CPUC GROUP A IMPACT EVALUATION - FINAL REPORT

Forward-looking Smart Thermostat Study

California Public Utilities Commission
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1 EXECUTIVE SUMMARY

1.1 Background and approach

California program administrators (PAs)[1] installed over 400,000 smart thermostats[2] through various residential rebate and direct install[3] energy efficiency (EE) programs from program year (PY) 2018 through PY2021. The programs targeted electric and gas residential customers in single-family, multifamily, and mobile homes.

DNV evaluated the impact of smart thermostats offered in these program years.[4] To estimate this impact, we applied best practice consumption data analysis using data from participants and matched non-participants who were chosen based on their pre-program consumption similarity to the participants.[5] We found energy savings were significantly lower than claimed in all program years.

Despite the similarity in pre-program energy consumption patterns between participants and their matched non-participants, we also found that the energy consumption trend diverged for the two groups after the program in a way that thermostat installation alone cannot explain. This divergence in energy consumption trend is an example of self-selection bias caused by the unique characteristics of the participants who self-select to participate.[6] This was particularly the case for rebate program participants. In our rebate program evaluations, we made adjustments to account for the effect of the differential trends between the two groups on smart thermostat savings.

In the current study, we address the problem of self-selection through a modeling approach that explicitly accounts for the differences between participants and matched non-participants that lead to self-selection bias.[7] This approach provides a more informed adjustment than was applied in our earlier studies by leveraging analysis of baseload trends and shifts in reference temperatures (outdoor temperature at which cooling and heating start). For HVAC savings to occur, average smart thermostat setpoints must shift, and those shifts will be evident in reference temperature shifts. Our model estimates the reference temperature shifts to evaluate the impact of smart thermostats.[8]

We used this approach to understand savings for different customer segments and over time based on the data from the large installed base of smart thermostats delivered in PY2018. We supplemented the analysis of the impact of smart thermostats using vendor data on the operation of smart thermostats. We also used data from smart thermostats installed through PA PY2018 to PY2021 programs to gain insights into program participation. Additionally, we assessed smart thermostats' peak load reduction potential in demand response (DR) programs to help fulfill recent California Public Utilities

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1 Pacific Gas & Electric (PG&E), Southern California Edison (SCE), Southern California Gas Company (SoCalGas or SCG), and San Diego Gas & Electric (SDG&E).

2 A WI-FI-enabled thermostat allows users to create automatic and programmable temperature settings.

3 Direct install programs provide energy-saving technologies or upgrades for no or low cost to participating customer homes through installation contractors.

4 The following links include DNV's residential smart thermostat program impact evaluations published on calmac.org:
https://www.calmac.org/publications/CPUC_Group_A_PY2021_Residential_Install_Program_Impact_Evaluation_-_Final_Report_CALMACES.pdf
https://www.calmac.org/publications/CPUC_Group_A_Report_Smart_Thermostat_PY_2018_CALMAC.pdf,
https://www.calmac.org/publications/CPUC_Group_A_SCT_PY_2018_Report_Update_final_toCALMAC.pdf
https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf
https://www.calmac.org/publications/Group_A_Residential_PY2020_RES_HVAC_Final_Report_CALMAC.pdf.

5 The matching process identifies the non-participant mathematically the least distance from a participant. Pre-period consumption is essential for the matching process, so participants and matched non-participants have similar pre-program consumption by design.

6 Self-selection bias is a systematic and non-random difference between participants and non-participants. The participation of customers systematically different from the non-participating utility customer base will result in effects that reflect their differences instead of that of the program.

7 DNV's consistent single modeling framework used a panel data modeling approach. Panel data refers to observations over time and across all customers. The model based on panel data enables us to estimate the long-term effectiveness of program interventions.

8 Like all models, the model we used in this study approximates complicated realities. It controls for trend differential and offers information on how this differential affects smart thermostat impacts. The model provides value by indicating how smart thermostats trigger heating or cooling to begin in response to the outdoor temperature (shift in the reference temperature). One potential limitation of the model is that while outdoor temperature changes affect thermostat setpoints, additional activities and changes in the home could also affect the setpoints. Hence, the estimated reference temperature shifts may capture the effect of factors other than outdoor temperature changes.

Commission (CPUC) decisions to reduce peak load. Based on this assessment, we identified program opportunities to increase smart thermostat penetration in air-conditioned households in designated hot climate zones.[9]

1.2 Key findings and recommendations

The study enabled us to validate and strengthen our understanding of the approach used in the PY2018 study. It also helped to confirm that the magnitude of overall energy savings (to the extent they exist) is small. The aggregate thermostat data provided by Google on Nest thermostat installations, while not comprehensive or granular enough, provided some insights on the energy savings potential of smart thermostats.[10] The key findings from this study and resulting recommendations and implications for programs that will include or employ smart thermostats are summarized below.

1.2.1 Participant characteristics

The California PAs facilitated the installation of smart thermostats through rebate and through direct install programs that provided them at no or low cost in participating customer homes. Fifty to seventy percent of smart thermostats delivered by the California PA programs from PY2018 to PY2021 were via direct install channels. While direct install programs had no income requirements for participation, they sought to reach low- to medium-income customers. Since programs not explicitly tailored for low-income customers tend to underserve such customers, our analysis aimed to gauge the effectiveness of smart thermostat programs in reaching these specific customer segments.[11] We evaluated participation among hard-to-reach (HTR),[12] disadvantaged community (DAC),[13] and multifamily customers as these segments likely encompass a higher proportion of individuals with lower to moderate incomes.

Our analysis indicates that the proportion of vulnerable customers (DAC, HTR, and non-metro area customers) receiving smart thermostats via direct install programs has increased significantly from PY2018 through PY2021, even as the participation of customers from these segments in smart thermostat rebate programs has remained flat. Participation of multifamily customers in direct install programs has also been significantly high at 57% over this period.[14] These findings indicate improved targeting of these populations.

Continue targeting key underserved demographic customer segments in direct install programs. Direct install programs should continue serving the state's vulnerable customers, given this customer segment's limited resources to take advantage of rebate programs' EE offerings. Direct install programs should also continue serving the multifamily sector, which makes up one-third of the state's residential population since this is the primary channel for multifamily households to access IOU EE program offerings.

We also examined participation by other customer segments, including energy consumption quartiles. We found that top-quartile consumption rebate program participants achieved significantly higher electric and gas savings than customers in lower consumption quartiles, at 151 kWh versus 3 kWh per household and 12 therms versus -6 therms per household, respectively.

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[9] This report refers to climate zones 9 to 15, which are inland regions in California, as hot climate zones. These climate zones experience relatively high summer temperatures associated with high cooling needs.

[10] DNV requested device data from two of the most commonly installed brands and received information only from Google on Nest thermostats. On average, approximately 75% of program installations from PY2018 through PY2021 were Google's Nest smart thermostats.

[11] https://www.aceee.org/files/proceedings/2016/data/papers/2_542.pdf.

