

Residential Smart Thermostats Impact Analysis - Electric Findings

Prepared for ComEd and the
Illinois Stakeholder Advisory Group

February 26, 2016



Content of Report

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1 » Program Description

2 » Evaluation Objectives & Approach

3 » Data Cleaning & Verification

4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper Updates

7 » Next Steps

Program Description

- » This pilot program was offered to ComEd account holders with a Nest thermostat controlling an air conditioner, connected to Wi-Fi, and paired with a Nest account.
- » Qualifying customers received a \$100 rebate on the purchase of a Nest thermostat after enrolling in the program.

Program Description

Total enrollment through November 2014, the latest month for which Navigant used data for this analysis, was 3,193 participants.

Figure 1. ComEd Smart Thermostat Enrollment

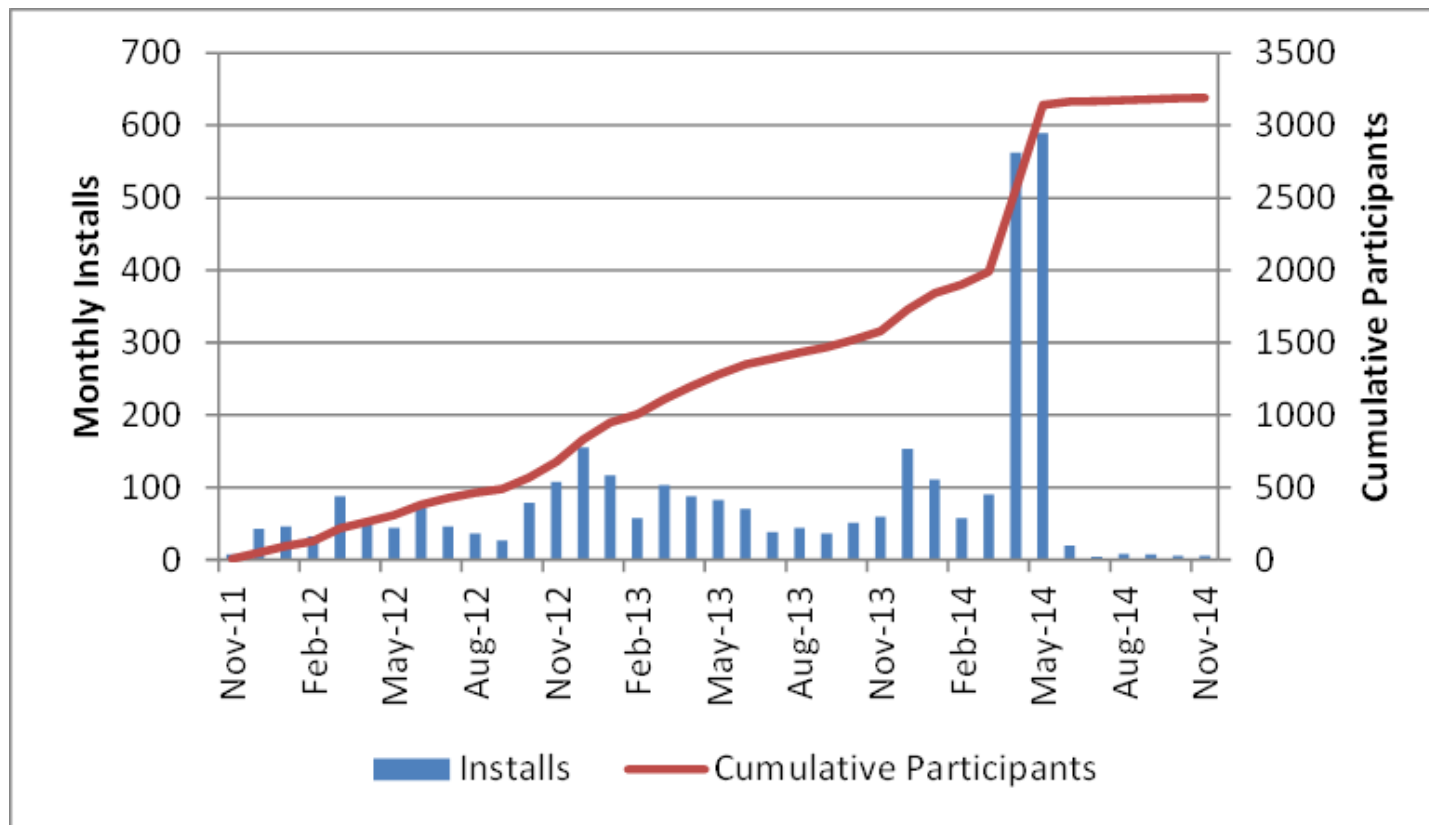


Table of Contents

1 » Program Description

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4 » Details of the Regression Models

5 » Results

6 » TRM Workpaper Updates

7 » Next Steps

Evaluation Objectives

- » 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 #1 are included in this presentation
- » The study period was the 12-month period June 2014 – May 2015
- » The regression analysis applies to the 12-month study period June 2014-May 2015. All participants in the analysis installed a Nest thermostat before the study period.
- » To estimate kWh savings, Navigant used all available participants (after data cleaning and processing) with smart thermostats installed before June 2014

