NAVIGANT

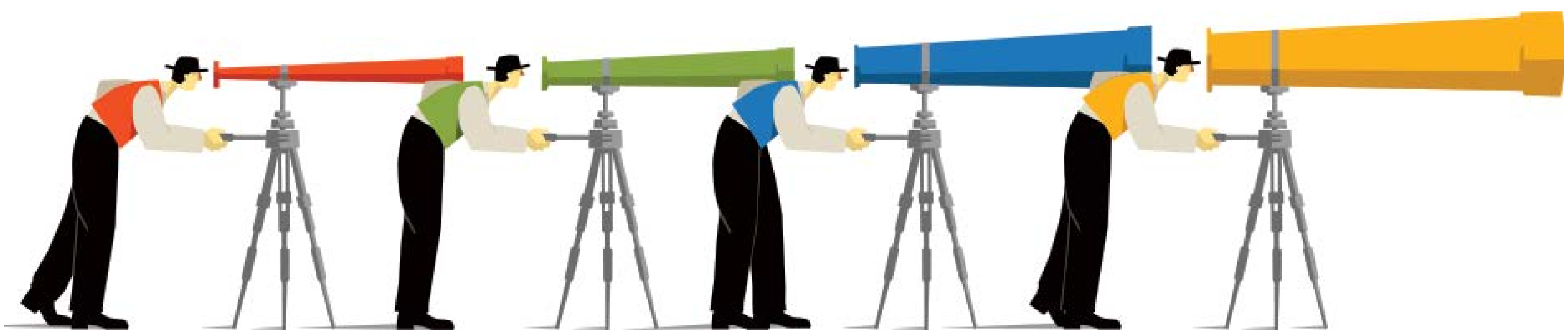
ENERGY

Residential Smart Thermostats

Impact Analysis - Gas Preliminary Findings

Prepared for the Illinois Stakeholder Advisory Group

December 16, 2015



DISPUTES & INVESTIGATIONS • ECONOMICS • FINANCIAL ADVISORY • MANAGEMENT CONSULTING

Content of Report

This presentation was prepared by Navigant Consulting, Inc. **exclusively for the benefit and internal use of** Nicor Gas, Peoples Gas and North Shore Gas and/or its affiliates or subsidiaries. No part of it may be circulated, quoted, or reproduced for distribution outside these organization(s) without prior written approval from Navigant Consulting, Inc. The work presented in this report represents our best efforts and judgments based on the information available at the time this report was prepared. Navigant Consulting, Inc. is not responsible for the reader's use of, or reliance upon, the report, nor any decisions based on the report.

NAVIGANT CONSULTING, INC. MAKES NO REPRESENTATIONS OR WARRANTIES, EXPRESSED OR IMPLIED.

Readers of the report are advised that they assume all liabilities incurred by them, or third parties, as a result of their reliance on the report, or the data, information, findings and opinions contained in the report.

December 16, 2015

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT
ENERGY

Evaluation Objectives

- Navigant is conducting an impact evaluation of the smart thermostat program.
- This evaluation has three objectives:
  1. Estimate average annual customer kWh savings
  2. Estimate average peak demand (kW) savings, defined as average hourly savings (from 1PM-5PM CT on non-holiday weekdays in June, July and August)
  3. Estimate average gas (therm) savings during the heating season (October-April)
- Results for Objective #3 are included in this presentation.
- Using the results for Objective #3, Navigant made recommendations to update the IL TRM workpaper through the TAC process.
- Results for Objective #3 and the IL TRM workpaper recommendations are included in this presentation.

NAVIGANT
ENERGY

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT ENERGY

Evaluation Approach

- The evaluation approach for therm savings involves forming a set of matched control customers and using this set with the set of participants in a post-enrollment regression analysis
- This approach is common in program evaluation and has become the preferred approach in the academic literature
  - See, for instance, the econometrics texts by Imbens and Rubin (2015), and Angrist and Pischke (2009)
- The basic logic of matching as a “design phase” in regression analysis is to balance the participant and non participant samples by matching on the exogenous covariates known to have a high correlation with the outcome variable, to mimic the set of participants and non participants one would observe in an RCT
  - The primary variable used for matching is the customer’s energy use in a similar period in the past
- Regression analysis is used to control for remaining observable non-program differences between participants and their matches
- Navigant used two models to estimate heating season therm savings:
  - Ex Post
  - Ex Ante

