



**Verified Carbon
Standard**

IMPROVING ENERGY EFFICIENCY IN HOMES THROUGH SMART THERMOSTAT OPTIMIZATION

Anew and ecobee

Project Title	Improving Energy Efficiency in Homes Through Smart Thermostat Optimization
Version	1.2
Date of Issue	07/07/2022
Prepared By	Seth Baruch, Carbonomics
Contact	9000 Crow Canyon Road, Suite S-522, Danville CA 94506

CONTENTS

1	PROJECT DETAILS	4
1.1	Summary Description of the Project.....	4
1.2	Sectoral Scope and Project Type	4
1.3	Project Eligibility	4
1.4	Project Design	5
1.5	Project Proponent	5
1.6	Other Entities Involved in the Project	5
1.7	Ownership.....	6
1.8	Project Start Date	6
1.9	Project Crediting Period	6
1.10	Project Scale and Estimated GHG Emission Reductions or Removals	7
1.11	Description of the Project Activity	8
1.12	Project Location	9
1.13	Conditions Prior to Project Initiation	9
1.14	Compliance with Laws, Statutes and Other Regulatory Frameworks	9
1.15	Participation under Other GHG Programs.....	10
1.16	Other Forms of Credit	10
1.17	Sustainable Development Contributions	10
1.18	Additional Information Relevant to the Project.....	11
2	SAFEGUARDS	11
2.1	No Net Harm	11
2.2	Local Stakeholder Consultation.....	11
2.3	Environmental Impact.....	11
2.4	Public Comments.....	11
2.5	AFOLU-Specific Safeguards	12
3	APPLICATION OF METHODOLOGY.....	12
3.1	Title and Reference of Methodology	12
3.2	Applicability of Methodology.....	12
3.3	Project Boundary.....	14
3.4	Baseline Scenario	14
3.5	Additionality	14

3.6	Methodology Deviations	15
4	QUANTIFICATION OF GHG EMISSION REDUCTIONS AND REMOVALS.....	19
4.1	Baseline Emissions.....	19
4.2	Project Emissions	20
4.3	Leakage	21
4.4	Net GHG Emission Reductions and Removals	21
5	MONITORING	22
5.1	Data and Parameters Available at Validation.....	22
5.2	Data and Parameters Monitored	26
5.3	Monitoring Plan.....	30
	APPENDIX A: CONNECTED LOAD ASSUMPTIONS	35
	APPENDIX B: CONNECTED LOAD RESEARCH	37
	APPENDIX C: 2021 E GRID EMISSION FACTORS	41
	APPENDIX D: REGRESSION MODELING	42
	Regression Model Design Considerations.....	42
	Data Sampling outputs.....	42
5.4	Regression Models	43
	Results 44	
5.5	Exhibit 1 - Detailed Regression Results.....	45

1 PROJECT DETAILS

1.1 Summary Description of the Project

This project activity will use smart thermostats installed in homes to reduce the heating and cooling usage. The thermostats are manufactured by ecobee which also has developed a thermostat optimization software platform to control these devices remotely in a manner that deepens the levels of energy savings beyond what would have occurred in the absence of this enhanced functionality. The energy efficiency optimizations resulting from this platform generate no additional revenue for ecobee but do represent a significant cost. This approach reduces both electricity and natural gas usage in air conditioning and heating units in residential homes. The project boundary will include the United States, and the project will be grouped by climate and equipment type as detailed in Appendix D. This project activity will result in approximately **4,076,188** tons of CO₂ reduced over the crediting period, the average annual emission reductions being 582,313 tCO₂.

1.2 Sectoral Scope and Project Type

Sectoral Scope 3. This is a grouped project.

1.3 Project Eligibility

The project meets all the criteria set out in the VCS Program Guide, the VCS Standard and the AMS II.C methodology approved under the CDM program. The project will reduce emissions by improving the efficiency with which homes heat and cool their homes. It meets all of the applicability criteria of the methodology being used. Section 2.1 of the VCS Standard (v4.2) lays out the scope of the VCS program, including the following:

- 1) The six Kyoto Protocol greenhouse gases (this project will reduce CO₂ as explained in Section 4 of this document)
- 2) Ozone-depleting substances (not applicable)
- 3) Project activities supported by a methodology approved under the VCS Program through the methodology approval process (not applicable)
- 4) Project activities supported by a methodology approved under an approved GHG program (this project will follow AMS II.C., an approved methodology under CDM)
- 5) Jurisdictional REDD+ programs and nested REDD+ projects as set out in the VCS Program document Jurisdictional and Nested REDD+ (not applicable)

Section 2.1 of the VCS Standard also outlines a number of excluded project types, such as HFC-23. None of these apply to this particular project activity.

1.4 Project Design

When completing a draft project description for the purpose of listing on the pipeline as under development, complete the following information; otherwise, delete this text:

- ☐ The project includes a single location or installation only
- ☐ The project includes multiple locations or project activity instances, but is not being developed as a grouped project
- ☒ The project is a grouped project

Eligibility Criteria

Because this is a grouped project, the project proponents will specify the criteria for including individual homes into the project boundary. These criteria include homes that have connected thermostats manufactured by ecobee that have been upgraded with a thermostat optimization software platform and are therefore owned by the main project proponent, Anew, formerly known as Element Markets, which has a contractual agreement with ecobee. No other homes may be included within the grouped project. Project instances must also comply with all of the applicability criteria in AMS II.C, which are outlined in Section 3.2.

1.5 Project Proponent

Organization name	Anew
Contact person	Mark Havel
Title	Director, Environmental Products
Address	3200 SW Fwy, Suite 1310, Houston, TX 77027
Telephone	(281) 207-7217
Email	mhavel@anewclimate.com

1.6 Other Entities Involved in the Project

Organization name	ecobee
Role in the project	Technology provider
Contact person	Tamara Dzubay
Title	Director, Energy and Emerging Markets
Address	25 Dockside Drive, Suite 700, Toronto, ON, M5A 0B5, Canada
Telephone	(630) 269-1779
Email	tamara.d@ecobee.com

1.7 Ownership

Anew will be the owner of the carbon offsets from this project. The company has an agreement with ecobee to own and transact the VCU's generated from this activity, and this contract can be provided to the VVB upon project validation.

ecobee has the right to claim ownership over the GHG attributes from its customers through the following clauses in its terms & conditions. *"s.5(h). So long as it does not conflict with any incentives provided to you under s. 5(f). ecobee shall be eligible to claim any qualifying environmental attributes, benefits, credits, awards or bounties from third parties resulting from savings gained by the benefit of eco+."* For more details please see <https://www.ecobee.com/en-us/eco-plus/legal/>

Additionally, ecobee includes the following clause in its Standard Software Agreement, Schedule B, s. 1.4, *"Both parties agree that ecobee shall be eligible to claim any qualifying environmental attributes, benefits, credits, awards or bounties from third parties resulting from customer incremental savings gained by the benefit of eco+ or other software upgrades that are outside the scope of the services stipulated in this Schedule B"*

1.8 Project Start Date

The project start date is 1 March 2021. The company finished an initial pilot in September 2020 which was the beta trial to make sure the platform was delivering the intended impacts before ecobee implemented a phased rollout of the software to all existing and new devices. This rollout was completed by 1 Mar. 2021.

1.9 Project Crediting Period

The crediting period will be 7 years, renewable twice.

1.10 Project Scale and Estimated GHG Emission Reductions or Removals

When completing a draft project description for the purpose of listing on the pipeline as under development, complete the following information; otherwise, delete this text.

The estimated annual GHG emission reductions/removals of the project are:

- ☐ <20,000 tCO₂e/year
- ☐ 20,000 – 100,000 tCO₂e/year
- ☒ 100,001 – 1,000,000 tCO₂e/year
- ☐ >1,000,000 tCO₂e/year

In all other cases, indicate the scale of the project (project or large project) and the estimated annual GHG emission reductions or removals for the project crediting period.

Project Scale	
Project	
Large project	X

Year	Estimated GHG emission reductions or removals (tCO ₂ e)
2021	275,271
2022	354,313
2023	446,940
2024	570,032
2025	725,850
2026	831,113
2027	872,669
Total estimated ERs	4,076,188
Total number of crediting years	7

Average annual ERs**582,313**

1.11 Description of the Project Activity

ecobee is a developer of smart thermostat technology for homes and buildings. A smart thermostat is a device that regulates a home's temperature by controlling HVAC equipment and allows users to designate a schedule through home and away set points. A smart thermostat is Wi-Fi-enabled and connects with an application on a smartphone or tablet, which allows users to monitor and control their heating and cooling remotely. This connectivity enables manufacturers to add and adjust features and user settings.

Building on these features, ecobee has developed advanced software to make personalized, automated adjustments to the set point of HVAC systems through special features that offer energy efficiency optimization. The energy efficiency optimizations use individual customer comfort preferences, real-time and historical occupancy patterns, and data regarding a home's specific thermodynamic properties and HVAC system performance to create personalized, real-time optimization. The optimizations utilize occupancy sensing, which identifies when a home is vacant, learning algorithms that use machine learning to establish customer schedules and temperature preferences, geolocation, which determines a customer's proximity to home, and the ability to adjust for indoor humidity conditions. This advanced software helps people lower their energy use without sacrificing comfort.

This project activity will cover devices equipped with the advanced software that enables additional functionality resulting in personalized energy efficiency optimization that will further reduce heating and cooling usage in the home beyond what would happen without the advanced software. Enabling this additional functionality has both one-time and on-going costs that ecobee has to incur, which it cannot do without the recurring revenue from selling carbon offsets.

This additional functionality is called eco+ and is a thermostat optimization platform to improve the energy performance of residential HVAC systems with minimal effort. The platform prompts customers to indicate their desired balance of comfort versus savings. Then, eco+ tailors an algorithm unique to the customer for the optimization that best represents their comfort preferences and the thermal profile of the home.

The platform consists of three categories of algorithms.

- Demand Response (DR) – Presented to users as Community Energy Savings (CES), this feature shifts cooling loads away from peak hours when the electrical grid is most constrained through customized pre-cooling of the home and temporary temperature setbacks during system peak hours.
- Time-of-Use Optimization (TOU) – For ecobee owners whose retail electricity rate varies by hour of the day, the TOU algorithm shifts energy use from high price hours to lower price hours while maintaining the desired comfort levels through customized pre-cooling and temporary temperature setbacks.

The project proponent is NOT seeking to generate carbon offsets from the two categories above. The third category, described below, is the added functionality that will be the primary project activity.

- Energy Efficiency (EE) – Features like Enhanced Smart Away, Schedule Assistant, and Adjusting for Humidity are designed to help ecobee owners lower their overall heating and cooling energy consumption.

- o Enhanced Smart Home & Away – builds on the existing Smart Home & Away feature by adjusting for vacancy faster.

- o Schedule Assistant – recommends updates to users’ thermostat schedules to match their occupancy patterns.

- o Adjusting for Humidity – a technology patented¹ by ecobee that accounts for fluctuations in indoor humidity to ensure users’ homes always feel like the temperature they have set on their thermostat. This keeps their home energy efficient and comfortable even in periods of unusually high or low humidity.

ecobee undertook a pilot study in 2019 and 2020 to assess the results of eco+ including this third category.² During this time, the eco+ platform was deployed across North America to a large pilot group of ecobee thermostats to demonstrate the capabilities of the platform. The pilot included a population of approximately 240,000 ecobee thermostats. The results of this pilot showed measurable energy efficiency improvements over those who did not participate in the pilot, and these results were consistent across a range of climactic zones. This project activity will expand this functionality to 2.3 million ecobee thermostats already installed in the US, with this ability to be embedded in all new deployments. The sale of carbon offsets will finance the additional costs ecobee will have to incur for a program that generates no additional income for the company.