Evaluation Approach

- » The evaluation approach for kWh savings involved two steps
 - First, each participant is matched to a nonparticipant based on kWh usage in the twelve months before the participant installs the Nest thermostat.
 - Second, standard regression analysis is then applied to the sample of participants and the matched controls.
 - The regression analysis applies to the 12-month study period June 2014-May 2015. All participants in the analysis installed a Nest thermostat before the study period.
- » The evaluation approach (matching as a “design phase” followed by regression analysis) is relatively new in the academic literature. See, for instance, the econometrics texts by Imbens and Rubin (2015), and Angrist and Pischke (2009)
- » The regression models rely heavily on spatial and temporal fixed effects
 - Spatial fixed effects: zip code indicator variables
 - Temporal fixed effects: monthly indicator variables
 - Fixed effects are a nonparametric way for controlling for unobserved spatial and temporal variables.
- » Navigant estimated two types of models to estimate annual kWh savings:
 - “Ex Post” models generate an average treatment effect for the study period
 - “Ex Ante” models include terms to determine how the treatment effect varies with HDD and CDD, and can be used to predict savings as a function of these variables.

Table of Contents

- 1 » Program Description
- 2 » Evaluation Objectives & Approach
- 3 » Data Cleaning & Verification**
- 4 » Details of the Regression Models
- 5 » Results
- 6 » TRM Workpaper Updates
- 7 » Next Steps

Data Cleaning & Verification

- » Navigant performed data cleaning steps to prepare for the matching process and regressions analyses
- » After performing data cleaning steps and running the matching algorithm, Navigant matched 1,887 participants to 1,791 controls
- » Issues identified and addressed are summarized in the table below

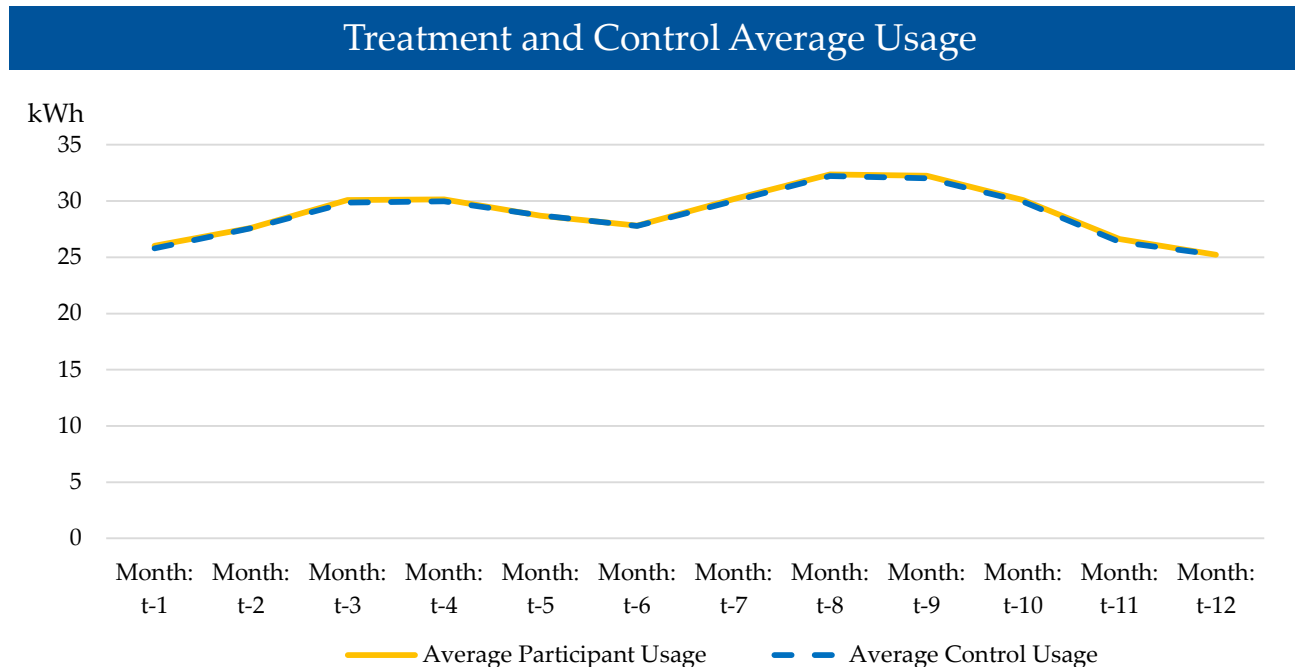
Issue	Action
Negative usage	Removed accounts (all accounts were controls)
Long/Short bills	Restricted bills to less than 40 days and greater than 20 days
RRTP customers included	Removed accounts
No install date for participant	Removed accounts
Install date after June 2014	Removed accounts
Same account in both single and multifamily	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 10 standard deviations above/below median energy use in the sample

- » 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.

