Memorandum

To: Ameren Illinois Company, Commonwealth Edison, ICC Staff
From: Opinion Dynamics and Navigant
Date: January 22, 2018
Re: Home Energy Report Weather Normalization Study – Final Analysis Results

This memo provides results from an analysis of Commonwealth Edison's (ComEd) Home Energy Report (HER) Program and Ameren Illinois Company's (AIC) Behavior Modification (BM) Program related to weather normalization methods. This research has two objectives:

1. Determine to what extent gas and electric savings from the programs are sensitive to weather conditions.
2. Determine the reliability and accuracy of the weather normalization method outlined in the Illinois Technical Reference Manual (IL-TRM) [1]

The findings presented within this memo are a compilation of electric results from research conducted by Navigant for ComEd and gas results from research conducted by Opinion Dynamics for AIC.

Overall, we found that both gas and electric savings are sensitive to weather conditions, but that the sensitivity is quite low. The evaluation teams recommend using a weather normalization method when accounting for persistence with cooling degree day (CDD) and heating degree day (HDD) interaction terms in the regression model (see Equation 1 below) to weather normalize. The evaluation teams recommend keeping the current IL-TRM references to weather normalization as a part of the custom savings calculation included in Version 6. The current language is weather normalization method agnostic and the research teams would prefer to keep it this way to be consistent with the measure's references to other portions of the custom savings analysis. Additional discussion is included below.

Study Overview and Overall Findings

ComEd's and AIC's programs are implemented as randomized controlled trials (RCTs) where customers selected for inclusion in the program are randomly allocated between a treatment group (who receive the HER) and a control group (who do not). We evaluate these programs using regression models to determine the savings of the treatment group relative to the control group. Because the treatment and control group, on average, experience the exact same weather conditions in a given year, the RCT design means that there is no need to control for weather in the regression models to produce an accurate estimate of program savings for one year.

However, the behavioral persistence measure in the IL-TRM V6.0 compares savings from the programs across multiple years to account for the persistence of savings from one year to the next. As a result, if program

[1] "Adjustments to Behavior Savings to Account for Persistence" is measure 6.1.1 in Version 6.0 Volume 4 of the TRM.

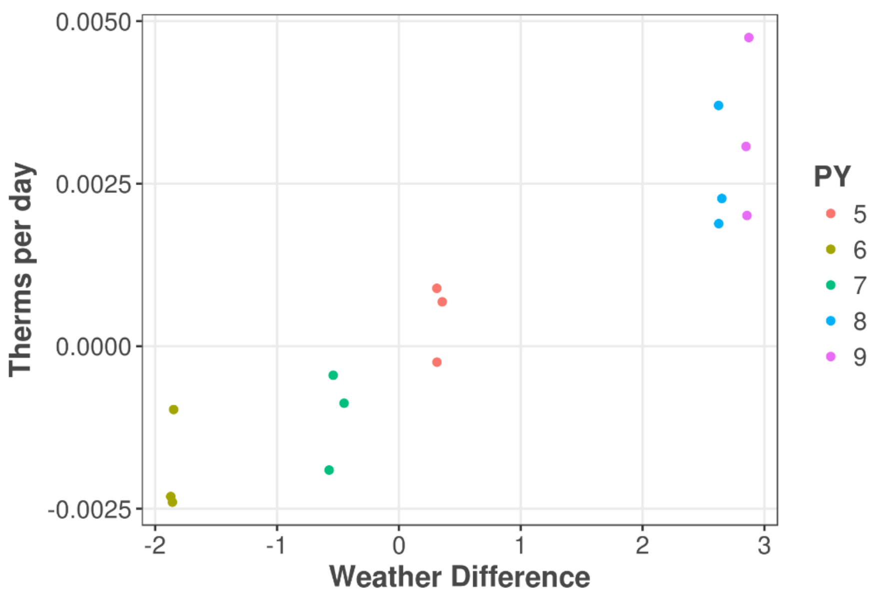
savings are weather sensitive, then comparing actual, non-weather normalized savings across years will not correct for the weather sensitivity of savings. In this case, for comparison across years, the evaluation teams would need to weather normalize the savings across different years.

