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Memorandum

To: Fernando Morales, Ameren Illinois; Jennifer Morris, ICC Staff

From: Opinion Dynamics Evaluation Team

Date: May 4, 2020

Re: 2019 Behavioral Modification Initiative Persistence Study – Year Two

This memo summarizes results from the second year of the Ameren Illinois Company's (AIC) behavioral persistence study. Overall, the 2019 research suggests statistically significant evidence of savings decay for both gas and electric customers. We find that 86% of savings persist two years after terminating Home Energy Report (HER) treatment for gas customers, while 73% of electric savings persist two years after terminating HER treatment. We did not find consistently significant decay one year after treatment termination, suggesting that it can take some time for the effect of treatment cessation to be measurable.

Study Background

In 2018, a substantial portion of AIC's Behavioral Modification Initiative treatment group customers, who were added to the Initiative between PY3 (2009) and the Transition Period (2017), stopped receiving HERs. This cessation of treatment created a natural experiment that allowed the evaluation team to estimate persisting savings for previously treated customers. Persisting savings is defined as the savings that occur after a treated customer stops receiving reports due to changes in energy efficiency equipment or habituated behaviors. After estimating the persisting savings, the evaluation team calculated a persistence factor (i.e., the percentage of savings that persist after cessation of treatment) to estimate how long savings continue after stopping treatment.[1]

The evaluation team designed this study to answer the following research questions:

- What are the persisting electric and gas savings in 2018 and 2019 for customers experiencing a stoppage in treatment?
- What is the difference in initiative savings between customers who received reports for a longer duration and those customers who received reports for a shorter duration?
- What is the persistence factor?

Behavior Modification Initiative Summary

AIC began the Behavioral Modification program in 2009, and continued adding cohorts until 2018, when they stopped sending HERs to all but one cohort (Expansion Cohort 1). Expansion Cohort 1 continued treatment in

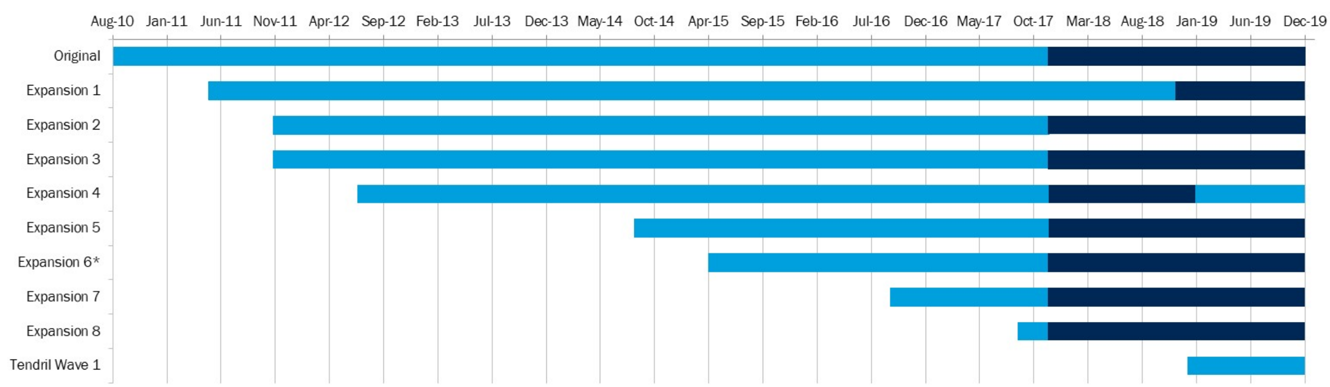
[1] A persistence factor is the percentage of savings that persist after cessation of treatment. To calculate a persistence factor, the evaluation team compared the savings from the year after the customers stopped receiving reports to the final year in which treated customers received reports (i.e., 2018 savings divided by 2017 savings).

