Work Paper SCE17HC054
Revision 0

Southern California Edison

Residential Smart Communicating Thermostat

AT-A-GLANCE SUMMARY

Measure Codes	See section 1.1
Measure Description	Residential Smart Thermostat
Base Case Description	A combination of programmed Setback Programmable Thermostats and Non-Programmable Thermostats (or not programmed setback thermostats)
Units	1 unit = 1 Smart Thermostat
Energy Savings	Refer to Attachment
Full Measure Cost ($/unit)	$186.5
Incremental Measure Cost ($/unit)	$92.38
Effective Useful Life	EUL: 11 years (No DEER ID available) RUL: 3.66 years
Measure Installation Type	IOU's: Replace on Burnout (15%) and Early Retirement (ER) (85%) POU's: Replace on Burnout
Net-to-Gross Ratio	IOU's: 0.55 (Res-Default>2) POU's: 0.96 Refer to description below for details
Important Comments	This work paper is intended to replace the interim smart thermostat work paper already submitted by SoCal Gas. This work paper includes heating and cooling data (and savings) for all climate zones. This work paper has a complementary Ex Ante Database data set that will be provided in a separate submission to the California Public Utilities Commission (CPUC).

REVISION HISTORY

Rev	Date	Author	Summary of Changes
0	2/17/2017	SCE/NEST Collaboration: Jeff Gleeson (Nest), Aaron Berndt (Nest), Andres Fergadiotti (SCE)	New work paper, first version

COMMISSION STAFF AND CAL TF COMMENTS

Rev	Party	Submittal Date	Comment Date	Comments	WP Developer Response
					Consolidated comments to draft WP included in Attachment #5

Cal TF website: http://www.caltf.org/

SECTION 1. GENERAL MEASURE & BASELINE DATA

1.1 MEASURE DESCRIPTION & BACKGROUND

A **Smart Thermostat** is a device that controls heating, ventilation, and air-conditioning (HVAC) equipment to regulate the temperature of the room or space in which it is installed, has the ability to make automated adjustments to the set point of the HVAC system to drive energy savings (electric and gas), and has the ability to communicate with sources external to the HVAC system. For connection, the Smart Thermostat may rely on a home area network (e.g. Wi-Fi) and an internet connection that is independent of the Smart Thermostat.

This workpaper (wp) details the installation of a Residential Smart Thermostat. This measure characterizes the household heating and cooling energy savings from the installation of a Smart Thermostat. Smart Thermostats reduce energy consumption using a combination of features described in Section 1.2 Technical Description.

The calculation approach utilized in this workpaper ensures the range in energy savings (both increases and decreases) associated with smart thermostat installations are captured and studied in the analysis and therefore the results create the average net savings by climate zone.

Base, Standard, and Measure Cases

Case	Description of Typical Scenario
Measure	Residential Smart Communicating Thermostat with two way communication and automatic scheduling capabilities
Existing Condition	Setback Programmable Thermostats or Non-Programmable Thermostats

Measures and Codes

Measure Codes					Measure Name
SCG	SDG&E	SCE	PG&E	POU's	
TBD	TBD	CE-18623	TBD	TBD	Residential Smart (Communicating) Thermostat

*all POU measures will be filed as ROB

Technologies that customers are replacing:

In PG&E's recent smart thermostat ET Study[35], the surveys results indicated that only 1% of customers had an existing smart thermostat that they were replacing. 15%[1] of customers had manual thermostats, which are very likely to be operating past their EUL, based upon the code requirements for programmable thermostats. The remaining 85% of customers stated having a programmable thermostat. Based on CalTF and Ex-Ante team feedback, this measure is most appropriately classified as a blend of ROB and ER given the data. To accomplish this, measure impacts are reported with both ROB and RET/ER offerings. When savings claims are filed, they will be submitted as 15% as ROB and 85% RET/ER to account for forecasted installation types. This

[1] This 15% value is further supported by a PG&E Codes and Standards: Home Energy Use Study [36] that found 14% of households answered that they had a manual thermostat.

approach reasonably estimate market conditions while providing conservative savings estimates given they are based on output of two independent studies with comparable results.

POU Programs: In PG&E's recent smart thermostat ET Study[35], 85% of customers stated having a programmable thermostat. Given that the reported customer demographics of the study showed that 78% of customers live in a home built prior to the year 2000, the age of home indicates that a good portion of those thermostats as well would also be past their EUL. With that data, it is possible that up to 78% of the installations could be classified as ROB. While this data doesn't represent a definitive answer on the RUL of programmable thermostats that are in market, it does represent reasonable support that most of the installations would be classified as ROB (i.e. not likely at the IOU requirement for preponderance of evidence) and therefore it is most appropriate to file POU smart thermostat measures as ROB.

General Eligibility Requirements[2]

a. PA shall employ QA/QC procedures to ensure that the thermostat is installed in an eligible home and is attached to the type of HVAC equipment that is being incentivized, whether it is for natural gas or electricity savings.
b. PA shall confirm that the customer has a newly purchased smart thermostat. At minimum, the PA shall obtain a copy of the thermostat sales receipt and the PA shall confirm the purchase date is on or after the program's start date.
c. Customer eligibility shall be determined by each PA prior to paying rebates. Upon request, all data associated with determining eligibility shall be provided to Energy Division. PAs shall extend this requirement to any third party vendors in who assist PAs with determining customer eligibility. To the extent that they are used to determine eligibility, data regarding dates of purchase, location of home, customer HVAC equipment type, pre-installation HVAC energy use, and etcetera shall be made available.

Device Eligibility Requirements:

- A qualified Wi-Fi thermostat per guidelines described below in Section 1.2

Customer Eligibility Requirements:

- Customer segment: residential
- Must use the thermostat to control heating and/or cooling equipment supplied by fuels provided by the utility paying the end-customer incentive
    - For single-fuel utilities (or dual-fuel utilities in a portion of their service area where they only supply one fuel), only savings for the applicable delivered fuel may be claimed
    - Eligible heating equipment: gas forced-air furnace, electric forced-air furnace, heat pump
    - Eligible cooling equipment: central air conditioning

Program Design Options:

1. **Downstream energy efficiency rebate (no demand response):**

[2] Items in Disposition for WPSCGREHC160624A (SCG Smart Thermostat) issued November 8, 2016 That Impact Future Smart Thermostat Workpapers

- Customer must purchase and install a qualifying product in order to receive an energy efficiency (EE) rebate
- Customer who purchase qualifying equipment, but choose not to join a demand response (DR) program, can still receive a rebate.
- *Applicable utilities: SDG&E, SCE, SoCal Gas and PG&E.*

2. **Downstream energy efficiency rebate with Demand Response rebate (or incentive) to encourage IDSM:**
    - Customer must purchase and install a qualifying product in order to receive the energy efficiency (EE) rebate
    - Additional Demand Response (DR) rebate or incentive can be provided to the customer if they choose to enroll in a DR program after installing their new device.
    - Some customers will only redeem the EE rebate. A portion of customers will redeem both the EE and DR.
    - *Applicable utilities: SDG&E, SCE, SoCal Gas and PG&E.*

Implementation and Installation Requirements:

- **Climate Zones:** All 16 California Climate Zones are eligible (no cooling savings defined for Climate Zone 1)
- **Building Types:** Single Family Residential Building Types (including SFM, MF, and DMo)

1.2 Technical Description

Smart thermostats are enhanced by data gathering and analytics functionalities, which enables them to use a variety of methods to optimize HVAC settings for efficient and automated energy consumption. Specifically, a smart thermostat is defined as a thermostat that is compatible with the participant's HVAC system, and has

- Two-way communication,
- Occupancy detection (through the use of occupancy sensors, geofencing, etc.), and
- At least two of the features in following Table

Explanations of how these features save energy is provided in Table below

Smart Thermostat Features[1]

Feature	Feature Description
Schedule learning	Thermostat learns occupant patterns with little to no effort from the customer.
Heat pump auxiliary heat optimization	Thermostat optimizes the use of the refrigerant heating cycle in preference to auxiliary heat, while still enabling the home to achieve a comfortable set point.
Upstaging / downstaging optimization	Thermostat optimizes the use of the lowest and most efficient stage of heating or cooling in preference of the higher capacity stage, while still enabling the home to achieve a comfortable set point.
Humidity control	Thermostat uses a humidity sensor to optimize HVAC operation.
Weather-enabled optimization	Thermostat uses weather predictions and weather data to optimize the HVAC system.
Free cooling / economizer capability	Thermostat recognizes the indoor/outdoor temperature difference and uses the outside air instead of the air conditioner or heating system to cool or heat the home when possible.

[1] In addition to the features listed, smart thermostats typically have easy-to-use set point scheduling, fan dissipation, and behavioral features. Fan dissipation enables compressors or heaters to turn off early, while the fan continues to run and condition the home with air in the duct system that is still cold or warm. Also, smart thermostats often have behavioral features such as default or recommended setback temperatures, and energy scorecards.

1.3 Installation Types and Delivery Mechanisms

Installation Type Descriptions

Installation Type	Savings		Life	
	1st Baseline (BL)	2nd BL	1st BL	2nd BL
Replace on Burnout (ROB)	Above Customer Existing	-	EUL	-
Retrofit or Early Replacement (RET/ER)*	Above Customer Existing	Above Code or Standard	RUL	EUL-RUL

A delivery mechanism is a delivery method paired with an incentive method. Delivery mechanisms are used by programs to obtain program participation and energy savings.

Early Retirement (ER)/Retrofit (RET) - In this delivery approach, units (thermostats) that are still functional, but needing replacement will be retired prematurely before reaching the end of their useful life. The program will provide incentives to the homeowner (customer) via Down-Stream or Direct Install incentive mechanisms. Part of the application process will include verification procedures for ensuring that existing HVAC controlling thermostats are installed and operational and currently controlling existing HVAC equipment.

Note that Resolution E-4818, which focus on measure level baseline assignment and preponderance of evidence guidance to establish eligibility for an accelerated replacement baseline treatment, and dated March 02, 2017, permits the Program Administrators to apply a

normal replacement baseline to any measure or program, regardless of the default category, and without a burden of proof.

Incentive Method Descriptions

Incentive Method	Description
Financial Support	The program motivates customers, through financial incentives such as rebates or low interest loans, to implement energy efficient measures or projects.

Delivery Method Descriptions

Delivery Method	Description
Downstream Incentive	The customer installs qualifying energy efficient equipment and submits an incentive application to the utility program. Upon application approval, the utility program pays an incentive to the customer. Such an incentive may be deemed or customized.
Direct Install	The program implements energy efficiency measures for qualifying customers, at no cost to the customer.

1.4 Measure Parameters

1.4.1 DEER Data

DEER Difference Summary

DEER Item	Used for Workpaper?
Modified DEER methodology	No
Scaled DEER measure	See details below for manufactured and multifamily residences
DEER Base Case	See details below for description of the RASS Base Case Calibration Factor, which leverages the same data used to create the DEER programmable thermostat base case
DEER Measure Case	No
DEER Building Types	No
DEER Operating Hours	No
DEER eQUEST Prototypes	No
DEER Version	-
Reason for Deviation from DEER	The DEER 2016 database does not contain an updated measure for Smart Thermostats.
DEER Measure IDs Used	-

1.4.2 Net-to-Gross Ratio

The Net-to-Gross (NTG) Ratio for this smart thermostat measure uses the default 0.55 value, based on the Nov 8, 2016 Smart Thermostat workpaper disposition. This value is significantly lower than comparable values from program jurisdictions across the country, as noted in Section 1.4.2.1. Section 1.4.2.2 also shows that having a smart thermostat rebate/program in a market has a significant uplift in program participation. Based on this data, it is recommended that an EM&V study be designed and completed to appropriately capture customer information needed to ensure the default NTG value is adjusted accordingly. This study has been noted in Section 1.6.4 Future Data Needs. In support of this effort, smart thermostat vendors could provide data to support the research effort. Additional data may be available from manufactures. The data available can vary by manufacture on its availability and form, however most should be able to

provide a subset of data to support and could be updated on a regular basis for program monitoring purposes – such as activation rates, leakage, high level system characteristics. In addition to these metrics, Nest regularly survey's new smart thermostat customers and asks them if a rebate influenced their purchase. This data could be provided to the EM&V contractor in a similar format outlined in Section 1.6.2.