Research Objective 1: Determine Sensitivity to Weather Conditions

Overall, we found that both gas and electric savings are sensitive to weather conditions, but that the sensitivity is quite low.

For gas savings, changing from actual weather to typical meteorological year (TMY) weather[2] changes savings by approximately 0.005 therms per day.[3] Figure 1 shows the relationship for the three modeled cohorts for PY5 through PY9.[4] The x-axis plots the weather difference in HDD between actual weather and TMY, and the y-axis plots the difference in average daily savings. This plot shows that gas savings are sensitive to HDD; CDD are not shown because the results show that gas savings are not sensitive to CDD.

Figure 1. Plot of Gas Savings Difference by Weather Difference



Source: Opinion Dynamics analysis of AIC data

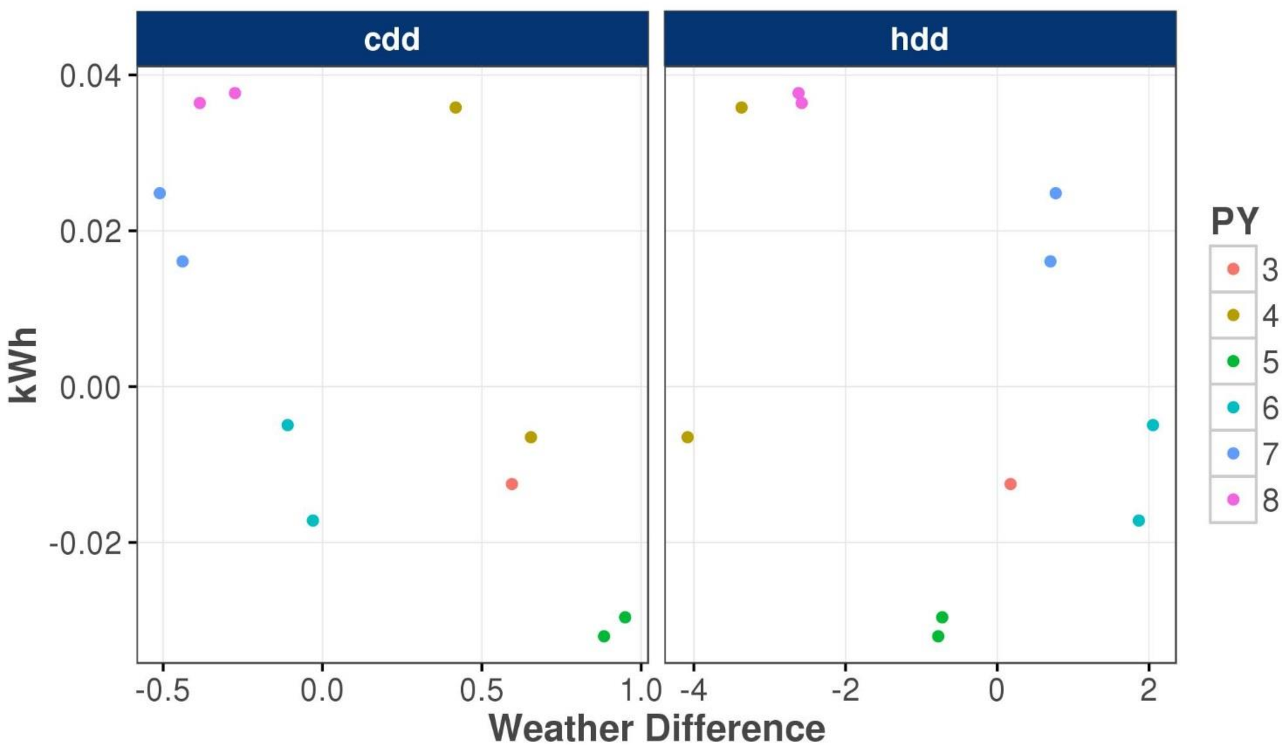
[2] For this work, we incorporated the latest TMY3 dataset derived from 1991-2005 weather from NREL, the official source.