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT ENERGY

Data Cleaning and Verification

- Navigant performed the necessary data cleaning steps to prepare for the matching process and regressions analyses
- After performing data cleaning steps and running the matching algorithm, Navigant matched 2,118 participants to 2,058 controls
- Matching was performed on the 12 months just prior to enrollment
- Issues identified and addressed are summarized in the table below

Issue	Action
Negative usage	Removed single account
Long/Short bills	Restricted bills to less than 40 days and greater than 20 days
No install date for participant	Removed accounts
Install date after October 2014	Removed accounts
Participant account numbers in control data	Removed participants from controls
Missing data in matching algorithm	Threshold for missing data is 4 months during the matching period
Outliers	Removed observations above/below 10 standard deviations from the median usage for treatment and controls

NAVIGANT ENERGY

Data Cleaning and Verification

» Each participant was matched to a non-participant based on average daily usage in the 12 months before a customer installed the Nest thermostat

- The standard claim for this "design phase" is that a sample where treatment and control customers are balanced with respect to "important" covariates is more robust to the model specification, and generates more precise estimates.
- An "important" covariate is one that is highly correlated with the dependent variable in a regression. From previous experience, we know that past energy use is highly correlated with current energy use.

NAVIGANT ENERGY

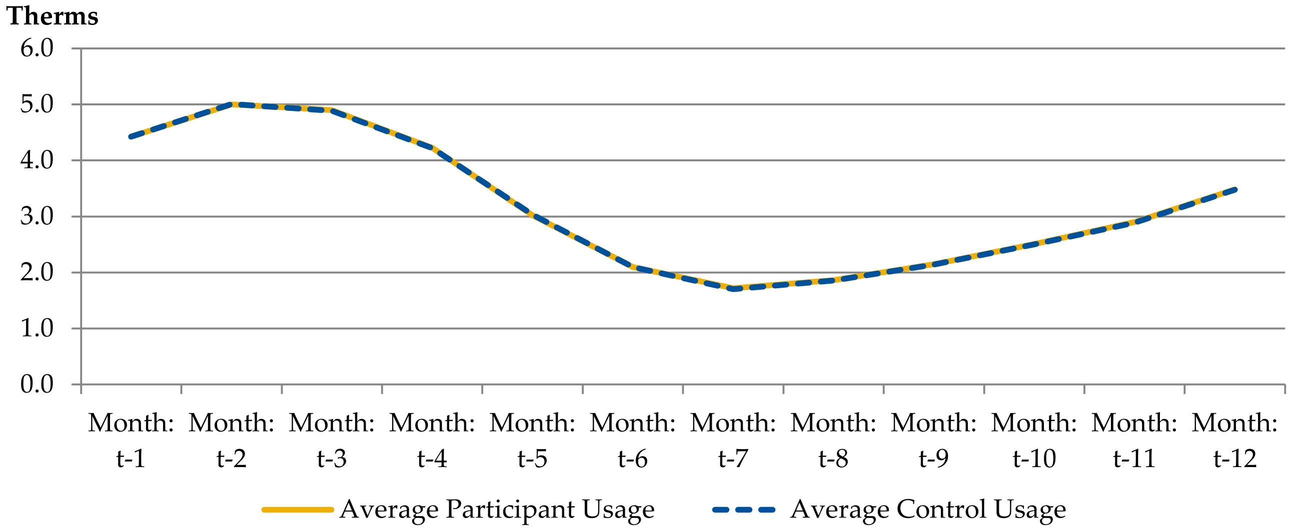
Data Cleaning and Verification

» Matching results were generally excellent, exhibiting close usage between treatment and controls, and good geographic representation

» In the figure below, Month *t* is defined as the install date. Month *t*-1 is defined as one month prior to the install date (and so on until Month *t*-12,or 12 month before install date)

– For example, a particular participant may have an install date of May 2014. Average usage for this participant in Month *t* is May 2014 and average usage for Month *t*-1 is April 2014. The same months are used for that participant's matched control