[12] Hard to reach (HTR): The criteria for residential HTR customers is the combination of a geographic prerequisite plus at least one of the following criteria: primary language, income, or housing type. Commercial HTR customers are defined by a combination of a geographic requirement plus at least one of the following criteria: primary language, business size, or leased or rented facility. For specific details, please see the Statewide Deemed Workpaper Rulebook.

[13] CPUC, "Disadvantaged Communities," *cpuc.gov*, 2021, https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/infrastructure/disadvantaged-communities.

[14] In contrast, rebate participation among multifamily customers is low at 4%, which reflects that property managers and not individual tenants are the decision-makers for program participation in this sector.

Smart thermostat savings may be improved by factoring in household energy consumption levels in program targeting. Rebate programs should consider using the level of energy consumption as a key targeting variable.

1.2.2 Energy savings

The study used a single, consistent modeling approach to address self-selection bias and estimate annual and multi-year savings for PY2018 installations. The model estimated different energy consumption trends between participants and matched non-participants and captured shifts in reference temperature values among participants. This updated model structure is referred to as the "panel" model in this report because, unlike the approaches used for the prior evaluations, the model stacks data over time and across customers into a single dataset to assess impact.

Model results indicate that, as hypothesized in the previous evaluations, the energy consumption trends of participants and non-participants are statistically significantly different. These differences affect estimated electric rebate and direct install smart thermostat savings estimates but have limited effect on gas savings. Accounting for trend differences increases estimated rebate smart thermostat savings (rebate electric savings estimate goes from negative to positive) and decreases direct install smart thermostat savings (direct install electric savings estimate goes a positive to a small negative number).

These results indicate the presence of differential trends between participants and non-participants that can bias results, particularly for rebate programs. When feasible, evaluations should identify and correct for these possible biases when estimating the effect of opt-in programs[15] using consumption data analysis.

The evidence suggests that energy savings from smart thermostats installed in PY2018, while small, increased over time despite the possibility that COVID-related increased occupancy eroded the saving potential for thermostats. DNV's new model results, presented in Table 1-1, show that electric and gas savings, from both the rebate and direct install channels, are higher when estimated using data from all three years after installation compared to the pre-COVID first post-year. The higher savings over time could be due to thermostat optimization.[16]

Table 1-1. Trend-adjusted panel model estimates of PY2018 rebate and PY2019 direct install savings per household[17]

Fuel	Delivery type	First-year savings	Three-year average savings
Electric (kWh)	Rebate	29	45
	Direct Install	-13	4
Gas (therm)	Rebate	-10	-2
	Direct Install	5	9

Thermostat optimization could improve smart thermostat energy savings performance. Additional studies that track smart thermostat savings over time are needed to strengthen this finding.

15 Opt-in programs are programs where participation is voluntary. The act of opting in can lead to self-selection bias.

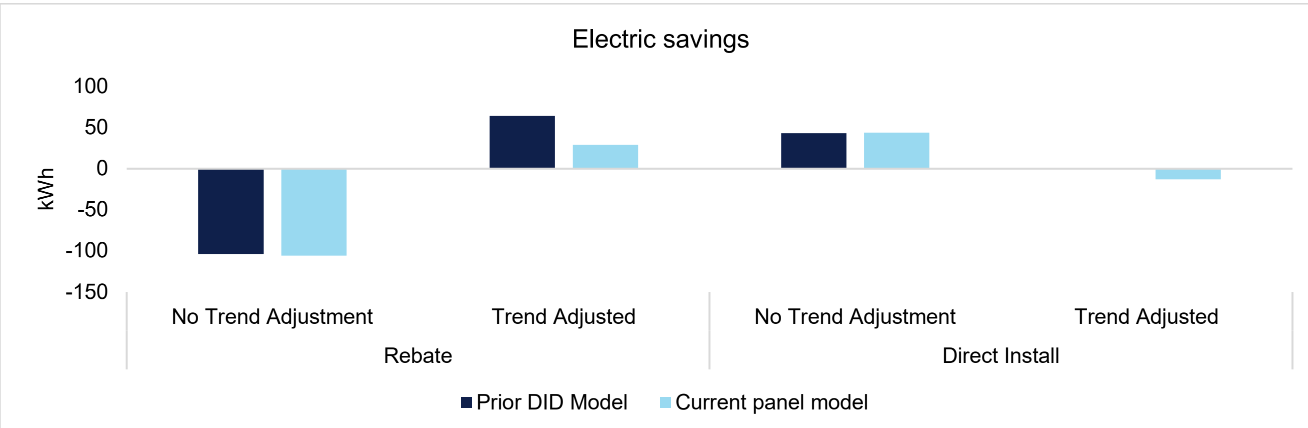
16 Thermostat optimization is a process designed to save additional energy through additional setpoint adjustments that balance each home's response to weather conditions and energy use habits.

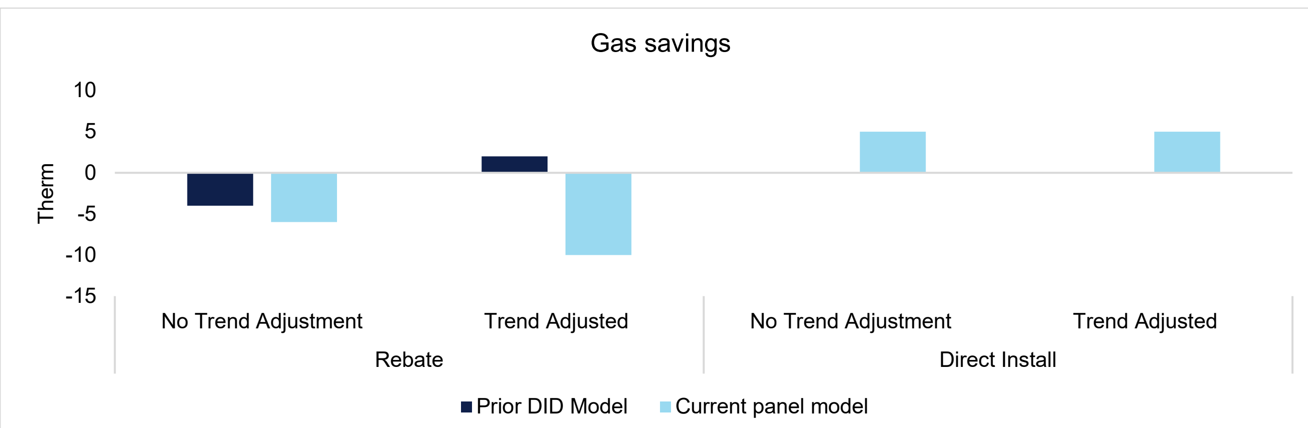
17 Negative values indicate dissavings.

Our findings also indicate that earlier studies may have overstated first-year smart thermostat savings. Figure 1-1 compares the current panel model results, with and without trend adjustment, to the previous evaluations' difference-in-difference (DID) model results, with and without added adjustment.

