# MICHIGAN TIER 3 THERMOSTAT EXPLORATORY RESEARCH

SAVINGS POTENTIAL FINDINGS

PRESENTATION TO THE ENERGY WASTE REDUCTION COLLABORATIVE

JUNE 18, 2019





Background	3
Analysis Methodology	5
Modeled HVAC Loads	15
Savings Potential	21
Findings & Recommendations	27
Appendix A: Evaluability Assessment	29
Appendix B: Detailed Methods	31
Appendix C: Comparison to Runtime Data	35
Appendix D: Citations	38

#### Background

Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

# BACKGROUND

DTE Energy and Consumers Energy identified two study areas for the Tier 3 Thermostats Exploratory Research Study following the calibration study.

#### **Demographic Distribution**

- Assess statistical differences in demographics between participants and the matched control group given concerns about potential selection bias.
- Describe the demographic characteristics of Tier 3 thermostat participants in MI.
- Results previously presented suggested demographics should be considered in future analyses

#### **Savings Potential**

- Estimate electric & gas HVAC loads using utility-provided data. Vendorprovided data serves as a check on the reasonableness of estimated loads.
- Develop a range of savings estimates using estimated loads and assumptions regarding percent savings values to inform savings potential prior to launching a new calibration study.
- Results presented today inform the potential for energy savings from Tier 3 thermostats

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Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

## ANALYSIS METHODOLOGY OVERVIEW

Navigant used whole-home data to model HVAC load, and used vendorprovided runtime data to validate results. Multiplying the modeled HVAC load by percent savings values yields a range of *potential* energy savings.



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Navigant leveraged whole-home consumption data for the analysis.

- Study population
  - Customers who installed tier 3 thermostats in 2017
  - DTE customers included in analysis: 11,890 electric and 10,578 gas
  - Consumers Energy customers included in analysis: 3,080 electric and 6,724 gas
- Whole-home consumption data
  - From 2016, the year prior to installation
  - Gas: monthly billing data
  - Electric: daily data (aggregated from hourly AMI)
- Vendor-provided runtime data
  - Customers who installed tier 3 thermostats in 2017 and are still active in 2019

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- Aggregated by utility and fuel type



## ANALYSIS METHODOLOGY REGRESSION MODEL

Navigant used customer-specific temperature balance points to model daily HVAC load (i.e., a Variable Base Degree Day approach).

- Estimate customer-specific regressions<sup>1</sup>
  - Electric model specification:  $Use_t = \alpha + \beta_1 \cdot HDD_t + \beta_2 \cdot CDD_t + \epsilon_t$
  - Gas model specification:  $Use_t = \alpha + \beta_1 \cdot HDD_t + \epsilon_t$
- Test a range of degree day base temperatures (50-80 degrees)
- Select the base temperature that generates the model of best fit (highest R<sup>2</sup>)



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<sup>1</sup> Navigant first attempted hourly pooled regression models, but results did not align well with vendor-provided runtime data. As an alternative, we used the VBDD approach using daily data which aligned well with vendor-provided runtime data.

#### ANALYSIS METHODOLOGY MODELED HVAC LOAD

Navigant modeled customer-level HVAC load using the regression output, then calculated the average for Tier 3 installers.



Step 2: Calculate average HVAC load for Tier 3 installers

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As a check on the reasonableness of our modeling, Navigant converted vendorprovided aggregate cooling runtime data to load.

Cooling runtime to power conversion<sup>1</sup>

 $\widehat{kW} = 0.0013 + 0.8170 \cdot \frac{\% \operatorname{Runtime} \cdot \frac{Btu}{hr}}{\operatorname{SEER} \cdot 1,000} + 0.0012 \cdot CDH + 0.0055 \cdot \frac{\% \operatorname{Runtime} \cdot \frac{Btu}{hr}}{\operatorname{SEER} \cdot 1,000}$ 

- Equipment assumptions<sup>2</sup>
  - AC capacity = 2.8 tons
  - Efficiency = 10 SEER