1.12 Project Location

The project boundary will cover the entire United States, and the project will be grouped by climate and equipment type as detailed in Appendix D.

1.13 Conditions Prior to Project Initiation

See Section 3.4 (Baseline Scenario)

1.14 Compliance with Laws, Statutes and Other Regulatory Frameworks

¹<https://patents.google.com/patent/US20210302052A1/en?inventor=kevin+trinh&assignee=ecobee&oq=kevin+trinh+ecobee>

² Evaluation Performed by Demand Side Analytics, available at <https://www.ecobee.com/en-us/ecoplusemv/>

This project is in compliance with all relevant national, state and local regulations. In addition, the use of this technology is not required by any law or regulation anywhere within the project boundary.

1.15 Participation under Other GHG Programs

1.15.1 Projects Registered (or seeking registration) under Other GHG Program(s)

This project has not been registered, nor is Anew seeking registration, under any other GHG programs.

1.15.2 Projects Rejected by Other GHG Programs

This project has not been rejected by any other GHG program

1.16 Other Forms of Credit

1.16.1 Emissions Trading Programs and Other Binding Limits

When completing a draft project description for the purpose of listing on the pipeline as under development, complete the following information; otherwise, delete this text:

Does the project reduce GHG emissions from activities that are included in an emissions trading program or any other mechanism that includes GHG allowance trading?

☐ Yes

☒ No

1.16.2 Other Forms of Environmental Credit

When completing a draft project description for the purpose of listing on the pipeline as under development, complete the following information; otherwise, delete this text:

Has the project sought or received another form of GHG-related credit, including renewable energy certificates?

☐ Yes

☒ No

1.17 Sustainable Development Contributions

This project will contribute to sustainable development by allowing heating and cooling appliances in homes to operate with the same comfort levels but with lower levels of energy usage. This contributes to lower fossil fuel emissions both at power plants and in the homes themselves that use natural gas or heating oil, the result being lower emissions of other harmful pollutants, such as NO_x, SO_x, particulates and even carbon monoxide.

1.18 Additional Information Relevant to the Project

Leakage Management

The applied methodology, AMS II.C states that: “If the energy efficiency technology is equipment transferred from another activity, leakage is to be considered.” For this project, the equipment involved is not being transferred from another project – the thermostats are deployed for this project activity specifically. Thus, leakage does not need to be considered.

Commercially Sensitive Information

N/A

Further Information

N/A

2 SAFEGUARDS

2.1 No Net Harm

There are no negative consequences associated with this project. This project activity involves only the installation of smart thermostats in homes – along with a software upgrade – and does not involve the construction of any facility or other action that would have a measurable environmental impact.

2.2 Local Stakeholder Consultation

This project activity is taking place in homes that already exist and for which environmental impacts have already been incurred. The specific project activity only involves the installation of a unique thermostat, which is being used in a unique manner that lowers the fuel and electricity usage associated with heating and cooling these homes. There will be no additional air or water impacts as a result of this GHG reduction project and no incremental impacts in the community. As a result, no stakeholder consultation was conducted.

2.3 Environmental Impact

For the reasons described in Section 2.1, no environmental impact statement was required for this specific GHG-reducing activity.

2.4 Public Comments

Not applicable

2.5 AFOLU-Specific Safeguards

Not applicable

3 APPLICATION OF METHODOLOGY

3.1 Title and Reference of Methodology

AMS II.C. Demand Side Energy Efficiency Activities for Specific Technologies, Version 15.

3.2 Applicability of Methodology

This methodology has the following applicability criteria, and the right column describes how this project activity complies with that criterion.

Criterion	Project
This methodology is only applicable if the service level (e.g. rated capacity or output) of the installed, project energy-efficient equipment is between 90% and 150% of the service level of the baseline equipment. Examples of service levels are light output for lighting equipment, water output and temperature for water heating systems, and rated thermal output capacity of air conditioners. The relationship of the service level of the project energy-efficient equipment to the baseline equipment can be one to one replacement (e.g. replacement of inefficient refrigerator with new and efficient refrigerator) or many-to-one (e.g. replacement of small multiple chillers with a central chiller plant). In the latter case, the service level of the project and baseline can be compared on an aggregate basis.	<i>The thermostats affect the levels of output from heaters and air conditioners in homes and thus will never have the ability to impact the service level of the appliances as defined in this methodology.</i>
Requirements pertaining to the baseline of the retrofit projects and projects involving capacity increase are indicated in paragraphs 20 to 21 if the methodology in	<i>Note that while this applicability criterion exists in the methodology, the project will</i>

the above cited general guidelines to SSC CDM methodologies. In the event that project output in year y is greater than the average historical output (average of the three most recent years prior to the project implementation ³) and the demonstration of the baseline for the incremental capacity is not undertaken, the value of the output in year y is capped at the value of the historical average output level.	<i>follow Option 2, which states that for the regression analysis: <u>“The data for the analysis must cover a period of 12 continuous months.”</u></i>
If the energy-efficient equipment contains refrigerants, then the refrigerant used in the project case shall have no ozone depleting potential (ODP).	<i>Not applicable to this project as the project activity only includes the installation of thermostats and software upgrades to control existing appliances and will not install new appliances.</i>
This methodology credits emission reductions only due to the reduction in electricity and/or fossil fuel consumption from use of more efficient equipment. However, the calculation of project emissions shall include any incremental emissions, as compared to the baseline, associated with refrigerants used in the project equipment. ⁴	<i>This project will only calculate the reduction in energy use from the consumption. The criterion around refrigerants is not applicable as the project activity only includes the installation of thermostats and software upgrades to control existing appliances and will not install new appliances.</i>
The aggregate energy savings by a single project may not exceed the equivalent of 60 GWh per year for electrical end-use energy efficiency technologies. For fossil fuel end-use energy efficient technologies, the limit is 180 GWh thermal per year in fuel input.	<i>This project will limit individual projects to 60 GWh; however as a grouped project, the project proponents will add projects similar to a PoA structure.</i>

³ A maximum of +10% variation is permitted.

⁴ See EB 34 report, paragraph 17.

3.3 Project Boundary

Source	Gas	Included?	Justification/Explanation
Baseline	CO ₂	Yes	CO ₂ is the main GHG associated with the combustion of electricity and natural gas associated with home heating and cooling equipment
	CH ₄	No	Excluded – emissions likely to be very small
	N ₂ O	No	Excluded – emissions likely to be very small
	Other	No	Not applicable
Project	CO ₂	Yes	CO ₂ is the main GHG associated with the combustion of electricity and natural gas associated with home heating and cooling equipment
	CH ₄	No	Excluded – emissions likely to be very small
	N ₂ O	No	Excluded – emissions likely to be very small
	Other	No	Not applicable

3.4 Baseline Scenario

The baseline scenario is the level of appliance use without the eco+ functionality enabled, which as described in Section 3.5 would be the case because running the energy efficiency optimizations resulting from the eco+ software platform generates no economic benefit other than the carbon credits. ecobee devices did not have this advanced eco+ functionality until recently. The baseline is the device without eco+ which was the case for over a decade and the enhanced eco+ capability is not common practice in the industry.

3.5 Additionality

AMS II.C requires the application of the CDM Tool, *Demonstration of Additionality of Small-Scale Project Activities*, the procedures for which are outlined below.

Project participants shall provide an explanation to show that the project activity would not have occurred anyway due to at least one of the following barriers:

- (a) Investment barrier: a financially more viable alternative to the project activity would have led to higher emissions;*
- (b) Technological barrier: a less technologically advanced alternative to the project activity involves lower risks due to the performance uncertainty or low market share*

of the new technology adopted for the project activity and so would have led to higher emissions;

(c) Barrier due to prevailing practice: prevailing practice or existing regulatory or policy requirements would have led to implementation of a technology with higher emissions;

(d) Other barriers: without the project activity, for another specific reason identified by the project participant, such as institutional barriers or limited information, managerial resources, organizational capacity, financial resources, or capacity to absorb new technologies, emissions would have been higher.

For this project, the project proponents can select Option (a). Eco+ is provided to customers as a free thermostat optimization platform developed by ecobee to improve the energy performance of residential HVAC systems. ecobee employs a team of engineers to work towards continuous refinement and improvement of Energy Efficiency features. In order to continue offering these free features to customers, ecobee will need carbon revenue to cover the large expense of software development, implementation and on-going maintenance. eco+ is a free software offered to existing customers and all development cost has been incurred by the company. Additional details on the financial costs of implementing eco+ will be provided to the VVB upon project validation.

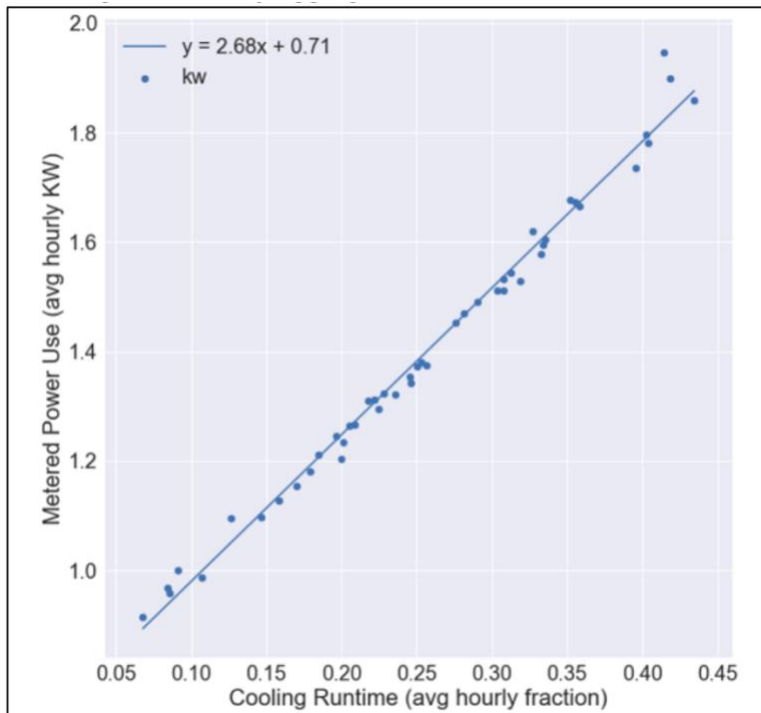
3.6 Methodology Deviations

AMS II.C requires that baseline and post-project electricity consumption are monitored directly, according to CDM Methodology Tool 5, which stipulates the use of electricity meters to measure consumption at “individual project electricity consumption sources”.

ecobee proposes an alternative path to metering. Internet of things (“IoT”) technology has advanced since the latest revision of AMS II.C in 2016. Advanced technologies now have embedded metering which directly measures outputs. ecobee smart thermostats have accompanying telemetry data which directly measures granular intervals of time that an HVAC system is running. Using this data is the most accurate approach to measure the project activity because telemetry data does not include the noise of other end uses and those impacts on energy use that are unrelated to the project activity. Additionally, given the number of individual homes within the project boundary, it is not feasible to get utility data from all of them because not all utilities have installed advanced metering infrastructure (AMI) for residential customers (in these instances, the utility meter only measures monthly consumption). Even in instances where utilities have installed AMI meters for residential customers, not all utilities have established a protocol to share this data with third parties. Even in instances where utilities have an established protocol for sharing interval consumption data with third parties, the customer authorization process is so cumbersome that very few customers complete the steps required to do so.