The "No Trend Adjustment" rebate program results indicate similar savings for both gas and electric when neither approach corrects for trend differences. However, for the trend-adjusted rebate results, the current panel model results reveal that the prior PY2018 ad hoc corrections somewhat overstated both electric and gas rebate savings. Previous evaluations did not adjust direct install results because the evidence of bias was more limited than for the rebate program. However, they also indicate that the unadjusted PY2019 electric direct install evaluation may have overstated savings.[18]

Figure 1-1. Current panel and prior model estimates of first-year savings per household





We recommend continued evaluation of new installations to confirm results identified in this study.

Both rebate and direct install HTR and multifamily participants do not achieve electric savings with smart thermostats, while non-HTR and single-family participants do. HTR and multifamily participants likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy deprivation. Customer responses from participant surveys conducted for our PY2019 to PY2020 impact evaluations indicate a significant increase in customer comfort post

[18] The no trend adjustment DID direct install gas results indicated 0 savings, thus are not visible on the chart. In contrast, the direct install, trend-adjusted DID bars are non-existent for both gas and electric since the prior study did not apply adjustments to the DID results.

smart thermostat installation.[19] Generally, thermostats produce savings by reducing consumption in ways that do not undermine comfort. The promise of smart thermostats to regulate and reduce energy use and cost could have led some of these participants to increase their comfort and use more energy inadvertently. It is not uncommon for customers to change behaviors in ways that increase consumption after a program installation, referred to as takeback. Since it is in the best interest of the PAs to prevent takebacks from occurring in the post-implementation period, more customer education on how smart thermostats and other energy-efficiency technologies function and save money in the home can help prevent such unwanted increases.

There is higher energy consumption post-installation among some customer segments. Given this, we recommend improved customer education on how smart thermostats work and how they provide energy and cost savings. The PAs cannot require “eco” settings on these program-provided thermostats, but they need to find a way to encourage more participants to adopt those settings.

The smart thermostat programs offered thermostats from multiple vendors. Unlike direct install programs that delivered largely the same smart thermostat technology type to participants, rebate program participants purchased different smart thermostat types. Using these data, DNV estimated the electric savings of one vendor’s device (Technology 1) to be 55 kWh per household and another vendor’s device (Technology 2) to be 17 kWh per household. Neither device type provided statistically significant gas savings.

The savings potential of smart thermostats continues to change even after installation due to software updates. Programs should factor in variations in technology and evolving algorithms that result in notably different outcomes when considering this measure for programs.

PAs should assess savings by specific technologies periodically to understand if there are differences and calibrate technology/measure package recommendations accordingly.

1.2.3 Peak savings

California Public Utilities Commission (CPUC) decision D. 21-12-015 (in Rulemaking R.20-11-003), adopted in December 2021, is designed to reduce load in hot climate zones 9-15 and directs PAs to subsidize smart thermostats for customers in these climate zones. The absolute number of smart thermostats installed cumulatively in these climate zones through the PAs’ direct install programs from PY2018 through PY2021 is approximately 286,000. The total installed base of smart thermostats in these climate zones is more than 286,000 since it will also include those provided at low to no cost by other energy efficiency programs like the Energy Savings Assistance (ESA) program and non-program adoption of smart thermostats.

Assuming a non-program smart thermostat adoption rate of 25%[20] and a statewide average annual ESA program footprint of 260,000,[21] the smart thermostat installed base is likely much lower than the estimated 3.5 million of five million households

[19] DNV’s impact evaluations of the PAs for PY2018, 2019, and 2020:
https://www.calmac.org/publications/CPUC_Group_A_Report_Smart_Thermostat_PY_2018_CALMAC.pdf (Table 4-9),
https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf (Table 4-9),
https://www.calmac.org/publications/Group_A_Residential_PY2020_RES_HVAC_Final_Report_CALMAC.pdf (Table 5-8)

[20] The prevalence of smart thermostats among non-participant households is estimated in the CPUC Group A PY2019 Smart Thermostat Evaluation.
https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf
The prevalence of smart thermostats among non-participant households is estimated in the CPUC Group A PY2019 Smart Thermostat Evaluation.
https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf

[21] The PY2015-2017 ESA Program Impact Evaluation indicated the statewide average annual footprint of the program. 2015-2017_ESA_Impact_Evaluation_-_FINAL_-_CALMAC_Posting.pdf

that use air-conditioning[22] in these specific climate zones. Households with air-conditioning contribute to grid stress from increased cooling demand during peak periods from May through October. These households represent ideal targets for energy efficiency and demand response programs that deploy smart thermostats.

There are program opportunities to increase smart thermostat penetration in households with air-conditioning in hot climate zones. Programs should aim to expand the penetration of smart thermostats that can operate as part of a "fleet" and serve as virtual power plants (VPPs) to provide direct relief to the overloaded parts of the grid.[23]

Smart thermostats' peak load reduction potential makes them suitable for use in DR programs. However, DR program enrollment among smart thermostat program participants has been modest at 7% for rebate program participants and no more than 6% for direct install participants.

Programs delivering free or subsidized smart thermostats should consider automatically enrolling direct install program participants in DR programs with an opt-out option and providing information on DR programs for rebate program participants to maximize peak load savings.[24]

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[22] The EIA's RECS survey estimates that 70% of CA households have air-conditioning. Applying this penetration to the five million households in climate zones 9-15 results in an estimated 3.5 million households with air-conditioning. https://www.eia.gov/consumption/residential/data/2020/state/pdf/State%20Air%20Conditioning.pdf
The EIA's RECS survey estimates that 70% of CA households have air-conditioning. Applying this penetration to the five million households in climate zones 9-15 results in an estimated 3.5 million households with air-conditioning. https://www.eia.gov/consumption/residential/data/2020/state/pdf/State%20Air%20Conditioning.pdf

[23] VPPs adjust the power use of a fleet of electric devices and appliances like smart thermostats, heat pumps, and induction stoves to reduce stress on the grid.

[24] Smart thermostat program participants could be enrolled in PA and other DR programs such as Power Saver Rewards, OhmConnect, SmartRate Plan, Summer Discount Plan, Smart Energy Program, AC Saver (Summer Saver) Program, and AC Saver Thermostat Program. SCE's PY2021 Residential Direct Install Program that leveraged SCE's smart thermostat DR program is an example of a successful application of such an integrated demand side management (IDSM) approach. The initiative has yielded success in its first year of operation. Survey results showed a higher proportion of participants became aware of and enrolled in the smart thermostat DR program due to the IDSM campaign.

2 INTRODUCTION

2.1 Background

Smart thermostats are Wi-Fi-enabled devices that help customers to maintain desired temperature levels by controlling HVAC system performance through automatic setpoint adjustments based on occupancy sensing capabilities.

California program administrators (PAs) have installed over 400,000 smart thermostats through various residential energy efficiency (EE) rebate and direct install programs from 2018 through 2021. The programs, which were offered to both electric and gas customers, targeted residential customers in single-family, multifamily, and mobile homes.

DNV evaluated the impact of smart thermostats offered in these program years. To estimate this impact, we applied best practice consumption data analysis using data from participants and matched non-participants who were chosen based on their pre-program consumption similarity to the participants. We found energy savings were significantly lower than claimed in all program years.