Treatment and Control Average Usage



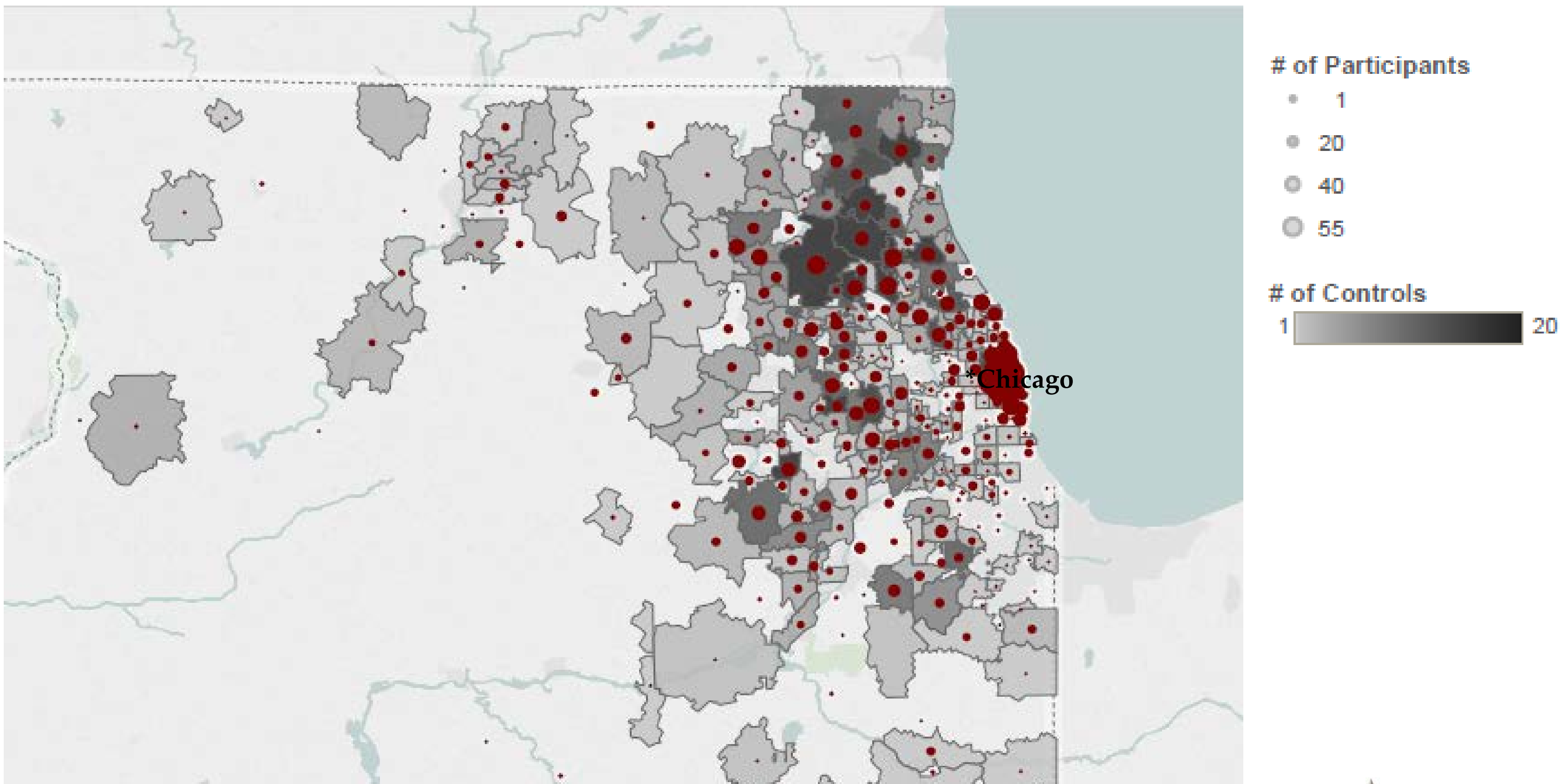
Source: Navigant analysis.