Data Cleaning & Verification

» Matching details

- Defining t as the month in which a participant installs a Nest thermostat, the matching period for the participant is the year-long period $t-1$ to $t-12$.
- Among the set of feasible nonparticipants, the customer matched to a participant is the one for which the sum of squared differences in monthly electricity use between the nonparticipant and the participant over the twelve-month matching period is smallest.
- On average matches are excellent, as shown below.



Source: Navigant analysis.

Data Cleaning & Verification

- » The geographic distribution of participants and their matches is similar, as shown below.

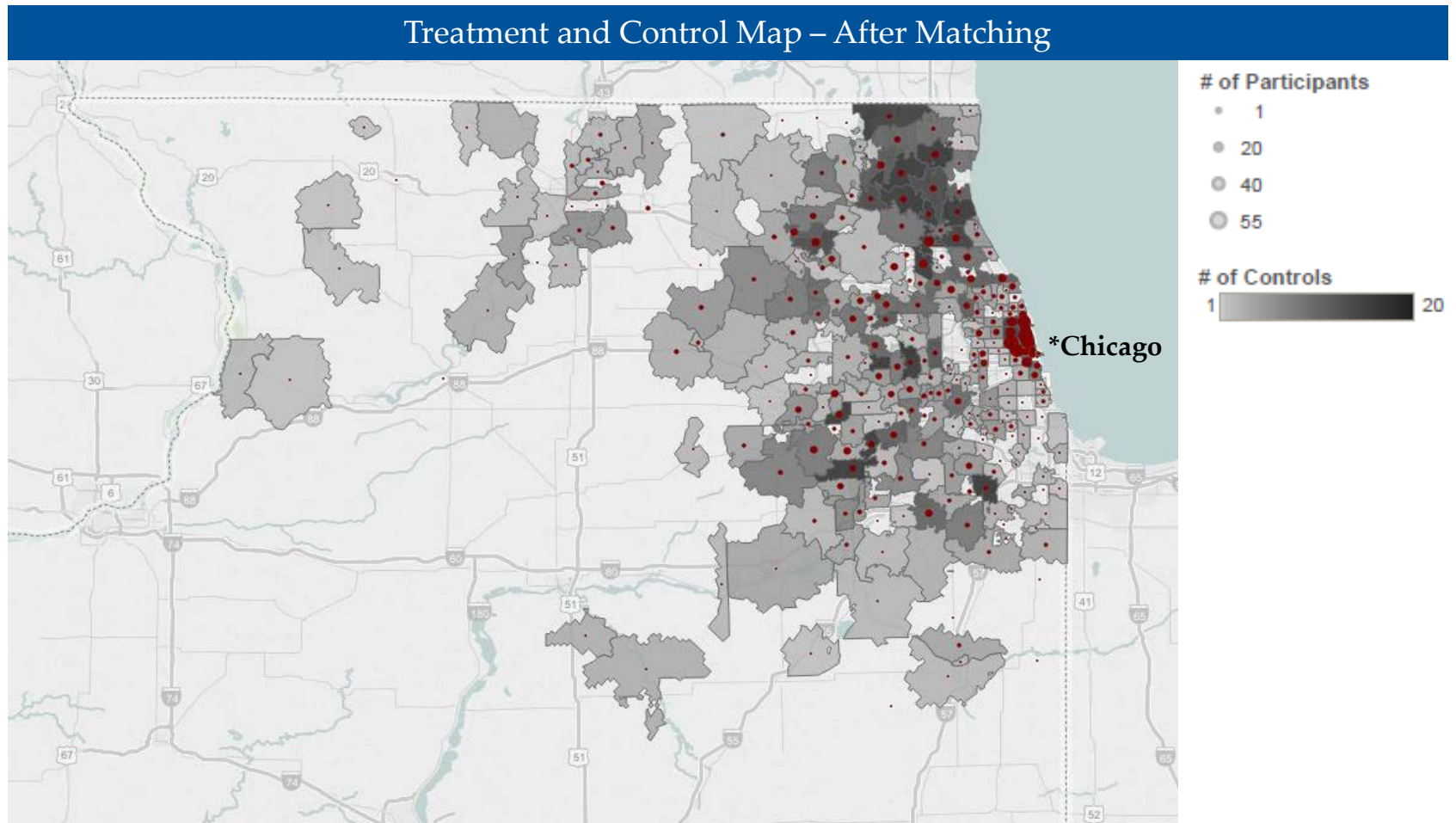


Table of Contents

- 1 » Program Description
- 2 » Evaluation Objectives & Approach
- 3 » Data Cleaning & Verification
- 4 » Details of the Regression Models**
- 5 » Results
- 6 » TRM Workpaper Updates
- 7 » Next Steps

Details of the Regression Models

- » To estimate kWh savings, Navigant used all available participants (after data cleaning and processing) with smart thermostats installed before June 2014
- » The study period was the 12-month period June 2014 – May 2015
 - Navigant also estimated two seasonal models:
 1. Cooling Season (June to September 2014 and May 2015)
 2. Heating Season (October 2014 – April 2015)
- » Two model types were estimated:
 - “Ex Post” models generate an average treatment effect for the study period
 - “Ex Ante” models include terms to determine how the treatment effect varies with HDD and CDD, and can be used to predict savings as a function of these variables.
- » The models relied on temporal and spatial fixed effects to account for time-correlated and spatially-correlated unobservable variables
- » The regression models rely heavily on spatial and temporal fixed effects
 - Spatial fixed effects: zip code indicator variables
 - Temporal fixed effects: monthly indicator variables
 - Fixed effects are a way to control for unobserved spatial and temporal variables.