Regarding the Nov, 8, 2016 Smart Thermostat workpaper disposition, the proposed sales data tracking to estimate the program specific NTG for this measure is not an appropriate methodology for a downstream delivery as it is for upstream, market transforming delivery methods. According to the CA Evaluation guidelines, sales data tracking is a more appropriate metric for measuring a change in market (market effect) for a market transforming measure. A sales lift can be caused by other confounding factors such as economic and market activity thereby not accurately capturing the program influence. Hence a more appropriate methodology to use is as guided by the CA evaluation framework, which includes either econometric methods or survey-based methods. Evaluation of the measure NTG will be guided by these protocols. [3]

[3] Referenced text from CA EM&V Framework: The NTGR can be expected to vary depending upon the maturity of the equipment or service, the type of delivery in the program, the maturity of the program, and the customer sector. This means that the best NTGR estimate for program planning is the latest estimate for that program or a similar program. A deemed estimate based on one or more of these dimensions can be the fallback position for program planning. Pg134

The impact evaluation roadmap categorizes NTGR methods very simply into those that are econometric methods (comparing participant and non-participants and adjusting for selectivity biases through econometric models) and those that are survey-based (asking participants what they would have done) Pg 135.

1.4.2.1 NTG Ratios from existing smart thermostat programs in North America

Utility Company	Location	Date	Smart Thermostat Program	Products Eligible for EE Rebate	Net-to-Gross
Commonwealth Edison	Illinois	June, 2015	$100 downstream energy efficiency rebate and additional $40 for optional enrollment in Demand Response	Allure EverSense, ecobee3, Honeywell Lyric, Lennox iComfort S30, LUX/GEO, Nest Learning Thermostat, Radio Thermostat CT50, Radio Thermostat CT80	0.96[5]
National Grid		2013-2015 Program Years	$100 downstream energy efficiency rebate and additional $40 for optional enrollment in Demand Response	Building 36 Intelligent Thermostat, ecobee Smart Si, Honeywell Wi-Fi 9000, Nest Learning Thermostat	1.00[33]
Enbridge Natural Gas	Ontario (CAN)	December, 2015	$100 downstream energy efficiency rebate	Nest Learning Thermostat and the ecobee3	0.96[7]
Vectren		June, 2015	$100 energy efficiency downstream rebate	Extensive list published on Vectren site[4]	1.00[8]

The 0.96 NTG value used for both of these programs is based on a white paper by CLEAResult Consulting, "Smart Thermostats: A CLEAResult White Paper Prepared for Commonwealth Edison."[34] The report shows that:

"Given the higher cost of smart thermostats, as well as low saturation in Illinois as reported by sales representatives for Honeywell, Ecobee, and Nest, a smart thermostat program is likely to see low free ridership and thus a strong NTG figure."

1.4.2.2 Net-to-Gross Ratio: Supporting Program Data

In addition to documented smart thermostat program NTG values, prior program results demonstrate that, because of the price elasticity of smart thermostat products, customers who were "sitting on the sidelines" because of the high upfront cost of the technology will make the decision to purchase after an up-front rebate or incentive is offered via a utility program.

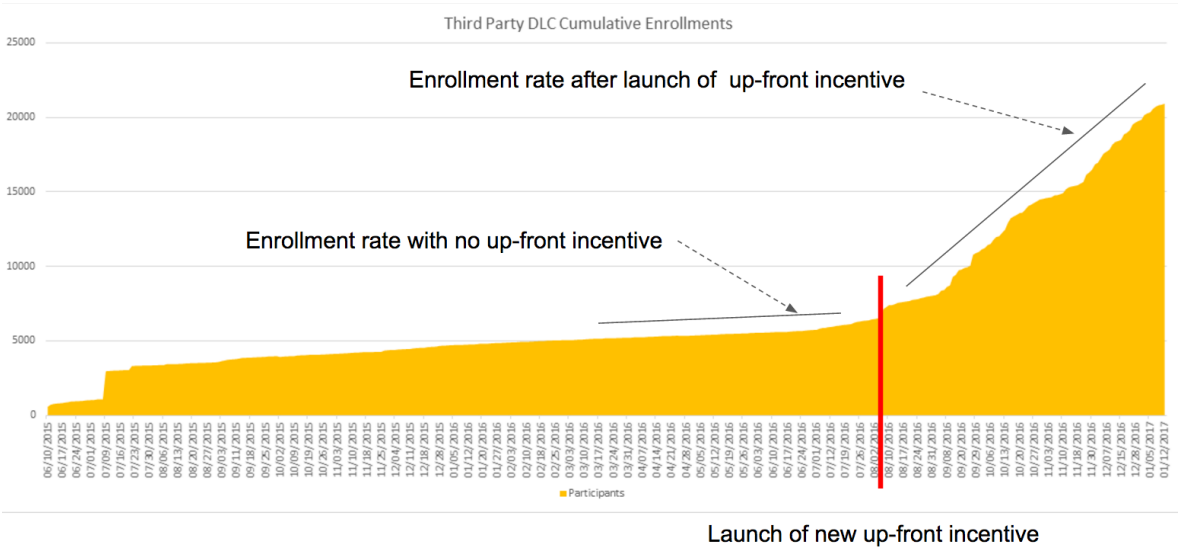
SCE and SoCal Gas Joint Rebate Drives Significant Participation and Device Purchase Ramp-Up

The new $125 up-front incentive jointly offered by SCE and SoCal Gas, although launched less than 8 months ago as of this writing, has already driven a remarkable ramp-up in demand response program participation. Most notably, the percentage of devices enrolling in the program that were purchased after program launch is significant. The figure below shows very clearly that program engagement, when an up-front incentive is offered, increases dramatically. The daily rate of

[4] Vectren qualifying product list: https://www.vectren.com/assets/cms/pdfs/rebates/list_res_program_thermostat_wifi.pdf

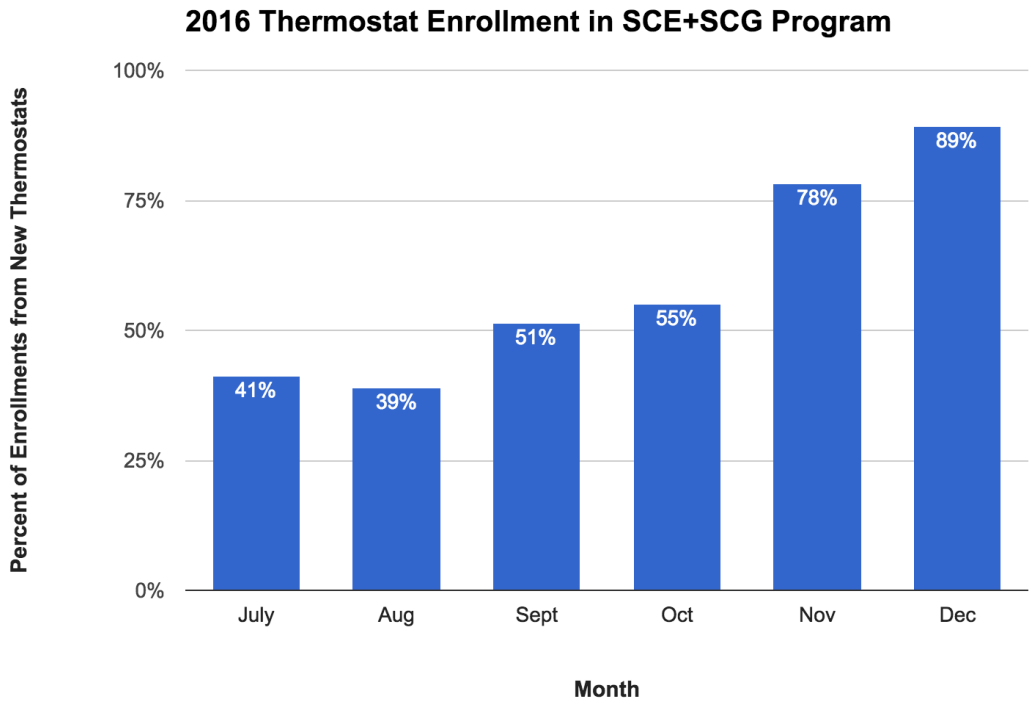
program enrollments increased over 6 fold as compared to the prior program design that did not include an upfront incentive.

Enrollment in SCE's PTR Program Before and After Launch of Up-Front Incentive



The SCE/SoCal Gas program examples show that up-front incentives drive smart thermostat activity and engagement that would not take place without utility program intervention.

As mentioned, not only did the up-front incentives drive new program enrollments, it drove increased adoption of the technology as the chart below shows. Initial new enrollments were from customers who already had the technology, but that quickly transitioned to a high portion of new customers.



1.4.2.3 Net-to-Gross Ratio: Alignment with IDSM and AB793 Strategies

It is also important to consider the context of smart thermostat programs that deliver benefits to multiple utility programs. Because smart thermostats can deliver energy savings alongside demand response or Time of Use load management, it is important that the NTG Ratio for this measure be assessed in an integrated manner that is consistent with the goals of AB793, California's Long Term Strategic Energy Efficiency Plan, and California's long stated goals for integrated demand side management. These strategic drivers encourage the adoption of this type of technology - which can deliver EE and DR - to encourage the integration of demand side programs to achieve maximum savings and load management benefit, avoid duplicative efforts, reducing transaction costs, and reducing customer confusion.

The relevant NTG values for the measures in this work paper are in the table below.

NTGR ID	Description	Sector	BldgType	Measure Delivery	NTGR
Res-Default>2	All other EEM with no evaluated NTGR; existing EEM with same delivery mechanism for more than 2 years	Res	Any	Any	0.55
Res-Default-HTR-di	All other EEM with no evaluated NTGR; direct install hard-to-reach only.	Res	Any	Any	0.85
TBD	NTG Value for POU Programs	Res	Any	Any	0.96*

* Per the policy manual the IOU programs are mandated to initially file a 0.55 default NTG for new measures. POU programs will utilize the substantial data outlined in this section to support a more reasonable 0.96 NTG based on market conditions and being more aligned with several current programs operating across the US.

1.4.3 Spillage Rate

Spillage rates are not tracked in work papers; they are tracked in an external document which will be supplied to the Commission Staff as discussed in the Future Data Needs section.

1.4.4 Installation Rate

The installation rate (IR) value was obtained using the DEER 2016, READI v2.4.3 tool. The relevant IR value for this wp measure is shown below.

Gross Savings Installation Adjustment Rate

GSIA ID	Description	Sector	BldgType	ProgDelivID	GSIAValue
Def-GSIA	Default GSIA values	Any	Any	Any	1

1.4.5 Effective and Remaining Useful Life

Effective Useful Life:

Information about effective useful life of the measure can be gleaned by an empirical analysis of currently available field data.[5] In order to estimate the expected persistence of residential smart thermostat energy-saving features, we present a model that takes into account the reduction over time in NLTs that are on-line, makes certain adjustments to account for likely off-line operation, and develops an empirical prediction of the persistence of energy savings associated with smart thermostats following installation.

The NLT can be operated both online and offline. To project the measure's effective life, we used survival analysis methods on Internet connectivity data for the full population of Nest thermostats. This analysis will likely understate the true measure life unless an adjustment is made for thermostats that are offline but still providing energy savings. (I.e. In many cases, even if an NLT goes offline, it can continue to deliver many of its energy saving features.) Nest does not have firm data on this issue, but conservatively estimates a range of 10%-40% of off-line devices will still be providing savings. The results of this statistical survival analysis currently suggest that the energy savings associated with NLT deployment persist for approximately 9.2 - 13.8 years. Based on this data and analysis, we have selected the conservative mid-point of that range and projected 11 years as the measure EUL for purposes of this analysis, which is consistent with the EUL for energy savings associated with programmable thermostats.