2018, but stopped in 2019. In 2019, AIC initiated delivery of HERs to two additional treatment groups , one new wave (Tendril Wave 1) and one legacy wave (Expansion 4). As a result of these program implementation choices, this study estimates persistence for the following years and cohorts:

- 2018 Stoppage Wave: For Cohorts who stopped treatment in 2018, we evaluated persistence in 2018 and 2019 relative to their last year of treatment (2017).
- 2019 Stoppage Wave: For the Cohort who stopped treatment in 2019 (Expansion Cohort 1), we evaluated persistence in 2019 relative to their last year of treatment (2018).

The Initiative treatment and stoppage dates are summarized in Figure 1 where a light blue color indicates years in which customers received reports and dark blue indicates years in which the reports were stopped.

Figure 1. Behavior Modification Initiative Treatment and Stoppage Timeline



* Approximately 4,000 of these customers were moved to Tendril Wave 1 and treated. They are excluded from this analysis.

Persisting Savings Methodology

Estimating persistence factors requires the construction of a "counterfactual," (i.e., what the treated customers' usage would have been if they continued receiving reports). To estimate this counterfactual properly, the approach would ideally be a Randomized Control Trial (RCT) that includes three groups of customers for each cohort: 1) customers that continue to receive reports, 2) customers that stopped receiving reports, and 3) customers that never received reports. However, given that in 2018, AIC discontinued treatment for customers for all cohorts except for Expansion Cohort 1 rather than randomly selecting customers to stop receiving treatment, the evaluation team could only use the latter two customer groups in the analysis. The experimental design was further complicated by the resumption of treatment of Legacy Wave 4 in 2019. Because we do not have an RCT for treatment stoppage, we instead compare savings after treated customers stopped receiving reports to savings for the last year the treated customers were in the program to estimate savings persistence.[2]

[2] The approach used to estimate an AIC-specific persistence factor in this study is distinct from the Commonwealth Edison (ComEd) approach, which incorporated all three groups given that the program randomly stopped treatment for a portion of customers within a cohort.

Our 2018 evaluation of the first year after stopping HER treatment found no evidence of statistically significant savings decay for any of the cohorts or fuel types.[3] We hypothesized in that study that this was due to the limited statistical power of cohort-level modeling given the very small effects that were measured. In 2019, the evaluation team updated our methodological approach to provide more power and confidence to the persistence factor results given the way in which AIC suspended treatment. In particular, the 2019 approach uses a pooled regression model that incorporates all cohorts within the Behavioral Modification Initiative within each stoppage wave. The combined model includes both the treatment and control groups from the original Randomized Control Trial (RCT) that randomly allocated customers within a treatment and control group to receive reports, which controls for exogenous factors that may affect energy savings or consumption within a household over time. Through this pooled approach, the evaluation team believed it would be more likely to estimate statistically significant persistence factors across all cohorts that stopped receiving reports. However, the pooled approach means we are unable to estimate cohort-level results.