Regression Model >> Ex Post

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

$$\begin{aligned}ADU_{kt} = & \alpha_{0t}M_t + \alpha_1Zip_k \\ & + \alpha_{2t}PREkWh_{kt} \cdot M_t + \alpha_3Treatment_k + \alpha_4Multifamily_k \\ & + \alpha_5HER_k + \alpha_6HER_Treat_{kt} + \varepsilon_{kt}\end{aligned}$$

Where

- M_t = Month/year-specific indicator variable (and thus α_{0t} is a monthly fixed effect);
- Zip_k = Customer's zip code (effectively a spatial fixed effect);
- $PREkWh_{kt}$ = The average daily electricity use by household k in the month of the matching period corresponding to month t . For instance, if household k enrolled in August 2013, the value of $PREkWh_k$ for June 2014 is June 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

Regression Model >> Ex Ante

- » The ex ante model can be used to estimate savings for a typical weather year
- » This model is identical to the ex post model, but includes 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

Table of Contents

- 1 » Program Description
- 2 » Evaluation Objectives & Approach
- 3 » Data Cleaning & Verification
- 4 » Details of the Regression Models
- 5 » Results**
- 6 » TRM Workpaper Updates
- 7 » Next Steps

Results – Ex Post

- » Over the 12-month study period the Nest thermostat is estimated to have decreased average customer electricity use by 0.40 kWh per customer per day (s.e. = 0.22 kWh/day), which is 1.5% of average daily usage over the period (s.e.= 0.82%).
 - Over the 12 month study period, this provides an average savings of 146 kWh per customer
- » This result is statistically significant at the 90% confidence level.

Type of Statistic Standard errors are in parentheses*	Value
Number of Participants	3,552
Participants in Analysis	1,887
Sample Size, Matched Controls	1,791
Average savings per customer per day (kWh)	0.40 (s.e. 0.22)
Percent Savings	1.5% (s.e. 0.82%)

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

Results – Ex Ante

- » Over the 12-month study period the Nest thermostat is estimated to have decreased average customer electricity use by 0.40 kWh per customer per day (s.e. = 0.22 kWh/day), which is 1.5% of average daily usage over the period (s.e.= 0.82%).
 - Over the 12 month study period, this provides an average savings of 146 kWh per customer
- » This result is statistically significant at the 90% confidence level.
- » For all practical purposes, the ex-post and ex-ante models generate identical savings

Type of Statistic Standard errors are in parentheses*	Value
Number of Participants	3,552
Participants in Analysis	1,887
Sample Size, Matched Controls	1,791
Average savings per customer per day (kWh)	0.40 (s.e. 0.22)
Percent Savings	1.5% (s.e. 0.82%)

*Standard errors are clustered at the customer level

Source: Navigant analysis.

Results – Expected Annual Savings Based on the Ex Ante Model

- » Expected annual savings are calculated as the average of the estimated savings predicted for each of the nine years 2006-2014
 - Actual savings vary by year 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
 - The formula for this calculation is outlined in the next slide
- » Full year expected annual savings per year is 164 kWh (0.45 kWh/day)
- » Navigant also estimated the average annual kWh savings per customer for the HDD and CDD values observed in 2007, which had the *median average* daily temperature among the past nine years. The estimated average annual savings for this case is 168 kWh (0.46 kWh/day)

Notes and Cautions:

- » A significant assumption underlying predictions of savings per year is that the participant behavior generating savings during the study period is stable and continues in the future
- » 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 using the Nest thermostat to replace a programmable thermostat).

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:

$$\text{Savings}_{kt} = \hat{\alpha}_3 \text{Treatment}_k + \hat{\alpha}_7 \text{Treatment}_k \cdot \text{HDD}_{kt} + \hat{\alpha}_8 \text{Treatment}_k \cdot \text{CDD}_{kt}$$

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

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

- » 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.;
- » $T = 12$ (number of months in the year)
- » $K = 1,887$ (the number of participants in the sample)

Table of Contents

- 1 » Program Description
- 2 » Evaluation Objectives & Approach
- 3 » Data Cleaning & Verification
- 4 » Details of the Regression Models
- 5 » Results
- 6 » TRM Workpaper Updates**
- 7 » Next Steps