Our analysis further explored the persistence of energy saving feature usage by analyzing thermostat setting behavior across multiple years. We analyzed data for the month of January in the years 2014, 2015, and 2016 and found that thermostat settings across hundreds of thousands of operating devices in each year became slightly more efficient over time -- implying increasing energy savings over the years. The average January heating set point was 67.5°F in 2014, 67.4°F in 2015, and 67.3°F in 2016 for the group with data from all three years. This 0.2°F decline in

[5] Residential smart thermostat manufacturers define respective warranty periods for their hardware offerings, which may vary from one manufacturer to another. For example, Nest provides consumers a two-year limited warranty on the Nest Learning Thermostat (NLT), or, where the product is sold through authorized professional installers, a five-year limited warranty. The aim of this working paper is not to analyze or modify such warranty periods, but rather to determine the expected persistence of energy savings associated with smart thermostat deployment based upon statistical analysis of available data.

average heating temperature implies about a 1% increase in annual percent heating savings over time. Dating back to 2012, the average percentage of devices with energy savings features like Auto-Away is 83% of devices - a value that is already incorporated into the energy savings methodology outlined in this workpaper (i.e. the analysis incorporates devices with and without Auto-Away in order to ensure that the workpaper includes energy decreases and increases in average savings values). Furthermore, the time spent in Auto-Away actually grew slightly from 93 hours in 2014 to 96 hours in 2015 to 98 hours in 2016. Based on this data, it appears that the persistence of energy-saving feature usage for smart thermostats is excellent.

Standard/Code technology After RUL:

Smart thermostat technology is in an early stage of market adoption. Indeed, this was a main driver for AB793 legislation, which requires the utility programs to promote this type of technology to drive wider adoption. It is worth noting that the definition of smart thermostats, for the purpose of this work paper, only includes those devices that provide enough software intelligence, combined with hardware features, to help customers automatically save energy. This definition very purposefully does not include those thermostats that are simply connected to the internet. It is worth noting that in most market projections connected thermostats are combined with smart thermostats. The market penetration for the whole category is low, and when limiting to smart thermostats, even lower.

Here is the research summarizing the early stages of adoption of the smart thermostats:

- Market penetration for Smart Thermostats, while growing each year, remains on the order of magnitude that places it in the early-adopter stage of the technology adoption cycle. Research by Berg Insights estimates that smart thermostats were installed in 4.5 million North American homes as of 2015[(1)]. Given the total number of households in the US - close to 125 million - this single-digit adoption percentage shows that the market is still predominantly comprised of early adopters, and that it will take many years for the technology to become standard.
- Indeed, a report by Business Insider found that "the US smart home market as a whole is in the 'chasm' of the tech adoption curve..."[(3)]
- A report by Parks Associates found the market penetration, measured by the adoption of smart-home energy management technologies (which includes smart thermostats), to be on the order of 7% of all U.S. broadband households[(2)]. It is worth noting that this includes additional smart home technology, not just smart thermostats.
- The Business Insider research, and an additional report by Parks Associates[(4)], found that high up-front product costs and low overall familiarity are two significant barriers to adoption.
- Market Penetration study conducted by e-Source in February, 2017 (which was primarily based on the Nielsen Energy Behavior Trach research) suggests that smart (communicating) thermostats in U.S. Single Family homes had a market penetration of 6% in 2016 doubling from 3% in 2014. For California, the study suggests a market penetration of 9% in 2016.
- PGE's Code and Standards study – Home Energy Use Study (HEUS) by Evergreen Economics, dated January 2017, including approximately 1,000 on-site surveys, suggests a 3% market penetration of the smart communicating smart technology with 14% and 83% for manual (non-programmable) and programmable thermostat respectively.

Because of this low market penetration, the standard/code technology after the RUL period is a blend of programmable thermostats (code) and a portion of smart thermostats. Since a portion of the market will be selecting smart thermostats, savings were reduced for the 2nd baseline time period accordingly. This methodology is outlined in Section 2.3.7.

Measure classification: Much research of the past indicates that energy savings from thermostatic control devices are dependent on thermostat setting behavior. Many of the past programmable thermostat measure savings could not be fully realized because of manual practices of users and inability to program thermostats to realize savings from changing set points. A smart thermostat addresses issue by taking the manual behavior out of the equation so that programming on set-points is built-in for realizing savings from tweaking consumers existing set-points without having them change their behavior. [6] Therefore, we disagree that the smart thermostat is purely a BRO measure and as such have treated as a hardware measure, with corresponding life.

EUL ID	Description	Sector	UseCategory	Life	
				1st Baseline	2nd Baseline
TBD (ROB – 15%)	Smart Thermostats	Res	HVAC	11 (EUL)	N/A
TBD (RET/ER – 85%)	Smart Thermostats	Res	HVAC	3.66* (RUL)	7.34 (EUL-RUL)
TBD – POU Programs	Smart Thermostats	Res	HVAC	11 (EUL)	N/A

*one third of the expected useful life of a programmable thermostat that has an EUL of 11 years

1.4.6 Codes and Standards Analysis

This measure falls under the jurisdiction of Title 24 as listed in Table below. Smart Thermostats have the capability to respond to a demand response signal, and therefore; exceed the functionality of thermostats that meet current 2015 Title-24 standards.

Code Summary

Code	Reference	Effective Dates
Title 20 (2016)	N/A	N/A
Title 24 (2016)	Title 24, part 6 Section 110 Thermostats	January 1, 2017

[6] References: CA EM&V Protocols definitions
PRACTICE - Generally refers to a change in a customer's behavior or procedures that reduces energy use (e.g., thermostat settings and maintenance procedures).

THERMOSTAT - An automatic control device designed to be responsive to temperature and typically used to maintain set temperatures by cycling the HVAC system.

Title 20: This measure does not fall under Title 20 of the California Code of Regulations
Title 24: Thermostats do fall under Title 24 of the California Code of Regulations, but smart thermostats discussed in this work paper do not. Title 24, part 6 states[i]:

Section 110.2 Mandatory Requirements for Space Conditioning Equipment

Thermostats. All unitary heating or cooling systems, including heat pumps, not controlled by a central energy management control system (EMCS) shall have a setback thermostat.
1. Setback Capabilities. All thermostats shall have a clock mechanism that allows the building occupant to Program the temperature set points for at least four periods within 24 hours. Thermostats for heat pumps shall meet the requirements of Section 110.2(b). Space-conditioning systems shall be installed with controls that comply with the applicable requirements of Subsections (a) through (i).

Section 120
Thermostatic Controls for Each Zone. The supply of heating and cooling energy to each space-conditioning zone or dwelling unit shall be controlled by an individual thermostatic control that responds to temperature within the zone and that meets the applicable requirements of Section 120.2(b).

EXCEPTION to Section 120.2(a): An independent perimeter heating or cooling system may serve more than one zone without individual thermostatic controls if:
1. All zones are also served by an interior cooling system;
2. The perimeter system is designed solely to offset envelope heat losses or gains;
3. The perimeter system has at least one thermostatic control for each building orientation of 50 feet or more; and
4. The perimeter system is controlled by at least one thermostat located in one of the zones served by the system.

(b) Criteria for Zonal Thermostatic Controls. The individual thermostatic controls required by Section 120.2(a) shall meet the following requirements as applicable:
1. Where used to control comfort heating, the thermostatic controls shall be capable of being set, locally or remotely, down to 55°F or lower.
2. Where used to control comfort cooling, the thermostatic controls shall be capable of being set, locally or remotely, up to 85°F or higher.
3. Where used to control both comfort heating and comfort cooling, the thermostatic controls shall meet Items 1 and 2 and shall be capable of providing a temperature range or dead band of at least 5°F within which the supply of heating and cooling energy to the zone is shut off or reduced to a minimum.

EXCEPTION to Section 120.2(b)3: Systems with thermostats that require manual changeover between heating and cooling modes.
4. Thermostatic controls for all unitary single zone, air conditioners, heat pumps, and furnaces, shall comply with the requirements of Section 110.2(c) and Reference Joint

Appendix JA5 or, if equipped with DDC to the Zone level, with the Automatic Demand Shed Controls of Section 120.2(h).

Appendix JA5 - Technical Specifications For Occupant Controlled Smart Thermostats
The Occupant Controlled Smart Thermostat (OCST)2 shall be self- certified by the manufacturer to the Energy Commission to meet the requirements described in this section. This document provides a high level technical specification for an OCST.
All CST shall comply with the specifications set forth in this document or a specification approved by the Executive Director.

JA5.2 Required Functional Resources

JA5.2.1 Setback Capabilities
All OCSTs shall meet the requirements of Section 110.2(c). Thermostats for heat pumps shall also meet the requirements of Section 110.2(b).

JA5.2.2 Communication Capabilities
OCSTs shall include communication capabilities enabled through either:

(a) At least one expansion port which will allow for the installation of a removable module containing a radio or physical connection port to enable communication; or

(b) Onboard communication device(s)

Shut-off and Reset Controls for Space-conditioning Systems. Each space-conditioning system shall be installed with controls that comply with the following:

1. The control shall be capable of automatically shutting off the system during periods of nonuse and shall have:
A. An automatic time switch control device complying with Section 110.9, with an accessible manual override that allows operation of the system for up to 4 hours; or
B. An occupancy sensor; or
C. A 4-hour timer that can be manually operated.

EXCEPTION to Section 120.2(e)1: Mechanical systems serving retail stores and associated malls, restaurants, grocery stores, churches, and theaters equipped with 7-day programmable timers.

2. The control shall automatically restart and temporarily operate the system as required to maintain:
A. A setback heating thermostat set point if the system provides mechanical heating; and

EXCEPTION to Section 120.2(e)2A: Thermostat setback controls are not required in nonresidential buildings in areas where the Winter Median of Extremes outdoor air temperature determined in accordance with Section 140.4(b)4 is greater than 32°F.

B. A setup cooling thermostat set point if the system provides mechanical cooling.

EXCEPTION to Section 120.2(e)2B: Thermostat setup controls are not required in nonresidential buildings in areas where the Summer Design Dry Bulb 0.5 percent temperature determined in accordance with Section 140.4(b)4 is less than 100°F.

Federal Standards: These measures do not fall under Federal DOE or EPA Energy Regulations.

Note that the applicable codes and standards for these measures dictate only that the thermostats be capable of shutting systems off and adjusting temperature set points during unoccupied hours. There are no requirements to actually shut down systems during unoccupied hours, or to make any specific unoccupied temperature set point adjustments

[i] Appendix H – 2013 Building Energy Efficiency Standards, Section 110.2

1.5 EM&V, Market Potential, and Other Studies – Base Case and Measure Case Information

Based on thorough review conducted by the IOU M&V teams on related evaluation and pilot studies, relevant smart thermostat studies that can be leveraged to support measure impacts are included below - screening criteria included experimental methods (including level of documentation describing/confirming experimental methods); source of the data (excluding those reports reporting from other sources); year of study (primarily recent studies reflecting and/or consistent with advances on thermostats optimization functionality/features); climate under evaluation; and technology. The list in this section also includes studies that were recommended for review during feedback received in CalTF meetings. The studies that were determined relevant for comparison purposes are described more in depth in Section 3.3.

1.5.1 PG&E Smart Thermostat Study: First Year Findings

- PG&E staff and M&V consultants
- Devices currently installed in-field, initial report released in Dec 2016
- Market Covered: PG&E's inland climate zones
- Techniques used: RCT and billing analysis
- **Relevance and impacts on this work paper:** The initial findings of the PG&E are discussed in Section 2.3.9. Initial analysis further shows that the average savings estimates this workpaper methodology has generated are in line with reasonable expected values for California.