<sup>1</sup> Navigant converted thermostat runtime to power based on an analysis of metering data from Phase 2 of the 2017 Massachusetts Baseline Study (n=92). Report available at: <u>http://ma-eeac.org/wordpress/wp-content/uploads/2017-NGrid-DR-Eval-Final-Report-2018-03-30.pdf</u>

<sup>2</sup> Assumed capacity is from the IL TRM v7.0. Assumed efficiency is the midpoint of two values. The first is the IL TRM v7.0, which includes a SEER of 9.3. The second is a field study (n=52) of Massachusetts DR program participants conducted by Navigant in October 2017, which includes a SEER of 10.7. The IL TRM is available at: http://www.ilsag.info/technical-reference-manual.html



As a check on the reasonableness of our modeling, Navigant converted vendorprovided aggregate heating runtime data to gas load.

- Heating runtime to power conversion<sup>1</sup>  $\widehat{MCF} = \left(Runtime \ hours \cdot \frac{Btu}{hour}\right) \cdot \frac{1 \ MCF}{1,037,000 \ Btu}$
- Equipment assumptions<sup>2</sup>
  - Output capacity = 86 kBtu/hr

<sup>1</sup> The runtime conversion assumes a single stage unit. Fewer than 4% of customers have two stage units, according to vendor-provided information. <sup>2</sup> Assumed capacity is from the DTE Energy 2016-2017 Residential Baseline Study, conducted by Navigant Consulting. The output capacity corresponds to the average home square footage of 1,780.



## ANALYSIS METHODOLOGY WEATHER NORMALIZATION

TMY3 data (1991-2005) are used to model HVAC loads under typical weather patterns.

- AMI data are from 2016, while runtime data are from 2018.
- Both years had hotter summers and milder winters than the TMY3 data.



-Observed 2016-Observed 2018-TMY

Source: National Solar Radiation Database (<u>https://rredc.nrel.gov/solar/old\_data/nsrdb/1991-2005/tmy3/</u>)



## ANALYSIS METHODOLOGY PERCENT SAVINGS VALUES

Navigant applied a range of percent savings values to its TMY3 modeled HVAC loads to determine a range of *potential* energy savings values.

- Savings percentages are informed by secondary literature and the ENERGY STAR (ES) Metric.
- A recent secondary literature review<sup>1</sup> found:
  - Average electric savings of 5.67% of cooling load (N = 15 studies)
  - Average electric savings of 7.05% of heating load (N = 7 studies)
  - Average gas savings of 7.02% of heating load (N = 14 studies)
- Environmental Law & Policy Center (ELPC) provided, on behalf of Google and ecobee, a blended ES Metric savings percentages for cooling (16.485%) and heating (9.04%).
  - This metric assumes a single comfort temperature (i.e., no setbacks) and as a result overstates potential savings.
  - Navigant de-rated the savings percentage by 25% and 50% based on DTE Energy's 2017 baseline study and field data collected for program evaluation in 2018 which suggested between 25% and 50% of customers adjust their thermostat setpoints.<sup>2</sup>

<sup>1</sup> The secondary literature review included smart thermostat evaluation studies across the U.S. conducted between 2013 and 2018 by third-party evaluators. Average savings are calculated as a simple average of study results. Refer to Appendix D for a comprehensive list of all studies reviewed.



<sup>&</sup>lt;sup>2</sup> Google similarly de-rated the ES metric savings percentages by 50% for a workpaper in California (SCE17HC054) based on the 2009 Residential Appliance Saturation Study regarding use of thermostat setbacks.

#### Navigant acknowledges the following limitations of this study.

- Estimating HVAC load from whole-home data is inherently difficult, due to confounding variation from weather-dependent loads and non-weather-dependent loads.
- The econometric approach relies on averages of customer-specific regressions and therefore does not present confidence intervals.
  - Parameter estimates from the customer-specific regressions are statistically significantly different from zero at the 90% confidence level for the majority of customers.
    - Gas model (HDD): 98.8% of customers
    - Electric model (CDD): 93.6% of customers
    - Electric model (HDD): 81.9% of customers
- The runtime to power conversion relies on assumptions about equipment capacity and efficiency, which may differ from the actual equipment values.



Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

## MODELED HVAC LOAD MONTHLY GAS

A comparison of the modeled gas HVAC use to the observed whole-home use shows HVAC accounts for most gas use.<sup>1</sup>

• Modeled HVAC load accounts for 73% of annual gas use and 84% of heating season use.<sup>2</sup>



- Observed whole-home load - Modeled HVAC load

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<sup>1</sup> Using 2016 weather data.

<sup>2</sup> Heating season includes November through March.

## MODELED HVAC LOAD COMPARISON TO HEATING RUNTIME DATA

# Modeled gas HVAC loads from runtime data are similar in shape and magnitude to modeled gas HVAC loads from whole-home data.<sup>1,2</sup>

- Average modeled HVAC load is 6.41 MCF/month from runtime data and 6.55 MCF/month from whole-home data (difference of 0.14 MCF/month).
- Differences in the underlying data include:
  - Participants (Whole-home: 2017 installers; Runtime: 2017 DTE dual fuel installers active in 2019<sup>2</sup>)
  - Timeframe of original data (Whole-home: 2016, prior to install; Runtime: 2018, post install)



Modeled HVAC load from runtime data, 2018 weather
Modeled HVAC load from whole-home data, 2018 weather

<sup>1</sup> Using 2018 weather data.

<sup>2</sup> Modeled HVAC load from whole-home data is based on customer-specific regressions.

<sup>3</sup> Modeled load using runtime data for CE dual fuel, CE elec/DTE gas, and DTE elec/CE gas is shown in Appendix C. Modeled load is qualitatively similar for all groups.



## MODELED HVAC LOAD DAILY ELECTRIC

Modeled HVAC load mimics the whole-home load shape, with HVAC use concentrated in the summer and winter months.

 Modeled HVAC load accounts for 32% of annual electric use<sup>1</sup>, 42% of summer electric use<sup>2</sup>, and 24% of winter electric use<sup>2,3</sup>



Observed whole-home load — Modeled HVAC load

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<sup>1</sup> Using 2016 weather data.

<sup>2</sup> Summer includes June through September. Winter includes November through March.

<sup>3</sup> EIA reports 6% of MI residents use electricity for their primary heating fuel. Source: EIA Household Energy Use in Michigan (<u>https://www.eia.gov/consumption/residential/reports/2009/state\_briefs/pdf/MI.pdf</u>)

## MODELED HVAC LOAD COMPARISON TO COOLING RUNTIME DATA

# Modeled summer HVAC loads from runtime data are similar in shape to modeled HVAC loads from whole-home data.<sup>1,2</sup>

- Average modeled summer HVAC load is 15.1 kWh/day from runtime data and 13.2 kWh/day from whole-home data (difference of 1.9 kWh/day).
- Differences in the underlying data include:
  - Participants (Whole-home: 2017 installers; Runtime: 2017 DTE dual fuel installers active in 2019<sup>3</sup>)
  - Timeframe of original data (Whole-home: 2016, prior to install; Runtime: 2018, post install)



Modeled HVAC load from runtime data, 2018 weather
Modeled HVAC load from whole-home data, 2018 weather

<sup>1</sup> Using 2018 weather data.

<sup>2</sup> Modeled HVAC load from whole-home data is based on customer-specific regressions.

<sup>3</sup> Modeled load using runtime data for CE dual fuel, CE elec/DTE gas, and DTE elec/CE gas is shown in Appendix C. Modeled load is qualitatively similar for all groups.



#### HVAC load is estimated to be 2,436 kWh and 75 MCF annually.<sup>1</sup>

- Modeled loads are weather-normalized using TMY3 data.
- Weather-normalized electric HVAC load is highest in the summer, accounting for approximately 58% of annual HVAC load.

Season	Months	Modeled Electric HVAC Load (kWh)	Modeled Gas HVAC Load (MCF)
Summer	Jun - Sep	1,414	2
Winter	Nov - Mar	791	44
Shoulder	Apr, May, Oct	231	29
Annual		2,436	75

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<sup>1</sup> Modeled HVAC load from whole-home data is based on customer-specific regressions.