Despite the similarity in pre-program energy consumption patterns between participants and their matched non-participants, we also found that the energy consumption trend diverged for the two groups after the program in a way that thermostat installation alone cannot explain. This divergence in energy consumption trend is an example of self-selection bias caused by the unique characteristics of the participants who self-select to participate. This was particularly the case for rebate program participants. In our PY2018 and PY2020 rebate program evaluations, we made adjustments to account for the effect of the differential trends between the two groups on smart thermostat savings.

In the current study, we address the problem of self-selection through a modeling approach that explicitly accounts for the differences between participants and matched non-participants that lead to self-selection bias. This approach provides a more informed adjustment than was applied in our earlier studies by leveraging analysis of baseload trends and shifts in reference temperatures (outdoor temperature at which cooling and heating start). For HVAC savings to occur, average smart thermostat setpoints must shift, and those shifts will be evident in reference temperature shifts. Our model estimates the reference temperature shifts to evaluate the impact of smart thermostats.

We used this approach to understand savings for different customer segments and over time based on the data from the large installed base of smart thermostats delivered in PY2018. We supplemented the analysis on the impact of smart thermostats using vendor data on the operation of smart thermostats. We also used data from smart thermostats installed through PA PY2018 to PY2021 programs to gain insights into program participation. Additionally, we assessed smart thermostats' peak load reduction potential in demand response (DR) programs to help fulfill recent California Public Utilities Commission (CPUC) decisions to reduce peak load. Based on this assessment, we identified program opportunities to increase smart thermostat penetration in air-conditioned households in designated hot climate zones.

2.2 Study objectives

Energy impact. Despite well-matched energy consumption between participants and matched non-participants before smart thermostat installations, DNV's PY2018 study identified an energy consumption trend difference between the two groups. Thus, one of the main objectives of this study was to examine the energy (kWh and therm) savings of smart thermostats that account for this difference. We sought to:

1. Use a single consistent modeling approach to address the trend difference identified in the previous evaluation – Because the difference understated savings, the PY2018 analysis had made an ad hoc adjustment to control for its effect. The present study used a consistent modeling approach, which incorporates the underlying assumptions of the PY2018 ad hoc adjustment, to test the reasonableness of the prior adjustment and results and to identify shifts

in reference temperature values that reflect changes in the effective thermostat setpoints (a key effect of smart thermostats) and the associated energy consumption changes.

2. Examine savings over time – Smart thermostat savings can change over time due to occupant learning, increased or improved vendor-operated optimization, or COVID.[25] We used the modeling approach to estimate savings by individual year since installation and across multiple years. We also used HVAC runtime data from devices to get additional insights into smart thermostat operating patterns and their impacts.

3. Examine savings by different customer segments – We also used the modeling approach to understand variation in savings by different customer segments.

Participant characterization. Another objective of the study was to examine how and to what extent the demographic profile of smart thermostat adopters has changed over time, with a focus on HTR/DAC participant groups. We used data from PY2018 through PY2021 participants for this analysis. Using this data, we sought to understand:

1. Access - How access to this technology has changed over time by different customer segments. Since ratepayers funded the programs that delivered smart thermostats, our examination sought to understand the extent to which the programs gave access to the technology among different population segments, including those in DAC and HTR populations.

2. Smart Deployment - What proportion of customers located in climate zones with high cooling needs and in DR programs the programs served. Since this technology has the potential to contribute to more efficient energy use both annually and during periods of high energy demand and grid stress, we sought to understand if programs deployed smart thermostats in areas and among customer segments where they were most effective.

[25] COVID primarily affected 2020 and 2021 savings.

3 METHODOLOGY

This section details the approach DNV used in this evaluation. We provide the list of data sources used for these purposes first, followed by the impact and participant characterization approaches for smart thermostats delivered PA programs from PY2018 to PY2021.

3.1 Data sources

Table 3-1 provides the data sources used in the study and the purpose of their inclusion in the analysis.

Table 3-1. Summary of data sources and applicable measure groups

Data sources	Description	Purpose in analysis
Program tracking data	PA program data that includes number of records, savings per record, program type, name, measure groups, measure description, incentives etc.	Identify program participants, installed measures, and claimed (ex-ante) savings
Advanced Metering Infrastructure (AMI) Data	Detailed, time-based energy consumption information	Estimate energy savings
Weather data	Actual and typical meteorological year (TMY) temperature data[26]	Weather normalized energy consumption
Customer data	Customer location (zip code), climate zones, and CARE/FERA[27] status	Understand savings by different segments and changes in participant characteristics over time
CalEnviroScreen	Data measuring economic, health, and environmental burdens at the census tract level	Identify DAC and HTR customers
American Community Survey (ACS) data	Census block-level demographic information (primary language, household size and composition by age, home ownership status)	Determine changes in participant characteristics over time
Survey data	Customer surveys that collect information on demographics and energy use behavior	Understand engagement with smart thermostats over time
Device data	Information on the operation of smart thermostat	Smart thermostat impact on energy use

[26] We sourced weather data from the National Oceanic and Atmospheric Administration (NOAA) and climate zone (CZ) 2022 reference temperature files (CZ2022) from CALMAC.org to include in regression models accounting for weather sensitivity. CZ2022 provides typical meteorological year (TMY) weather data for select California weather stations useful for long-term weather normalization. The study also used climate zone information available by zip code from the California Energy Commission (CEC). Data were at the hourly level for each station.

[27] California Alternate Rates for Energy (CARE) and Family Electric Rate Assistance Program (FERA) provide energy bill discounts for income qualified households in California.

3.2 Participant characterization

We present the methodology used to examine if and how the smart thermostat program participant population has changed over PY2018 to PY2021. DNV compared such possible changes against the demographics of the general population in California.

We assembled a premise-level dataset of PG&E, SCE, SCG, and SDG&E customers to support this analysis. Some of the analysis variables were available at the premise level from the PAs, while others were available at the census block, census tract, or county-level. The PAs provided the premise-level information, along with geospatial information which we used to geo-locate the premises and assign them the geography-based variables (census block, census tract, county, climate zone).

With the location-level information, we determined if a premise was HTR based on the following two conditions defined by the California Public Utilities Commission (CPUC):[28]

- First, geographically, a premise must either be in a DAC or a non-metro area community (outside selected core-based or metropolitan statistical areas).[29]
- Second, a resident in the premise must either be a multi-family or manufactured home renter or face a language or an income barrier. A multi-family or manufactured home resident is classified as a renter if the premise is in the top quartile multi-family or mobile home rental block group. A resident faces a language barrier if the premise is in the top quartile limited English households block group. If a resident qualifies for California Alternate Rates for Energy (CARE) or Family Electric Rate Assistance Program (FERA), the resident faces an income barrier.

Additional variables we used in the analysis are summarized in Table 3-2.