1.5.2 Nest Learning Thermostat Pilot Study (Draft)[32]

- Prepared for SoCal Gas by Navigant Consulting
- Study designed and conducted to measure gas savings
- Foundation for the smart thermostat work paper submitted to CPUC by SoCal Gas in 2016
- **Relevance and impacts on this work paper:** According to the authors, this study is not useful for estimating electric savings, because "the study was designed around gas usage and spanned multiple utilities with different rate structures and billing practices."

1.5.3 Nest - Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results [18]

- Nest Labs

- Completed: February, 2015
- Market Covered: Nationwide
- Techniques used: Billing analysis
- **Relevance to and impacts on this work paper:** the billing analysis conducted in this study, as well as the randomized control trials it summarizes, identified smart thermostat percent savings close to those generated by this work paper analysis.

1.5.4 Energy Trust of Oregon Heat Pump Control Pilot Evaluation [19]

- Prepared for Energy Trust of Oregon Prepared by Apex Analytics LLC
- Completed: October, 2014
- Market Covered: state of Oregon
- Techniques used: Billing analysis and surveys
- **Relevance to and impacts on this work paper:** a thorough study that found significant energy savings for heat pump customers driven by Nest Thermostats, providing validation of the level of savings identified in this work paper. Although this work paper does not focus on heat pumps, the level of savings in this Energy Trust study provide a good check of reasonableness for the final heating savings estimates included herein.

1.5.5 Evaluation of the 2013–2014 Programmable and Smart Thermostat Program[20]

- Prepared for Vectren Corporation by The Cadmus Group
- Completed: January, 2015
- Market Covered: Central Indiana
- Techniques used: Billing analysis with some onsite data collection
- **Relevance to and impacts on this work paper:** a pre/post billing analysis that found % energy savings equivalent to those found in the analysis for this work paper, providing a good check of reasonableness for the final savings estimates included herein.

1.5.6 Evaluation of the 2013–2014 Programmable and Smart Thermostat Program[21]

- Prepared for Northern Indiana Public Service Company by The Cadmus Group
- Completed: January, 2015
- Market Covered: Northern Indiana
- Techniques used: Billing analysis with some onsite data collection
- **Relevance to and impacts on this work paper:** a pre/post billing analysis that found % energy savings equivalent to those found in the analysis for this work paper, providing a good check of reasonableness for the final savings estimates included herein.

1.5.7 CPS Energy Nest Pilot Evaluation FY2015 – FINAL [22]

- Prepared for CPS Energy by Nexant
- Completed: November, 2014
- Market Covered: Greater San Antonio, Texas area
- Techniques used: RCT billing analysis
- **Relevance to and impacts on this work paper:** This report documented the impacts of a smart thermostat demand response pilot. As a result, this paper is not additive to this work paper but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.8 Evaluation of the Space Heating and Cooling Energy Savings of Smart Thermostats in a Hot-Humid Climate using Long-term Data [23]

- D. Parker, K. Sutherland, D. Chasar Florida Solar Energy Center (FSEC)
- Completed: June, 2016
- Market Covered: Florida
- Techniques used: Pre-Post Analysis
- **Relevance to and impacts on this work paper:** This FSEC report is particularly valuable for this work paper, as described in more detail below. Because this report included multiple years of pre/post sub-metering data for smart thermostat study participants, this study validates that the use of set points in the savings regression model, instead of indoor temperatures, provides accurate savings estimates. In addition, it helps to validate that the approach described in this work paper accounts for any shifting of HVAC runtime to various times of day.

1.5.9 Demand Response Technology Evaluation of AutoDR Programmable Communicating Thermostats [24]

- Design & Engineering Services, Southern California Edison
- Completed: December, 2012
- Market Covered: SCE Territory
- Techniques used: Field measurements to evaluate the Demand Response (DR) capabilities of Programmable Communicating Thermostats (PCTs) leveraging Open Automated Demand Response (OpenADR).
- **Relevance to and impacts on this work paper:** This paper is not additive to this work paper but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.10 Residential Programmable Communicating Thermostat Customer Satisfaction Survey [25]

- Design & Engineering Services, Southern California Edison
- Completed: March, 2006
- Market Covered: SCE Territory
- Techniques used: This report summarizes the responses of residential customers to a Programmable Communicating Thermostat (PCT) installed in their home to control their heating, ventilation, and air conditioning (HVAC) systems.
- **Relevance to and impacts on this work paper:** Aside from documenting that customers like and are interested in this type of technology, this paper is not additive to this work paper but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.11 Impact Of PCTs On Demand Response – PHASE II [26]

- Design & Engineering Services, Southern California Edison
- Completed: April, 2007
- Market Covered: SCE Territory
- Techniques used: This project analyzes the potential electricity demand response of small commercial HVAC systems and residential split air-conditioners due to the use of programmable communicating thermostats (PCTs).
- **Relevance to and impacts on this work paper:** This paper is not additive to this work paper but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.12 Assessment of Programmable Communicating Thermostats: Technology, Costs and Required Functionality [27]

- Design & Engineering Services, Southern California Edison
- Completed: September, 2005
- Market Covered: SCE Territory
- Techniques used: This document characterizes the attributes of existing and potential programmable communicating thermostats (PCTs), assesses utility program experience, PCT hardware, installation, and communication-related costs.
- **Relevance to and impacts on this work paper:** This paper begins to document relevant features and costs associated with the smart thermostat category but cannot be directly leveraged here but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.13 Residential Programmable Communicating Thermostat Customer Satisfaction Survey [28]

- Design & Engineering Services, Southern California Edison
- Completed: March, 2007
- Market Covered: SCE Territory
- Techniques used: This report summarizes the survey responses of residential customers who were selected to participate in a test of a Programmable Communicating Thermostat (PCT) installed in their home to control their heating, ventilation, and air conditioning (HVAC) systems.
- **Relevance to and impacts on this work paper:** Aside from documenting that customers like and are interested in this type of technology, this paper is not additive to this work paper but the team wanted to acknowledge it here and note that it was considered for relevance.

1.5.14 A Look Inside the Eye on the Wall: Sub-metering Data Analysis and Savings Assessment of the Nest Learning Thermostat (BPA report)[29]

- Phillip Kelsven, Robert Weber, Bonneville Power Administration
- Completed: 2016 ACEEE Summer Study
- Market Covered: Pacific Northwest
- Techniques used: several, including sub-metering
- **Relevance to and impacts on this work paper:** This study provides additional data from a highly sub-metered study that found energy savings driven by smart thermostats.

1.5.15 Thriller in Asilomar: Battle of the Smart Thermostats [30]

- Noah Lieb and Scott Dimetrosky, Apex Analytics, Dan Rubado, Energy Trust of Oregon
- Completed: 2016 ACEEE Summer Study
- Market Covered: Pacific Northwest
- Techniques used: Billing analysis
- **Relevance to and impacts on this work paper:** This paper, based on a pre/post billing analysis, provides a useful comparison point for the percent savings that should be expected for smart thermostats during heating season.

1.5.16 Do Connected Thermostats Save Energy? [17]

- Abigail A. Daken, United States Environmental Protection Agency, Alan K. Meier, Lawrence Berkeley National Lab, Douglas G. Frazee, ICF International
- Completed: 2016 ACEEE Summer Study
- Market Covered: -
- Techniques used: -
- **Relevance to and impacts on this work paper:** This report describes the EPA approach to calculating savings from smart thermostats, which was leveraged in this workpaper.

1.5.17 National Study of Potential of Smart Thermostats for Energy Efficiency and Demand Response[31]

- Jen Robinson, Electric Power Research Institute, Ram Narayanamurthy, Electric Power Research Institute, Bienvenido Clarin, Electric Power Research Institute, Christine Lee, Electric Power Research Institute, Pranshu Bansal, University of California, Los Angeles
- Completed: 2016 ACEEE Summer Study
- Market Covered: National
- Techniques used: RCTs and quasi-experimental
- **Relevance to and impacts on this work paper:** A summary of smart thermostat potential for customer engagement and savings for those interested in additional industry detail.

1.6 Data Quality and Future Data Needs

1.6.1 Data utilized for this California work paper

The purpose of this paper is to provide an energy savings analysis in support of a deemed measure work paper for smart thermostats in California. The analysis herein is based on more than 13 million days of data from more than 100,000 Nest Learning Thermostats across California and includes savings estimates by climate zone for both cooling and heating HVAC consumption (as well as electric savings from reduced furnace fan usage during the heating season). No thermostats from the 100k devices were excluded from the analysis ensuring that the savings estimates generated are average savings seen (i.e. incorporates customers that may have seen an increase in energy usage and decrease).

The distribution of thermostats used for this study is outlined in the table below and was included to show that the data from the 100,000 thermostats was not overly concentrated in just a few climate zones.

California Climate Zone	Distribution of Thermostats in Sample (heating)	Distribution of Thermostats in Sample (cooling)
CZ01	Under 1%	Under 1%
CZ02	1% - 10%	1% - 10%
CZ03	10% - 20%	1% - 10%
CZ04	10% - 20%	10% - 20%
CZ05	Under 1%	Under 1%
CZ06	1% - 10%	1% - 10%

CZ07	1% - 10%	1% - 10%
CZ08	1% - 10%	1% - 10%
CZ09	10% - 20%	Over 20%
CZ10	1% - 10%	1% - 10%
CZ11	1% - 10%	1% - 10%
CZ12	10% - 20%	10% - 20%
CZ13	1% - 10%	1% - 10%
CZ14	Under 1%	Under 1%
CZ15	1% - 10%	1% - 10%
CZ16	1% - 10%	Under 1%

On average, the homes within California that were utilized to support this study have 1.29 thermostats and the breakout is broken down in the table below.

CZ	Area (Sqft)	Tstats
1	2059	1.39
2	2177	1.28
3	2106	1.3
4	2090	1.23
5	2116	1.22
6	2320	1.34
7	2153	1.23
8	2138	1.21
9	2155	1.3
10	2355	1.24
11	2301	1.27
12	2259	1.24
13	2255	1.29
14	2260	1.2
15	2181	1.51
16	2187	1.36
Average	2195	1.29

Model input data

This analysis was conducted with actual data from some Nest Thermostats currently in use throughout the state of California. Most notably, the model is built on the following data:

- The average set points and comfort temperature calculations were based on heating and cooling runtime weighted averages for more than 150,000 Nest thermostats in California with data covering the full year of May 2015 through April 2016.
    - The average set points are a time-weighted average set point across a day.
    - The comfort temperature is defined in Section 2.3.1. It is a value that is calculated and recorded automatically onboard every thermostat.
- The pooled fixed effects regression modeling, which assessed the energy savings per degree set point change, was based on data from more than 100,000 thermostats and included more than 6M device-days of heating data (from January, 2016 - February, 2016) and more than 7M device-days of cooling data (from July, 2015 - September, 2015). The regression model sample was restricted to single stage HVAC systems to avoid the uncertainty introduced by the unknown relative capacities of the stages.

1.6.2 Underlying Data for Calculations

The underlying data used to calculate energy savings and metrics for this workpaper can be provided, in an anonymized format, to an independent EM&V contractor for analysis subject to such EM&V contractor entering into a written agreement with nest governing the use and protection of such data.

1.6.3 Data Quality

The data underlying the analysis for this work paper were obtained from two sources that provide the best-available data on the subject of thermostat usage by real customers in California. It is likely that this study is the largest smart thermostat energy savings study ever conducted. The two sources are:

1. RASS survey data:
    a. CA customer set points and setback behavior for heating and cooling
    b. Average HVAC system sizes for CA customers
2. Data from more than 100,000 Nest Thermostats currently installed in CA:
    a. Heating and cooling comfort temperatures calculated automatically by each thermostat
    b. Actual average set points
    c. Actual runtime
    d. Furnace fan usage
    e. Divided by climate zone
    f. Heating and cooling data combined provides 13 million days of data
    g. No thermostats were excluded from the analysis ensuring the average savings estimates incorporate energy increases and decreases

1.6.4 Future Data Needs

Firmware Updates

One of the benefits of connected products within the home is that they can be easily updated with the latest software to help ensure they stay up to date. Many of the thermostats that will meet the requirements of this workpaper will have the capability to do "over-the-air" firmware updates. In general, these updates will benefit customers through increased functionality, security, and likely increased energy savings. It is worth noting, that to remain eligible, devices need to continue to maintain the ability to meet the technical requirements outlined in Section 1.2 Technical Description.