Background Analysis Methodology Modeled HVAC Loads

**Savings Potential** 

Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations



## SAVINGS POTENTIAL COOLING AND HEATING SAVINGS

Navigant calculated a range of *potential* energy savings by multiplying modeled HVAC load with savings percentages informed by a secondary literature review and the adjusted ES metric.

We calculate a range of electric cooling savings of 80-175 kWh per customer, electric heating savings of 36-56 kWh per customer, and gas heating savings of 2.0-3.1 MCF per customer.<sup>1</sup>

Source	Percent Cooling Savings	Average Cooling kWh	Source	Percent Heating Savings	Average Heating kWh	Average Heating MCF
75% of ENERGY STAR <sup>1</sup>	12.364%	175	75% of ENERGY STAR <sup>1</sup>	6.78%	54	3.0
50% of ENERGY STAR <sup>1</sup>	8.243%	117	50% of ENERGY STAR <sup>1</sup>	4.52%	36	2.0
Literature Review <sup>2</sup>	5.67%	80	Literature Review <sup>2</sup>	7.05%	56	-
			Literature Review <sup>2</sup>	7.02%	-	3.1

<sup>1</sup> There are an average of 1.1 devices per home, according to vendor-provided information.

<sup>2</sup> As described on slide 10, Navigant de-rated the ES metric savings percentage by 25% and 50% to account for DTE data which suggests between 25% and 50% of customers adjust their thermostat setpoints.

<sup>2</sup> The secondary literature review included smart thermostat evaluation studies across the U.S. conducted between 2013 and 2018 by third-party evaluators. Refer to Appendix D for a comprehensive list of all studies reviewed.



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## SAVINGS POTENTIAL ELECTRIC SAVINGS

This figure presents the range of *potential* electric energy savings.



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## SAVINGS POTENTIAL ELECTRIC SAVINGS

This figure presents the range of *potential* electric energy savings.



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#### SAVINGS POTENTIAL GAS SAVINGS

This figure presents the range of *potential* gas energy savings.





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#### SAVINGS POTENTIAL GAS SAVINGS

This figure presents the range of *potential* gas energy savings.



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Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations Key findings & recommendations are summarized below.

- Findings
  - Cooling savings estimates range from 80 to 175 kWh per customer.
  - Heating savings estimates range from 36 to 56 kWh and 2.0 to 3.1 MCF per customer.
- Recommendations
  - Utilities may consider these ranges of potential savings and revisit cost effectiveness to inform whether a new calibration study is desired.
  - Follow recommended methods from the Uniform Methods Protocol chapter on smart thermostats (in progress, expected March 2020).



Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

## APPENDIX A: EVALUABILITY ASSESSMENT SUMMARY OF FINDINGS

The electric AMI and gas billing data sets provided by CE and DTE are sufficient for the savings potential analysis, requiring only minor adjustments.

Data Set	# 2017 Adopters	% With 2016 Data	% Move-In Post 2016	Difference in Use (2017)	# Outages
CE – Electric	4,531	73%	27%	0.2%	20 days
CE – Gas	9,311	80%	20%	9%(1)	0 months
DTE – Electric	14,739	83%	15%	19%	8 days
DTE – Gas	13,846	83%	14%	13%(1)	0 months

Notes: (1) The gas usage differences decrease over time and likely reflect customer move-ins.

Adjustments:

 CE & DTE electric: drop data on outage days where load differs by more than 10% compared to nearby days.

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• DTE electric: Installers who moved in after 2016 have lower load than installers with 2016 usage data. Apply seasonal adjustment factor to estimated HVAC load.

Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

## APPENDIX B: DETAILED METHODS HOURLY ELECTRIC MODEL

Navigant attempted to estimate hourly HVAC load shapes using AMI data, but results did not align well with vendor-provided thermostat runtime data.

