, we do not recommend adjusting the previous savings estimates.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1 CONCLUSIONS

As noted earlier, the primary goal of this report is to outline a methodology to evaluate the MyMeter program and to assess the program impacts.

8.1.1 Savings Results

Our research shows that the MyMeter program has delivered savings reductions for residential customers, ranging from 1.8% to 2.8% on average per household. Further, these savings are unique of other program effects.

The MyMeter program savings were within the expected range for similar online feedback programs utilizing the same evaluation approaches, with the MyMeter savings values trending higher than those previously reported for other programs.

8.1.2 Evaluation Approach

Recent evaluations of opt-in programs have used matching approaches to mimic the effect of a purely randomized control group by using observable characteristics, such as energy use, to match treatment customers to a target comparison group with the theory that such matching accounts for *unobservable* characteristics that might be correlated with both one's likelihood to enroll in the program and one's overall energy consumption during treatment. Past regulator-accepted evaluations of the WMECo Western Mass Saves and Cape Light Compact Smart Home Energy Monitoring Pilot, previously led by ILLUME author Anne Dougherty with the Opinion Dynamics and Navigant Consulting teams used bias-corrected matching set forth by Abadie and Imbens (2011).[15,16] We implemented the same approach for the MyMeter program.

8.2 RECOMMENDATIONS

For the purposes of future MyMeter program evaluations, we recommend drawing on these learnings. Specifically:

- **Future evaluations of the MyMeter should use the Imbens Bias Adjustment Matching Approach.** We recommend using the bias-corrected matching set forth by Abadie and Imbens (2011)[17,18] for the MyMeter program.

- **To refine the Imbens model, we recommend stratifying customers based on the variation of their usage over time prior to matching.** Not all energy use is equal. For this reason, we recommend first stratifying customers based on the range of their energy use (high-to-low) prior to matching customers. This allows for better matching across homes with similar usage profiles.

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15 Abadie, Alberto, and Guido Imbens. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business and Economic Statistics* 29(1): 1-11.

16 Note this approach was used in the 2013 impact evaluations for the WMECo and CLC efforts.

17 Abadie, Alberto, and Guido Imbens. 2011. Bias-corrected matching estimators for average treatment effects. *Journal of Business and Economic Statistics* 29(1): 1-11.

18 Note this approach was used in the 2013 impact evaluations for the WMECo and CLC efforts.

A. DATA CLEANING DISPOSITIONS

Table 9. Summary of Data Cleaning Dispositions by Utility

	Beltrami	**Lake Region**	**Stearns**	**Wright-Hennepin**
Original opt-in count	2,540	3,287	2,141	6,188
Less: Insufficient identifiers	0	4	0	91
Less: Zero use in pre or post period	18	11	1	12
Less: Post base use dropped >50%	116	112	27	150
Less: Post base use increased >50%	220	258	81	480

B. DETAILED MODEL COEFFICIENTS

B.1 BELTRAMI

Number of Observations Read	100100
Number of Observations Used	100100

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	347037734	173518867	283694	<.0001
Error	100097	61223396	611.64067		
Corrected Total	100099	408261130			

Root MSE	24.73137	**R-Square**	0.850039
Dependent Mean	2.88E-16	**Adj R-Square**	0.850036
Coeff Var	8.59E+18		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-2.66E-14	0.07817	0	1
PreAvekWh	1	0.87058	0.00116	753.16	<.0001
Partic	1	-1.78818	0.15634	-11.44	<.0001

Covariance of Estimates

Variable	Intercept	PreAvekWh	PreAvekWh
Intercept	0.006110296	-4.13E-20	-3.42E-21
PreAvekWh	-4.13E-20	1.34E-06	1.11E-07
Partic	-3.42E-21	1.11E-07	0.0244412

B.2 LAKE REGION

Number of Observations Read	50292
Number of Observations Used	50292

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	177967672	88983836	48261.6	<.0001
Error	50289	92721898	1843.7809		
Corrected Total	50291	270689571			

Root MSE	42.93927	**R-Square**	0.65746
Dependent Mean	1.998384E-15	**Adj R-Square**	0.657447
Coeff Var	2.15E+18		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.30E-14	0.19147	0	1
PreAvekWh	1	0.72109	0.00232	310.66	<.0001
Partic	1	-1.19259	0.38294	-3.11	0.0018

Covariance of Estimates

Variable	Intercept	PreAvekWh	Partic
Intercept	0.036661515	8.19E-20	7.24E-21
PreAvekWh	8.19E-20	5.39E-06	4.76E-07
Partic	7.24E-21	4.76E-07	0.146646102

B.3 STEARNS

Number of Observations Read	32462
Number of Observations Used	32462

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	111394015	55697007	101226	0.001
Error	32459	17859724	550.22408		
Corrected Total	32461	129253738			

Root MSE	23.456856	**R-Square**	0.861824
Dependent Mean	-2.08E-15	**Adj R-Square**	0.861816
Coeff Var	-1.13E+18		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-9.14E-15	0.13019	0	1
PreAvekWh	1	0.89768	0.002	449.93	<.0001
Partic	1	-0.95621	0.26038	-3.67	0.0002

Covariance of Estimates

Variable	Intercept	PreAvekWh	Partic
Intercept	0.01694979	-3.13E-20	2.68E-21
PreAvekWh	-3.13E-20	3.98E-06	-3.40E-07
Partic	2.68E-21	-3.40E-07	0.067799189

B.4 WRIGHT-HENNEPIN

Number of Observations Read	168026
Number of Observations Used	168026

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	435431315	217715658	165556	<.0001
Error	168023	220959836	1315.05708		
Corrected Total	168025	656391151			

Root MSE	36.263716	**R-Square**	0.663372
Dependent Mean	-1.96E-15	**Adj R-Square**	0.663368
Coeff Var	-1.85E+18		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-1.68E-14	0.08847	0	1
PreAvekWh	1	0.8048	0.0014	575.39	<.0001
Partic	1	-1.05984	0.17694	-5.99	<.0001

Covariance of Estimates

Variable	Intercept	PreAvekWh	PreAvekWh
Intercept	0.00782651	-3.60E-20	-1.61E-22
PreAvekWh	-3.60E-20	1.96E-06	8.78E-09
Partic	-1.61E-22	8.78E-09	0.031306038