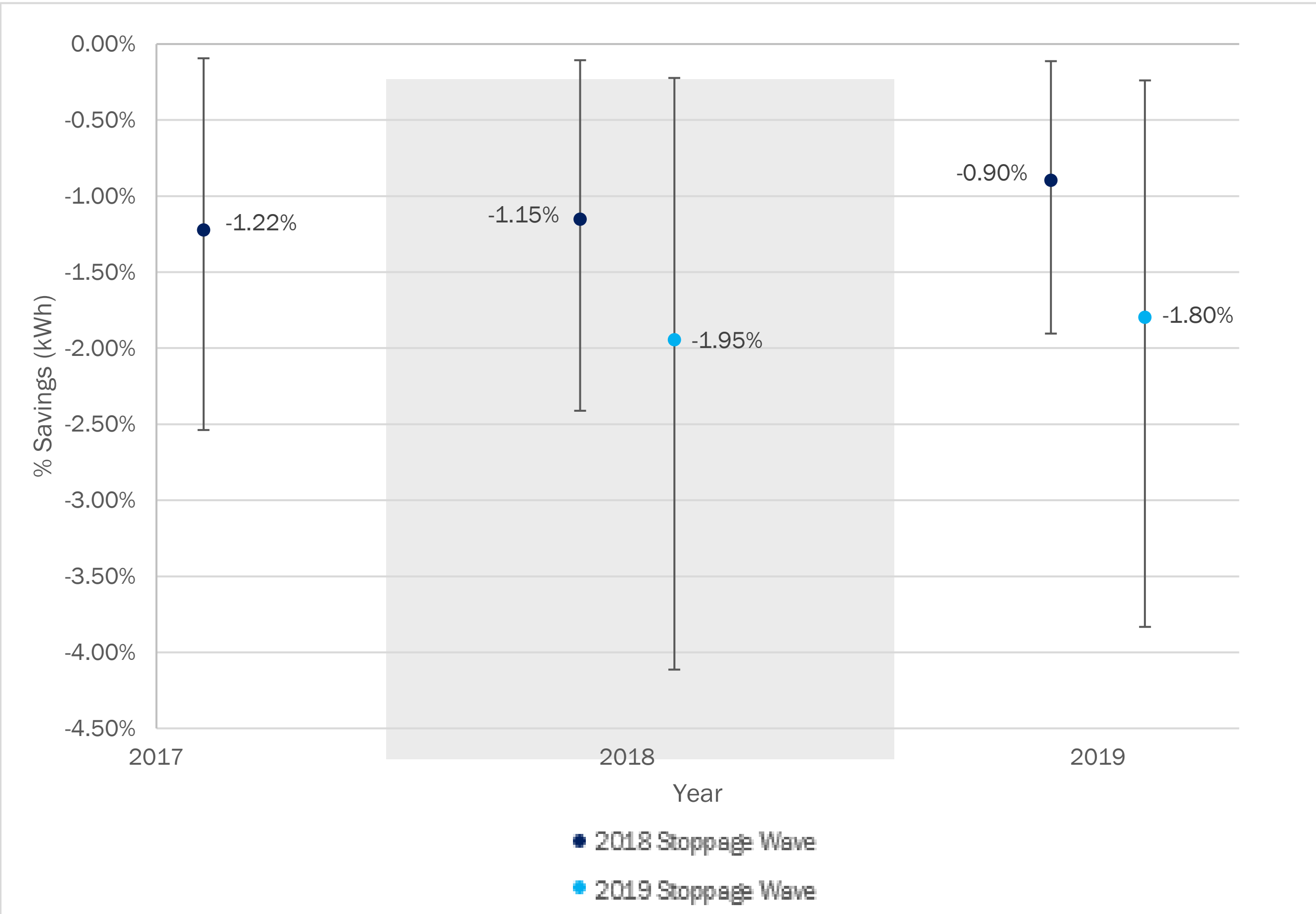
The evaluation team used a consumption analysis approach to determine savings from the last year customers received treatment (2017) and the first and second year after customers stopped treatment (2018 and 2019). The evaluation team utilized the treatment and control group customers' monthly billing data for the consumption analysis. This approach is consistent with the methodology used to evaluate this Initiative's annual program impacts. Once we estimated the savings in each year, we calculated the persistence from year to year.

Persisting Savings Results

In 2019, the evaluation found evidence of persisting savings after treatment ceased for each year evaluated for all fuels and Stoppage Waves. While savings persist for at least two years after treatment ends for both fuels, savings do decay each year (e.g. the amount of savings gets smaller every year after treatment stops). The one exception to this pattern is for gas customers in stoppage wave 2019, who had a slight increase in savings in the first year after treatment stopped (2019). Figures 2 and 3 show the differences in yearly average percent savings (represented by the blue dots) along with the combined standard error (represented by the error bars) for each Stoppage Wave and year, for electric and gas customers respectively.