NAVIGANT ENERGY

Data Cleaning and Verification

» The figure below illustrates the distribution (and density) of treatments (red dots) and matched controls (grey shaded areas) by zip code

Treatment and Control Map – After Matching



NAVIGANT
ENERGY

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT
ENERGY

Details of the Regression Models

» To estimate therm savings, Navigant used all available participants (after data cleaning and processing) with smart thermostats installed before October 2014

» The period of analysis included October 2014 – April 2015 (the "heating season")

» Two model types were estimated:
  - Ex Post
  - Ex Ante

» As previously noted, regression analysis was used to compare the therm use of participants to that of a matched control group

» The models relied on temporal and spatial fixed effects as a means of accounting for time-correlated and spatially-correlated unobservable variables
  - E.g. demographic characteristics of customers
  - E.g. changes in therm use over time due to weather, seasonal changes in daylight, changes in economic activity

» The following slides describe the regression model

NAVIGANT
ENERGY

Regression Model >> Ex Post

For a given month *t* and a given customer *k*, average daily energy use ADU_{kt} is denoted by:

$$ADU_{kt} = \alpha_{0t}M_t + \alpha_1 Zip_k + \alpha_{2t}PREtherm_{kt} \cdot M_t + \alpha_3 Treatment_k + \alpha_4 Multifamily_k + \alpha_5 HER_k + \alpha_6 HER\_Treat_{kt} + \varepsilon_{kt}$$

Where

- M_t= Month/year-specific indicator variable (and thus α_{0t} is a monthly fixed effect);
- Zip_k = Customer's zip code;
- $PREtherm_{kt}$= The average daily therm use by household *k* in the month of the matching period corresponding to month *t*. For instance, if household *k* enrolled in August 2014, the value of $PREtherm_k$ for October 2014 is October 2013.
- $Treatment_k$= An indicator variable for a Nest thermostat (the variable of interest)
- HER_k= An indicator for participation in an HER experiment
- HER_Treat_{kt}= An indicator for active treatment in an HER experiment
- $Multifamily$= An indicator variable for a multifamily residence
- ε_{kt}=Model error term

NAVIGANT ENERGY

- The ex ante model can be used to estimate savings for a typical weather year
- This model is an extension of the ex post model, with the inclusion of four additional terms:
  - Average daily heating and cooling degree days, HDD_{kt} and CDD_{kt} ;
  - Interactions between $Treatment_k$ and HDD_{kt} and CDD_{kt}, i.e., the terms $Treatment_k \cdot HDD_{kt}$ *and* $Treatment_k \cdot CDD_{kt}$
  - Continues to use fixed effects to account for unobservable variables
  - The focus is on how the treatment effect –the effect of the Nest thermostats on energy use –varies with changes in the weather
- In this model, the effect of the Nest thermostat is given by,

$$\alpha_3 Treatment_k + \alpha_7 Treatment_k \cdot HDD_{kt} + \alpha_8 Treatment_k \cdot CDD_{kt}$$

- If the ex-ante model is reasonable, it should generate savings similar to the ex post model
  - The ex post model is the preferred model because it makes no assumptions about the treatment (savings) function, and thus should serve as the baseline for comparison.

NAVIGANT
ENERGY

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT ENERGY

Results – Ex Post

- Heating season average therm savings per customer per day are 6.0% (standard error (s.e. 0.6%), or 0.29 therms (s.e. 0.03 therm).
  - Over the heating season, this provides an average savings of 61 therms per customer
- Percent savings are calculated by taking the estimated coefficient on the treatment variable (average savings per customer per day) and dividing by average heating season therm usage in the post period for the control customers
- These results are statistically significantly different than zero at the 90% confidence level

Type of Statistic **Standard errors (s.e.) are in parentheses***	**Value**
Number of Participants	2,899
Participants in Analysis	2,118
Sample Size, Matched Controls	2,058
Average savings per customer per day (therm)	0.29 (*s.e. 0.03*)
Percent Savings	6.0% (*s.e. 0.6%*)

*Standard errors are clustered at the customer level.
Source: Navigant analysis.