Summary of Results

- » Using the same model and dataset, as the analysis above, Navigant estimated savings for the cooling and heating season.
- » Cooling season savings (from air conditioning) were 85 kWh/yr (1.8%).
- » Heating season savings (from furnace fan) were 59 kWh/yr.
- » For the TRM workpaper, Navigant analyzed cooling season savings

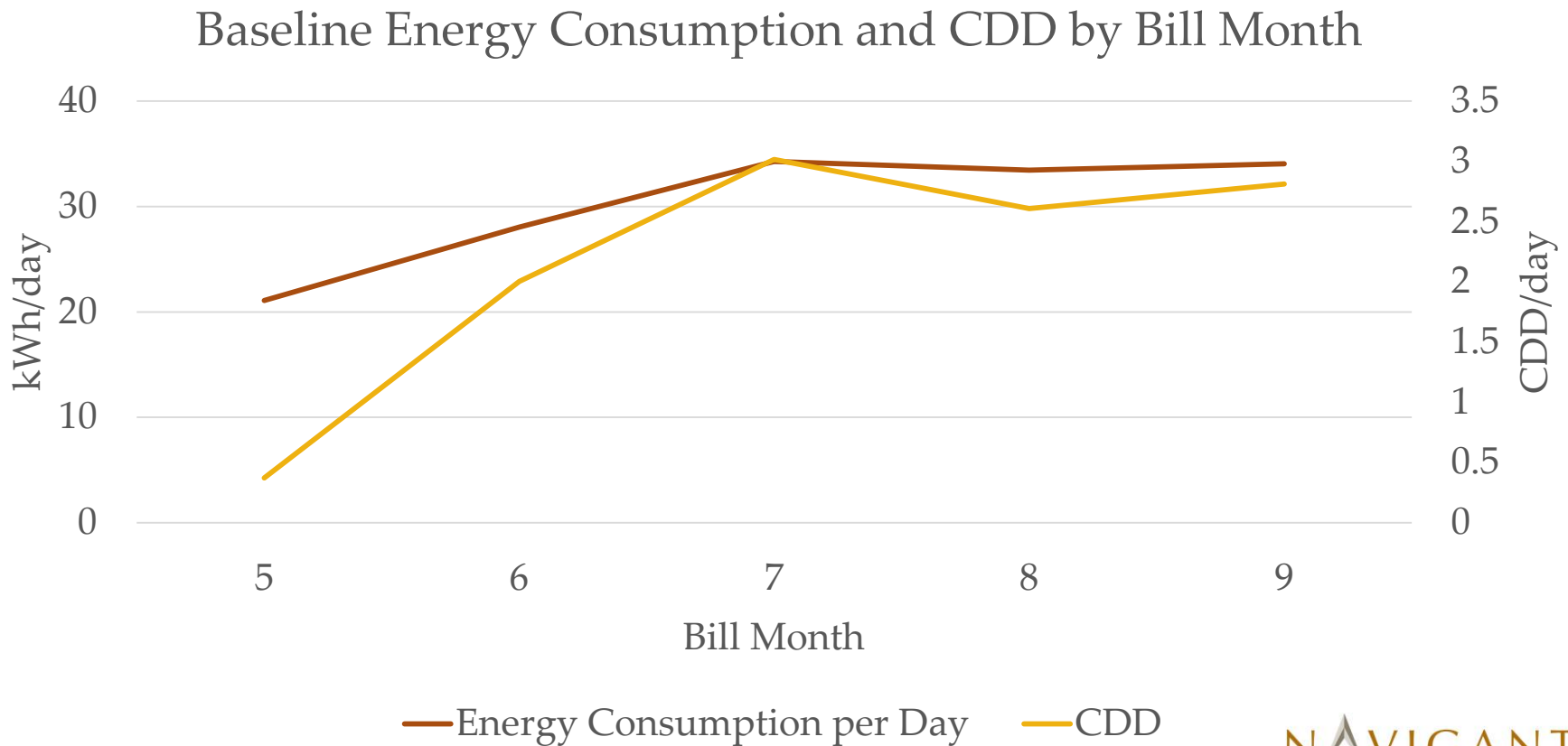
Time Period	Average savings per customer per day (kWh)	S.E. (kWh/day)	Non-Weather Normalized Annual Savings (kWh/yr)	Savings as a Percent of Total Energy Consumption
Full Year	0.40	0.22	146	1.5%
Cooling Season (May-Sept)	0.56	0.26	85	1.8%
Heating Season (Oct-Apr)	0.28	0.25	59	N/A

Range of Savings Estimates from VBDD Approach

- » The Variable Base Degree Day (VBDD) approach was used to estimate natural gas heating load
- » However, this approach proved less reliable for disaggregating site specific heating/cooling loads for both electric energy consumption and for smaller heating/cooling signals with results varying significantly with small changes in assumptions
- » Due to the volatility of the outcomes using a VBDD approach, Navigant chose to use a simpler and more robust approach to estimate the cooling load for this analysis – based on a linear regression