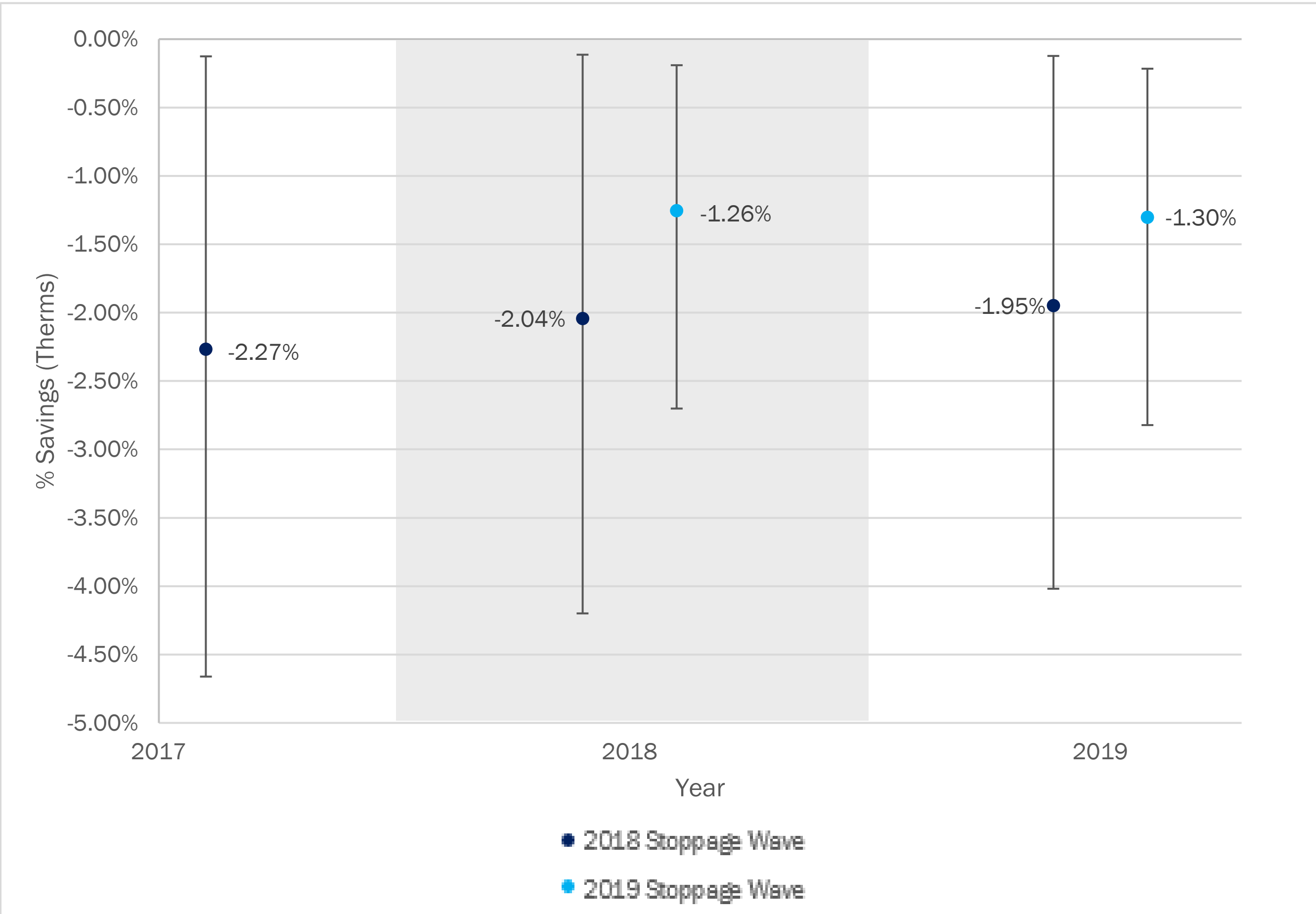
[3] When comparing the 2018 estimated savings to the savings generated from the final year treated customers received reports (i.e., 2017 savings), the evaluation team did not find statistically significant differences in savings at the 90% confidence level.

Figure 2. Percent Savings per Stoppage Wave (kWh)



Note: A negative percent savings (represented by the blue dots below the 0 % savings axis) indicates the continued savings percent in each year. Savings that get closer to zero year over year indicate that the amount of savings is decaying. The savings for all years and Stoppage Waves were significant.