NAVIGANT
ENERGY

Results – Ex Ante

- Under the ex ante model, heating season average therm savings per customer per day are 6.0% (standard error (s.e.) of 0.6%), or 0.29 therms (s.e. 0.03 therms)
  - Over the heating season, this provides an average savings of 61 therms per customer
- Percent savings are calculated taking the estimated effect of the Nest thermostat (average savings per customer per day) and dividing by average heating season therm usage in the post period for the control customers
- The ex-ante model generates savings similar to the ex post model
- These results are statistically significantly different than zero at the 90% level

Type of Statistic **Standard errors (s.e.) are in parentheses***	**Value**
Number of Participants	2,899
Participants in Analysis	2,118
Sample Size, Matched Controls	2,058
Average savings per customer per day (therms)	0.29 *(s.e. 0.03)*
Percent Savings	6.0% *(s.e. 0.6%)*

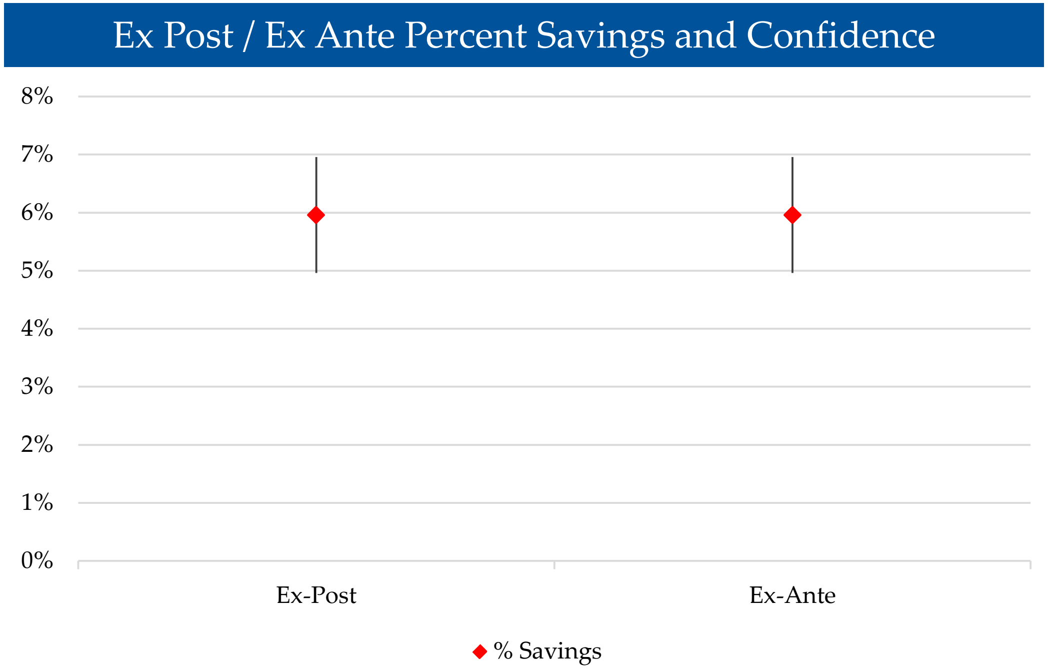
*Standard errors are clustered at the customer level
Source: Navigant analysis.

NAVIGANT
ENERGY

Ex Post and Ex Ante Comparison

» The graph below illustrates the estimated treatment effects and the calculated confidence bounds at 90% confidence for the ex post and ex ante models

» In repeated samples from the same population, we would expect that the estimated savings would fall between the upper and lower bounds 90% of the time



Source: Navigant analysis.