Outlined in detail in Appendix A and D, ecobee’s approach directly measures reductions in **run-time** of the HVAC equipment. This data is complemented by conducting a sample of actual changes in electricity consumption at homes with ecobee thermostats installed. As Figure 1 below shows, there is a very high correlation ($R^2 = 0.988$) between ecobee’s telemetry/runtime data and the associated utility meter data. This demonstrates that if ecobee can measure changes in run-time pre and post project, estimating the actual reductions in electricity and gas consumption (as is required in AMS II.C) will be very accurate.

Figure 1 - Correlation of HVAC Runtime Data to Metered Data



Thus, for this project activity, ecobee is seeking to deviate from AMS II.C. by not collecting utility metered electricity and gas consumption data. Instead of data on electricity consumed by project building unit j in the baseline and project in kWhs, ecobee would collect data in **run-time** of HVAC appliances controlled by the ecobee thermostat.

Smart thermostats measure granular intervals of time that an HVAC system is running. To convert this to kWh, there needs to be an assumption on HVAC power draw. There has been extensive field research done in state technical reference manuals regarding average HVAC connected load at the state/regional level as detailed in Appendix B. Technical Reference Manuals (TRMs) are valuable resources for state regulators, utilities, and program administrators and implementers for estimating the energy and demand savings of end-use energy efficiency measures. Using these resources to determine average HVAC connected load, smart thermostat runtime data can be used as a proxy for retail

meter data for measurement and verification (M&V) purposes as detailed in Appendix A & D.

In fact, thermostat runtime data is commonly used in this way for utility thermostat optimization evaluation, and the Department of Energy Uniform Method Protocol for evaluating smart thermostats specifically allows for the use of thermostat runtime data and recommends a uniform method on how to use thermostat runtime data to quantify energy impacts.⁵ A 2019-2020 evaluation prepared for the Massachusetts Program Administrators stated that an impact analysis on smart thermostat programs “relied exclusively on thermostat telemetry data to estimate impacts after converting thermostat runtime data to estimated energy.” Table 1 below includes a sample of other examples of utility programs evaluated using thermostat runtime/telemetry data.

Table 1- Examples of North American Utility Programs Using Thermostat Telemetry for Measurement & Verification

Utility	Program Name	Link
Xcel Energy New Mexico	Saver’s Stat	https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Rates%20&%20Regulations/Regulatory%20Filings/NM-DSM-2017-Annual-Report-with-Attachments.pdf
Xcel Energy Colorado	Smart Thermostat Pilot	https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Rates%20&%20Regulations/Regulatory%20Filings/CO-Smart-Thermostat-Pilot-Evaluation.PDF
National Grid	ConnectedSolutions	http://ma-eeac.org/wordpress/wp-content/uploads/2017-NGrid-DR-Eval-Final-Report-2018-03-30.pdf
CPS Energy	Rush Hour Rewards Pilot Program	https://www.sanantonio.gov/Portals/0/Files/Sustainability/STEP/CPS-FY2015.pdf

⁵ In section 3.2.2 of the June 2022 draft protocol, the DOE supports the use of thermostat runtime/telemetry data as appropriate for measurement and verification by stating: “Telemetry data analysis is an option because thermostat data are usually available for the periods before and after activating the optimization schedule for the study population. Evaluators can use the telemetry data to construct an accurate picture of baseline HVAC runtimes. Also, for some optimization program evaluations, telemetry data may be the only option. If hourly savings estimates are needed, and AMI meter data are unavailable from the utility, analysis of telemetry data will be the only approach for measuring the savings.” (pg. 27)

Available upon request at: <https://www.nrel.gov/ump/>

Vectren	Residential Smart Thermostat Pilot	http://vectrened.com/assets/downloads/planning/irp/IRP-2018-smart-cycle-evaluation.pdf
---------	---------------------------------------	---

An illustrative example would be that ecobee runtime data shows a reduction of HVAC runtime of 0.1624 hours compared the baseline. The state/regional Technical Reference Manual lists the average HVAC system size (connected load) to be 3.6 kW. In order to obtain the impacts, the coefficient impacts can be multiplied by the connected load assumption.

$$-0.1624 \text{ hours} * 3.60 \text{ kW per hour} = -0.58 \text{ kW}$$

$$(\text{Runtime}_{\text{project,hrs}} - \text{Runtime}_{\text{baseline,hrs}}) * \text{ConnectedLoad}_{\text{kW}} = \text{Impacts}_{\text{kWh}}$$

Note that a negative Impact implies savings.

4 QUANTIFICATION OF GHG EMISSION REDUCTIONS AND REMOVALS

4.1 Baseline Emissions

AMS II.C has three options to determine baseline emissions. This project activity will use Option 2 as described below.

Option 2 – Variable load device(s), regression approach

This option is limited to the retrofit of existing equipment and does not apply to Greenfield projects. It applies to baseline equipment for which the rate of energy consumption, demand (kW), varies in response to independent variable(s) such as weather. An example is cooling equipment used to condition an office space where demand changes with outdoor dry bulb and wet bulb temperatures, solar gain and office occupancy. A mathematical function has been developed, using regression techniques, to determine baseline energy consumption as a function of the relevant independent variable(s). The independent variables are measured during the crediting period and used in the regression function to predict baseline energy consumption throughout the crediting period.

The baseline emissions under Option 2 are calculated as follows:

$$E_{BL,y} = \sum_i (n_i \times kWh_i) / (1 - l_y) \quad \text{Equation (1)}$$

$$BE_y = E_{BL,y} \times EF_{CO2,ELEC,y} + Q_{ref,BL} \times GWP_{ref,BL} \quad \text{Equation (2)}$$

Where:

kWh_i = Annual average electric energy use for the equipment in group i . Based on regression analysis⁶ of relevant independent variables that have a physical influence on energy use, for example outside air dry bulb temperature for space cooling applications. Takes for example the form of:

$kWh = f(x) + \epsilon$, where x are the independent variable(s) causing the device(s) to use energy and ϵ is the error term. As stated in Section 3.6 and Appendix A, this parameter will be based on runtime and assumed size of the equipment based on data presented in Appendix A & B.

⁶ Regression analysis is a statistical method used to establish cause-effect for the investigation of relationships between the variables.

$EF_{CO_2,ELEC,y}$	=	Electricity emissions factor using eGrid measurements from US EPA.
n_i	=	Number of pieces of equipment of the group of i baseline equipment
l_y	=	Average annual technical grid losses (transmission and distribution) during year y for the grid serving the locations where the devices are installed, expressed as a fraction. The average annual technical grid losses shall be determined using recent, accurate and reliable data available for the host country. This value can be determined from recent data published either by a national utility or an official governmental body. The reliability of the data used (e.g. appropriateness, accuracy/uncertainty, especially exclusion of non-technical grid losses) shall be established and documented by the project participant. A default value of 0.1 shall be used for average annual technical grid losses, if no recent data are available or the data cannot be regarded accurate and reliable.
$Q_{ref,BL}$	=	Average annual quantity of refrigerant used in the baseline to replace the refrigerant that has leaked (tonnes/year). This is not applicable to this project.
$GWP_{ref,BL}$	=	Global Warming Potential of the baseline refrigerant (tCO ₂ e/t refrigerant), This is not applicable to this project.

If the energy displaced is fossil fuel-based, the energy baseline is the existing level of fuel consumption or the amount of fuel that would be used by the technology that would have been implemented otherwise. The emissions baseline is the energy baseline multiplied by an emission factor for the fossil fuel displaced. Reliable local or national data for the emission factor shall be used; IPCC default values should be used only when country or project-specific data are not available.

4.2 Project Emissions

Project Emissions are determined as follows:

$$PE_y = EP_{PJ,y} \times EF_{CO_2,y} + PE_{ref,y} \quad \text{Equation (3)}$$

Where:

PE_y	=	Project emissions in year y (tCO ₂ e)
$EP_{PJ,y}$	=	Energy consumption in project activity in year y. This shall be determined ex post based on monitored values

- $EF_{CO_2,y}$ = Emission factor for electricity or thermal baseline energy. The emissions associated with grid electricity consumption will use US EPA eGrid data. For fossil fuel displaced reliable local or national data for the emission factor shall be used; IPCC default values should be used only when country or project-specific data are not available or difficult to obtain
- $PE_{ref,y}$ = Project emissions from physical leakage of refrigerant from the project equipment in year y (tCO₂e/y) (not applicable to this project)

Project energy consumption in the case of project activities that displace grid electricity is determined as follows using the data of the project equipment or system:

$$EP_{PJ,y} = \sum_t \sum_i (n_i \times \rho_i \times o_i) / (1 - l_y) \quad \text{Equation (4)}$$

Where:

- n_i = Number of group i project devices operating in time interval t year y
- ρ_i = Electrical power demand (kW) of the group i project devices measured during the time interval t in year y . This variable will be determined using the approach described in Section 3.6 and Appendix A & B.
- o_i = Operating hours of group of i project devices in the time interval t in year y – this variable will be the run-time of the devices described in Appendix A & D and Section 3.6

4.3 Leakage

The applied methodology, AMS II.C states that: “If the energy efficiency technology is equipment transferred from another activity, leakage is to be considered.” For this project, the equipment involved is not being transferred from another project – the thermostats are deployed for this project activity specifically. Thus, leakage does not need to be considered.

4.4 Net GHG Emission Reductions and Removals

Year	Estimated baseline emissions or removals (tCO ₂)	Estimated project emissions or removals (tCO ₂)	Estimated leakage emissions (tCO ₂)	Estimated net GHG emission reductions or removals (tCO ₂)
2021	6,662,330	6,387,059	0	275,271
2022	8,375,368	8,021,055	0	354,313

2023	10,593,596	10,146,656	0	446,940
2024	13,599,607	13,029,575	0	570,032
2025	17,206,820	16,480,970	0	725,850
2026	18,067,161	17,236,048	0	831,113
2027	18,970,519	18,097,850	0	872,669
Total	93,475,400	89,399,212	0	4,076,188

5 MONITORING

5.1 Data and Parameters Available at Validation

Data / Parameter	Average capacity of devices in group <i>i</i>
Data unit	kW, BTU/hour or tons
Description	a) kW – This is usually determined by spot measurements of instantaneous power draw or trending measurements of power or current. b) Tons – A measure of cooling output, or capacity. One ton is the amount of heat required to melt one ton of ice in a 24-hour period (288,000 BTU or 12,000 BTU per hour). c) Capacity in BTU per Hour – Interchangeable with tons.
Source of data	Technical Reference Manuals, Appliance Saturation Studies
Value applied	Will Vary
Justification of choice of data or description of measurement methods and procedures applied	See Section 3.6 and Appendix A & B
Purpose of Data	To calculate baseline emissions
Comments	Extensive field research has been conducted to estimate average HVAC system size per geography, and this

	information is available in Technical Reference Manuals and/or appliance saturation studies. See Appendix B for a comprehensive compilation.
--	--

Data / Parameter	Average daily outdoor dry bulb temperature
Data unit	Degrees Fahrenheit
Description	This represents the average daily temperature for the thermostat from its nearest weather station.
Source of data	ISM
Value applied	Will Vary
Justification of choice of data or description of measurement methods and procedures applied	HVAC demand is a function of outdoor temperature. This data is standard weather data relayed to ecobee customers as part of the ecobee service. ecobee's weather service provider for the evaluation period has been DarkSky (https://darksky.net)
Purpose of Data	• Calculation of baseline emissions • Calculation of project emissions
Comments	Provide any additional comments