- Navigant tested several weather variables in the hourly regression model for summer weekdays:
  - Cooling degree hours (CDH)
  - 6- and 24- hour lags of CDH
  - Temperature humidity index (THI)
  - Heat index
  - 6- and 24- hour lags of heat index
- Given the unreasonable parameter estimates, Navigant aggregated AMI data to the daily level and estimated customer-specific VBDD models, in alignment with the gas modeling.



#### APPENDIX B: DETAILED METHODS GAS: DISTRIBUTION OF CUSTOMER-SPECIFIC BASE TEMPS

Navigant tested HDD balance temperatures ranging from 50 to 72 degrees F. For each customer, the model with the highest R<sup>2</sup> value was selected.

• Distribution of customer-specific balance temperatures





#### APPENDIX B: DETAILED METHODS ELECTRIC: DISTRIBUTION OF CUSTOMER-SPECIFIC BASE TEMPS

Navigant tested degree day balance temperatures ranging from 55 to 82 degrees F. For each customer, the model with the highest R<sup>2</sup> value was selected.

• Distribution of customer-specific balance temperatures



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Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

## APPENDIX C: COMPARISON TO RUNTIME DATA GAS

HVAC load modeled from runtime data is shown below for CE dual fuel, DTE dual fuel, CE elec/DTE gas, and DTE elec/CE gas customers. Modeled gas HVAC loads are similar for all four customer groups.



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- CE Gas and DTE Elec

# APPENDIX C: COMPARISON TO RUNTIME DATA SUMMER

HVAC load modeled from runtime data is shown below for CE dual fuel, DTE dual fuel, CE elec/DTE gas, and DTE elec/CE gas customers. Modeled HVAC loads are similar for all four customer groups.



CE Elec and CE Gas
CE Gas and DTE Elec
Predicted
CE Elec and DTE Gas
DTE Elec and DTE Gas

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Background Analysis Methodology Modeled HVAC Loads Savings Potential Findings & Recommendations Appendix A: Evaluability Assessment Appendix B: Detailed Methods Appendix C: Comparison to Runtime Data Appendix D: Citations

#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	F	uel <sup>1</sup>	
ComEd	IL TRM Advanced Thermostat Savings Evaluation	IL TRM Advanced Thermostat Cooling Savings Evaluation. Touch- Point Meeting with Regression Outputs. Navigant Consulting, Inc. Goodman, Pace. Sierzchula, Will. April 2018.	EH	EC	G
ComEd	IL TRM Advanced Thermostat Savings Evaluation	IL TRM Advanced Thermostat Cooling Savings Evaluation. Touch- Point Meeting with Regression Outputs. Navigant Consulting, Inc. Goodman, Pace. Sierzchula, Will. April 2018.	EH	EC	
ComEd	IL TRM Advanced Thermostat Savings Evaluation	IL TRM Advanced Thermostat Cooling Savings Evaluation. Touch- Point Meeting with Regression Outputs. Navigant Consulting, Inc. Goodman, Pace. Sierzchula, Will. April 2018.	EH	EC	
ComEd	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7: Suggestion 1	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7, Navigant, Goodman et al, May 2018		EC	
ComEd	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7: Suggestion 2	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7, Navigant, Goodman et al, May 2018		EC	
ComEd	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7: Suggestion 3	Navigant's Proposed update for the Residential Advanced Thermostat Measure for IL TRM v7, Navigant, Goodman et al, May 2018		EC	
DTE	Michigan Tier 3 Thermostat Calibration Study	Michigan Tier 3 Thermostat Calibration Study, Navigant Consulting Inc., Podolefsky, Molly, 2018. pg. 28. https://www.michigan.gov/documents/mpsc/Tier_3_Tstat_Calibration_ Study_EWR_Presentation_623038_7.pdf	EH	EC	G
MA	HES Impact Evaluation Engineering Results WORKING DRAFT	MA RES 34 - HES Impact Evaluation Working Draft, Cadeo Group, 2018.			G

<sup>1</sup> EH = Electric Heating, EC = Electric Cooling, G = Gas.