Linear Regression Approach

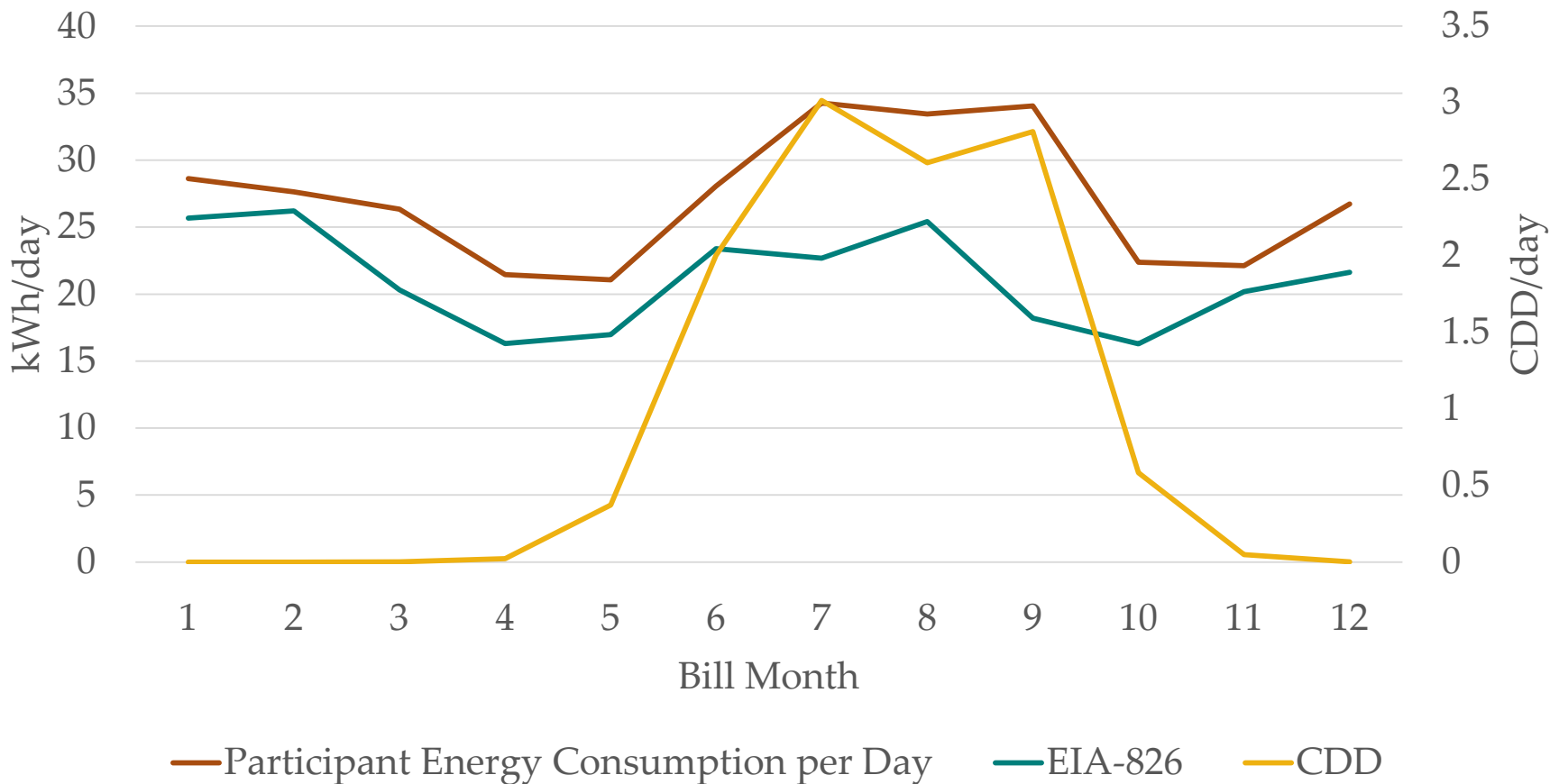
- » Graphing average daily energy consumption and cooling degree days (CDD) by bill month indicates that energy consumption closely follows CDD



Linear Regression Approach

- » Layering in the EIA-826 data for ComEd indicates that the participant group uses more energy than average residential customers, especially in the summer