[3] Assuming a cohort with 100,000 customers who were all in the Program for the entire year, this would change total savings by 182,500 therms (0.005 therms/customer/day * 365 days * 100,000 customers).

[4] The PY5 program year began June 1, 2012 and ended May 31, 2013. The PY9 program year began June 1, 2016 and ends December 31, 2017; this research represents results through May 31, 2017 for PY9.

For electric savings, changing from actual weather to TMY weather changes savings by approximately 0.02 kWh per day.[5] Figure 2 shows the relationship between kWh savings and HDD and CDD for the two modeled ComEd electric waves for PY3 through PY8.[6]

Figure 2. Plot of Electric Savings Difference by Weather Difference



Source: Navigant analysis of ComEd data

To determine the extent to which program savings are sensitive to weather conditions, the evaluation teams estimated a model with interactions between a treatment indicator and CDD/HDD for several program years and program waves, as shown in Equation 1 below. This model is consistent across the AIC and ComEd analyses.

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[5] Assuming a wave with 100,000 customers who were all in the Program for the entire year, this would change total savings by 730 MWh $\left(\frac{0.02 \text{ kWh/customer/day} * 365 \text{ days} * 100{,}000 \text{ customers}}{1{,}000}\right)$.

[6] The PY3 program year began June 1, 2010 and ended May 31, 2011. The PY8 program year began June 1, 2015 and ended May 31, 2016.

Equation 1

$$ADU_{kt} = \beta_1 Treatment_k + \beta_2 Treatment_k \cdot CDD_{kt} + \beta_3 Treatment_k \cdot HDD_{kt} + \beta_4 CDD_{kt} + \beta_5 HDD_{kt} + \sum_J \beta_{6j} Month_{jt} + \sum_J \beta_{7j} Month_{jt} \cdot ADUlag_{kt} + \varepsilon_{kt}$$

Where

ADU_{kt}	is average daily energy usage (gas or electric) by household *k* in bill period *t.*
$Treatment_k$	is a binary variable taking a value of 0 if household k is assigned to the control group, and 1 if assigned to the treatment group.
CDD_{kt}	is the CDD experienced by household *k* in bill period *t.*
HDD_{kt}	is the HDD experienced by household *k* in bill period *t.*
$Month_{jt}$	is a binary variable taking a value of 1 when j = t and 0 otherwise.[7]
$ADUlag_{kt}$	is household *k*'s energy use in the same calendar month of the pre-program year as the calendar month of month *t.*
e_{kt}	is the cluster-robust error term for household *k* during billing cycle *t.*[8]

In Equation 1, β_1 captures the treatment effect when CDD and HDD are zero, β_2 captures the impact of CDD on the treatment effect, and β_3 captures the impact of HDD on the treatment effect. The treatment effect under any specified weather conditions is captured by $\beta_1 + \beta_2$*CDD + β_3*HDD; for example, the average treatment effect in program year t is captured by $\beta_1 + \beta_2$*mean(CDD_{kt}) + β_3*mean(HDD_{kt}). This average treatment effect is similar to the savings estimated using a model without weather terms. If β_2 and β_3 are large compared to β_1, it would suggest that the program savings are weather sensitive. The weather normalized treatment effect is captured by replacing the program year CDD and HDD values with TMY values, i.e., β_1 + β_2*mean(CDD_{kTMY3}) + β_3*mean(HDD_{kTMY3}).

Table 1 and Table 2 provide gas and electric savings using actual and TMY weather.

7 In other words, if there are *T* post-program months, there are *T* monthly dummy variables in the model, with the dummy variable $Month_{tt}$ the only one to take a value of 1 at time t. These are, in other words, monthly fixed effects.