#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	Fuel	1
PG&E	PG&E Smart Thermostat Study: Second Year Findings (Thermostat 1)	PG&E Smart Thermostat Study: Second Year Findings. AEG. Ryan, Barb & Marrin, Kelly. March 2018. Pg 9, 13. https://www.etcc-ca.com/reports/smart-thermostat- study		
PG&E	PG&E Smart Thermostat Study: Second Year Findings (Thermostat 2)	PG&E Smart Thermostat Study: Second Year Findings. AEG. Ryan, Barb & Marrin, Kelly. March 2018. Pg 9, 13. https://www.etcc-ca.com/reports/smart-thermostat- study		
PG&E	PG&E Smart Thermostat Study: Second Year Findings (Thermostat 2)	PG&E Smart Thermostat Study: Second Year Findings. AEG. Ryan, Barb & Marrin, Kelly. March 2018. Pg 9, 14. https://www.etcc-ca.com/reports/smart-thermostat- study		
Nest/UK gov't	Evaluating the Nest Learning Thermostat	Evaluating the Nest Learning Thermostat, Behavioral Insights Team, Park, Toby, October 2017, Pg 32, https://www.behaviouralinsights.co.uk/publications/evaluating-the-nest-learning- thermostat/.		G
NREL	Adopting Energy Efficiency in Connected Homes	Adopting Energy Efficiency in Connected Homes. CLEAResult, Kemper, Emily & Christensen, Dane. September 2017, Pg 10, https://www.nrel.gov/docs/fy18osti/70267.pdf.	EC	G
UK gov't	Evaluating the Nest Learning Thermostat	Evaluating the Nest Learning Thermostat, Behavioral Insights Team, Park, Toby, October 2017, Pg 14, https://www.behaviouralinsights.co.uk/publications/evaluating-the-nest-learning- thermostat/		G
UK gov't	Evaluating the Nest Learning Thermostat	Evaluating the Nest Learning Thermostat, Behavioral Insights Team, Park, Toby, October 2017, Pg 20, https://www.behaviouralinsights.co.uk/publications/evaluating-the-nest-learning- thermostat/		G

<sup>1</sup> EH = Electric Heating, EC = Electric Cooling, G = Gas.



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#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	Fu	lel <sup>1</sup>	
UK gov't	Evaluating the Nest Learning Thermostat	Evaluating the Nest Learning Thermostat, Behavioral Insights Team, Park, Toby, October 2017, Pg 27, https://www.behaviouralinsights.co.uk/publications/evaluating-the-nest-learning- thermostat/			
Vivint Smart Home	Vivint Smart Home™ Energy Savings Study Heating and Cooling Results	Vivint Smart Home Energy Savings. WattzOn Study. Amram, Martha. September 2017, pg 2. http://www.wattzon.com/wp-content/uploads/2016/07/Vivint-Smart-Home-Thermostat-Study-September-2017-f.1.pdf.	ł	EC	G
Xcel Energy	Excel Energy Colorado Smart Thermostat Pilot - Evaluation Report	Xcel Energy Colorado Smart Thermostat Pilot - Evaluation Report. Xcel Energy. Nexant, Inc. Schellenberg, Josh. May 12, 2017.			
Xcel Energy	Excel Energy Colorado Smart Thermostat Pilot - Evaluation Report	Xcel Energy Colorado Smart Thermostat Pilot - Evaluation Report. Xcel Energy. Nexant, Inc. Schellenberg, Josh. May 12, 2017.			
ACEEE	National Study of Potential of Smart Thermostats for Energy Efficiency and Demand Response	National Study of Potential of Smart Thermostats for Energy Efficiency and Demand Response, ACEEE, Robinson et al, 2016, Pg 2- 6https://aceee.org/files/proceedings/2016/data/papers/2_1172.pdf.			
ComEd	Residential Smart Thermostats: Impact Analysis – Electric Findings	Residential Smart Thermostats Impact Analysis - Electric Findings. Prepared for ComEd and the Illinois Stakeholder Advisor Group. Navigant Consulting, Inc. February 26, 2016. http://ilsagfiles.org/SAG_files/Technical_Reference_Manual/Version_5/Illinois_Smar t_Thermostat_Electric_Impact_Findings_2016-02-26.pdf	ł	EC	
Energy Trust of Oregon	Energy Trust of Oregon Smart Thermostat Pilot Evaluation	Energy Trust of Oregon Smart Thermostat Pilot Evaluation. Apex Analytics, LLC. March 1, 2016.			G

<sup>1</sup> EH = Electric Heating, EC = Electric Cooling, G = Gas.