Coincident Peak Demand

A future iteration of this work paper would benefit from a study of the coincident peak demand reduction delivered by smart thermostats.

Baseline Adjustment Factors

CalTF members discussed the fact that the RASS Base Case Calibration factor as outlined in Section 2.3.5 results in savings estimates that are likely too conservative, as they remove all energy savings benefits from customers who have a setback schedule, ignoring the impacts of features like Auto-Away that reduce HVAC usage when a customer is not home. Future analysis could be completed to refine the approach - potentially through updated surveys as well as a potential billing data study, if it is possible to capture a large enough sample size to be relevant.

Installation

To help address concerns about rebated devices getting installed in California (versus a customer purchasing and not installing, or purchasing in CA and getting a rebate, but installing outside of CA), the IOU's could collect the device serial number for the eligible thermostats during the rebate application process and then get semi-regular reports from device manufacturers that includes data on the percent of devices that were installed in CA.

Behavior Savings

Smart Thermostats have may features built into them to automate energy savings for customers. In addition, many of them include features that engage customers further with their energy usage - such as monthly reports and phone and web applications. The calculation methodology outlined in Section 2 of this document does not include any incremental savings driven through behavior change (non-smart thermostat driven behavioral savings) as the savings estimates are calculated through HVAC system run time reduction, not whole house billing analysis. A future study could include aspects to determine if incremental behavior savings are present. Not including those savings further supports the conservative savings estimates outlined in this workpaper. This is further discussed in Section 2.3.11 Conservative Assumptions.

Net-To-Gross Evaluation Study

It is recommended that an EM&V study be designed and completed to capture appropriate customer survey data and information needed to update the default NTG value.

SECTION 2. CALCULATION METHODOLOGY

The calculation methodology outlined in this section is a large scale analysis of the efficiency of Nest customer thermostat set point schedules with projected heating and cooling savings as compared to baseline behavior using pooled Fixed Regression Model and Comfort Temperature Analysis.

The table below outlines the differences between this workpaper and the initial interim gas savings workpaper submitted by Southern California Gas Company.

Work Paper Input	SCG Work Paper (previously submitted)	Nest-SCE Work Paper (this document)
Study design	RCT with matched control group	Pooled fixed effects regression model and comfort temperature set point analysis
Sample size	~500 thermostats	Over 150,000 thermostats (CA Specific)
Data Collection Period	Winter 2014 - 2015	May 2015 – April 2016
Climate zones captured in input data set	8, 9, 10, 15, 16	1 (heating only), 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16
End-uses analyzed	Heating	Heating and cooling
Demographics	Single Family Home	Single Family Home

2.1 Overview

The analysis of actual thermostat settings, combined with pooled fixed regression modeling, described in this paper provides estimates of energy savings from Nest Learning Thermostats installed in California's unique climate zones, which are widely understood to be generally milder than most regions in the United States. For a broader assessment of Nest's energy savings based on pre/post billing data analysis across the United States, please see the white paper "Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results," released by Nest in February, 2015.[7]

2.2 Methodology Overview -- Leveraging the emerging EnergySTAR®metric

The overall energy savings estimation is based on four steps:

1. **Analyze Nest customer temperature set points to assess the efficiency of their schedules.** This analysis calculates average (i.e., mean) set points and "comfort temperatures" for the heating and cooling seasons for each customer. The "comfort"

[7] Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results, Feb. 2015. https://nest.com/downloads/press/documents/energy-savings-white-paper.pdf

temperatures -- defined as the 90th percentile of the customer's heating set points and the 10th percentile of their cooling set points -- are meant to represent typical settings when people are home and want to be comfortable. This definition is based on a similar approach to the current working definition being used by the EPA in their development of a smart thermostat metric for EnergySTAR®. the output of this analysis creates one comfort temperature setpoint for the heating season (specific to each thermostat/customer) and one comfort temperature setpoint for cooling season. These set points define the customer's flat schedule to estimate savings per Step 3. As described below, the savings estimates are then adjusted by the RASS Baseline Calibration Factor to account for the fact that some people do not live exclusively with a flat temperature baseline.

2. **Estimate the percent change in heating and cooling runtime per degree change in temperature set point using a regression model fit separately for each climate zone.** This step is also similar to the current EPA metric except it employs a pooled model rather than aggregating across individual device-specific models.
3. **Estimate the heating and cooling energy savings compared to a constant set point at the comfort temperature.** The savings are calculated based on the savings per degree set point change found in step 2 and the difference between the average and comfort temperatures calculated in step 1. Again, this basic approach is being used in the EPA metric.
4. **Adjust the overall savings calculated in step 3 to account for customer's maintaining more efficient average baseline set points than a constant comfort temperature.** This step is not being used in the EPA metric because the EPA goal is to develop a metric of set point efficiency. Energy savings could then be calculated as the difference between a thermostat's efficiency metric and the efficiency of any specified baseline condition. The method for this calibration is outlined in Section 2.3.5 using RASS base case data.

This methodology is based on actual smart thermostat temperature settings compared to an occupant's preferred comfort temperature (i.e. the temperature most likely "set" on manual thermostats or older programmable thermostats that are used in 'hold' mode or without an effective schedule). Temperature setbacks on smart thermostats are driven by features to automatically generate more efficient schedules for customers. As previously mentioned, the structure is quite similar to the current metric under development by EPA. The methodology is outlined in more detail below. For additional details outlining the specific calculations underlying the EPA approach, those can be reviewed in a recent ACEEE paper, Do Connected Thermostats Save Energy? [17].

Measure Impacts Scaling for MF and DMo

Measure impacts for MF and DMo Residential building types (for both electric cooling - kWh and gas heating - Therms) were estimated by scaling measure impacts on SFM with scaling factors determined using DEER2017 residential system upgrade measure – "RE-HV-ResAC-lt45kBtuh-15S."

The DEER2017 measure and scaling factors are included in the calculation workbook under the "DEER_Scaling" workbook tab – See Attachment 1.

2.3 Methodology Details

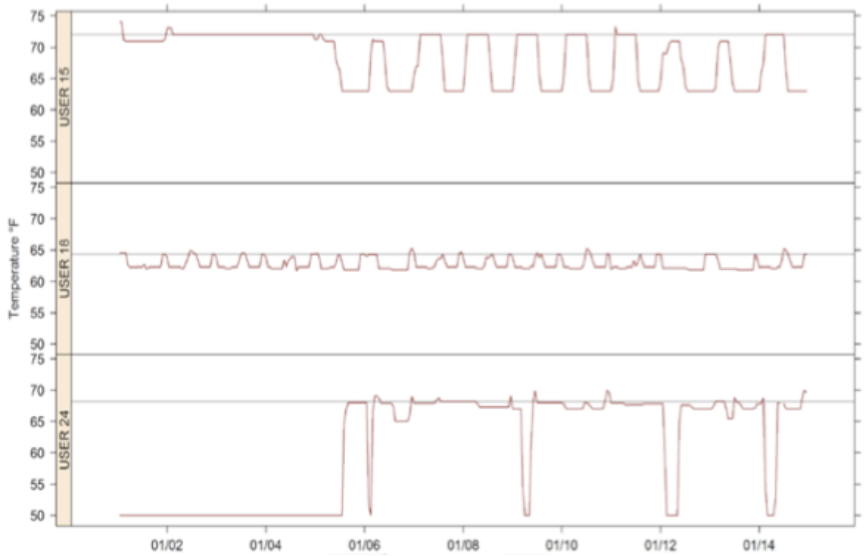
2.3.1 Determining individual customer comfort temperature (Step 1)

The methodology leverages the concept of a comfort temperature, which can be thought of as the temperature at which a given individual prefers to keep their home during a particular season.

- **Heating season comfort temperature:** a customer's preferred temperature during the Winter.
    - Defined as the 90th percentile of target temperature set points for a particular customer throughout a heating season (i.e. only 10% of the time during the heating season does this customer have a warmer temperature set point).
    - This comfort temperature is automatically calculated by each Nest Thermostat for each month. The seasonal average comfort temperature for each customer was calculated as the heating run-time weighted average across the season.
    - Heating data from January, 2016 - February, 2016.

- **Cooling season comfort temperature:** a customer's preferred temperature during the Summer.
    - Defined as the 10th percentile of target temperature set points (i.e. only 10% of the time during the cooling season does this customer have a cooler set point).
    - Same calculation approach as for heating season.
    - Cooling data from July, 2015 – September, 2015.

Chart indicating heating comfort temperatures for a few customers compared with time series plots of hourly temperatures is shown below.



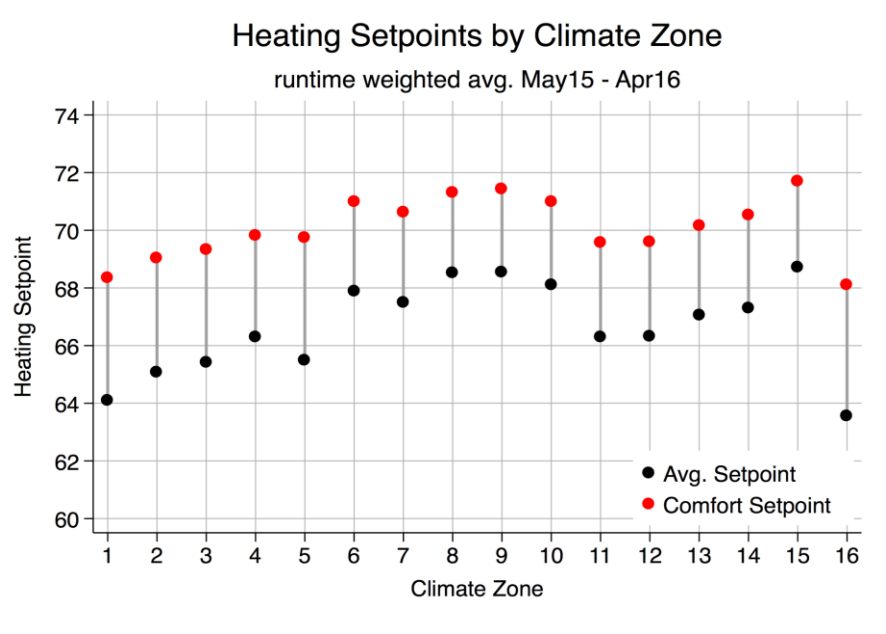
"Comfort" temperature = 90th percentile of heating set points. This chart shows that comfort temperature, in this case at the 90th percentile, can be reliably calculated and subsequently compared to average set points. As you can see, the 90th percentile is a good characterization of the common temperature people prefer when they are at home and want to be comfortable.

As discussed, the output of this analysis creates one comfort temperature setpoint for the heating season (specific to each thermostat/customer) and one comfort temperature setpoint for cooling season. These set points define the customer's flat schedule to estimate savings as outlined in Section 2.3.2. As described below, the savings estimates are then adjusted by the RASS Baseline Calibration Factor to account for the fact that some people do not live exclusively with a flat temperature baseline.