Data / Parameter	Average daily indoor control dry bulb temperature
Data unit	Degrees Fahrenheit
Description	This represents the average daily indoor temperature for the home, which is used to control HVAC operation.
Source of data	ISM
Value applied	Will Vary
Justification of choice of data or description of measurement	HVAC demand is a function of the indoor control temperature. This is a critical parameter in our model since indoor temperatures are likely to vary between the pre- and post-periods due to covid lockdown measures that coincided with the broad launch of eco+ which began in 2020.

methods and procedures applied	This indoor control temperature is comprised of blend of temperature measurements from the ecobee thermostat itself and any connected ecobee room sensors, and modified by eco+ optimizations.
Purpose of Data	• Calculation of baseline emissions • Calculation of project emissions
Comments	Provide any additional comments

Data / Parameter	Tau _{cool} , Tau _{heat}
Data unit	Degrees Fahrenheit
Description	This parameter in the regression model represents the collective thermal model of the homes in the analyses.
Source of data	Determined empirically (via grid search) to maximize our overall regression model fit
Value applied	(0,2,4,6,8,10,12,14,16,18)
Justification of choice of data or description of measurement methods and procedures applied	Generally, HVAC demand is a function of the temperature difference between the indoors and outdoors. The larger the difference, the more runtime is required to maintain a temperature setpoint. However, there are internal heat gains (i.e. a Tau value) in the home that also influence the demand. For example, this is why a home at 72 degF typically does not need any heating even though its only 70F outside. We determine the optimal Tau value for both heating and cooling seasons separately by choosing the model that produces the greatest coefficient of determination (i.e., the R² value). There is precedent for this modelling approach. See the EPA's Energy Star Connected Thermostat Method to Demonstrate Field Savings here: https://www.energystar.gov/sites/default/files/Version%201.0%20Method%20to%20Demonstrate%20Field%20Savings%20of%20ENERGY%20STAR%20Connected%20Thermostats.pdf
Purpose of Data	• Calculation of baseline emissions • Calculation of project emissions
Comments	Provide any additional comments

Data / Parameter	Post
Data unit	Integer (a unitless dummy variable)
Description	Indicator equal to 1 for the post (aka treatment) period when eco+ was enabled; zero otherwise.
Source of data	ISM
Value applied	1 if datapoint is from the post period (After eco+ enabled) 0 if datapoint is from the pre period (before eco+ enabled)
Justification of choice of data or description of measurement methods and procedures applied	This is used for the regression model to determine the efficacy of the eco+ treatment.
Purpose of Data	• Calculation of baseline emissions • Calculation of project emissions
Comments	Provide any additional comments

Data / Parameter	Month _i
Data unit	Categorical variable
Description	This variable captures the month of year
Source of data	ISM
Value applied	One of 12 values are applied based on month of year
Justification of choice of data or description of measurement methods and procedures applied	This is used to capture any consumption variance unique to the month. For example, summer months may lead to different household consumption patterns.
Purpose of Data	• Calculation of baseline emissions • Calculation of project emissions
Comments	Provide any additional comments

5.2 Data and Parameters Monitored

Data / Parameter	RT _i
Data unit	Hours
Description	Average daily run-time for device equipment at various stages <i>i</i> if configured/available on the thermostat. These include: - compCool1 (compressor-based cooling at first stage) - compCool2 (compressor-based cooling at second stage) - compHeat1 (compressor-based heating at first stage, applies to heat pumps only) - compHeat2 (compressor-based heating at second stage, applies to heat pumps only) - auxHeat1 (furnace-based heating at first stage, or resistance-based heating at first stage for heat pumps) - auxHeat2 (furnace-based heating at second stage, or resistance-based heating at second stage for heat pumps)
Source of data	ecobee
Description of measurement methods and procedures to be applied	See Appendix A & D
Frequency of monitoring/recording	The underlying data is continuous, recorded on 5-minute intervals
Value applied	Will vary
Monitoring equipment	See Section 5.3
QA/QC procedures to be applied	See Section 5.3

Purpose of data	• Calculation of baseline emissions • Calculation of project emissions
Calculation method	See Appendix D.
Comments	

Data / Parameter	Equipment staging ratios
Data unit	unitless
Description	Runtime from multistage equipment must be normalized to the highest stage of operation, which is reflective of the connected load. We apply industry standard ratios in our calculations: - Compressor_1to2_ratio = 0.8 - Furnace_auxHeat_1to2_ratio = 0.65 For example, if a thermostat is connected to a 2 stage air conditioner, we assume that compCool1 is running at 80% capacity and compCool2 runs at 100% capacity.
Source of data	ecobee
Description of measurement methods and procedures to be applied	
Frequency of monitoring/recording	Fixed, constant value
Value applied	- Compressor_1to2_ratio = 0.8 - Furnace_auxHeat_1to2_ratio = 0.65
Monitoring equipment	n/a
QA/QC procedures to be applied	n/a
Purpose of data	• Calculation of baseline emissions • Calculation of project emissions

Calculation method	See Appendix D.
Comments	

Data / Parameter	hasHeatPump
Data unit	boolean
Description	This is a flag representing if a thermostat has a heatpump connected or not.
Source of data	ecobee
Description of measurement methods and procedures to be applied	This flag is determined based on wiring configuration of the HVAC system to the thermostat at time of set up. This impacts how auxHeat fields are interpreted and what fuel type is assumed to be consumed from auxHeat fields. See Connected Load Assumptions in Appendix A.
Frequency of monitoring/recording	Assumed constant throughout study
Value applied	- True or False
Monitoring equipment	n/a
QA/QC procedures to be applied	n/a
Purpose of data	• Calculation of baseline emissions • Calculation of project emissions
Calculation method	See Appendix A & D.
Comments	

Data / Parameter	EF _{CO2,elec,y}
Data unit	tCO2/MWh
Description	Emissions factor of the grid where the device(s) are located

Source of data	US EPA eGrid
Description of measurement methods and procedures to be applied	Use latest eGrid data available from US EPA.
Frequency of monitoring/recording	Check for updated data for validation and each verification
Value applied	Will vary. See Appendix C
Monitoring equipment	N/A
QA/QC procedures to be applied	N/A
Purpose of data	• Calculation of baseline emissions • Calculation of project emissions
Calculation method	See Appendix D.
Comments	

Data / Parameter	EF _{CO2,natgas}
Data unit	tCO2/mmbtu
Description	Emissions factor of the natural consumption
Source of data	US EIA: https://www.eia.gov/environment/emissions/co2_vol_mass.php
Description of measurement methods and procedures to be applied	Use latest eGrid data available from US EPA.
Frequency of monitoring/recording	Check for updated data for validation and each verification
Value applied	0.05306
Monitoring equipment	N/A
QA/QC procedures to be applied	N/A

Purpose of data	• Calculation of baseline emissions • Calculation of project emissions
Calculation method	See Appendix D.
Comments	

5.3 Monitoring Plan

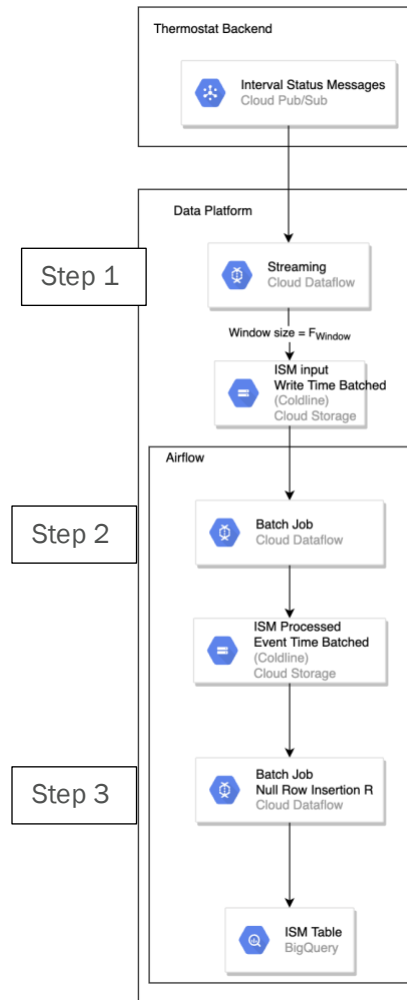
Method of Measurement

To cause an HVAC system to run, ecobee thermostats power specific relays on the back of the device corresponding to specific HVAC systems. When a relay is powered, its corresponding system runs. In regular operation, ecobee thermostats record whether a relay is powered or unpowered. This information is discretized on device to 5 minute intervals. Every 15 minutes, a packet of data corresponding to the previous 3 intervals is sent from the device to ecobee's servers. This data is then consumed on the server side, preprocessed, and stored in a Google Cloud BigQuery table known as ISM (Interval Status Messages). It is from the ISM table that runtime data was pulled for the purposes of this analysis. Broadly, the server side processing can be abstracted as 3 steps:

1. Read and store data sent from devices
2. Validate data
3. Group data by thermostat and writes data to table

The architecture diagram in Figure 2 below illustrates the flow of data from its reception on the server side to its storage in the ISM table.

Figure 2 - Architecture diagram to illustrate the flow of data from its reception on the server side to its storage in the ISM table



Organization Responsibilities and Competencies

The above pipeline is managed by the Data Platform team at ecobee. This team is comprised of skilled professionals in the field of Data Engineering. The transmission of the data from the device to the server is managed by the Firmware team. This team is comprised of skilled professionals in the field of Firmware development, some of whom have been overseeing this process for >5 years without issue.

Oversight Policies and Internal Auditing

Firmware: The Firmware Team executes a series of integration tests that are run using ecobee's thermostat simulation platform to ensure that, for a given version of firmware, the runtime values sent from the device in simulation are as expected.

Server: Along with managing the automated execution of the pipeline itself, the Data Platform team also manages an alerting policy to ensure pipeline health. If the number of unprocessed messages exceeds 1,000,000 (this corresponds to ~2 minutes of inactivity/delay), an alert is sent to a person on call. There is a person on call 24 hours a day, every day of the year.

The Data Platform team also monitors that the ISM table upload pipelines run successfully. Any issues with this pipeline are committed to be resolved within 24 hours.

The pipelines that populate the ISM table also include writes to cold storage (as illustrated in the architecture diagram above). This ensures that if ISM data is ever lost, it can be recreated using the exact data from which it was originally generated. While this provides a safety net in the case of larger issues, this recreation has never been necessitated.

In addition to this, there exist integration tests for all 3 pipelines used for ISM table population. Any time a change is made to any of these pipelines, these tests are run to ensure that the pipelines still operate as desired.

Data Recording: Runtime data fields that are recorded are listed in the data dictionary presented in Table 2 below.

Sampling:

The sampling protocol had the following steps:

- 1) Pre-Screening of eligible thermostats:
 - a. Must be a thermostat located in the US
 - b. Must be a thermostat registered prior to January 1, 2018
 - c. Must be a thermostat enrolled into eco+ by September 30, 2020
 - d. Must be a thermostat with Humidity-based optimization (i.e., adjusting for humidity) enabled
- 2) Sampling Protocol:
 - a. To ensure an even distribution of thermostats across all regions, samples were taken from the 22 largest eGrids in the US (excludes ones in AK, and HI).
 - b. Within each eGrid region 5% of pre-screened eligible devices were randomly selected for our analysis.

- 3) Post-Screening of Data. Once a thermostat is sampled into our pool, we must ensure there is enough ISM data to provide a meaningful, unbiased analysis. The following post-screening criteria are used
- If a thermostat has more than 30 days of ineligibility in either of the pre-period or post-period days it is excluded from the analysis.
 - For a thermostat-day to be considered eligible, it may not be missing more than a single hour of data (i.e., less than 5% of data can be missing due to connectivity issues).
 - Only eligible thermostat-days (i.e., days missing less than an hour of data) are included for analyses.