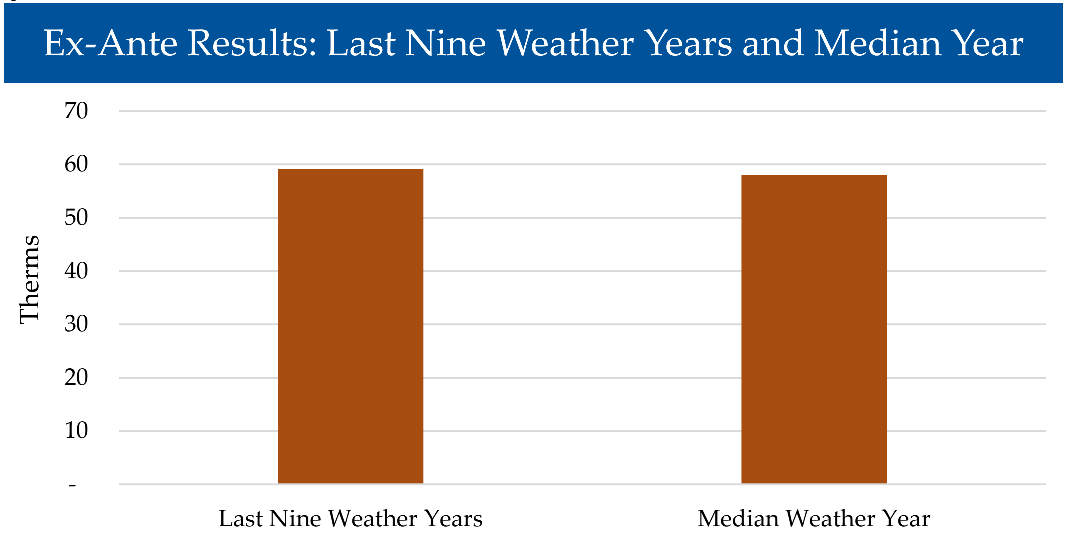
NAVIGANT ENERGY

Results – Expected Heating Season Savings Based on the Ex Ante Model

- Expected heating season savings are calculated as the average of the estimated savings predicted for each of the nine heating seasons over the years 2006-2014
  - Actual savings vary by heating season because HDD and CDD vary by year
  - In the calculation, the HDD and CDD used for each customer is based on the weather station closest to the customer
  - The time frame for the calculation is limited to the past nine years because for some weather stations in the study area the HDD and CDD data are very spotty before 2006
- Navigant also estimated the average therm savings for the 2007/2008 heating season, which is the median heating season in the past nine years with respect to *average* daily temperature
- Results for this analysis are presented on the following slide

Results – Expected Heating Season Savings Based on the Ex Ante Model

- Heating season expected savings over the last nine years are 59 therms (0.28 therms/day)
  - The formula for this calculation is outlined in the next slide
- Estimated heating season savings for the median weather heating season are 58 therms (0.27 therms/day)



Notes and Cautions:

- A significant assumption underlying this estimate of expected savings per year is that the participant behavior generating savings during the study period is stable and continues in the future.
- Caution is warranted; if the program is expanded, savings could be quite different than those estimated for the pilot due to a change in the enrolling population (such as more or fewer customers with programmable thermostats).

NAVIGANT ENERGY

Results – Expected Annual Savings Based on the Ex Ante Model

Expected Annual Savings Calculation

» Indexing the customer by k and the bill end month by t, daily savings due to the treatment effect are estimated by:

$$\text{Savings}_{kt} = \hat{\alpha}_3 Treatment_k + \hat{\alpha}_7 Treatment_k \cdot HDD_{kt} + \hat{\alpha}_8 Treatment_k \cdot CDD_{kt}$$

» Where HDD_{kt} and CDD_{kt} are average daily values for month t. Adding a subscript y to index the calendar year, average heating season savings are given by the expression:

$$\frac{\sum_{y=1}^{Y}\left[\sum_{k=1}^{K}\left[\sum_{t=1}^{T}\left[\hat{\alpha}_3 + \hat{\alpha}_7 \cdot HDD_{kty} + \hat{\alpha}_8 \cdot CDD_{kty}\right]\right]\right]}{Y \cdot K \cdot T}$$

» Where it deserves emphasis that HDD and CDD are the average daily heating and cooling degree days, respectively, for calendar month t, and

» $Y = 9$ (number of years in the calculation), with $y = 1$ corresponding to 2006, $y = 2$ corresponds to 2007, etc.;

» T =7 (number of months in the heating season)

» $K = 2,889$ (the number of participants in the sample)

NAVIGANT ENERGY

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT ENERGY

IL TRM Workpaper – Heating Load Disaggregation (Preliminary Findings)

» As discussed, Navigant estimates heating season savings as 0.29 therms/day, or 6.0% of the total heating season gas consumption (4.83 therms/day)

» Navigant estimates gas heating loads to be 89% of the total gas energy consumption* in the evaluation dataset (i.e., during the heating season)

» Heating loads of 89% and savings of 6.0% of total consumption correspond to 6.7% savings of heating load (see equation and table below for more details)

$$Savings\ [\%\ of\ Heating] = \frac{Savings\ [\%\ of\ total\ consumption]}{Heating\ Load\ [\%\ of\ total\ consumption]}$$