Table 3-2. Participant characterization variables

Variable	Source	Description
Geography-based variables		
Top Quartile Limited English Census Block[30]	U.S. Census: American Community Survey	A census block-level variable used to determine whether a premise is located in a census block with a high share of households with limited English speakers.
Top Quartile Multi-Family Rental / Mobile Home Rental Census Block[31]	U.S. Census: American Community Survey	A census block-level variable used to determine whether a premise is located in a block with a higher share of households with multi-family or mobile home rental homes.
Metro / Non-Metro Designation	U.S. OMB	A county-level variable indicating that a premise is located in a metro or non-metro statistical area.
Emergency Load Reduction Program (ELRP) Climate Zones	California Public Utility Commission (CPUC)	Climate zones designated as hot by California's 2021 Summer Reliability Decision.[32]
Disadvantaged Community (DAC)	CalEnviroScreen	A census tract-level variable based on CalEnviroScreen that is used to determine whether a premise is located in a disadvantaged community.

[28] Specific details can be found here: Statewide Deemed Workpaper Rulebook, p. 22.

[29] Non-metro areas are regions outside the U.S. Office of Management and Budget (U.S. OMB)-defined core-based statistical areas (CBSAs). We used the CBSAs covering the San Francisco Bay area, the greater Los Angeles area, and the greater Sacramento. We also included the metropolitan statistical area of San Diego.

[30] This is built using the ACS variable household limited English proficiency, ACS Table ID: C16002 - the number of households where no one over the age of 14 in the home speaks English "very well" relative to total households in the block group.

[31] This is built from the ACS variable tenure, ACS Table ID: B25032 - the number of renter- and owner-occupied housing units by dwelling type including multifamily buildings with 2-4 units and mobile homes, each relative to total housing units within each dwelling type within the block group.

[32] CPUC, "Phase 2 Decision Directing Pacific Gas And Electric Company, Southern California Edison Company, And San Diego Gas & Electric Company To Take Actions To Prepare For Potential Extreme Weather In The Summers Of 2022 And 2023," *docs.cpuc.ca.gov,* 12/2/2021. https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M427/K639/427639152.PDF.

Variable	Source	Description
Premise-level Variables[33]		
Customer Information	CEDARS[34] / CIS data	Key customer information such as premise ID, PA, and location.
Energy Consumption	Utility billing and AMI data	Electric and gas energy usage data.
Dwelling Type	CEDARS / CIS data	A variable that indicates whether each premise is a single family (SF), multi-family (MF), or mobile home (MH)
Solar/EV Adoption	Utility billing data	A variable indicating that a customer has net metering or an electric vehicle.
CARE	Utility billing data	A variable that indicates the premise is on the income-based CARE electric or gas rate.
FERA	Utility billing data	A variable that indicates the premise is on the income-based FERA electric or gas rate.
Program Participant Information	CEDARS / CIS data	Smart thermostat program participation information such as program name, year, and claimed savings – participants only.
Program Delivery Type	Utility billing data	A variable that indicates whether a smart thermostat was acquired through a direct install or rebate program – participants only.
Calculated Variables		
Hard To Reach (HTR)	CalEnviroScreen, the U.S. OMB, U.S. Census ACS, utility CIS data	The HTR variable is assigned to each premise based on multiple variables listed above. To be designated as HTR, a premise must meet one geographic category and one other category: 1. Geographic category: DAC designation or rural 2. Other category: CARE rate, FERA rate, top quartile limited English, or top quartile MF/MH rental

3.3 Impact approach

We discuss the data we used to estimate the impact of smart thermostats overall, by customer segments, and over time in the sections that follow. We also provide the approach we used for this purpose.

3.3.1 Analysis data

For the impact analysis, we used data from PY2018 installations, where 66% of the approximately 200,000 installations were in homes that received the measure through direct install programs. Among the direct installations, 68% were in single-family, multifamily, and mobile homes that only received smart thermostats. We estimated approximately 8% to 9% of customers who received this measure through direct install channels were master-metered.[35] We excluded these customers from the analysis because the energy consumption of only those who received the measure was unavailable. Since a subset of direct install participants with only smart thermostat installations, not master-metered, and with sufficient data was large enough, we restricted our analysis to homes where this was the only measure installed. Estimated whole-home savings for direct install smart thermostat installations thus reflect savings from smart thermostats installed alone.

Smart thermostats delivered through the rebate channel were, in approximately 90% of cases, the only utility-incentivized measure installed by participants who primarily lived in single-family homes. We based our analysis on homes with only this

[33] Data available for all participants and non-participants, except where specified otherwise.
[34] California Energy Data and Reporting System (CEDARS), "Welcome to CEDARS," cedars.sound-data.com, https://cedars.sound-data.com/
[35] We used a threshold of more than three smart thermostat installations for any customer and premise ID combination to approximate the proportion of master-metered customers served by direct install programs.

measure for smart thermostats provided through rebate programs. Estimates of whole-home energy consumption reduction are thus for rebate smart thermostats installed alone.

Table 3-3 provides the number of electric and gas customers that received direct install and rebate smart thermostats in 2018, the number that only installed smart thermostats, and the final count of customers whose energy consumption data we used in the evaluation. The final count reflects customers that are not net-metered (electric-only) and have the required one year of pre- and at least one year of post-installation data.

Table 3-3. Customer counts used in the evaluation by delivery channel and fuel

Participant data attrition	Direct install		Rebate	
	Electric	Gas	Electric	Gas
Customers with smart thermostat (SCT) installations	126,929	128,971	45,071	74,143
Customers with SCT installations and not master-metered	76,222	61,564	40,439	65,719
Customers with SCT-only installations and not master-metered	52,221	41,961	34,796	59,321
Customers with SCT-only installations, sufficient data, not mater-metered	15,395	10,951	17,271	45,113

DNV used energy consumption data provided by the PAs covering the years 2017 through 2021. These data were at multiple levels of granularity, including monthly, daily and hourly. Details of the data preparation are provided in the PY2020 evaluation.[36]

In addition to data from participants, we also used data from non-participants for the evaluation. We constructed a panel dataset based on daily electric and gas data from 2018 participants and their matches for all analyses. The data covers the period one year before program participation through the end of 2021 or the end of customers' tenure at their current premise, whichever is later. We attached demographic, consumption level, and smart thermostat technology information to this data to conduct our analysis using the sources identified in the data section.

3.3.2 Analysis approach

We used a panel data method to evaluate the impact of the PY2018 smart thermostat installations. In general, panel data methods use observations from participants and non-participants over time to estimate the effect of an intervention. In the current context, panel data methods take advantage of cross-sectional and time series variations in energy consumption to appraise the impact of thermostat installations. These methods make it possible to estimate impact across all and different segments of participants. Panel data approaches are consistent with best practices delineated in State and Local Energy Efficiency Action Network's (SEE Action) Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations.[37] They are also widely used for program analysis.

The panel data approach is different from the two-stage consumption data analysis we used to estimate annual energy savings in our PY2018 and PY2019 smart thermostat impact evaluations. However, it still allowed us to obtain energy impacts by comparing the energy consumption of participants and matched non-participants based on data from pre-and post-installation periods. Similar to the prior approach, this analysis used the same comparison groups to control for exogenous change.