Table 2- ecobee eco+ Evaluation, Measurement and Verification: Data Dictionary

Data Item	Description
1. Runtime data (hourly)	- hashed unique ID - Count (1-12; # of records aggregated to produce the hourly value) - UTC Date - UTC Hour Starting (0-23) - HvacMode (at the top of hour) - compCool1 Runtime (s) - compCool2 Runtime (s) - compHeat1 Runtime (s) - compHeat2 Runtime (s) - auxHeat1 Runtime (s) - auxHeat2 Runtime (s) - Outdoor Temperature (Mean degF *10) - Outdoor Humidity (Mean %RH) - Indoor Control Temp (Mean degF *10) - Indoor Drybulb Temp (Mean degF *10) - Indoor Control Humidity (Mean %RH) - Heat Setpoint (Mean degF *10) - Cool Setpoint (Mean degF *10) - CalendarEvent – DR Precool Time (s) - CalendarEvent – DR Setback Time (s) - CalendarEvent – TOU Precool Time (s) - CalendarEvent – TOU Setback Time (s) - CalendarEvent – SA/ESA Home Time (s)

	x) CalendarEvent – SA/ESA Away Time (s)
2. Thermostat characteristics (per thermostat)	a) hashed unique ID b) Account ID (if applicable) c) Home ID (if applicable) d) Experimental Cell (if applicable) e) Status flag (eco+ invitation status, if applicable) f) Status last update (date) g) Time zone (string) h) State/Province (string) i) Country (string) j) Zip Code/Postal Code (string) k) InstalledCompStages (int) l) InstalledAuxHeatStages (int) m) Has a Heat Pump flag (bool) n) AllowCompWithAux flag (bool)
3. eco+ Feature Configuration (daily)	a) hashed unique ID b) Configuration Date c) Enabled flag (bool) d) Comfort Setting (Slider level (1-5)) e) Occupancy enabled flag (for Smart Away / Enhanced Smart Away) f) Humidity enabled flag (for Adjusting for Humidity) g) Demand response enabled flag (for Community Energy Savings) h) Schedule recommender enabled flag (for Schedule Assistant) i) Electricity rate enabled flag (for TOU) j) Utility rate id (OpenEI / Genability; string)
4. DR Event Data (per event)	a) thermostat_id_hash b) utility_ref c) Event Date d) Targeted flag (bool) e) Dispatched flag (bool) f) OptOut flag (bool)

APPENDIX A: CONNECTED LOAD ASSUMPTIONS

Translating HVAC runtime, or changes in runtime, to energy usage and demand requires the project proponent to make an assumption about the size of the HVAC units connected to ecobee thermostats. Because ecobee does not directly know the size of its customers' HVAC units, the company collected HVAC unit size and efficiency measurements/assumptions from various technical reference manuals (TRMs), appliance saturation studies, and evaluation reports which are presented in Appendix B. In these industry sources, air conditioning size information is generally presented in one of three metrics:

a) kW – The main metric of interest as this is a direct parameter in the methodology. This is usually determined by spot measurements of instantaneous power draw or trending measurements of power or current. It may or may not include the power draw of the indoor circulating fan.

b) Tons – A measure of cooling output, or capacity. One ton is the amount of heat required to melt one ton of ice in a 24-hour period (288,000 BTU or 12,000 BTU per hour).

c) Capacity in BTU per Hour – Interchangeable with tons.

Since the metrics of cooling capacity are output measurements, an assumption about the efficiency of the system is required to convert output capacity to the input power requirement. To facilitate this conversion and leverage size ratings in tons or BTU/hour ecobee collects average Seasonal Energy Efficiency Ratio (SEER) values for existing air conditioner stock and uses the values to convert to kW. SEER ratings include the fan power requirements.

ecobee categorized each source from the literature review presented in Appendix B into one of five climate zones and used the results to inform assumed HVAC unit size for each climate zone. Tables 1, 2 and 3 below show the results of the company's research and final assumptions by climate zone.

Table 1: Connected Load Assumption by Climate Zone, Cooling

Climate Zone	Tons	SEER	kW per Device
01 Cold	2.75	10.5	3.10
02 Dry	3.25	10.5	3.48
03 Hot Humid	3.25	10.5	3.60
04 Mixed Humid	2.75	10.5	3.04
05 Marine	2.60	10.5	2.93

Table 2: Connected Load Assumption by Climate Zone, Heating (Furnace)

Region	Furnace Size (kBTU/hour)	Furnace Fan (kW)
01 Cold	77.7	0.56
02 Dry	60.0	0.56
03 Hot Humid	65.0	0.56
04 Mixed Humid	75.5	0.56
05 Marine	62.5	0.56

Table 3: Connected Load Assumption by Climate Zone, Heating (Heat Pump)

Region Name	Heat Pump Compressor Size (kW)	Heat Pump Auxiliary Size (kW)
01 Cold	3.47	9.53
02 Dry	2.88	7.91
03 Hot Humid	2.42	7.68
04 Mixed Humid	3.02	8.32
05 Marine	3.00	8.25

APPENDIX B: CONNECTED LOAD RESEARCH

Document Name	Document Type	State	Year Effective	Climate Zone	URL	Page/ Table/ Other Source	Size (tons)	SEER for Existing Units
Wisconsin Focus on Energy 2019 Technical Reference Manual	TRM	WI	2019	Cold/Very Cold	https://www.focusonenergy.com/sites/default/files/Focus_on_Energy_2019_TRM-Update.pdf	Pg. 937	2.425	12.1
State of Minnesota Technical Reference Manual for Energy Conservation Improvement Programs version 3.0	TRM	MN	2020	Cold/Very Cold	http://mn.gov/commerce-stat/pdfs/mn-trm-v3.0.pdf	Pg. 42	2.5	11.5
Iowa Energy Efficiency Statewide Technical Reference Manual Version 2.0	TRM	IA	2017	Cold/Very Cold	https://efs.iowa.gov/cs/groups/external/documents/docket/mdax/njq1/~edisp/1645801.pdf	Pg. 121	3	8.6
2019 Illinois Statewide Technical Reference Manual for Energy Efficiency Version 7.0	TRM	IL	2019	Cold/Very Cold	http://ilsagfiles.org/SAG_files/Technical_Reference_Manual/Version_7/Final_9-28-18/IL-TRM_Effective_010119_v7.0_Vol_3_Res_092818_Final.pdf	Pg. 79	2.8	9.3
Technical Reference User Manual (TRM) No. 2014-87	TRM	VT	2015	Cold/Very Cold	https://puc.vermont.gov/sites/psbnew/files/doc_library/ev-technical-reference-manual.pdf	Pg. 531 of document	3	
Rhode Island Technical Reference Manual For Estimating Savings from Energy Efficiency Measures - 2018	TRM	RI	2018	Cold/Very Cold	http://www.ripuc.org/eventsactions/docket/4755-NGrid-2018-TRM-RI.pdf	Pg. M-51	2.7	10

Program Year								
Missouri Technical Reference Manual Volume 3 Residential Measures - Final March 31, 2017	TRM	MO	2017	Mixed-Humid	https://exportmissouri.mo.gov/docs/default-source/default-document-library/mo_trm-2017_vol-3_res_measures_033117_final.pdf?sfvrsn=0	Pg. 120	2.8	10
DC SEU TRM Characterizations	TRM	DC	2017	Mixed-Humid	-	Pg. 87	2.67	
Xcel Deemed Savings Technical Assumptions	Survey	CO	N/A	Cold/Very Cold	https://www.xcelenergy.com/staticfiles/xcelresponsive/Company/Rates%20&%20Regulations/Regulatory%20Filings/CO-DSM-HEAC-Deemed-Savings.pdf	Pg. 4	3	10
The Effect of Residential Equipment Capacity on Energy Use, Demand, and Run-Time	Survey	FL	1997	Hot-Humid	http://www.fsec.ucf.edu/en/publications/html/FSEC-PF-328-97/index.htm	Table 3	3.29	
Analysis of Historical Residential Air-Conditioning Equipment Sizing Using Monitored Data	Survey	WA	1993	Marine	https://digital.library.unt.edu/ark:/67531/metadc1310394/m2/1/high_res_d/10134448.pdf	Pg. 10	2.635	
Technical Reference Manual for APS Energy Efficiency Programs Program Year 2013	TRM	AZ	2014	Hot-Dry/Mixed-Dry	https://images.edocket.azcc.gov/docketpdf/0000150538.pdf	Pg. 23, Table 3.3	3.75	11
Texas Technical Reference Manual Version 6.0 Volume 2: Residential Measures Program Year 2019	TRM	TX	2019	Hot-Humid	http://www.texasefficiency.com/images/documents/RegulatoryFilings/DeemedSavings/TRMv6.0%20Vol%202%20Residential%20Measures_Final.pdf	Pg. 2-345	3.7	
Energy Trust of Oregon	Survey	OR	2017	Cold/Very Cold	https://www.energytrust.org/wp-content/uploads/2017/12/Energy-Trust-of-Oregon-Nest-Seasonal-Savers-Pilot-Evaluation-FINAL-wSR.pdf	Pg. 6-47	3	12

Seasonal Savings Pilot Evaluation								
DSA Research	Field Survey	GA	N/A	Hot-Humid	-		DSA Research	2.9
DSA Research	Field Survey	NM	N/A	Hot-Dry/Mixed-Dry	-		DSA Research	2.614
Single-Family Weatherization Baseline Assessment (R5) Final Report Submitted to The Connecticut Energy Efficiency Fund, Connecticut Light and Power, & The United Illuminating Company	Survey	CT	2014	Cold/Very Cold	https://www.energizect.com/sites/default/files/R5-Connecticut%20Weatherization%20Baseline%20Assessment-FINAL%2006-04-14.pdf		Table 6-15 and 6-16	310.4
National Grid Rhode Island Residential Appliance Saturation Survey (Study RI2311) Report	Survey	RI	2018	Cold/Very Cold	http://www.ripuc.org/eventsactions/docket/6.%20National%20Grid%20RI2311%20RASS%20Final%20Report%2011OCT2018.pdf		Table 6	10.9
NEEA Residential Stock Assessment II Single-Family Homes Report 2016-2017 Revised 04/2019	Survey	WA	2019	Marine	https://neea.org/img/uploads/Residential-Building-Stock-Assessment-II-Single-Family-Homes-Report-2016-2017.pdf		Table 53	12.2
2018 Pennsylvania Statewide Act 129 Residential Baseline Study	Survey	PA	2019	Cold/Very Cold	http://www.puc.state.pa.us/Electric/pdf/Act129/SWE-Phase3_Res_Baseline_Study_Rpt021219.pdf		Table 90	12.2

2017 Residential Programs Evaluation Report	Survey	Ontario	2018	Canada	http://www.ieso.ca/-/media/Files/IESO/Document-Library/conservation/EMV/2017/2017-Residential-Programs-Evaluation-Report.pdf?la=en	Pg. D-206	2.14	
2014 Consumer Program Evaluation Volume 1: Report	TRM	Ontario	2014	Canada	http://www.ieso.ca/-/media/Files/IESO/Document-Library/conservation/EMV/2014/PY2014-IESO-CP-Evaluation-Final-Report.pdf?la=en	Table 3-9	2.167	
Quick Start Energy Efficiency Annual Report Program Year 1 November 2014 – October 2015	TRM	LA	2014	Hot/Humid	https://www.all4energy.org/uploads/1/0/5/6/105637723/entergy-quick-start-energy-efficiency-2014-2015-annual-report.pdf	Pg. 4-2		11.2