#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	F	uel <sup>1</sup>	
Energy Trust of Oregon	Energy Trust of Oregon Smart Thermostat Pilot Evaluation	Energy Trust of Oregon Smart Thermostat Pilot Evaluation. Apex Analytics, LLC. March 1, 2016.			G
Florida Energy Center	ACEEE Evaluation of the Space Heating and Cooling Energy Savings of Smart Thermostats in a Hot- Humid Climate using Long-term Data.	Evaluation of the Space Heating and Cooling Energy Savings of Smart Thermostats in a Hot-Humid Climate using Long-term Data. D. Parker, K. Sutherland, and D. Chaser. Florida Solar Energy Center. Presented at the 2016 ACEEE Summer Study on Energy Efficiency in Buildings. http://aceee.org/files/proceedings/2016/data/papers/8_163.pdf	EH	EC	
Franklin Public Utility District (FPUD)	A Look Inside the Eye on the Wall: Sub-metering Data Analysis and Savings Assessment of the Nest Learning Thermostat. Prepared by Bonneville Power Administration. Presented at the 2016 ACEEE Summer Study on Energy Efficiency in Buildings	http://aceee.org/files/proceedings/2016/data/papers/1_351.pdf			
KCP&L	Do Smart Thermostats Make for Smart Demand Response Programs?	Do Smart Thermostats Make for Smart Demand Response Programs?. Researhc into Action Inc. Wirtshafter et al. April 2018. pg 18. https://www.cooperative.com/programs- services/bts/Documents/TechSurveillance/TS-Smart-Thermostats-April- 2018.pdf.			
PG&E	PG&E Smart Thermostat Study: First Year Findings (Thermostat 1)	Smart Thermostat Study, Applied Energy Group, Ryan, Barb & Marrin, Kelly, 2016, https://www.etcc-ca.com/reports/smart-thermostat-study?dl=1532122620			
PG&E	PG&E Smart Thermostat Study: First Year Findings (Thermostat 2)	Smart Thermostat Study, Applied Energy Group, Ryan, Barb & Marrin, Kelly, 2016, https://www.etcc-ca.com/reports/smart-thermostat-study?dl=1532122620			
PG&E	PG&E Smart Thermostat Study: First Year Findings (Thermostat 3)	Smart Thermostat Study, Applied Energy Group, Ryan, Barb & Marrin, Kelly, 2016, https://www.etcc-ca.com/reports/smart-thermostat- study?dl=1532122620			
$^{1}$ EH = Electric	Heating EC = Electric Cooling G = Gas				

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#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	F	<sup>-</sup> uel <sup>1</sup>	
University of California, Davis and Berkeley.	Do occupancy-responsive learning thermostats save energy? A field study in university residence halls	Do occupancy-responsive learning thermostats save energy? A field study in university residence halls. Pritoni, Marco; Woolley, Jonathan. Energy and Buildings. Volume 127. 1 September 2016. pg. 469- 478.http://www.sciencedirect.com/science/article/pii/S0378778816303851	EH	EC	
Illinois Stakeholder Advisory Group	Residential Smart Thermostats: Impact Analysis - Gas Preliminary Findings	Residential Smart Thermostats Impact Analysis - Gas Preliminary Findings. Navigant Consulting Inc. December 2015. http://ilsagfiles.org/SAG_files/Meeting_Materials/2015/December_2015_M eetings/Presentations/Smart_Tstat_Preliminary_Gas_Impact_Findings_2015- 12-08_to_IL_SAG.pdf			G
Nicor Gas & ComEd	Home Energy Management System Utilizing a Smart Thermostat	1022: Home Energy Management System Utilizing a Smart Thermostat. Final Public Project Report Executive Summary. Spentzas, Steve. Gas Technology Institute. May 4, 2015. https://www.nicorgasrebates.com/- /media/Files/NGR/PDFs/ETP/1022_Smart_Thermostat- HEMS_FINAL_APPROVED_Public_Project_Report_to_Nicor_Gas_05-04- 2015.pdf		EC	G
Puget Sound Energy	Web-Enabled Thermostat Impact Evaluation 2014	,Web-Enabled Thermostat Impact Evaluation. PES. Tomamlin, Dane. August 2015. pg 17. https://conduitnw.org/_layouts/Conduit/FileHandler.ashx?RID=2965			
SoCalGas	Getting Smarter? Evidence of Savings from the Nest Thermostat	Getting Smarter? Evidence of Savings from the Nest Thermostat. 2015 Behavior, Energy & Climate Change Conference. Navigant Consulting Inc. Brennan, Debbie. October 2015. http://beccconference.org/wp- content/uploads/2015/10/presentation_brannan.pdf			G