Figure 3. Percent Savings per Stoppage Wave (Therms)



Note: A negative percent savings (represented by the blue dots below the 0 % savings axis) indicates the continued savings percent in each year. Savings that get closer to zero year over year indicate that the amount of savings is decaying. The savings for all years and Stoppage Waves were significant.

Because we used a pooled model to have enough statistical power to estimate results, we were unable to measure the savings for each cohort individually. As a result, we were also unable to compare the impact of treatment duration on persistence directly. We did, however, include a term in our model for time-since-the-pre-period which found that the length of treatment does correlate with increased savings. The magnitude of this effect varied substantially by model and we believe additional research is needed on this subject.

The evaluation team calculated the difference in average percent savings in stoppage years compared to prior years. Table 1 provides a summary of these results. We found that we were consistently able to find a significant difference in the savings rate when there were two years between measurements (e.g. comparing 2017-2019). However, it was more challenging to observe the difference in savings rate from year-to-year. Future evaluations may want to take this into consideration.

Table 1. Electric and Gas Difference in Percent Savings

Fuel Type	Wave	2017-2018		2018-2019		2017-2019	
		Difference in % Savings	Standard Error	Difference in % Savings	Standard Error	Difference in % Savings	Standard Error
Electric	Stoppage Wave 2018	-0.07%	0.09%	-0.26%*	0.09%	-0.33%*	0.09%
	Stoppage Wave 2019	NA	NA	-0.15%	0.20%	NA	NA
Gas	Stoppage Wave 2018	-0.22%*	0.10%	-0.09%	0.10%	-0.32%*	0.11%
	Stoppage Wave 2019	NA	NA	0.05%	0.18%	NA	NA

*Reflects statistically significant results at 90% confidence level.

Table 2 shows difference persistence factors by year and fuel type, along with the decay rate (defined as one minus the persistence factor). While we report persistence factors for all Stoppage Waves and years, note that in some cases (e.g. Stoppage Wave 2019 Gas 2018-2019), the persistence factors are calculated using savings estimates that are not significantly different from each other (reported in Table 1). One year after treatment stops, both electric stoppage waves see 92-94% persistence. For gas, we see less consistent results, with first year persistence estimates ranging from 90-104%. Two years after treatment stoppage, electric and gas customers see 73% and 86% persisting savings, respectively. These results are in a similar range as the existing literature, albeit electric typically has higher persistence factors than gas based on existing studies.

Table 2. Electric and Gas Persistence Factors

Fuel Type	Years	Persistence Factor			Decay Rate		
		2017-2018	2018-2019	2017-2019	2017-2018	2018-2019	2017-2019
Electric	Stoppage Wave 2018	94%	78%	73%	6%	22%	27%
	Stoppage Wave 2019	NA	92%	NA	NA	8%	NA
Gas	Stoppage Wave 2018	90%	95%	86%	10%	5%	14%
	Stoppage Wave 2019	NA	104%	NA	NA	-4%	NA

Future Research

Based on the findings, we offer the following considerations for future research:

- Continue to estimate persistence factors and associated decay rates for cohorts who no longer receive reports. This research suggests that multiple years of data provides more certainty in the estimates. We also note that we were unable to estimate cohort-level effects due to the lack of statistical power, which is at least partly a function of the experimental design. An alternative experimental design such as a RCT would control for exogenous variables more closely and would increase the likelihood of being able to model the cohorts at higher levels of granularity (this would also likely improve the estimates of the impact of duration). We understand that AIC currently does not offer Behavior Modification Initiative to any customers. However, should AIC offer HERs to customers in the future, the utility may want to consider implementing an RCT approach to stopping HER treatment for the purposes of informing persistence research.

- Continue to research duration of treatment and duration of stoppage as key inputs to persistence factors and associated decay rates. Our research suggests there is a correlation between longer duration in treatment and higher persistence factors, however, more data and more time will be required to confidently quantify a relationship between duration of treatment and persistence. One approach to measure duration would incorporate a two-stage model wherein we first use a pre/post model to estimate each individual customer’s persistence and then use those persistence estimates as the dependent variable in a pooled model with duration as the independent variable.