APPENDIX C: 2021 E GRID EMISSION FACTORS

	CO2 Factor	CH4 Factor	N2O Factor	CO2e Factor	CO2_E_factor
Primary eGRID Subregion					
AKGD	1114.400	0.098	0.013	1120.813	508.244393
AKMS	549.312	0.026	0.004	551.276	249.973644
AZNM	952.321	0.068	0.010	956.883	434.019052
CAMX	453.209	0.033	0.004	455.251	206.448770
ERCT	868.640	0.057	0.008	872.389	395.676013
FRCC	861.028	0.055	0.007	864.535	392.063606
HIMS	1185.595	0.143	0.022	1195.598	542.232041
HIOA	1694.541	0.185	0.028	1707.576	774.329625
MROE	1502.559	0.147	0.022	1512.599	686.042478
MROW	1098.353	0.119	0.017	1106.448	501.728090
NEWE	488.888	0.077	0.010	493.829	223.895279
NWPP	715.241	0.068	0.010	719.873	326.481460
NYCW	553.801	0.021	0.002	555.056	251.680964
NYLI	1208.975	0.157	0.020	1218.930	552.689151
NYUP	232.305	0.017	0.002	233.044	105.814849
PRMS	1537.308	0.084	0.013	1543.340	699.938722
RFCE	695.034	0.053	0.007	698.485	316.751005
RFCM	1189.335	0.114	0.016	1196.997	542.808557
RFCW	1067.679	0.099	0.014	1074.410	487.202260
RMPA	1242.611	0.117	0.017	1250.553	567.143314
SPNO	1069.971	0.112	0.016	1077.597	488.646951
SPSO	1001.985	0.070	0.010	1006.722	456.565296
SRMV	806.755	0.043	0.006	809.596	367.190889
SRMW	1584.391	0.169	0.025	1595.941	723.792218
SRSO	969.165	0.071	0.010	973.981	441.687932
SRTV	949.695	0.087	0.013	955.587	433.430743
SRVC	675.417	0.058	0.008	679.142	308.041131

APPENDIX D: REGRESSION MODELING

This analysis was completed by Kevin Trinh, Senior Data Scientist at ecobee in June of 2022.

Regression Model Design Considerations

We started this analysis by considering the methodology from our eco+ measurement and verification (M&V) study in 2019 and 2020 conducted by Demand Side Analytics. Following from a Randomized Encouragement Design of the study, they conducted a Difference-in-Differences regression analysis. Many different models were considered using combinations of the following independent variables: cooling and heating degree hours baselined at 60degF, hour of day, day of week, outdoor humidity, and a 24 hour heat storm variable, which represents a 24 hour moving average of outdoor temperature. Ultimately, they found that regardless of the combination of these variables, the coefficient of interest (for the treatpost term) remained stable and at a significant level. Furthermore, they showed that the overall impacts were not sensitive to whether an hourly or daily-aggregated model was used. Thus, to keep our analysis manageable, we focused on a daily-aggregated model, while aiming for model simplicity to avoid any overfitting issues.

There are two major differences with this analysis from that 2020 M&V study impacting the design of the regression model. First, is the use of a pre-post evaluation as specified in the AMS.II-C method. As such, no control or comparison group is required. The second difference is the requirement for annual pre- and post-treatment periods. This had a large impact on the design due to the eco+ rollout to the ecobee fleet of thermostats roughly coinciding with broad-scale and enduring Covid lockdown and work-from-home measures from early 2020 through to 2022. To address this issue we included indoor temperatures in our model to account for the differences in HVAC load based on occupancy and reduction in away periods, when customers usually employ temperature setbacks for savings.

We included two other broad variables to our models. We added a factor, Tau, to account for the home's propensity to retain heat. We follow the precedent for using this factor from the EPA Connected Thermostat Method to Determine Field Savings found here:

https://www.energystar.gov/products/spec/connected_thermostats_specification_v1_0_pd. Separate Tau's are determined for heating and cooling models to capture seasonal differences impacting the home. Tau values were determined using a grid search, to optimize the overall model coefficient of determination (i.e., the R^2 value). Finally, we found that adding a MonthOfYear variable consistently improved the overall model fit since consumption patterns vary not only by weather but by broad shifts in time of year (e.g. summer holiday season).

There were several other factors considered in our overall approach:

- Since we are examining CO₂ impacts from both electricity and natural gas savings we had separate regression models for both fuel types.
- We also distinguished electricity consumption between the cooling and heating seasons.
- Furthermore, we ran separate models for heat pump users and non-heat pump users due to differences in fuel consumption. We assume heat pumps solely require electricity for heating (including electrical resistance auxiliary heating), and furnaces or boilers require natural gas but still consume some electricity to circulate the air or water. Please refer to our connected load assumptions described in Appendix A.
- To account for HVAC systems with multiple stages, we normalize our measured equipment runtime to the highest stage and converted to fuel consumption using the connected load assumptions. Thus, fuel consumption, rather than equipment runtime, was our dependent variable in each regression model.

Data Sampling outputs

The pre-period was defined as January 1, 2018 - December 31, 2018.

The post-period was defined as October 1, 2020 - September 30, 2021.

From our sampling method outlined in Section 5.3, Table 1 summarizes the number of thermostats used for analysis.

Table 1 - Thermostat samples used

USBuildingClimateZone	hasHeatPump	Thermostat Count
Cold_Marine	False	2814
	True	117
Mixed_Humid_Hot_Dry	False	2430
	True	729

5.4 Regression Models

Overall, we ran 10 sets of regression models for the following full permutations of factors:

- 2x Climate groups (Cold-Marine; Mixed-Hot-Dry-Humid)
- 5x Equipment-Fuel groups:
 - heat pump, KWh consumed for cooling
 - heat pump, KWh consumed for heating
 - non-heat pump, KWh consumed for cooling
 - non-heat pump, KWh consumed for heating
 - non-heat pump, mmbtu consumed for heating

Each of the 10 sets of regressions comprised of a grid search of the respective Tau values to maximize the fit of the model (i.e., coefficient of determination, R^2 value). Here are the models used:

$$\begin{aligned}
 KWh_{cooling} &= b_1 + b_2 * Post + \sum_i (b_{3,i} * Month_i) + b_4 * ((T_{out} + Tau_{cool}) - T_{in})_+ \\
 KWh_{heating} &= b_5 + b_6 * Post + \sum_i (b_{7,i} * Month_i) + b_8 * (T_{in} - (T_{out} + Tau_{heat}))_+ \\
 mmbtu_{heating} &= b_5 + b_6 * Post + \sum_i (b_{7,i} * Month_i) + b_8 * (T_{in} - (T_{out} + Tau_{heat}))_+
 \end{aligned}$$

Where:

- $KWh_{cooling}$, $KWh_{heating}$, $mmbtu_{heating}$ = daily fuel consumed from respective HVAC cooling and heating operation modes converted from the normalized runtime multiplied by the assumed connected loads.
- $Post$ = Indicator equal to 1 for the treatment period when eco+ was enabled; zero otherwise.
- $Month_i$ = Categorical indicator of the calendar month; i is between 1 and 12.
- T_{out} , T_{in} = the average daily outdoor and indoor temperatures (degF) respectively.
- Tau_{cool} , Tau_{heat} = a constant representing the collective thermal model; determined empirically (via grid search) within a set of (0,2,4,6,8,10,12,14,16,18) degF, whichever value maximizes the model fit.
- $(\sim)_+$ indicates that the term is zero if its value would be negative.
- b_1 , b_5 = constants for baseline daily consumption.
- b_2 , b_6 = the coefficients of interest; this represents the average daily fuel impact of the eco+ treatment.
- $b_{3,i}$, $b_{7,i}$ = coefficients capturing the impact of the calendar month; i is between 1 and 12.
- b_4 , b_8 = coefficients capturing the impact of the temperature differences.

All models were implemented with thermostat level fixed effects and cluster robust standard errors. The fixed effects approach de-means the underlying interval data and models the within-device variation. Clustering standard errors are important when individual observations can be grouped into clusters where the model errors are correlated within a cluster but not between clusters. Not controlling for the within cluster correlation might lead to misleadingly small standard errors for the estimates and thus misleadingly narrow confidence intervals.

Results

Table 2 - Key regression model outputs:

USBuilding ClimateZone	Equipment	Metric	Optimized Tau	R ²	coeff_of_interest	P value	project_consumption	impact_pct
Cold_Marine	hp	KWh_consumed_cooling	8	0.664	0.1566	0.4047	5.84	n/a
		KWh_consumed_heating	12	0.6025	-1.6075	0.0087	13.45	-0.106757
	nohp	KWh_consumed_cooling	8	0.6668	-0.0496	0.1876	4.9	n/a
		KWh_consumed_heating	6	0.6528	-0.0696	0.0002	1.18	-0.055698
		mmbtu_consumed	6	0.6501	-0.0098	0.0001	0.1573	-0.058648
Mixed_Humid_Hot_Dry	hp	KWh_consumed_cooling	8	0.72	-0.372	0.0011	9.24	-0.038702
		KWh_consumed_heating	12	0.5737	-0.6419	0	4.46	-0.125816
	nohp	KWh_consumed_cooling	6	0.723	-0.3179	0	9.8	-0.03142
		KWh_consumed_heating	10	0.6047	-0.0219	0	0.51	-0.041173
		mmbtu_consumed	10	0.6098	-0.003	0	0.0645	-0.044444

Notes:

- pvalues for the Cold-hp-KWhCooling, Cold-nohp-KWhCooling models were >0.1. Thus, those results were not considered significant and resulting impacts were not carried forward.
- KWh impacts have not factored grid transmission losses yet.
- See Exhibit 1 for detailed regression outputs for each model.

Table 3a - Annual Impacts per Thermostat with No Heat Pump by Climate

US Building ClimateZone	noHP_KWhCooling_annualimpact_per_tstat	noHP_KWhHeating_annualimpact_per_tstat	noHP_mmbtu_annualimpact_per_tstat	noHP_tCO2_annualimpact_per_tstat	noHP_tCO2_annualproject_consumption_per_tstat
Cold/Marine	0.000	-26.826	-3.577	-0.201	4.019
Mixed_Humid_Hot_Dry	-122.527	-8.441	-1.095	-0.107	2.729

Table 3b - Annual Impacts per Thermostat with Heat Pump by Climate

US Building ClimateZone	HP_KWhCooling_annualimpact_per_tstat	HP_KWhHeating_annualimpact_per_tstat	HP_tCO2_annualimpact_per_tstat	HP_tCO2_annualproject_consumption_per_tstat
Cold_Marine	0.000	-619.575	-0.229	2.742
Mixed_Humid/Hot_Dry	-143.379	-247.406	-0.15	2.023

Column definitions for Tables 3a,3b:

- KWh annual impact columns: Represents estimated annual impacts per thermostat after factoring grid transmission losses for KWh
- tCO2 annual impact columns: Captures tonnes of CO₂ (tCO₂) impacts after converting the eGrid-level emissions factors

5.5 Exhibit 1 - Detailed Regression Results

See Rows 1-3 in each of the 10 output summaries below for the respective model specifications.