<sup>1</sup> EH = Electric Heating, EC = Electric Cooling, G = Gas.



#### The following studies were referenced in the calculation of the literaturebased savings values.

Entity	Title of Research	Reference	F	uel <sup>1</sup>
Vectren Corporation	Evaluation of the 2013-2014 Programmable and Smart Thermostat Program, 2015	Evaluation of the 2013–2014 Programmable and Smart Thermostat Program. Cadmus Group, Inc. Aarish, Carlyn et al. January 2015, http://www.cadmusgroup.com/wp- content/uploads/2015/06/Cadmus_Vectren_Nest_Report_Jan2015.pdf		G
Vectren Corporation	Evaluation of the 2013-2014 Programmable and Smart Thermostat Program, 2015	Evaluation of the 2013–2014 Programmable and Smart Thermostat Program. Cadmus Group, Inc. Aarish, Carlyn et al. January 2015, http://www.cadmusgroup.com/wp- content/uploads/2015/06/Cadmus_Vectren_Nest_Report_Jan2015.pdf		EC
Energy Hub	Understanding Energy Efficiency Benefits from Smart Thermostats in Southern California	Understanding Energy Efficiency Benefits from Smart Thermostats in Southern California. Ho, Ben, December 2014. pg 2. http://beccconference.org/wp- content/uploads/2014/12/presentation_Ho.pdf		EC
Energy Trust of Oregon	Energy Trust of Oregon Nest Thermostat Heat Pump Control Pilot Evaluation, 2014	Energy Trust of Oregon Nest Thermostat Heat Pump Control Pilot Evaluation, Apex Analytics. October 2014. pg 5 - 11. http://energytrust.org/library/reports/Nest_Pilot_Study_Evaluation_wSR.pdf	EH	
PG&E	Findings from the Opower/Honeywell Smart Thermostat Field Assessment, 2014	Findings from the Opower/Honeywell Smart Thermostat Field Asessment, Nexant, Inc. Churchwell, C & Sullivan M, July 2014. pg 17. http://www.etcc- ca.com/sites/default/files/reports/et11pge3074_opower_honeywell_final_report.pdf		
CenterPoint Energy and Earth Networks	Weatherbug Home Optimization Program Pilot, 2013	WeatherBug Home Optimization Program Pilot. Pionergy Consulting. Adib, Parviz Ph.D. November 2013. http://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7B86EB2003- 61B3-4DDD-800E-3B834BC885EF%7D		
Liberty Utilities	Wi-Fi Programmable Thermostat Pilot Program Evaluation, 2013	Wi-Fi Programmable Thermostat Pilot Program Evaluation. Cadmus Group, Inc. Johnson et al. July 2013. pg 12. http://www.puc.nh.gov/Regulatory/Docketbk/2012/12-262/LETTERS- MEMOS-TARIFFS/12-262%202013-08- 22%20ENGI%20DBA%20LIBERTY%20FILING%20ITS%20PROGRAM%20EVALUATION%20STUD Y.PDF		

<sup>1</sup> EH = Electric Heating, EC = Electric Cooling, G = Gas.