Parameter	Value	Source
Heating season therm savings per customer per day	0.29	Navigant's 2015 evaluation results
Heating season total therm consumption per customer per day	4.83	Navigant's 2015 evaluation results
Savings [% of total consumption]	6.0%	Navigant's 2015 evaluation results
Heating Load [% of total consumption]	89%	Navigant's estimate of non-treatment heating loads
Savings [% of Heating]	**6.7%**	***Calculation using formula above***

*Total gas heating consumption was 897 therms/year in the evaluation dataset. The IL TRM lists average gas heating consumption as 869 therms/year, ranging from 664 therms/year to 1,052 therms/year.

NAVIGANT
ENERGY

IL TRM Workpaper – Heating Load Disaggregation (Methods)

Navigant estimates heating and cooling loads using the variable base degree day (VBDD) method.

- » This method optimizes the following regression model for each site (k) individually at varying balance temperatures* (f)

$$Daily.therms_k = Intercept_{k,f} + HeatSlope_{k,f} * HDD.daily_{k,f}$$

  - This approach is industry standard
  - Navigant finds similar results when using the sum of squared error or r-squared as the optimization metric
  - Navigant removes sites with obviously poor model fits or inadequate data
  - Navigant finds similar results when rerunning the econometric model with only those sites that pass this data screening

* Balance temperature is the outdoor temperature at which a home requires heating or cooling. It is also the temperature used to calculate heating (or cooling) degree days.

» Navigant then uses the results from the VBDD optimization to calculate each site's heating load (see equations below)

$$HeatLoad_{k,f}\ [\%\ of\ total\ consumption] = \frac{\sum_t HeatSlope_{k,f} * HDD_{k,f,t}}{total\ consumption_k}$$

Where,

- k = site identifier
- f = optimal balance temperature for site k
- t = bill identifier
- HeatLoad = heating energy consumption over total energy consumption
- HeatSlope = slope between heating degree days and average daily energy consumption
- HDD = sum of heating degree days at each site's balance temperature during billing period t
- total consumption = sum of energy consumption for site k

NAVIGANT ENERGY

IL TRM Workpaper – Baseline Adjustment (Preliminary Findings)

» Navigant estimates the following % savings (as a % of heating load) for varying efficient equipment, baselines and program designs

Efficient Equipment	Non-Programmable Baseline *(Targeted DI Program Type)*	Blended Baseline *(DI Program Type)*	Blended Baseline *(TOS, RF Program Types)*	Programmable Baseline *(NC Program Type)*
Basic Smart	6.2%	4.0%	1.2%	0.0%
Adv. Smart	8.8%	6.7%	6.7%	5.6%

$$Savings\ [\%] = \frac{EC_{baseline}[\%\ of\ non.programmable] - EC_{efficient}[\%\ of\ non.programmable]}{EC_{baseline}[\%\ of\ non.programmable]}$$

Where

- Savings = % savings for each baseline, efficient equipment and program design
- $EC_{baseline}$ = baseline energy consumption as a % of energy consumption for a non-programmable thermostat~~s~~
- $EC_{efficient}$ = efficient energy consumption as a % of energy consumption for a non-programmable thermostat~~s~~

NAVIGANT ENERGY

Navigant calculated the savings for each scenario with the following inputs

- **% Savings** for advanced smart thermostats over a blended baseline and programmable thermostats over a non-programmable baseline

Equipment	Baseline	% Savings	Source
Programmable	Non-Programmable	6.2%	Illinois Statewide Technical Reference Manual for Energy Efficiency, Version 4.0, Final February 24, 2015, Measure 5.3.11 Programmable Thermostats
Advanced Smart	Blended	6.7%	Navigant's 2015 evaluation results

- **Baseline Blend**

Equipment	Blend*
Non-Programmable	35%
Programmable	65%

* Referencing the 2015 Nest whitepaper due to the expectation that participants are different than the general population.