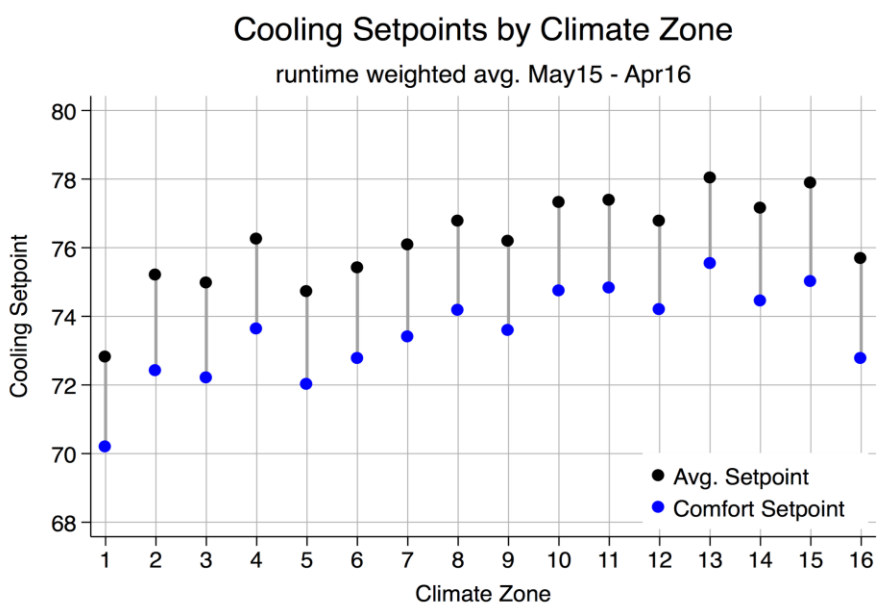
2.3.2 Average set points vs. comfort temperature (Step 2a)

The comfort temperature described above defines a baseline condition of a flat schedule (i.e. one without heating set-backs or cooling set-ups). The difference between the actual average set points and the comfort temperatures for each device is a measure of the efficiency of each customer's schedule resulting from Nest's feature set and customer preferences. We recognize that the flat comfort temperature baseline may understate the efficiency of prior thermostat setting behaviors and so we added a final step to adjust the calculation results to reflect a more efficient baseline.

Figures 2 and 3 below show the average comfort temperatures and average set points aggregated by climate zone (thermostats aggregated by climate zone based on zipcode). The connecting lines in each chart illustrate the impact of setbacks on the set point.



Heating set points by climate zone (runtime-weighted average May 2015 - April 2016). The data show a clear difference between comfort temperature and average set points. This difference drives a decrease in HVAC runtime and therefore energy savings.



Cooling set points by climate zone (runtime-weighted average May 2015 - Apr 2016). The data show a clear difference between comfort temperature and average set points.

2.3.3 Pooled Fixed Effects Regression Model (Step 2b)

The analysis of set points provides an estimate of the difference between the baseline comfort temperature and the average actual set points for each thermostat. The impact of these changes on HVAC run time, and on energy use, need to be estimated. The next step in the analysis was to fit a pooled fixed effects regression model to estimate the impact of thermostat set points on HVAC run time, accounting for weather. This analysis estimates the HVAC runtime savings expected from each °F reduced from an occupant's comfort temperature.

The regression modeled average daily HVAC runtime as a function of degree days (HDD60 for heating and CDD65 for cooling) and average set point and included thermostat level fixed effects. In Stata, the code for the heating model was.

```
xtreg heating_hours HDD60 heating_setpoint , i(thermostat_id) fe
```

The percent energy savings per degree F change in set point was calculated as the coefficient on the temperature set point term divided by the average daily hours of runtime in the dataset. The Stata code to calculate the estimate and its standard error was:

```
sum heat_hrs if e(sample), meanonly
lincom _b[tset_ht]/`r(mean)'
display "Percent Savings per F = "  r(estimate)
display "standard error = " r(se)
```

The percent energy savings per degree F change in set point was calculated as the coefficient on the temperature set point term (e.g., tset_ht above) divided by the average daily hours of runtime in the dataset. The Stata code to calculate the estimate and its standard error was, immediately following the xtreg command::

```
sum heat_hrs if e(sample), meanonly
lincom _b[tset_ht]/`r(mean)'
local pctsave_perF = r(estimate)
local pctsave_perF_se = r(se)
```

The output of the regression models -- expressed as percent HVAC runtime reduction per degree F -- are shown in Section 3.

Shoulder Periods: The analysis of set points and comfort temperatures was based on a full year of data. The regression modeling of how set points affect runtime, however, was restricted to the main portions of the heating and cooling seasons to provide the most robust indication of how set points affect runtime. Mild weather periods, where set points are more likely to be non-binding, can make the modeling results less reliable while trying to estimate impacts during periods of lower runtime.

2.3.4 Calculating energy savings estimated by regression model (Step 3)

After fitting the regression models, the raw percent energy savings for each climate zone were calculated as the difference between comfort and actual set points multiplied by the percent savings per degree F for that climate zone. To estimate energy savings these percent savings need to be applied to the estimated energy use of the heating and cooling systems. This energy use was estimated from the actual HVAC run time multiplied by the estimated energy input rate -- which is an estimate of post-retrofit energy use. Given that we have an estimate of post-retrofit energy use instead of pre-retrofit, the raw percent savings values need to be adjusted as shown below. Note that this approach ensures that increases and decreases in HVAC run times are incorporated in the average savings values that are created.

Adjusted % Energy Savings = 100%/(100% - raw % savings) -100%

So, for example, if the raw percent savings were 50% of heating and the heating use was 100 therms, then the true savings should be 100 therms -- the system would have used 200 therms but only used 100 therms. So the percent savings adjusted to be applied to post-retrofit usage is 100%/(100%-50%) -100% = 100% of post use.

These adjusted percent savings were used to estimate kWh and therm savings by multiplying them by the product of the average run times in each climate zone and the estimated system input capacities (as defined by DEER 2005 prototype home, discussed in Section 3.1).

Energy Savings estimated by regression model - Heating

Adjusted % energy savings x Average heating run time (by climate zone) *x DEER system size (by climate zone, Section 3.1) = Energy Savings estimated by regression model*

Energy Savings estimated by regression model - Cooling

Adjusted % energy savings x Average cooling run time (by climate zone) *x DEER system size (by climate zone, Section 3.1) = Energy Savings estimated by regression model*

It should be noted that some individual cases may trend in negative direction (increase energy usage). In other words, they will use more energy once a smart thermostat is installed. These outliers were not removed from analysis and therefore the approach truly captures the average energy savings per thermostat.

2.3.5 RASS Base Case Calibration (Step 4)

Why it's needed

To ensure the baseline approach outlined in this workpaper follows an approach similar to the 2004-2005 DEER update[9] (which updated the savings estimate from a base case of a flat-schedule to a blended average schedule based on RASS data), the analysis outlined in Section (2.3.1-4)

needs to be adjusted as well to account for the fact that by definition the EPA savings methodology leveraging the comfort temperature utilizes a flat-schedule base case. The RASS database confirms the fact that a portion of California customers do in fact have a setback schedule. Also, utilizing a flat-schedule baseline is inappropriate for a workpaper as it would asses the maximum savings versus the average savings appropriate for a deemed measure.

Approach

The 2009 Residential Appliance Saturation Study (RASS)[10] resulted in end-use saturations for 24,464 individually metered and 1,257 master-metered households and administered as a mail-in study. The sections of particular relevance to this workpaper are the Space Heating and Spacing Cooling Questions. One specific question in each section had a purpose of determining average thermostat temperature set points and are shown below as question B6 and C6. The average heating customer that had a flat schedule would select all of the bubbles in the 66-70° column. Those that utilize a setback schedule would move their answer up or down a column - signifying thermostat setting movement during that time period. There were roughly 10,200 heating customers and 5,800 for cooling across California who answered this question - making it one of the more robust datasets on self-reported thermostat behavior.

B6 If your main heating system is controlled by a thermostat, what is the average thermostat temperature usually set for each time period during the heating season? *(Choose one answer for each time period. Provide the average setting if it varies.)*

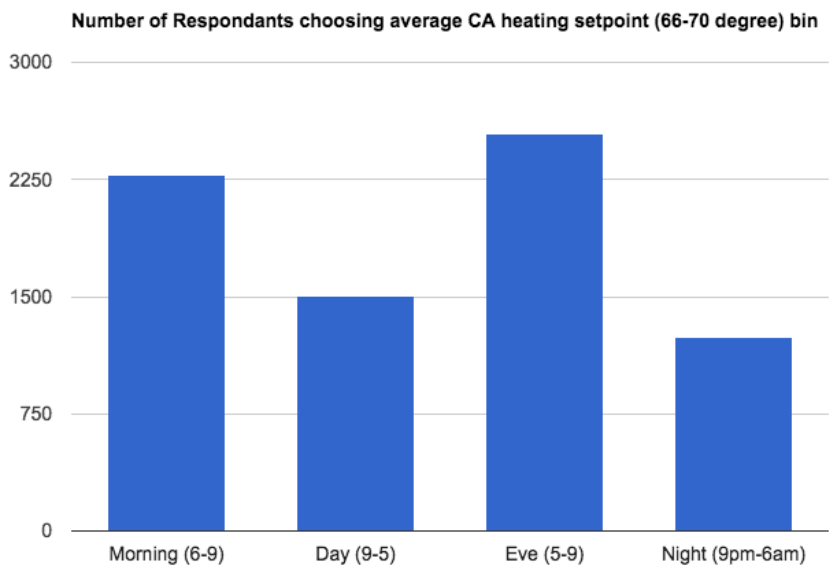
	Off	Below 55°F	55 – 60°F	61 – 65°F	66 – 70°F	71 – 75°F	Over 75°F
Morning *(6am-9am)* (HMRNSET)	1	1	1	1	1	1	1
Day *(9am-5pm)* (HDAYSET)	1	1	1	1	1	1	1
Evening *(5pm-9pm)* (HEVNSET)	1	1	1	1	1	1	1
Night *(9pm-6am)* (HNITESET)	1	1	1	1	1	1	1

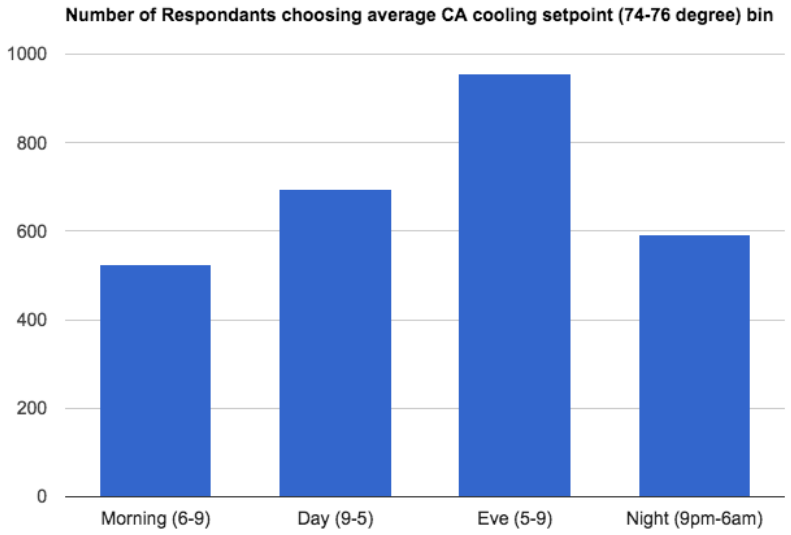
C5 What is the typical thermostat temperature setting of your main central cooling system for each time period during the cooling season? *(Choose one answer for each time period.)*

	Off	Below 70°F	70 – 73°F	74 – 76°F	77 – 80°F	Over 80°F
Morning *(6am–9am)* (CMRNSET)	1	1	1	1	1	1
Day *(9am-5pm)* (CDAYSET)	1	1	1	1	1	1
Evening *(5pm-9pm)* (CEVNSET)	1	1	1	1	1	1
Night *(9pm-6am)* (CNITESET)	1	1	1	1	1	1

A key question for our analysis is what percentage of customers utilized a thermostat schedule that included setbacks. To create a baseline percentage, we analyzed the compiled answers[11] for Single Family Home responses and analyzed how schedule patterns changed throughout the day. To begin, we examined the average heating and cooling set points as found in the RASS study and compiled in DEER 2004-2005 supporting analysis[12]. The average heating set point is 66.8 and the average cooling set point is 75.4. If all RASS respondents had a flat schedule set at the average temperature set point, they would have filled in the circle in the 66-70° F column and 74-76° f column for cooling.