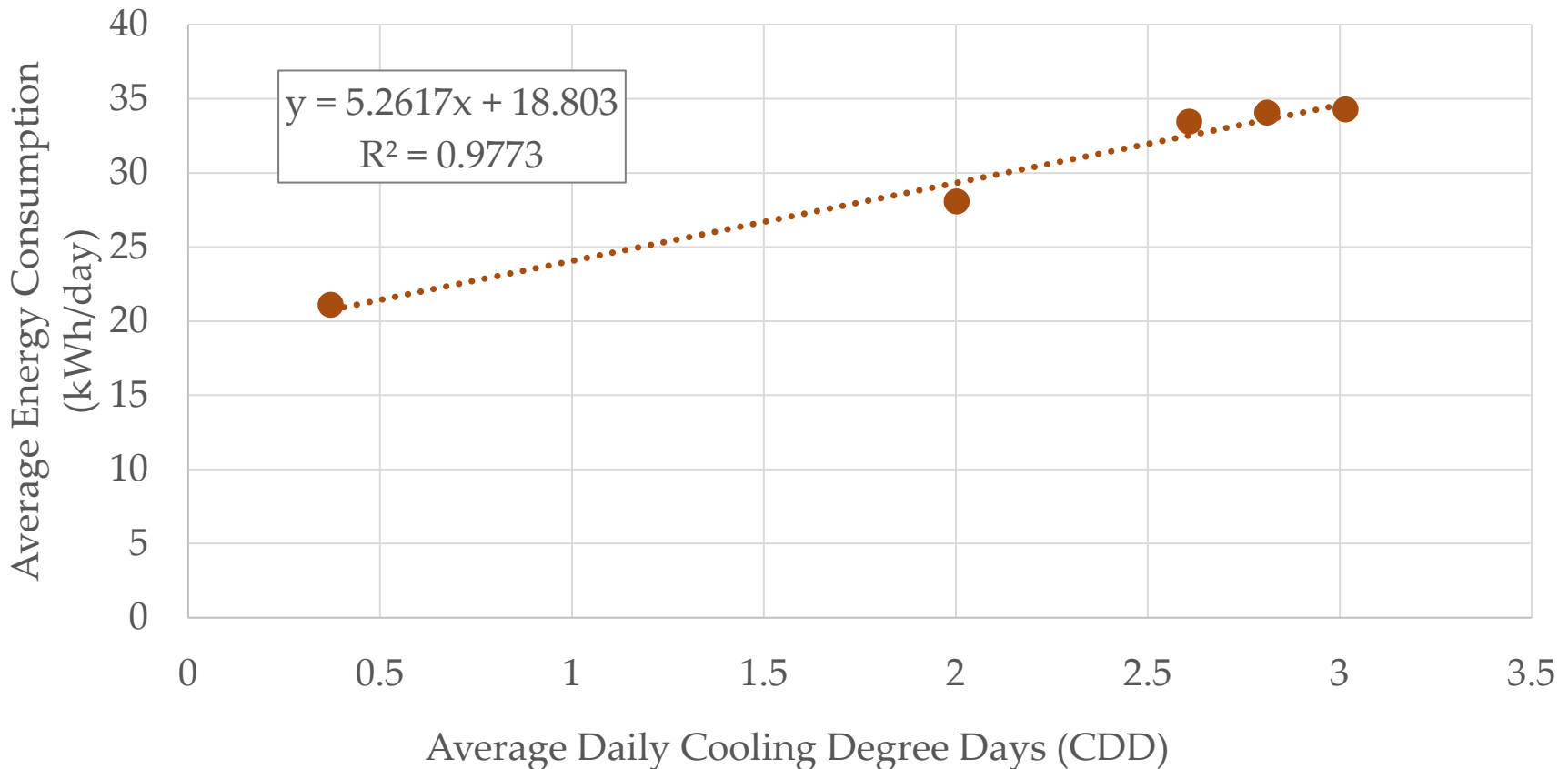
Baseline Energy Consumption and CDD by Bill Month



Linear Regression Approach

- » Conducting a simple regression of average baseline energy consumption versus CDD by bill month across participants produces a good fit (r-squared = 0.98)