8 Cluster-robust errors account for heteroskedasticity and autocorrelation at the household level.

Table 1. Gas Savings with Actual Weather and with TMY Weather

AIC Behavioral Modification Cohort	PY	Actual Weather Average Daily Savings	TMY Weather Average Daily Savings
Original	5	0.021	0.022
	6	0.027	0.024
	7	0.021	0.020
	8	0.020	0.022
	9	0.019	0.022
Expansion 1	5	0.031	0.032
	6	0.034	0.032
	7	0.027	0.025
	8	0.029	0.033
	9	0.031	0.036
Expansion 2	5	0.009	0.009
	6	0.014	0.013
	7	0.012	0.012
	8	0.013	0.015
	9	0.013	0.015

Source: Opinion Dynamics analysis of AIC data

Table 2. Electric Savings with Actual Weather and with TMY Weather

ComEd HER Wave	PY	Actual Weather Average Daily Savings	TMY Weather Average Daily Savings
Wave 1	3	0.91	0.90
	4	0.99	0.98
	5	1.05	1.02
	6	1.11	1.09
	7	1.01	1.02
	8	1.09	1.13
Wave 3	4	0.73	0.76
	5	1.19	1.16
	6	1.27	1.26
	7	1.36	1.38
	8	1.24	1.28

Source: Navigant analysis of ComEd data
Note: Wave 3 did not begin until PY4.

Research Objective 2: Determine the Accuracy of the IL-TRM Weather Normalization Method

The evaluation teams verified that the CDD/HDD interaction method shown in Equation 1 is accurate by checking that entering the actual weather CDD/HDD values into the model returned the same treatment effect as a model with weather included. Based on this analysis, the evaluation teams recommend that the TRM keep the current references to weather normalization as a part of the custom savings calculation currently included in Version 6. The current language is weather normalization method agnostic and the research teams would prefer to keep it this way to be consistent with the measure's references to other portions of the custom savings analysis. Currently, Opinion Dynamics and Navigant each plan to use the weather normalization method described in the previous section but reserve the right to use a different method if they believe it is appropriate in the future.

Appendix A. Detailed Methodology and Results

Program Information

AIC

Approximately 302,500 customers participated in the AIC Behavioral Modification Program in PY9, representing roughly one-third of AIC's residential customers. In 2010, the program began as a pilot by targeting dual-fuel customers with higher-than-average energy consumption. Oracle, the program implementer, developed each expansion cohort based on several characteristics: energy usage tier, residential customer, and available energy use history. Original Cohort customers are now in their seventh year with the program. Over the following 6 years, seven additional cohorts were added to the program. All cohorts were dual-fuel customers, except for Expansion Cohort 3, which is gas only. The most recent cohort, Expansion Cohort 7, began receiving reports late in PY9, making PY9 this group's first full year in the program. Table 3 provides a breakdown by cohort of all treatment customers who received reports for at least 1 month in PY9.

For this analysis, we selected just the first three cohorts, the Original cohort and Expansion Cohorts 1 and 2. We selected these cohorts because they have many years of participation data and are among the largest.

Table 3. AIC Behavioral Modification Program Participation in PY9

Cohort Name	Fuel Type	Number of Treated Customers in PY9	Start Date	Program Year
Original Cohort	Dual-Fuel	32,519	August 2010	7th year in the program
Expansion Cohort 1	Dual-Fuel	49,057	April 2011	6th year in the program
Expansion Cohort 2	Dual-Fuel	72,536	November 2011	6th year in the program
Expansion Cohort 3	Gas-Only	11,732	November 2011	6th year in the program
Expansion Cohort 4	Dual-Fuel	20,146	June 2013	4th year in the program
Expansion Cohort 5	Dual-Fuel	45,191	September 2014	3rd year in the program
Expansion Cohort 6	Dual-Fuel	27,647	April 2015	3rd year in the program
Expansion Cohort 7	Dual-Fuel	43,692	September 2016	1st year in the program
	Total	302,520		

ComEd

ComEd's HER program included almost 2 million electric customers in PY9. Customers in Wave 1 and Wave 3 were used in this analysis; these waves were chosen because they are two of the largest and longest running waves in the program.

The program was rolled out in nine different waves:

1. A pilot program targeting 50,000 residential customers kicked off in July 2009 (Wave 1).
2. A wave of about 3,000 customers (Wave 2) targeted for program enrollment started in September 2010 to "fill-in" for Wave 1 dropouts.