Appendix – Detailed Methodology

Stoppage of Treatment Program Design

There are a variety of methods for estimating persistence, generally dictated by program design and implementation changes made to who receives HERs. One of the most common methods is to randomly sample a group of treated customers to stop receiving reports (terminated group), while the rest of the treated customers continue to receive reports (continued group) within a particular treated customer group. This allows for both the terminated group and the continued group to include similar treated customers. For this type of design, persistence is calculated by estimating the relationship in savings between the terminated and continued groups for similar treated customers within the year when reports were discontinued. This approach was used to estimate persistence factors for Commonwealth Edison from 2013 through 2017.

Another method is to terminate treatment for all treated customers within a particular treated customer group, which is the approach employed for this analysis. This is because the Behavioral Modification Initiative terminated treatment for eight of the nine cohorts in the Initiative in 2018 and for the ninth cohort (Expansion Cohort 1) in 2019. As a result, all treated customers were in the 'terminated' group for each of the cohorts that stopped receiving reports. Since this method cannot compare savings between a terminated group and a continued group for similar treated customers (as described above), it relies on comparing savings after treated customers stopped receiving reports to savings for the last year the treated customers were in the program to estimate savings persistence.

Table 3 shows the difference in calculating the persistence factor across the two most common methods. The terminated/continued group method compares savings within the same year across two treatment groups (i.e., terminated group and continued group), whereas the method used for the Behavioral Modification Initiative compares savings for a given year to the savings from the prior year (i.e., 2018 vs 2017 savings) for each cohort.

Table 3. Comparison of Persistence Factor Equations Across Methods

	Commonwealth Edison Method (Terminated/Continued Group)	Ameren Illinois Method (Terminated Year/Prior Year)
Persistence Factor Equation	$\frac{Year_t\ Savings_{Terminated\ Group}}{Year_t\ Savings_{Continued\ Group}}$	$\frac{Year_t\ Percent\ Savings}{Year_{t-1}\ Percent\ Savings}$

Model Specification

The evaluation team used a consumption analysis approach to determine savings during the last year of treatment (2017) and the first and second year of savings after stoppage of treatment (2018 and 2019 for Stoppage Wave 1; 2019 only for Stoppage Wave 2). Given that these programs use an experimental design, the evaluation team utilized the treatment and control group customers' monthly billing data for the consumption analysis. This approach is consistent with the methodology used in evaluating this Initiative's annual program impacts.[4]

In 2019, we used a pooled model to increase our power for estimating statistically significant savings. This was a departure from the 2018 effort which estimated impacts by cohort but was unable to find significant

[4] 2019 Ameren Illinois Company Residential Energy Efficiency Program Annual Evaluation Report.

results. In addition, we conducted a sensitivity analysis incorporating both 2018 and 2019 in a combined model, essentially pooling annual results. We also did not find substantive differences in results in that model.

For each Stoppage Wave, the pre-period reflects each of the cohorts within each Stoppage Wave's pre-enrollment period (i.e., the year before the cohort enrolled in the Initiative). Using each cohort's distinct pre-period across each model allowed for a proper assessment of savings when estimating persistence. This program began as early as 2010 for some cohorts, so the pre-period covers a substantial portion of time.

The evaluation team used a consumption analysis approach for this analysis that is similar to the method used for the PY2019 Behavioral Modification Initiative evaluation. The evaluation team estimated savings using a lagged dependent variable (LDV) model (Equation 1), that incorporates the post-treatment period only.

LDV models use seasonal usage from the pre-treatment period and explicitly incorporates monthly weather data (from NOAA). Information from the pre-treatment period is used only to calculate pre-usage variables that are incorporated into the LDV model, but pre-period usage is not directly modeled. The LDV model used three levels of pre-treatment period usage for each customer: overall pre-treatment period average daily consumption (ADC), summer pre-treatment period ADC, and winter pre-treatment period ADC. The LDV model uses the control group in the same way as the LFER model, in that the treatment effect is corrected for control group ADC so that the coefficient of the treatment variable is the average ITT effect.