Filter: nohp

USBuildingClimateZone: Cold_Marine

Formula: KWh_consumed_cooling ~ C(Period, levels=levels_period) + C(Month) + C_deltaT8

OLS Regression Results

Dep. Variable: KWh_consumed_cooling R-squared: 0.667

Model: OLS Adj. R-squared: 0.666

Method: Least Squares F-statistic: 832.5

Date: Fri, 24 Jun 2022 Prob (F-statistic): 0.00

Time: 09:34:53 Log-Likelihood: -5.5736e+06

No. Observations: 1784180 AIC: 1.115e+07

Df Residuals: 1781623 BIC: 1.115e+07

Df Model: 13

Covariance Type: cluster

=====

	coef	std err	t	P> t	[0.025	0.975]	
Intercept	0.0101	0.055	0.181	0.856	-0.099	0.119	
C(Period, levels=levels_period)[T.Post]	-0.0496	0.038	-1.318	0.188	-0.123	0.024	
C(Month)[T.2]	-0.0044	0.006	-0.790	0.430	-0.015	0.007	
C(Month)[T.3]	0.0145	0.008	1.858	0.063	-0.001	0.030	
C(Month)[T.4]	0.1635	0.018	9.184	0.000	0.129	0.198	
C(Month)[T.5]	1.0547	0.057	18.347	0.000	0.942	1.167	
C(Month)[T.6]	2.5972	0.098	26.439	0.000	2.405	2.790	
C(Month)[T.7]	3.3914	0.114	29.760	0.000	3.168	3.615	
C(Month)[T.8]	3.0863	0.115	26.777	0.000	2.860	3.312	
C(Month)[T.9]	1.7289	0.079	21.779	0.000	1.573	1.885	
C(Month)[T.10]	0.0721	0.023	3.095	0.002	0.026	0.118	
C(Month)[T.11]	-0.0191	0.008	-2.313	0.021	-0.035	-0.003	
C(Month)[T.12]	0.0063	0.004	1.563	0.118	-0.002	0.014	
C_deltaT8	1.5270	0.017	88.893	0.000	1.493	1.561	

=====

Omnibus: 560635.186 Durbin-Watson: 0.635

Prob(Omnibus): 0.000 Jarque-Bera (JB): 10427313.568

Skew: 1.042 Prob(JB): 0.00

Kurtosis: 14.659 Cond. No. 65.7

=====

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: nohp

USBuildingClimateZone: Cold_Marine

Formula: KWh_consumed_heating ~ C(Period, levels=levels_period) + C(Month) + H_deltaT6

OLS Regression Results

Dep. Variable: KWh_consumed_heating R-squared: 0.653

Model: OLS Adj. R-squared: 0.652

Method: Least Squares F-statistic: 1101.

Date: Fri, 24 Jun 2022 Prob (F-statistic): 0.00

Time: 09:36:04 Log-Likelihood: -2.4142e+06

No. Observations: 1784180 AIC: 4.828e+06

Df Residuals: 1781623 BIC: 4.829e+06

Df Model: 13

Covariance Type: cluster

coef std err t P>|t| [0.025 0.975]

Intercept	1.5464	0.672	2.302	0.021	0.229	2.864
C(Period, levels=levels_period)[T.Post]	-0.0696	0.018	-3.777	0.000	-0.106	-0.033
C(Month)[T.2]	-0.0657	0.012	-5.386	0.000	-0.090	-0.042
C(Month)[T.3]	-0.6730	0.207	-3.253	0.001	-1.079	-0.267
C(Month)[T.4]	-1.0673	0.337	-3.168	0.002	-1.728	-0.407
C(Month)[T.5]	-1.5403	0.557	-2.765	0.006	-2.633	-0.448
C(Month)[T.6]	-1.5453	0.641	-2.410	0.016	-2.803	-0.288
C(Month)[T.7]	-1.5252	0.654	-2.332	0.020	-2.808	-0.242
C(Month)[T.8]	-1.5247	0.654	-2.330	0.020	-2.808	-0.242
C(Month)[T.9]	-1.5779	0.618	-2.555	0.011	-2.789	-0.367
C(Month)[T.10]	-1.2834	0.414	-3.096	0.002	-2.096	-0.471
C(Month)[T.11]	-0.7082	0.235	-3.012	0.003	-1.169	-0.247
C(Month)[T.12]	-0.2635	0.095	-2.778	0.006	-0.450	-0.078
H_deltaT6	0.0489	0.020	2.437	0.015	0.010	0.088

Omnibus: 2569960.842 Durbin-Watson: 0.560

Prob(Omnibus): 0.000 Jarque-Bera (JB): 43215104869.896

Skew: -7.284 Prob(JB): 0.00

Kurtosis: 765.298 Cond. No. 315.

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: nohp

USBuildingClimateZone: Cold_Marine

Formula: mmbtu_consumed ~ C(Period, levels=levels_period) + C(Month) + H_deltaT6

OLS Regression Results

Dep. Variable: mmbtu_consumed R-squared: 0.650

Model: OLS Adj. R-squared: 0.650

Method: Least Squares F-statistic: 1067.

Date: Fri, 24 Jun 2022 Prob (F-statistic): 0.00

Time: 09:35:51 Log-Likelihood: 1.1575e+06

No. Observations: 1784180 AIC: -2.315e+06

Df Residuals: 1781623 BIC: -2.315e+06

Df Model: 13

Covariance Type: cluster

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.2030	0.092	2.209	0.027	0.023	0.383
C(Period, levels=levels_period)[T.Post]	-0.0098	0.003	-3.895	0.000	-0.015	-0.005
C(Month)[T.2]	-0.0092	0.002	-5.569	0.000	-0.012	-0.006
C(Month)[T.3]	-0.0902	0.028	-3.187	0.001	-0.146	-0.035
C(Month)[T.4]	-0.1412	0.046	-3.065	0.002	-0.232	-0.051
C(Month)[T.5]	-0.2030	0.076	-2.665	0.008	-0.352	-0.054
C(Month)[T.6]	-0.2028	0.088	-2.313	0.021	-0.375	-0.031
C(Month)[T.7]	-0.2000	0.089	-2.236	0.025	-0.375	-0.025
C(Month)[T.8]	-0.1999	0.089	-2.234	0.026	-0.375	-0.024
C(Month)[T.9]	-0.2074	0.084	-2.456	0.014	-0.373	-0.042
C(Month)[T.10]	-0.1696	0.057	-2.993	0.003	-0.281	-0.059
C(Month)[T.11]	-0.0944	0.032	-2.936	0.003	-0.157	-0.031
C(Month)[T.12]	-0.0359	0.013	-2.770	0.006	-0.061	-0.011

H_deltaT6	0.0067	0.003	2.438	0.015	0.001	0.012
-----------	--------	-------	-------	-------	-------	-------

```
=====
Omnibus:          2610127.036  Durbin-Watson:          0.561
Prob(Omnibus):    0.000  Jarque-Bera (JB):  47707823876.772
Skew:            -7.517  Prob(JB):          0.00
Kurtosis:        803.948  Cond. No.          315.
=====
```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: hp

USBuildingClimateZone: Cold_Marine

Formula: KWh_consumed_cooling ~ C(Period, levels=levels_period) + C(Month) + C_deltaT8

OLS Regression Results

```
=====
Dep. Variable:  KWh_consumed_cooling  R-squared:          0.664
Model:          OLS  Adj. R-squared:    0.663
Method:         Least Squares  F-statistic:        49.86
Date:           Fri, 24 Jun 2022  Prob (F-statistic):    3.58e-40
Time:           09:54:20  Log-Likelihood:    -2.5405e+05
No. Observations:  78412  AIC:          5.081e+05
Df Residuals:      78287  BIC:          5.083e+05
Df Model:          13
Covariance Type:  cluster
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-0.1046	0.330	-0.317	0.752	-0.758	0.549
C(Period, levels=levels_period)[T.Post]	0.1566	0.187	0.836	0.405	-0.214	0.528
C(Month)[T.2]	0.0224	0.043	0.525	0.600	-0.062	0.107
C(Month)[T.3]	0.2897	0.263	1.102	0.273	-0.231	0.811
C(Month)[T.4]	0.3916	0.117	3.351	0.001	0.160	0.623
C(Month)[T.5]	2.1455	0.364	5.888	0.000	1.424	2.868
C(Month)[T.6]	3.7390	0.478	7.815	0.000	2.791	4.687

C(Month)[T.7]	4.9611	0.543	9.140	0.000	3.886	6.037
C(Month)[T.8]	4.2491	0.549	7.739	0.000	3.161	5.337
C(Month)[T.9]	2.9045	0.402	7.226	0.000	2.108	3.701
C(Month)[T.10]	0.7017	0.144	4.872	0.000	0.416	0.987
C(Month)[T.11]	0.0359	0.039	0.912	0.364	-0.042	0.114
C(Month)[T.12]	0.0280	0.016	1.784	0.077	-0.003	0.059
C_deltaT8	1.6842	0.098	17.217	0.000	1.490	1.878

```
=====
Omnibus:          37761.990  Durbin-Watson:          0.597
Prob(Omnibus):    0.000  Jarque-Bera (JB):    1264561.824
Skew:             1.692  Prob(JB):           0.00
Kurtosis:         22.380  Cond. No.           63.8
=====
```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: hp

USBuildingClimateZone: Cold_Marine

Formula: KWh_consumed_heating ~ C(Period, levels=levels_period) + C(Month) + H_deltaT12

OLS Regression Results

```
=====
Dep. Variable:    KWh_consumed_heating  R-squared:          0.602
Model:            OLS  Adj. R-squared:    0.602
Method:           Least Squares  F-statistic:        28.93
Date:            Fri, 24 Jun 2022  Prob (F-statistic):    1.04e-29
Time:            09:54:26  Log-Likelihood:    -3.1885e+05
No. Observations:  78412  AIC:            6.377e+05
Df Residuals:      78287  BIC:            6.378e+05
Df Model:          13
Covariance Type:   cluster
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	6.4494	1.316	4.899	0.000	3.841	9.058

C(Period, levels=levels_period)[T.Post]	-1.6075	0.602	-2.671	0.009	-2.800	-0.415
C(Month)[T.2]	-0.7073	0.716	-0.988	0.325	-2.126	0.711
C(Month)[T.3]	-2.6449	0.760	-3.480	0.001	-4.151	-1.139
C(Month)[T.4]	-4.4650	0.996	-4.483	0.000	-6.439	-2.491
C(Month)[T.5]	-5.6803	1.172	-4.846	0.000	-8.003	-3.358
C(Month)[T.6]	-5.4549	1.299	-4.199	0.000	-8.029	-2.880
C(Month)[T.7]	-5.5114	1.311	-4.205	0.000	-8.109	-2.914
C(Month)[T.8]	-5.5672	1.306	-4.263	0.000	-8.155	-2.979
C(Month)[T.9]	-5.6297	1.259	-4.473	0.000	-8.124	-3.136
C(Month)[T.10]	-5.7348	1.065	-5.385	0.000	-7.845	-3.624
C(Month)[T.11]	-2.5841	0.812	-3.182	0.002	-4.193	-0.975
C(Month)[T.12]	-1.4855	0.576	-2.581	0.011	-2.626	-0.345
H_deltaT12	1.4244	0.099	14.387	0.000	1.228	1.621

```

=====
Omnibus:          41886.189  Durbin-Watson:          0.494
Prob(Omnibus):    0.000  Jarque-Bera (JB):    953415.060
Skew:             2.094  Prob(JB):          0.00
Kurtosis:         19.561  Cond. No.          214.
=====

```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: nohp

USBuildingClimateZone: Mixed_Humid_Hot_Dry

Formula: KWh_consumed_cooling ~ C(Period, levels=levels_period) + C(Month) + C_deltaT6

OLS Regression Results

```

=====
Dep. Variable:    KWh_consumed_cooling  R-squared:          0.723
Model:            OLS  Adj. R-squared:    0.723
Method:           Least Squares  F-statistic:        1194.
Date:            Fri, 24 Jun 2022  Prob (F-statistic):    0.00
Time:            09:39:36  Log-Likelihood:    -5.1681e+06