As described, temperature set point movement out of the average column was used to estimate the percentage of customers who have day or nighttime setbacks in their thermostat schedule. Selecting to review movement out of the average temperature bins was selected as it produced the most conservative estimates. If we had included customer answers from the other temperature bins using the same method, savings would be increased. This approach also assumes that any movement out of those temperature bins is in the more efficient direction - which we know is not the case as some customers like it cooler in the evening vs warmer due to their sleeping temperature preferences. Finally, since this approach is built using customer surveys, it inherently includes a customer's bias towards providing answers on how they feel they should be setting their schedule vs reality. This selection bias and conservative assumptions are documented in Section 2.5.11.





As can be seen in the charts, had everyone reported they had a flat schedule, these charts would be flat across. In the heating set point chart for example, you can see a clear reduction in the number of people in the average temp range during the day and night. To calculate the percent of customers with a setback schedule, we used the difference in the fraction of customer responses from evening to night as it is the most conservative approach (i.e. results in a higher % of customers with setback schedules for their baseline). The calculations used are outlined below and the baseline correction factors are listed in Table below. The night setback percentage was calculated for both heating and cooling (nighttime setback was used instead of daytime setback because the percentage of customers exhibiting nighttime setback behavior was higher than that of customers exhibiting daytime setback behavior, resulting in a larger, and therefore more conservative, reduction in the savings estimates).

<u>Night Setback Customers</u>

% of customers with night setback schedules = 1- (# evening respondents - # of night respondents) / (# evening respondents)

RASS Baseline Correction Factors

Operating Mode	Correction Factor
Heating	49%
Cooling	62%

These calibration factors are then applied (multiplied) to the heating and cooling savings estimates generated through the comfort set point analysis (which generates a flat-schedule savings

estimate) to develop the RASS baseline adjusted savings result tables as outlined in Section 3. This approach is likely overly conservative because it essentially eliminates any additional potential savings from customers that have a night setback but also use features like auto-away as captured through occupancy sensors and mobile phone presence. This calculation method ensures that the work paper savings are based on the best available data as well as being a conservative estimate. If more data or analysis becomes available to quantify those savings in the future they should be reviewed for potential inclusion.

Average temperature set points vs. indoor air temperature: During the work paper feedback process, members of the CALTF asked for clarification as to why the average temperature set point was used in the regression model instead of indoor air temperature. The primary driver of this question was a concern that using average set point could potentially overstate savings because HVAC systems do not instantly achieve the target set point. The second concern was that using a runtime analysis, instead of sub-metered HVAC data, could potentially overestimate savings if runtime were shifted to a cooler part of the day later in the evening.

This analysis focused on set point data instead of indoor temperature data because set points, unlike ambient temperatures, are something that customers can recall for the purposes of a survey. Indeed, the RASS thermostat survey data used as a baseline calibration factor for this study asked customers to indicate thermostat set points.

However, it is important to validate that the set point approach is reasonable given best-available data from a recent analysis that used sub-metered HVAC data. This section describes how that comparison was made for the purpose of leveraging sub-metered study data to validate the analysis herein.

The Florida Solar Energy Center recently published a study (see Section 1.5.8), based on a detailed sub-metering analysis of HVAC systems 28 homes that were equipped with smart thermostats. This study includes a full year of sub-metered, hourly temperature data, along with corresponding pre and post heating and cooling system operational data. This detailed data collection included the time periods prior to and after installation of the smart thermostat, which enabled a detailed evaluation of temperature-related changes.

The Florida study found an average of 9.5% savings for both heating and cooling. To ensure that the regression modeling approach outlined in this work paper will deliver savings results that are consistent with a sub-metering approach, which is indifferent to timing of runtime throughout a day and indoor temperatures vs. set points, we ran the same regression model described in this paper for Nest Thermostats currently installed in Florida. Using the same RASS baseline calibration factors to account for existing customer setback behavior in Summer and Winter, our analysis estimated 11% cooling savings and 8% heating savings for customers in Florida. Comparing these results to the 9.5% heating and cooling savings found in the Florida Solar Energy Center study provides a level of comfort that the regression approach using set point and comfort temperature

data, along with the RASS calibration factor, produces results in-line with a sub-metering approach.

End-Use Category	Savings Estimates: Florida Solar Energy Center Study based on sub-metered HVAC data	Savings Estimates: set point regression model used in this work paper, but based on data from thermostats installed in Florida	Delta
Heating Savings	9.5%	8%*	-1.5%
Cooling Savings	9.5%	11%*	+1.5%

Further supporting this argument are the results from the recent PG&E smart thermostat study as outlined by the table in Section 2.3.9. The savings estimates from this study also show that the output of the analysis method outlined in this workpaper are creating reasonable savings estimates.

2.3.7 Second Baseline Savings Adjustment

Based on feedback from CalTF and Ex-ante team during the development of the workpaper, the second baseline assumes a portion of the market is utilizing smart thermostats (vs just programmable thermostats) - as market share is currently very low but continues to grow. To account for this, the savings values during the second baseline period are reduced. To adjust for the fact that the install base of smart thermostats will have grown from measure installation to the start of the 2nd baseline period (3.6 yrs) a reduction factor is applied based on the forecasted market adoption of smart thermostats – at the point of transition to 2nd baseline. The methodology and calculation of that reduction factor is included in the Attachment section and utilizes best available third party market data to support the analysis. To calculate the second baseline savings values, the savings numbers in Section 3.2 table below are reduced by 5.79%.

2nd Baseline Savings Reduction Factor	5.79%

2.3.8 Method incorporates increases and decreases in energy usage

The analysis is based on average impacts and average baselines -- these values in no way preclude having negative savers in the mix and their increased usage is included in the output of the analysis. In other words -- customers with usage increases are accounted for in the analysis.

This approach accounts for the feedback received from some comments that some customers may increase usage once they have remote control capability - ie turning the ac/heat on before they get home. All of these setpoint changes are captured and studied in the analysis and therefore included in creating the average savings.

2.3.9 Comparison to PG&E Smart Thermostat Study

PG&E's study consisted of homes in climate zone 11, 12, and 13. The average electric savings from those climate zones was compared to the output of the methodology outlined above and compiled in the table below. The climate zones selected for PG&E's study were intentionally selected to provide a reliable estimate of electric savings. Because of the relatively low proportion of heating degree days in these climate zones compared to the wider PG&E territory, and CA as a whole, the gas savings identified in this study should be considered preliminary because they are likely not a reliable estimate of gas savings outside these three specific hot climate zones. While the second year of PG&E's study will provide additional data, the findings relating to gas savings will continue to have limited relevance beyond the study's three climate zones. Further research is needed in climate zones with a higher proportion of heating degree days.

Climate Zones	Fuel	PG&E Study Average	Workpaper Analysis Avg
11, 12, 13	Electric	278 kWh	253 kWh
	Gas	5.3 therms	21 therms

2.3.10 Comparison to SCG Smart Thermostat Study

SCG's study consisted of homes in climate zone 6,8,9. The average gas savings from those climate zones was compared to the output of the methodology outlined above and compiled in the paper below.

Climate Zones	Fuel	SCG Study Average	Workpaper Analysis Avg
6,8,9	Gas	16.3* therms	10 therms

* Due to the unusually mild winter in 2014-2015, Navigant also estimated savings under a typical meteorological year

2.3.11 Compilation of Conservative Assumptions

Below is a list of list of all conservative assumptions that were made through the methodology and calculation methods outlined in this workpaper.

- Assumed *none of the* customers showing setback behavior will save energy from features that are driven from occupancy sensors or geo-fencing - like Auto-Away and Auto-Schedule, as the way we are applying the RASS Baseline Correction factor essentially removes all savings from this population
- This analysis does not include any behavioral driven savings as discussed in Section 1.6.4, likely understating the overall impact of smart thermostats and the savings they can enable.
- The method of creating the RASS Baseline Correction Factor likely overestimates setback behavior given customer bias in survey responses over-estimating efficient behavior as this California specific study suggests. In the study, Comparison Of Self Reported And Measured Thermostat Behavior In New California Houses[13] they state "Respondents

under reported their heating set points and over reported their cooling set points" (ie they responded a more efficient set point versus their actual set point). This behavior was corroborated in a Pacific Northwest study[14], a Michigan State University study[15], and this New England study[16].

- The RASS Baseline Correction factor was set using the percentage of customers who had a nighttime setback schedule only - versus including the percentage of customers who had a daytime setback. This choice was made as including the daytime setback percentages increased energy savings (reducing the correction factor) produced the most conservative estimate
- The RASS Baseline Correction factor was set through looking at movement out of the average heating and cooling set points - signifying that they had a setback schedule. We did not include movement out of the other temperature bins in the RASS study as the percent of customers moving out of other temperature bands was lower, so we are applying the biggest savings reduction possible based on RASS data
- The RASS Baseline Correction factor methodology assumes everyone who moves out of the average temperature band does so in an efficient direction, although we know some customers move to inefficient temperatures at night (i.e. some make their homes cooler at night in the Summer)
- For the ROB method, the baseline for this measure should technically be state code, which would be programmable thermostats, but it was determined to instead adjust our savings estimates by a calibration factor built off of RASS customer survey data indicating setback behavior (description below). A baseline strictly made up of programmable thermostats would have increased energy savings estimates, as it is documented [12] that programmable thermostats actually increase energy usage over manual thermostats, and therefore would have increased our savings estimates. This approach aligns with the guidance to provide reasonable and conservative estimates.

2.3.12 Calculation of Energy Savings Results Tables

<u>First Baseline - Calculation for Cooling</u>

Savings estimated by regression model (Section 2.3.4) x RASS baseline calibration factor (Section 2.3.5) x PG&E Study Adjustment Factor = Energy Savings (Section 3.2)

<u>First Baseline - Calculation for Heating</u>

Savings estimated by regression model (Section 2.3.4) x RASS baseline calibration factor (Section 2.3.5) = Energy Savings (Section 3.2)

<u>Second Baseline - Calculation for Heating and cooling</u>

First Baseline Energy Savings x (1 - 2nd Baseline Adjustment (Section 2.5.7)) = Energy Savings (Section 3.2)

3.0 Results

3.1 System sizing assumptions

The system capacity sizing assumptions are based on 2005 DEER default house characteristics (Air Conditioner kW and Furnace kBtu/hr). For Furnace Fan kW, these values are averages across thermostats and were generated based on an automated system-sizing algorithm developed by Nest and primarily driven by local design temperatures.

System Sizing Assumptions

California Climate Zone	Air Conditioner kW	Furnace kBtu/hr	Furnace Fan kW
CZ01	Not used	Not used	Not used
CZ02	3.58	49	0.49
CZ03	3.08	42	0.33
CZ04	3.10	43	0.44
CZ05	3.52	49	0.41
CZ06	3.37	48	0.37
CZ07	2.79	41	0.41
CZ08	3.49	48	0.48
CZ09	3.68	50	0.66
CZ10	3.74	54	0.64
CZ11	3.53	51	0.72
CZ12	3.51	50	0.66
CZ13	3.38	49	0.73
CZ14	4.43	61	0.75
CZ15	4.21	51	0.77
CZ16	3.28	45	0.50

System Efficiency impacts on savings estimates: During the work paper feedback process, There was also some questions raised about the impact of variations in air conditioner power draw and cycling losses and how these factors may affect the estimated savings from smart thermostats.

The workpaper does not assume that the air conditioners are operating at peak load all year. The connected KW values used in the savings analysis were calculated from DEER prototype homes. The calculation was KW= ACtons * 12,000 / (SEER * 1,000). This calculation used SEER values and not EER values which would have estimated power draw during approximately peak conditions. By

using the SEER value, the power draw estimate is reduced to a level more consistent with average power draw. This calculation has an added conservatism because it does not adjust for actual air handler power draws that are typically greater than the default value used in SEER.