3. A major expansion targeting 200,000 customers began in May 2011 (Wave 3).
4. Another fill-in wave of 20,000 customers started in January 2012 (Wave 4).
5. A third fill-in wave of 20,000 customers introduced in July 2012 (Wave 5).[9]
6. A fourth fill-in of 10,000 customers and a major expansion targeting 90,000 customers began in June 2013 (Wave 6).
7. A "tsunami" wave of 1.2 million customers began in June 2014; this wave was split into two groups based on usage (Wave 7 Low and Wave 7 High).
8. A wave targeting customers who had just moved into a new home, this wave first started in September 2014 and was evaluated for the first time in PY8 (New Mover Wave).[10]
9. An expansion of 81,679 customers added to the program in July 2016 (Wave 8).

Data Cleaning Approach

AIC

The data used in the billing analysis came from three primary sources:

- Monthly billing data from July 2009 to May 2017, from AIC
- Program launch date specific to each customer (treatment and control), from Oracle
- Weather data (HDD and CDD), from NOAA (the data came from 46 weather stations across the state and are appended at the zip code level)

To develop the dataset used for the statistical analysis, the evaluation team conducted the following data processing steps:

- Cleaned billing data
  - Removed exact duplicates
  - Dropped billing periods in excess of 90 days
  - Dropped first and last billing periods with more than 60 days
  - Dropped first and last billing periods with less than 10 days
  - Combined overlapping billing periods
  - Combined estimated bills with actual bills to correct for bill estimation
- Removed observations and customers within each cohort based on the following criteria:

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[9] This wave has been referred to as Wave 5 Non-AMI in previous reports, but as Wave 5 AMI has been dropped from the program this distinction is no longer necessary.

[10] The New Mover Wave is made up of 21 groups of customers who received their first report in the same month (for example, customers who received their first report in September 2014 were one group, and customers who received their first report in March 2015 were another). Navigant estimated the impact for the New Mover Wave in two parts: for customers who started before PY8 and for customers who started during PY8.

- No first report dates
- First report date occurring after inactive date
- Out-of-range usage data
- Very low usage data
- No post-participation period data

- Determined the monthly usage for each customer based on his/her read cycle (each usage record has a start date and a duration; based on these two variables, the team identified the appropriate month for each read cycle)
- Matched weather data by customer to the geographically closest weather station

Depending on the cohort, data cleaning removed between <1% to 19% of customers in the gas analysis. The majority of these drops are due to insufficient pre-participation period billing data.

ComEd

The data used in the billing analysis came from two primary sources:

- Monthly billing data from July 2008 to May 2016, from Oracle
- Program launch date specific to each customer (treatment and control), from Oracle
- Weather data (HDD and CDD), from NOAA (the data came from 5 weather stations across the state and are appended at the zip code level)

To develop the dataset used for the statistical analysis, the evaluation team conducted the following data processing steps:

- Subset to the one year pre-program period and the one year analysis period for each regression
- Records with a bill duration of 0
- Bill Flattening - Aggregating records that ended in the same month[11]
- Observations with missing usage
- Observations with negative usage
- Customers with an active account and fewer than 11 bills or any customer with more than 13 bills in either the analysis period or pre-period
- Observations with fewer than 20 or more than 40 days in the billing cycle

[11] This does not remove any records but rather redistributes records for analysis purposes.

- Outliers, defined as observations with average daily usage more than one order of magnitude from the median usage.

Model Coefficients

Table 4 provides model coefficients for each selected gas cohort for PY5 through PY9 and Table 5 shows the same for each selected electric wave for PY3 through PY8.