The two-stage approach, which split consumption into heating, cooling, and baseload, enabled us to observe an increase in baseload among rebate participants, suggesting an overall trend differential between participants and matched non-participants. We made a proportional adjustment to savings to correct for the observed baseload difference, assuming it indicated a trend differential. The panel approach made it possible to quantify the adjustment necessary to account for

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[36] DNV, "Impact Evaluation of Residential HVAC Measures Residential Sector-Program Year 2020," *calmac.org*. June 3, 2022. [https://www.calmac.org/publications/Group_A_Residential_PY2020_RES_HVAC_Final_Report_CALMAC.pdf]

[37] The State and Local Energy Efficiency Action Network, "Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations," *energy.gov*, May 2012, https://www.energy.gov/sites/default/files/2021-08/emv_behaviorbased_eeprograms.pdf

possible trend differential more directly. Specifcally, the panel model included terms that captured shifts in reference temperature values to capture the impact of smart thermostats on energy consumption.

3.3.3 Model specification

The panel model we estimated, which included terms to account for the effect of weather, trend, and reference temperature changes, has the following general specification:

$$Y_{tj} = \alpha_g\left(1 + \lambda_g t\right) +$$
$$\beta_g\left(1 + \lambda_g t\right)\left[H_t\left(\tau_{Hj}\right)(1 - P_t) + H_t\left(\tau_{Hj} + \delta_H + \delta_{pH} * T_j\right)P_t\right] +$$
$$\gamma_g\left(1 + \lambda_g t\right)\left[C_t\left(\tau_{Cj}\right)(1 - P_t) + C_t\left(\tau_{Cj} + \delta_C + \delta_{pC} * T_j\right)P_t\right] +$$
$$\varepsilon_{tj}$$

(Equation 1)

In this model:

t = time period index, starting at $t = 1$

j = customer index

g = group index, where $g = p$ for participants and $g = np$ for non-participants

Y_{tj} = energy consumption for customer j at time period t

α_g = group-specific intercept term that captures baseload consumption of participants, where $g = p$ for participants and $g = np$ for non-participants

λ = trend term that increments daily energy consumption, with $\lambda_{np}t$ capturing trend for non-participants and $\lambda_p t$ capturing trend for participants

T_j = 0/1 dummy for customer j, which equals 1 if a customer is in the participant group, 0 otherwise

P_t = 0/1 dummy for time t, which changes from 0 to 1 at $t =$ participation date for participants and their matches

β = heating use per heating degree-day (HDD)

γ = cooling use per cooling degree-day (CDD)

$H_t(\tau_{Hj}) = HDD$ per day for customer j at heating reference temperature τ_{Hj}, at time period t

$C_t(\tau_{Cj}) = CDD$ per day for customer j at cooling reference temperature τ_{Cj}, at time period t

τ_{Hj} = heating reference temperature for customer j determined by site-level regression models

τ_{Cj} = cooling reference temperature for customer j determined by site-level regression models

δ_H = average shift in heating reference temperature for all customers in the post period

δ_C = average shift in cooling reference temperature for all customers in the post period

δ_{pH} = incremental shift in heating reference temperature for participants in the post period

δ_{pC} = incremental shift in cooling reference temperature for participants in the post period

The model includes terms that capture baseload consumption (alpha) for the participant and non-participant groups. These are interacted with trend terms (lambda) to capture possible differences in energy consumption trends between these two groups. The model also includes weather variables (CDD and HDD) to control for the effect of weather on energy consumption. The CDD and HDD variables were constructed using reference temperature estimates (τ_{Hj} and τ_{Cj}) derived from pre-period site-level models.[38] We also interacted these terms with the trend term interacted with baseload, which makes this the regression equivalent of the proportional adjustment we did in the two-stage analysis. The reference temperature shifts contend with a trend driver effectively driven by whatever trend difference exists in the baseload over time.

While the beta and gamma terms associated with heating and cooling terms capture the effect of weather on energy consumption, the model includes terms to estimate reference temperature changes (delta) of participants and non-participants. The delta terms for both groups capture reference temperature changes in the post-period. Additional reference temperature change terms for participants capture incremental changes following smart thermostat installations. The estimates of the incremental delta terms provide direct evidence of shifts in reference temperature that reflect the impact of smart thermostats on energy consumption.[39]

3.3.4 Panel data model variations

We ran a variety of panel models that do not constrain energy consumption response to weather or overall consumption trends to be the same for participants and non-participants. The models allow the two groups each to have their own baseload and heating and cooling load responses through separate alpha (α), beta (β), and gamma (γ) estimates.

The overall year-over-year consumption trend (lambda (λ)) is a significant addition to this model. It allows us to control for possible differences in energy consumption trends between participants and matched non-participants so we can isolate the effect of smart thermostats on energy consumption. For rebate installations, the lambda terms in the models provide the same function that the post-regression adjustments we applied in the PY2018 and PY2020 evaluations to deal with differential trends in energy consumption between rebate participants and their matches. Rather than a somewhat ad hoc proportional adjustment applied outside the regression context, this model estimates the average trends (lambda terms) for the two groups within the model, conditional on other cross-group balancing and with associated standard errors.

The model includes incremental reference temperature shift terms (delta (δ_p) terms associated with participants) that measure changes in reference temperature values due to smart thermostat installations among participants. We examined how savings estimates from these models compare to the results we obtained using the adjustments in the PY2018 and PY2020 rebate results. If estimated changes are lower from these models, then these indicate that our adjustments were generous.

If the comparison group is perfectly matched to the participant group, all the coefficients would be the same between the two groups, except that the reference temperature value will move in the direction of lower usage for the participants. By allowing separate coefficients for each group, we allow for some underlying differences even with a good matching process while still identifying the extent of a participant reference temperature shift beyond the “prevailing” shift exhibited by the comparison group. The incremental participant heating and cooling reference temperature shifts δ_{pH} and δ_{pC}, respectively, are the specific effects the smart thermostat is designed to induce. This modeling approach allows us to estimate them explicitly.

All-post-years model – We ran models that use one year of pre- and up to four years of post-installation data. These models include all available post year data for each participant and allow us to estimate savings estimates that capture the effect of smart thermostats over time.

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[38] Details of the weather normalization models are also provided in DNV's PY2020 impact evaluation report.

[39] Our analysis does not presume that $\tau_{.j}$ estimates setpoints. It assumes that shifts in setpoints result in shifts in $\tau_{.j}$ by the same amount, which is what basic PRISM theory states.

One post-year model – We ran models that use one year of pre- and only one-year of post-installation data. Estimates from these models allow us to compare smart thermostat impacts from our panel modeling approach with previous study results based on difference-in-difference (DID) models.

Annual shift model - We ran models where the estimate in trend is the same across all years, as are the alpha, beta and gamma terms that capture baseload estimates and response to weather, but where there are different reference temperature shifts for each of the post years. Different reference temperature shift estimates provide the effect of smart thermostats on energy consumption by year and indicate if there is a pattern in this effect over time.

No trend model - We also ran models that do not include trend terms to examine the extent of the distortions in smart thermostat savings estimates. We expect that when we do not control for differences in energy consumption trends, these will show up as smart thermostat savings or dissavings. We also used results from these models to compare to trend unadjusted savings estimates from our PY2018 rebate and PY2019 direct install smart thermostat studies.