There was also questions raised that using a constant power draw estimate may not accurately reflect savings due to how air conditioner KW draw varies with outdoor temperature (and, to a lesser extent, indoor wet bulb). Power draw typically increases by about 1% per degree F increase in outdoor temperature. If the changes in cooling set points from a smart thermostat led to a significant shift in cooling runtime toward times with higher outdoor temperatures, then the analysis could over-state energy savings. But the impact of a smart thermostat on cooling schedules would likely include more efficient set point temperatures during the hottest hours of the day when homes are less likely to be occupied. The net impact would be expected to shift runtime from hottest hours of the day to later in the afternoon and evening. This change would actually result in greater savings than the current analysis approach, not less savings. A significant overall shift of cooling to times of hotter outdoor temperatures seems an unlikely result.

3.2 First and Second Baseline Heating and cooling savings by CA climate zone

Following Tables shows the key results from the analysis by climate zone. The T-diff columns shows the average difference between the comfort temperature and actual average set point for each climate zone. The % Savings/°F columns show the estimated percent change in HVAC run time per degree change in set point. The Savings columns show the overall results from calculating energy savings using the T-diff and % Savings/°F columns in a calculation with the average annual HVAC run time hours (for the period May 2015 through April 2016) and the estimated average HVAC system input capacities, and then reducing those savings the RASS Base Case calibration factor as outlined in Section 2.3.5.

The table below shows that the analysis found meaningful kWh and therm savings across California's climate zones (no results shown for Climate zone 1 because of a limited sample size of data). Absolute savings values are higher inland, but still impactful in coastal zones.

For scaled measure impacts on MF and DMo Residential Building types refer to calculation sheet – Attachment 1.

First Baseline Savings by CA Climate Zone.

California Climate Zone	Cooling T-diff (comfort temp - avg actual setpoint)	% Cooling HVAC Savings/degree Fahrenheit difference (regression output)	Cooling Savings (kWh)	Heating T-diff (comfort temp - average actual setpoint)	% Heating HVAC Savings/degree Fahrenheit difference (regression output)	Heating Savings (kWh from furnace fan)	Total Gas Savings (therms)	Total Electric Savings (kWh)
CZ01	Cooling sample too small - leverage kWh savings from furnace fan reduction			4.27	10.9%	26	**49**	**26**
CZ02	-2.79	-8.1%	123	3.96	9.5%	26	**31**	**149**
CZ03	-2.77	-7.6%	84	3.91	9.5%	18	**29**	**102**
CZ04	-2.63	-7.8%	96	3.54	8.7%	17	**21**	**113**
CZ05	-2.71	-6.1%	77	4.27	7.9%	14	**20**	**91**
CZ06	-2.64	-7.8%	106	3.08	9.1%	8	**10**	**114**
CZ07	-2.68	-7.6%	113	3.14	9.6%	8	**10**	**121**
CZ08	-2.60	-7.5%	143	2.79	8.0%	7	**8**	**151**
CZ09	-2.60	-7.0%	207	2.89	7.5%	14	**12**	**221**
CZ10	-2.56	-8.2%	196	2.88	8.2%	11	**10**	**207**
CZ11	-2.56	-10.1%	261	3.29	9.7%	28	**23**	**289**
CZ12	-2.57	-9.0%	178	3.26	9.4%	25	**23**	**203**
CZ13	-2.50	-9.6%	319	3.11	9.8%	23	**19**	**341**
CZ14	-2.70	-8.9%	275	3.22	9.0%	27	**25**	**302**
CZ15	-2.86	-9.2%	391	2.99	10.8%	11	**7**	**402**
CZ16	-2.93	-8.4%	167	4.56	7.8%	35	**56**	**202**

Second Baseline Savings by CA Climate Zone.

California Climate Zone	Total Gas Savings (therms)	Total Electric Savings (kWh)
CZ01	47	24
CZ02	30	141
CZ03	28	97
CZ04	20	106
CZ05	19	86
CZ06	10	108
CZ07	9	114
CZ08	7	142
CZ09	11	208
CZ10	9	195
CZ11	22	272
CZ12	21	191
CZ13	18	321
CZ14	24	284
CZ15	7	379
CZ16	53	190

3.3 Comparison of Results to Prominent Independent Smart Thermostat Evaluations

The table below was compiled by the IOU's after extensive review of all smart thermostat studies that have been completed (Attachment 6) The studies below were selected as meaningful and relevant comparison studies and show the estimated percentage of HVAC savings resulting from the analysis in this work paper compared against the savings percentages estimated in well-regarded third party studies of smart thermostats in other jurisdictions across the U.S. The estimates for this work paper are well within a reasonable range of savings estimates compared to these other studies.

Study Title	Study Location	Study Sponsor	Author	Publish Date	Heating Savings	Cooling Savings	Coincident Demand Savings
PG&E Smart Thermostat Study: First Year Findings	California	Pacific Gas and Electric	Applied Energy Group	12/21/2016	**5.3 therms (avg)***	**4% savings at the meter (7-11%** cooling savings)**	N/A
Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results	National	Nest	Nest	2/1/2015	**9.6%**	**17.5%**	N/A
Evaluation of the 2013–2014 Programmable and Smart Thermostat Program	Indiana	Vectren (utility)	Cadmus	1/29/2015	**11-14%**	**9-19%**	N/A
A Look Inside the Eye on the Wall: Sub-metering Data Analysis and Savings Assessment of the Nest Learning Thermostat	Washington	Bonneville Power Administration	Bonneville Power Administration	Summer, 2016	**12.35% of heating/cooling (heat pump)**	**12.35% of heating/cooling (heat pump)**	N/A
Energy Trust of Oregon Smart Thermostat Pilot Evaluation	Oregon	Energy Trust of Oregon	Apex Analytics	3/1/0206	**6% control group adjusted - 10% non-control group adjusted**	**N/A**	N/A
Evaluation of the Space Heating and Cooling Energy Savings of Smart Thermostats in a Hot-Humid Climate using Long-term Data	Florida	Florida Solar Energy Center	Florida Solar Energy Center	6/6/2016	**9.5%**	**9.5%**	0.39 kW (4PM - 5PM)
Nest Learning Thermostat Pilot Study (SCG)	California	Southern California Gas	Navigant	8/29/2016	**2.3% and 5.4% (TMY)**		
Regression Model for this Work Paper	California	Southern California Edison	SCE, Nest Labs	Draft in September, 2016	**11%**	**12%**	N/A

*PG&E's study was designed to capture and estimate electric savings, not gas savings. Preliminary gas savings values are unusually low and being further analyzed at this time. Monitoring period for gas savings has been extended and can be updated when complete.

**Cooling savings were not calculated/estimated in the PG&E study, range is rough approximation

3.3.1 Comparison Report Summaries

Study: PG&E Smart Thermostat Study: First Year Findings[35]
Techniques used: Randomized Encouragement Design (RED) -Pooled Fixed Effects / Difference-In-Difference with adjustment for opt-in/out
Study Size: ~2200

Study: Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results[18]
Techniques used: 2-stage normalized / Pooled Fixed Effects
Study Size: National Sample

Study: Evaluation of the 2013–2014 Programmable and Smart Thermostat Program[20]
Techniques used: Combination of billing data, metered data, and customer survey data
Study Size: ~200

Study: A Look Inside the Eye on the Wall: Sub-metering Data Analysis and Savings Assessment of the Nest Learning Thermostat[29]
Techniques used: Pooled Fixed and Random Effects Model including "OAT Method" and "delta-t"
Study Size: 176 homes

Study: Energy Trust of Oregon Smart Thermostat Pilot Evaluation[19]
Techniques used: Two-Stage Sample Randomization Design / Billing analysis
Study Size: ~380

Study: Evaluation of the Space Heating and Cooling Energy Savings of Smart Thermostats in a Hot-Humid Climate using Long-term Data[23]
Techniques used: Sub metered data - method to analyze retrofit influences based on response to weather (and weather normalization)
Study Size: 24

Study: Nest Learning Thermostat Pilot Study (SCG)[32]
Techniques used: A post-program period regression model, a one-way linear fixed effects regression model, and a two-way linear fixed effects regression model.
Study Size: 505

SECTION 4. LOAD SHAPES

The closest load shapes that are applicable to the measures in this work paper are listed in the table below.

Building Types and Load Shapes

Building Type	Load Shape	E3 Alternate Building Type
RES	DEER:HVAC_EFF_AC	-

SECTION 5. COSTS

This wp consulted three readily available sources to document base case, measure case and incremental measure costs including:

1. 2010-2012 Work Order 17 Ex-Ante Measure Cost Study Final Report
2. 2008 DEER Measure Cost Summary Spreadsheet
3. Online Retailers Point of Sale Data

5.1 BASE CASE COST

2010-2012 Work Order 17 Ex-Ante Measure Cost Study Final Report

The 2010-2012 Work Order 17 (WO17) Ex-Ante Measure Cost Study Final Report was first consulted to see if updated base case costs were provided for setback programmable thermostats. WO17 does not provide base case costs for setback programmable thermostats. Given that WO17 does not provide base case costs for setback programmable thermostats, the 2008 DEER Measure Cost Summary Spreadsheet was consulted.

2008 DEER Measure Cost Summary Spreadsheet

The base case material cost for setback programmable thermostats within the DEER Measure Cost Summary (05_30_2008) Revised (06_02_2008) amounted to $94.12 as shown in Table below.

Online Retailers Point of Sale Data

Research was done at common online retailers' websites for point of sale data to assess the reasonableness of the 2008 DEER Measure Cost Summary Spreadsheet since the 2008 DEER cost data is approximately 8 years old. The prices found across these online retailer websites ranged from $19.45 to $145.40 with the average material equipment cost for all twenty-nine applicable setback programmable thermostats to be $57.13.

Therefore, this wp uses the 2008 DEER Measure Cost Summary Spreadsheet setback programmable thermostat material equipment cost of $94.12 as the base case cost because the 2008 DEER Measure Cost Summary Spreadsheet takes into account sales volume in addition to retail pricing.

DEER 2008 Base Case Costs for Setback Programmable Thermostats

Cost Case Description	Cost Case ID	Program Delivery Strategies	Material Cost
Setback Programmable Thermostats	ProgTStats	Downstream Prescriptive Rebates/Incentives	$94.12

5.2 Measure Case Cost

Smart Thermostats are not contained within WO17 or the 2008 DEER Measure Cost Summary Spreadsheet. Research was done at common online retailers for Smart Thermostats to support the measure equipment cost. The prices found across these online retailer websites ranged from $119 to $249 with the average material equipment cost for all six applicable Smart Thermostats to be $186.50. Until more updated studies are done, the online retail point of sales pricing is the best available data to support the measure equipment cost. The net present value of the second baseline period ($94.12) is $70.25. The E3 Calculator was used to compute the net present value.

The 2008 DEER Measure Cost Summary Spreadsheet provides labor costs associated with installing programmable thermostats at $56.48. Since there is no additional wiring involved with installing Smart Thermostats compared to setback programmable thermostats, labor costs are assumed to the same in both the base case and the measure case at $56.48.

5.3 Full and Incremental Measure Cost

The incremental measure cost are shown in Equation 5 and Table below.

Measure Case Equipment Cost ($186.50) – Base Case Equipment Cost ($94.12) = $92.38

Equation 5. Incremental Measure Cost Calculation

Full and Incremental Costs

Installation Type	Incremental Measure Cost	Full Measure Cost	
		1st Baseline	2nd Baseline
ROB	$92.38	$92.38	-
RET/ER	$92.38	$186.5	$92.38

ATTACHMENTS

1. SCE17HC054.0 A1 - Calculation Template_Final.xlsm
2. SCE17HC054.0 A2 - Full measure cost analysis and IMC analysis .xlsx
3. SCE17HC054.0 A3 - Calculations of Baseline Adjustment Factor.xlsx
4. SCE17HC054.0 A4 - Responses to Questions on Nest Labs Supplemental Data Report - 07222016.docx
5. SCE17HC054.0 A5 - Second baseline adjustment calculations.xlsx
6. SCE17HC054.0 A6 - Consolidated SW Smart Thermostat WP Responses.docx
7. SCE17HC054.0 A7 - EMV Summary of Studies v02.21.2017.xlsx

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