- **Effective In-Service Rate**

Efficient Equipment	Eff_ISR (Direct Install)	Eff_ISR (Other, or unknown)
Programmable*	100%	56%
Basic Smart**	100%	56%
Adv. Smart	100%	100%

* Effective in service rate is taken from the programmable thermostat measure defined in the Illinois Statewide Technical Reference Manual for Energy Efficiency, Version 4.0, Final February 24, 2015, Measure 5.3.11 Programmable Thermostats.
** Navigant assumes that basic smart thermostats will experience the same effective in service rate as programmable thermostats until better data is available.

IL TRM Workpaper – Baseline Adjustment (Methods Cont'd)

» Navigant provides an example of the baseline adjustment to better explain the process

Efficient Equipment	Non-Programmable Baseline *(Targeted DI Program Type)*	Blended Baseline *(DI Program Type)*	Blended Baseline *(TOS, RF Program Types)*	Programmable Baseline *(NC Program Type)*
Basic Smart	6.2%	4.0%	1.2%	0.0%
Adv. Smart	8.8%	6.7%	6.7%	**5.6%**

$$Savings\ [\%] = \frac{EC_{baseline}[\%\ of\ non.programmable] - EC_{efficient}[\%\ of\ non.programmable]}{EC_{baseline}[\%\ of\ non.programmable]}$$

$$5.6\% = \frac{(1 - 6.2\% * 56\%) - (1 * 35\% + (1 - 6.2\% * 56\%) * 65\%) * (1 - 6.74\%)}{(1 - 6.2\% * 56\%)}$$

NAVIGANT ENERGY

Thermostat Definitions

- Basic smart thermostat – Two way communication capabilities
- Advanced smart thermostat – Basic smart thermostat features, plus at least 4 of the enhanced energy savings features listed in the following table

Feature	Description
Free cooling	Thermostat recognizes the indoor/outdoor temperature difference and uses the outside air instead of the air conditioner to cool down the home when possible.
Optimal humidity/ humidity control/ AC overcool	Thermostat uses the air conditioner to lower indoor humidity in the absence of a dehumidifier. Residents are less likely to adjust thermostats to inefficient set points at appropriate humidity levels. Additionally, humidity control can prevent frost buildup on windows when it is cold outside with high humidity indoors.
Fan dissipation	Thermostat turns off the air conditioner or heat pump, and uses the fan to pass air over the still cool or warm coil for additional space conditioning.
Upstaging and downstaging	Thermostat optimizes usage of multi-stage HVAC equipment.
Occupancy detection	Thermostat recognizes if you are home or away through the use of occupancy sensors, geofencing, etc. and automatically adjusts the temperature set points to an “away” setback.
Heat pump lockout temperature control	Thermostat adjusts the lockout temperature on heat pumps to limit use of the auxiliary heat.
Behavioral features	Thermostat provides encouragement for efficient behavior. For example, Opower’s customer coaching and Nest’s leaf or seasonal savings features would qualify as behavioral features.

Table of Contents

1 » Evaluation Objectives

2 » Evaluation Approach

3 » Data Cleaning and Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper updates

7 » Next Steps

NAVIGANT ENERGY

Next Steps

- Provide feedback and comments
- Add findings to discussion of Illinois TRM measure characterization
- Work through load disaggregation and baseline adjustment approaches using gas savings as the example
  - Through the TAC process:
    - Discuss any potential changes
    - Discuss any adjustments to assumptions
  - Incorporate any updates into the draft work paper
- Apply refined approach to electric savings once evaluation results are available
- Develop list of recommended research to improve TRM estimates
  - Baseline blend
  - Effective in-service rate of programmable and basic smart thermostats
  - Basic smart thermostat energy savings

NAVIGANT
ENERGY

Key CONTACTS

Randy Gunn
Director-in-Charge
312.583.5714
randy.gunn@navigant.com

Kevin Grabner
Evaluation Director – PGL/NSG
608.497.2323
kevin.grabner@navigant.com

Charley Budd
Evaluation Director – Nicor Gas
312.583.4135
charley.budd@navigant.com

Josh Arnold
Project Manger
608.497.2328
josh.arnold@navigant.com

Bill Provencher
Technical Advisor
608.497.2327
bill.provencher@navigant.com

Amanda Ackerman
Lead Analyst
416.777.2473
amanda.ackerman@navigant.com

Pace Goodman
Analyst
303.728.2511
pace.goodman@navigant.com

NAVIGANT
ENERGY