3.3.5 Savings estimates

We calculated heating and cooling savings and total or combined savings from smart thermostats using panel model estimates. To illustrate how we accomplished this, we consider the impact of the installations using the following formulation.

For customer j in the participant or non-participant group, $g = p \text{ or } g = np$, energy consumption on day d is:

$$Y_{dj} = (1+\lambda_g)\Big[\alpha_g + \beta_g\big(HDD_{dj}(\tau_{Hj}) - HDD_{dj}(\tau_{Hj} + Post * (\delta_H + T * \delta_{pH}))\big) + \gamma_g\big(CDD_{dj}(\tau_{Cj}) - CDD_{dj}(\tau_{Cj} + Post * (\delta_C + T * \delta_{pC}))\big)\Big]$$

(Equation 2)

The DD terms are all daily DDs and $.DD_{dj}(\tau)$ is degree-days at the outside reference temperature τ on day d for the climate zone customer j is in, and $\tau_{.j}$ is the previously determined reference temperature for heating or cooling for customer j.

We calculated the heating and cooling savings using normal-year $.DD$ per day at the indicated reference temperature, for the climate zone of customer j, indicated by $.DD_{d0j}$. For a participant customer j, where $g = p$, the average heating and cooling savings per day due to the smart thermostat can be calculated by:

$$\Delta NAC = \begin{bmatrix} \beta_p * \big(HDD_{0j}(\tau_{Hj} + \delta_H) - HDD_{0j}(\tau_{Hj} + \delta_H + \delta_{pH})\big) + \\ \gamma_p * \big(CDD_{0j}(\tau_{Cj} + \delta_C) - CDD_{0j}(\tau_{Cj} + \delta_C + \delta_{pC})\big) \end{bmatrix} * [1 + \lambda_p * 365/2]$$

(Equation 3)

In Equation (3)

- The degree-day differences in $\big(HDD_{0j}(\tau_{Hj} + \delta_H) - HDD_{0j}(\tau_{Hj} + \delta_H + \delta_{pH})\big)$ and $\big(CDD_{0j}(\tau_{Cj} + \delta_C) - CDD_{0j}(\tau_{Cj} + \delta_C + \delta_{pC})\big)$ are the differences in the normal-year heating and cooling drivers with and without the participants' incremental reference temperature shift δ_{pH} and δ_{pC}. This incremental shift—over and above the prevailing reference temperature shift δ_H or δ_C that occurs without a smart thermostat—is the source of savings due to the smart thermostat installation. That is, the heating and cooling degree-day differences translate the heating and cooling reference temperature shifts accomplished by the smart thermostat into the differences in degree-days the heating and cooling systems need to serve.
- Multiplying the differences in heating and cooling degree-days by the corresponding heating and cooling slopes β_p and γ_p in turn produces the difference in heating and cooling energy use needed.

- By assumption in the model, all the primary coefficients α_p, β_p, and γ_p are inflated (or deflated) over time by the trend, at the rate of λ_p per day. The primary values multiplied by (1+365 λ_p/2) represent the average levels of the heating and cooling usage per degree-day over the first year of the analysis. This approach is a simplification, which avoids calculating the effects of the shifts on a daily basis and makes comparisons across different post-installation periods more straightforward.

3.4 Device data analysis

DNV received hourly aggregated data for all NEST thermostats activated from June 1, 2019 through December 31, 2020 in California's 16 climate zones. The data extended from June 1, 2019 through December 31, 2021. The file excluded 2019 data for climate zone one and most of June 2019 data for climate zone five due to insufficient numbers of thermostats to meet NEST's aggregation policies. The information we received did not indicate the number of activated thermostats used to generate the aggregate values. As a result, the aggregate data we received represents a growing underlying population for the first 19 months and then an additional year of data for the population as of December 31, 2020. Any comparison of parameters over time is compromised by the possibility of drift in parameters as the population grew.

The aggregated data we received included the following key smart thermostat operations for each hour and day over the mid-2019 to end-of-2021 period:

- Average cooling and heating setpoints
- Fraction of thermostats with cooling and heating setpoints
- Average cooling and heating runtimes in seconds
- Average number of fan-only runtimes
- Average outdoor temperature reported by the thermostats

Table 3-4 summarizes the average values of the key operation metrics by year for the summer (June through September) and winter (November through February) seasons. Since the data covers only two full winters (November 2019 through February 2020 and November 2020 through February 2021), we provide winter summaries for only 2019 and 2020.

Table 3-4. Winter and summer average smart thermostat operations by year

Metric		2019	2020	2021
Winter average	Heating runtime (minutes per hour)	4.90	4.93	
	Heating setpoint (°F)	64.6	65.6	
	Fraction with heating setpoint	0.72	0.71	
	Temperature (°F)	52.0	51.8	
Summer average	Cooling runtime (minutes per hour)	8.3	9.1	8.6
	Cooling setpoint (°F)	77.8	77.3	77.9
	Fraction with cooling setpoint	0.65	0.64	0.64
	Temperature (°F)	72.5	73.2	72.7

Our analysis of the impact of smart thermostats on energy consumption in the current and past studies used participant and non-participant household energy consumption data from the utility, which allowed us to model changes in energy consumption relative to baseline (pre-installation) energy consumption. The aggregate smart thermostat data we received from NEST, by its nature, begins after thermostat installation. Hence, it does not make it possible to model changes in smart thermostat operations compared to baseline conditions.

Given that we do not have baseline operating conditions against which to compare smart thermostat operations, we examined changes in these operations over the three-year period for which we received data. We also focused on any changes in smart thermostat operations due to COVID.[40]

To study these changes, it was necessary to control for different weather conditions over the three years. We modelled hourly cooling runtime (measured in minutes) as a function of temperature for this purpose. For each climate zone and year, we estimated the following model:

$$CRT_{t,h} = \alpha_h * I + \beta_h * Temp_{th} + \varepsilon_{t,h}$$

(Equation 4)

In this equation:

- $CRT_{t,h}$ is cooling runtime for hour h of day t
- I is an hourly indicator variable that takes the value of 1 during hour h and 0 otherwise
- $Temp_{th}$ is average outside temperature captured by smart thermostats during hour h on day t
- α_h and β_h capture average hourly cooling runtime and the effect of average daily temperature on cooling runtime during hour h
- $\varepsilon_{t,h}$ is model error term for day t, hour h

We used Tobit to estimate the relationship between runtime and temperature. The Tobit models censored data, which are constrained above and below. Observed runtime cannot be less than 0 nor greater than 60 minutes per hour. We consider these runtimes as censored observations on an underlying demand for heating or cooling that, in principle, could be negative (wanting anti-heating when it is hot or anti-cooling when it is cold) or exceed full operation (wanting more heating or cooling in an hour than the system can provide). The relationship between runtime and this unobservable underlying demand is linear in temperature. The Tobit structure models this linear relationship censored at 0 and 60 minutes per hour.