Since cohorts of customers were selected based in part on their potential for energy savings through HER treatment, it is possible that the persistence of savings is higher for cohorts that were established earlier in the initiative compared to those formed later. We included a term in the model to control for the amount of time between the pre-period and the cessation of treatment.

The evaluation team employed the following estimating equation:

Equation 1. Post-Treatment Period Only Model Estimating Equation

$$
\begin{aligned}
ADC_{it} = {} & \alpha_i + \beta_1 Treatment_i + \beta_2 PreUsage_i + \beta_3 PreWinter_i + \beta_4 PreSummer_i + \beta_5 MonthYear_t \\
& + \beta_6 PreUsage_i \cdot MonthYear_t + \beta_7 PreWinter_i \cdot MonthYear_t + \beta_8 PreSummer_i \\
& \cdot MonthYear_t + CDD_{it} + HDD_{it} + TimeSincePreperiod_i + \varepsilon_{it}
\end{aligned}
$$

Where:

ADC_{it} = Average daily consumption (therms or kWh) for household *i* at time *t*
α_i = Household-specific intercept
β_1 = Coefficient for the change in consumption for the treatment group
β_2 = Coefficient for the average daily usage across household *i* available pretreatment meter reads
β_3 = Coefficient for the average daily usage over the months of December through March across household *i* available pretreatment meter reads
β_4 = Coefficient for the average daily usage over the months of June through September across household *i* available pretreatment meter reads
β_5 = Vector of coefficients for month-year dummies
β_6 = Vector of coefficients for month-year dummies by average daily pretreatment usage
β_7 = Vector of coefficients for month-year dummies by average daily winter pretreatment usage
β_8 = Vector of coefficients for month-year dummies by average daily summer pretreatment usage
$Treatment_i$ = Variable to represent treatment and control groups (0 = control group, 1 = treatment group)
$PreUsage_i$ = Average daily usage for household *i* over the entire pre-treatment period

$PreWinter_i$ = Average daily usage for household *i* over the pre-treatment months of December through March
$PreSummer_i$ = Average daily usage for household *i* over the pre-treatment months of June through September
$MonthYear_t$ = Vector of month-year dummies
HDD_{it} = Vector of average monthly Heating Degree Days at the customer's nearest weather station
CDD_{it} = Vector of average monthly Cooling Degree Days at the customer's nearest weather station
$TimeSincePreperiod_{it}$ = Vector of the length of time (in years) since the pre-period
ε_{it} = Error

Estimating Persistence Factors

As stated above, the persistence factor equation is the relationship between the average percent savings in a year after the treated customers stopped receiving reports and the average percent savings from the last year treated customers received reports (i.e., 2018 and 2019 percent savings vs 2017 percent savings). Equation 2 shows this calculation, where δ_i is the persistence factor for cohort *i* for a year after they stopped receiving reports.

Equation 2. 2018 Persistence Factor Equation

$$\delta_i = \frac{Stoppage\ Year\ Average\ Percent\ Savings_i}{Treatment\ Year\ Average\ Percent\ Savings_i}$$

Where:

δ_i = persistence factor for cohort *i*
$\mathrm{Stoppage\ Year\ Average\ Percent\ Savings_i}$= average percent savings in a year after stoppage of treatment for cohort *i* (may be more than one year after treatment stops)
$\mathrm{Treatment\ Year\ Average\ Percent\ Savings_i}$ = average percent savings for the last year treated customers were in the Initiative for cohort *i*

Estimating Persisting Lifetime Savings and Measure Life

This study provides concrete evidence that (1) savings persist after HER treatment terminates and (2) savings decay over time. However, at present, we do not believe that there are sufficient years of data to accurately assess the shape of the decay, or to assess Persisting Lifetime Savings or Measure Life. This should be revisited in future years.