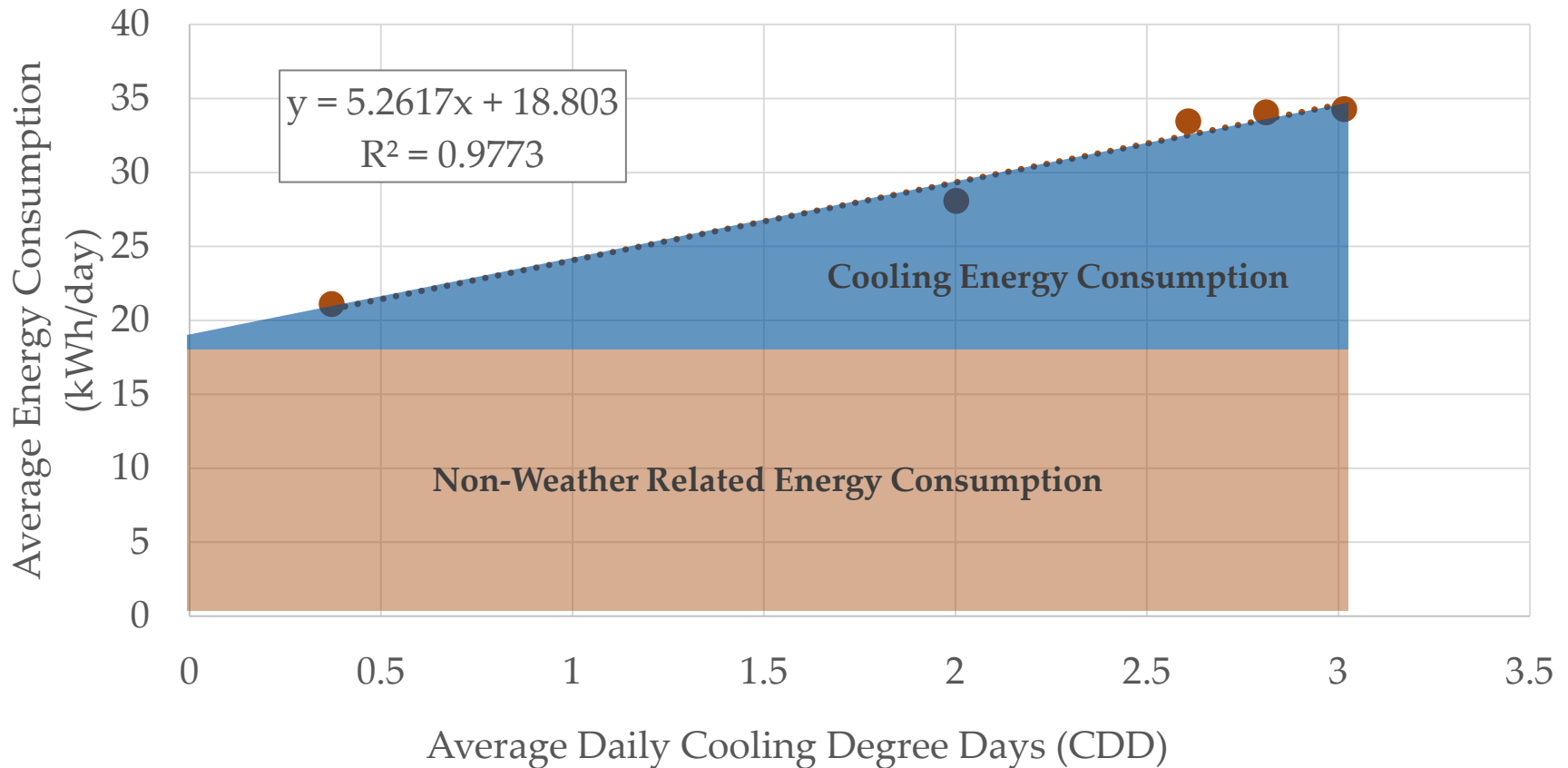
Baseline Energy Consumption vs CDD by Bill Month



Linear Regression Approach

- » Using this regression, Navigant then calculates a cooling load of 38%

Baseline Energy Consumption vs CDD by Bill Month



Linear Regression - Results

- » In summary, Navigant finds that the full-year evaluation leads to 4.8% savings as a percent of cooling load
- » To further corroborate these results, 4.8% savings leads to 107 kWh of savings per year in the TRM for a single family home in Chicago, which is within the error bands of the evaluation result (85 kWh/yr) and within any difference expected from varying weather conditions, home types, or cooling equipment efficiency

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

Parameter	Value	Source
Savings [% of total consumption – full year]	1.5%	Navigant's evaluation results
Savings [% of total consumption – cooling season]	1.8%	Navigant's evaluation results
Cooling Load [% of total consumption – cooling season]	38%	Navigant's estimate of non-treatment cooling loads
Savings [% of Cooling load]	4.8%	<i>Calculation using formula above</i>

Table of Contents

- 1 » Program Description
- 2 » Evaluation Objectives & Approach
- 3 » Data Cleaning & Verification
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- 7 » Next Steps**

Gaining more insight into baseline thermostats could help the program achieve additional savings

- » An important issue is whether the Nest thermostats replaced programmable thermostats or manual thermostats (including programmable thermostats used as manual thermostats).
- » Because the program is opt-in, with ComEd defraying a large share of the cost of the thermostat, it would seem quite likely that the program is populated by electricity-sensitive customers who replaced programmable thermostats that were already well-tuned to the heating and cooling preferences of the customer.
- » Options for collecting baseline data for existing thermostats include a participant survey and/or data collection by professional installers at the time of installation.
- » Collecting information about baseline thermostats could help the program achieve more savings by specifically recruiting customers that have a manual thermostat or a programmable thermostat that is being used as a manual thermostat.

Suggestions For Future Studies

- » Disaggregating heating and cooling loads could be refined in future analyses through:
 - Interval energy consumption
 - Interval energy consumption with a nested metered sample
 - Thermostat data (e.g., runtime and capacity per stage)
 - Thermostat data (e.g., runtime and capacity per stage) with a nested metered sample

- » Navigant could further investigate the variation in savings with the following information:
 - Pre-existing thermostat
 - Number of thermostats per home
 - Executed set points by hour (or sub-hourly)
 - Enabled features by thermostat (e.g., seasonal savings, auto-away, Nest's "leaf" activity)
 - Customer interaction with the thermostat (e.g., frequency of log-on)
 - Heating/Cooling system type
 - Customer demographics/ classifications

Next Steps

- » Add findings to discussion of Illinois TRM measure characterization
- » Discuss timing for future data sharing, evaluation efforts
- » Questions?

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