```

No. Observations: 1563066 AIC: 1.034e+07

Df Residuals: 1560824 BIC: 1.034e+07

Df Model: 13

Covariance Type: cluster

=====

	coef	std err	t	P> t	[0.025	0.975]	
Intercept	0.3104	0.100	3.100	0.002	0.114	0.507	
C(Period, levels=levels_period)[T.Post]	-0.3179	0.069	-4.606	0.000	-0.453	-0.183	
C(Month)[T.2]	0.4532	0.032	13.972	0.000	0.390	0.517	
C(Month)[T.3]	0.8256	0.040	20.745	0.000	0.748	0.904	
C(Month)[T.4]	1.7425	0.070	24.966	0.000	1.606	1.879	
C(Month)[T.5]	4.0609	0.107	37.820	0.000	3.850	4.271	
C(Month)[T.6]	6.1268	0.163	37.573	0.000	5.807	6.447	
C(Month)[T.7]	7.4473	0.198	37.660	0.000	7.060	7.835	
C(Month)[T.8]	7.5223	0.190	39.589	0.000	7.150	7.895	
C(Month)[T.9]	5.8601	0.138	42.326	0.000	5.589	6.132	
C(Month)[T.10]	3.1286	0.091	34.355	0.000	2.950	3.307	
C(Month)[T.11]	1.0125	0.047	21.645	0.000	0.921	1.104	
C(Month)[T.12]	0.1200	0.018	6.700	0.000	0.085	0.155	
C_deltaT6	1.4360	0.020	72.642	0.000	1.397	1.475	

=====

Omnibus: 370926.132 Durbin-Watson: 0.543

Prob(Omnibus): 0.000 Jarque-Bera (JB): 3672623.535

Skew: 0.861 Prob(JB): 0.00

Kurtosis: 10.309 Cond. No. 97.8

=====

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: nohp

USBuildingClimateZone: Mixed_Humid_Hot_Dry

Formula: KWh_consumed_heating ~ C(Period, levels=levels_period) + C(Month) + H_deltaT10

OLS Regression Results

```

=====
Dep. Variable:   KWh_consumed_heating   R-squared:           0.605
Model:           OLS   Adj. R-squared:       0.604
Method:         Least Squares   F-statistic:         504.2
Date:           Fri, 24 Jun 2022   Prob (F-statistic):    0.00
Time:           09:41:44   Log-Likelihood:      -1.6285e+06
No. Observations: 1563066   AIC:                 3.257e+06
Df Residuals:    1560824   BIC:                 3.257e+06
Df Model:        13
Covariance Type: cluster
=====

```

```

=====
              coef   std err      t   P>|t|   [0.025   0.975]
-----
Intercept                0.4100    0.083    4.962   0.000    0.248    0.572
C(Period, levels=levels_period)[T.Post] -0.0219    0.005   -4.227   0.000   -0.032   -0.012
C(Month)[T.2]             -0.0893    0.014   -6.322   0.000   -0.117   -0.062
C(Month)[T.3]             -0.2531    0.044   -5.725   0.000   -0.340   -0.166
C(Month)[T.4]             -0.3739    0.064   -5.805   0.000   -0.500   -0.248
C(Month)[T.5]             -0.4102    0.078   -5.242   0.000   -0.564   -0.257
C(Month)[T.6]             -0.4000    0.081   -4.924   0.000   -0.559   -0.241
C(Month)[T.7]             -0.3966    0.082   -4.861   0.000   -0.557   -0.237
C(Month)[T.8]             -0.3981    0.082   -4.878   0.000   -0.558   -0.238
C(Month)[T.9]             -0.4007    0.081   -4.931   0.000   -0.560   -0.241
C(Month)[T.10]            -0.4070    0.070   -5.849   0.000   -0.543   -0.271
C(Month)[T.11]            -0.2768    0.043   -6.366   0.000   -0.362   -0.192
C(Month)[T.12]            -0.0986    0.018   -5.498   0.000   -0.134   -0.063
H_deltaT10                0.0955    0.006   15.860   0.000    0.084    0.107
=====

```

```

=====
Omnibus:          2685620.488   Durbin-Watson:          0.612
Prob(Omnibus):    0.000   Jarque-Bera (JB):  301986257592.984
Skew:             -10.319   Prob(JB):           0.00
Kurtosis:         2156.231   Cond. No.           125.
=====

```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: nohp

USBuildingClimateZone: Mixed_Humid_Hot_Dry

Formula: mmbtu_consumed ~ C(Period, levels=levels_period) + C(Month) + H_deltaT10

OLS Regression Results

```

=====
Dep. Variable:    mmbtu_consumed  R-squared:            0.610
Model:            OLS  Adj. R-squared:        0.609
Method:          Least Squares  F-statistic:        487.4
Date:            Fri, 24 Jun 2022  Prob (F-statistic):    0.00
Time:            09:41:36  Log-Likelihood:        1.6045e+06
No. Observations: 1563066  AIC:                -3.209e+06
Df Residuals:    1560824  BIC:                -3.209e+06
Df Model:        13
Covariance Type: cluster
=====

```

```

=====
               coef  std err      t  P>|t|  [0.025   0.975]
-----
Intercept                0.0456   0.011   4.240   0.000   0.025   0.067
C(Period, levels=levels_period)[T.Post] -0.0030   0.001  -4.534   0.000  -0.004  -0.002
C(Month)[T.2]            -0.0105   0.002  -5.742   0.000  -0.014  -0.007
C(Month)[T.3]            -0.0279   0.006  -4.864   0.000  -0.039  -0.017
C(Month)[T.4]            -0.0412   0.008  -4.927   0.000  -0.058  -0.025
C(Month)[T.5]            -0.0457   0.010  -4.498   0.000  -0.066  -0.026
C(Month)[T.6]            -0.0442   0.011  -4.190   0.000  -0.065  -0.024
C(Month)[T.7]            -0.0438   0.011  -4.127   0.000  -0.065  -0.023
C(Month)[T.8]            -0.0439   0.011  -4.143   0.000  -0.065  -0.023
C(Month)[T.9]            -0.0443   0.011  -4.196   0.000  -0.065  -0.024
C(Month)[T.10]           -0.0455   0.009  -5.037   0.000  -0.063  -0.028
C(Month)[T.11]           -0.0309   0.006  -5.471   0.000  -0.042  -0.020
C(Month)[T.12]           -0.0123   0.002  -5.338   0.000  -0.017  -0.008
H_deltaT10                0.0124   0.001  15.831   0.000   0.011   0.014
=====

```

```
=====
Omnibus:          2824340.868  Durbin-Watson:          0.610
Prob(Omnibus):    0.000  Jarque-Bera (JB):  381983375081.775
Skew:            -11.591  Prob(JB):          0.00
Kurtosis:        2424.694  Cond. No.          125.
=====
```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: hp

USBuildingClimateZone: Mixed_Humid_Hot_Dry

Formula: KWh_consumed_cooling ~ C(Period, levels=levels_period) + C(Month) + C_deltaT8

OLS Regression Results

```
=====
Dep. Variable:  KWh_consumed_cooling  R-squared:          0.720
Model:          OLS  Adj. R-squared:    0.720
Method:         Least Squares  F-statistic:        396.3
Date:          Fri, 24 Jun 2022  Prob (F-statistic):    6.53e-311
Time:          09:54:50  Log-Likelihood:    -1.5428e+06
No. Observations:  485697  AIC:          3.086e+06
Df Residuals:    484988  BIC:          3.086e+06
Df Model:        13
Covariance Type:  cluster
=====
```

```
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
Intercept              0.2166   0.156   1.386   0.166  -0.090   0.524
C(Period, levels=levels_period)[T.Post] -0.3720   0.113  -3.289   0.001  -0.594  -0.150
C(Month)[T.2]           0.2129   0.050   4.295   0.000   0.116   0.310
C(Month)[T.3]           0.3604   0.055   6.596   0.000   0.253   0.468
C(Month)[T.4]           1.0760   0.100  10.729   0.000   0.879   1.273
C(Month)[T.5]           2.9786   0.182  16.409   0.000   2.622   3.335
C(Month)[T.6]           4.8133   0.275  17.508   0.000   4.274   5.353
C(Month)[T.7]           5.6858   0.308  18.467   0.000   5.081   6.290
=====
```

C(Month)[T.8]	5.8997	0.301	19.616	0.000	5.309	6.490
C(Month)[T.9]	4.5100	0.235	19.195	0.000	4.049	4.971
C(Month)[T.10]	2.2040	0.145	15.180	0.000	1.919	2.489
C(Month)[T.11]	0.6482	0.069	9.406	0.000	0.513	0.783
C(Month)[T.12]	0.0155	0.027	0.569	0.569	-0.038	0.069
C_deltaT8	1.0768	0.026	41.684	0.000	1.026	1.127

```
=====
Omnibus:          151362.461  Durbin-Watson:          0.522
Prob(Omnibus):    0.000  Jarque-Bera (JB):    1624309.822
Skew:             1.191  Prob(JB):           0.00
Kurtosis:         11.637  Cond. No.           129.
=====
```

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)

Filter: hp

USBuildingClimateZone: Mixed_Humid_Hot_Dry

Formula: KWh_consumed_heating ~ C(Period, levels=levels_period) + C(Month) + H_deltaT12

OLS Regression Results

```
=====
Dep. Variable:  KWh_consumed_heating  R-squared:          0.574
Model:          OLS  Adj. R-squared:    0.573
Method:         Least Squares  F-statistic:        167.0
Date:           Fri, 24 Jun 2022  Prob (F-statistic):    1.24e-203
Time:           09:55:32  Log-Likelihood:    -1.7125e+06
No. Observations:  485697  AIC:          3.425e+06
Df Residuals:      484988  BIC:          3.425e+06
Df Model:          13
Covariance Type:  cluster
=====
```

```
=====
              coef    std err          t      P>|t|   [0.025   0.975]
-----
Intercept          4.3613    0.924     4.718    0.000     2.546     6.176
=====
```

C(Period, levels=levels_period)[T.Post]	-0.6419	0.128	-5.017	0.000	-0.893	-0.391
C(Month)[T.2]	-2.6637	0.332	-8.024	0.000	-3.315	-2.012
C(Month)[T.3]	-3.2358	0.566	-5.717	0.000	-4.347	-2.125
C(Month)[T.4]	-3.9378	0.756	-5.212	0.000	-5.421	-2.454
C(Month)[T.5]	-4.1035	0.922	-4.453	0.000	-5.913	-2.294
C(Month)[T.6]	-4.0037	0.901	-4.444	0.000	-5.773	-2.235
C(Month)[T.7]	-4.0231	0.902	-4.461	0.000	-5.794	-2.253
C(Month)[T.8]	-4.0164	0.901	-4.458	0.000	-5.785	-2.247
C(Month)[T.9]	-4.0349	0.902	-4.475	0.000	-5.805	-2.265
C(Month)[T.10]	-4.2995	0.818	-5.253	0.000	-5.906	-2.693
C(Month)[T.11]	-3.9877	0.555	-7.183	0.000	-5.078	-2.898
C(Month)[T.12]	-3.0926	0.291	-10.631	0.000	-3.664	-2.521
H_deltaT12	1.3549	0.087	15.637	0.000	1.185	1.525

Omnibus:	542497.030	Durbin-Watson:	0.715
Prob(Omnibus):	0.000	Jarque-Bera (JB):	21968499631.397
Skew:	-4.025	Prob(JB):	0.00
Kurtosis:	1044.862	Cond. No.	101.

Notes:

[1] Standard Errors are robust to cluster correlation (cluster)