Table 4. Gas Billing Analysis Model Coefficients

AIC Behavioral Modification Cohort	PY	Variable	Coefficient	Standard Error
Original	5	Treatment	-0.00747	0.00414
		Treatment:CDD	0.00002	0.00003
		Treatment:HDD	-0.00003	0.00001
	6	Treatment	-0.00886	0.00526
		Treatment:CDD	0.00007	0.00007
		Treatment:HDD	-0.00004	0.00001
	7	Treatment	-0.01060	0.00530
		Treatment:CDD	0.00007	0.00008
		Treatment:HDD	-0.00002	0.00001
	8	Treatment	-0.00925	0.00455
		Treatment:CDD	0.00005	0.00006
		Treatment:HDD	-0.00003	0.00001
	9	Treatment	-0.00827	0.00447
		Treatment:CDD	0.00006	0.00005
		Treatment:HDD	-0.00003	0.00001
Expansion 1	5	Treatment	-0.01158	0.00548
		Treatment:CDD	0.00003	0.00004
		Treatment:HDD	-0.00005	0.00001
	6	Treatment	-0.01726	0.00709
		Treatment:CDD	0.00010	0.00009
		Treatment:HDD	-0.00004	0.00001
	7	Treatment	-0.02185	0.00723
		Treatment:CDD	0.00020	0.00011
		Treatment:HDD	-0.00002	0.00001
	8	Treatment	-0.01109	0.00618

		Treatment:CDD	0.00008	0.00009
		Treatment:HDD	-0.00005	0.00001
	9	Treatment	-0.01592	0.00588
		Treatment:CDD	0.00010	0.00007
		Treatment:HDD	-0.00005	0.00001
Expansion 2	5	Treatment	0.00074	0.00350
		Treatment:CDD	-0.00002	0.00002
		Treatment:HDD	-0.00002	0.00000
	6	Treatment	-0.00701	0.00468
		Treatment:CDD	0.00004	0.00006
		Treatment:HDD	-0.00002	0.00001
	7	Treatment	-0.00340	0.00479
		Treatment:CDD	0.00002	0.00008
		Treatment:HDD	-0.00002	0.00001
	8	Treatment	-0.00374	0.00417
		Treatment:CDD	0.00001	0.00006
		Treatment:HDD	-0.00002	0.00001
	9	Treatment	-0.00421	0.00397
		Treatment:CDD	0.00001	0.00004
		Treatment:HDD	-0.00002	0.00001

Source: Opinion Dynamics analysis of AIC data

Table 5. Electric Billing Analysis Model Coefficients

ComEd HER Wave	PY	Variable	Coefficient	Standard Error
Wave 1	3	Treatment	-0.81866	0.10846
		Treatment:CDD	-0.02046	0.01497
		Treatment:HDD	-0.00192	0.00372
	4	Treatment	-0.80198	0.10073
		Treatment:CDD	-0.03943	0.01215
		Treatment:HDD	-0.00473	0.00400
	5	Treatment	-0.77704	0.11243
		Treatment:CDD	-0.03794	0.01185
		Treatment:HDD	-0.00885	0.00401
	6	Treatment	-0.81851	0.11820
		Treatment:CDD	-0.04150	0.01868

ComEd HER Wave	PY	Variable	Coefficient	Standard Error
		Treatment:HDD	-0.00988	0.00367
	7	Treatment	-0.82512	0.12266
		Treatment:CDD	-0.04478	0.01981
		Treatment:HDD	-0.00512	0.00385
	8	Treatment	-0.84117	0.12438
		Treatment:CDD	-0.06177	0.02120
		Treatment:HDD	-0.00791	0.00473
Wave 3	4	Treatment	-0.59805	0.07416
		Treatment:CDD	0.00408	0.00877
		Treatment:HDD	-0.01012	0.00321
	5	Treatment	-0.92094	0.08653
		Treatment:CDD	-0.04285	0.00904
		Treatment:HDD	-0.00747	0.00332
	6	Treatment	-1.01961	0.09475
		Treatment:CDD	-0.05900	0.01542
		Treatment:HDD	-0.00555	0.00325
	7	Treatment	-1.18735	0.09538
		Treatment:CDD	-0.05413	0.01673
		Treatment:HDD	-0.00364	0.00327
	8	Treatment	-1.03847	0.09816
		Treatment:CDD	-0.06088	0.01719
		Treatment:HDD	-0.00503	0.00389

Source: Navigant analysis of ComEd data
Note: Wave 3 did not begin until PY4.