We used the estimated model coefficients to generate hourly cooling runtimes for each year standardized to 2020 weather data. The predicted hourly runtimes in each year represent the same weather conditions allowing us to determine changes in smart thermostat operations that are independent of the effect of weather. We examined changes in average hourly runtime over the three years and investigated the impact of COVID on the same metric based on this approach.

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[40] As noted above, it is possible changes over time represent drift in the population activating thermostats as well as changing behaviors of already included thermostats.

4 RESULTS

We examined the trend in program participation among different customer segments over the analysis period (PY2018 to PY2021). The details of these analyses are provided in the sections below. In Section 4.1, we discuss changes in participant characteristics over time and in Section 4.2, we present the the energy impact of the technology by different customer segements over time.

4.1 Participant characterization

In this section, we provide a high-level summary of the claims from the rebate and direct install programs that delivered smart thermostats. We also examine changes in participation rates overall and by different demographic segments. The participation analysis focuses on access to the technology and the effectiveness of the deployment of the technology over the four program years.

4.1.1 Summary of participation over time

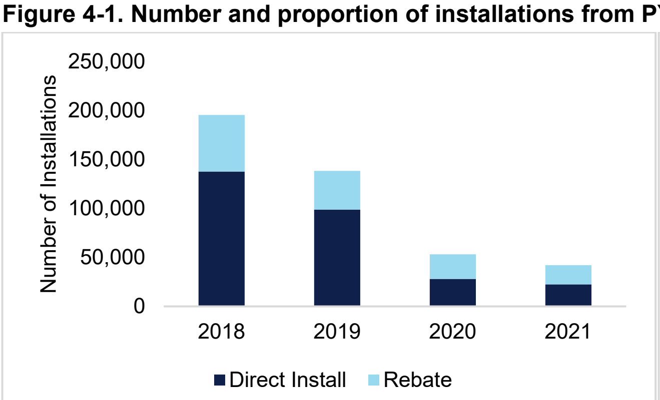
Table 4-1 summarizes the number of installations and claimed electric (kWh) and gas (therms) savings by direct install and rebate programs over the analysis period. The numbers indicate that the footprint of the programs has shrunk progressively over the analysis period.

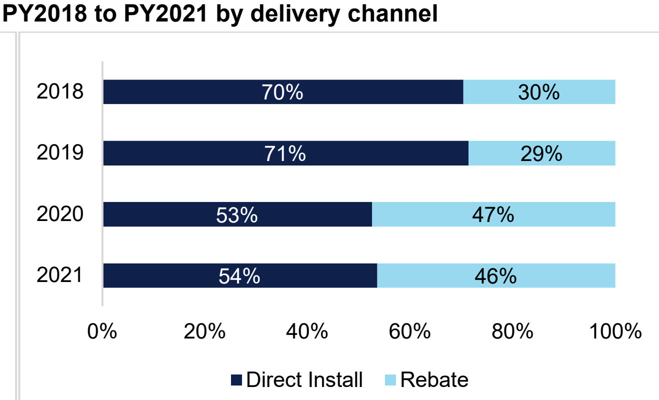
Table 4-1. Smart thermostat claims from PY2018 to PY2021 by delivery channel

	Direct Install				Rebate			
	2018	2019	2020	2021	2018	2019	2020	2021
Number Of Gas Claims	178,618	121,093	32,974	25,385	55,824	39,300	24,260	20,395
Number Of Electric Claims	145,474	95,697	30,812	21,073	45,411	39,797	25,591	16,213
Claimed Savings Therms	2,441,310	1,372,704	339,170	318,501	871,676	609,620	376,383	174,157
Claimed Savings kWh	34,545,563	21,534,258	5,445,877	4,694,138	7,975,185	6,368,835	2,903,944	1,482,808

Figure 4-1 shows the number of installations from PY2018 to PY2021. It indicates an overall decline in the number of installations and the proportion of direct install smart thermostats over the study period.

Figure 4-1. Number and proportion of installations from PY2018 to PY2021 by delivery channel



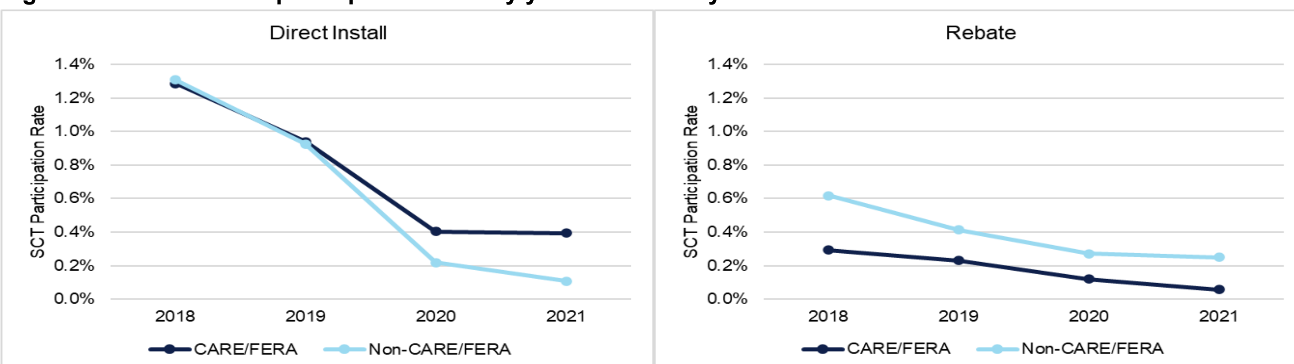


We also examined the trend in participation rates by delivery channel over the four program years. We defined participation rate as the proportion of households that received direct install or rebate smart thermostat relative to the total population. Figure 4-2 shows the participation rate in direct install and rebate programs broken out by CARE/FERA and non-CARE/FERA households. Like the preceding discussion indicates, the figure shows a decline in participation rate for all customer groups over the program years due to shrinking program footprints. Comparing participation rates between customers on the income-based CARE and FERA energy rates is instructive, even in the context of reduced program footprints, and provides some insight into whether there are disparities in participation across income groups.

In PY2018 and PY2019, the direct install participation rates for CARE/FERA households and non-CARE/FERA households were nearly the same, while the CARE/FERA household participation rate fell less than the non-CARE/FERA households in PY2020 and PY2021. Participation rate trends for direct install programs underscore these programs' focus on serving lower-income households. Despite a drop in participation in PY2020 and PY2021, the direct install programs maintain a greater focus on participation among CARE/FERA households.

On the other hand, the rebate program participation rate was consistently lower for CARE/FERA households compared to non-CARE/FERA households. While the rebate programs defrayed the cost of the smart thermostats, customers still had to pay the remainder to obtain the technology. As a consequence, rebate programs consistently have lower participation among CARE/FERA households.

Figure 4-2. CARE/FERA participation rates by year and delivery channel



4.1.2 Access to program benefits

We sought to understand how access to these technologies has changed over time by different customer segments. This analysis sheds light on the extent to which the publicly funded PA programs have provided access to this technology among population segments defined by income, dwelling type, energy consumption level, and location.

Fifty to seventy percent of smart thermostats delivered by the California PA programs from PY2018 to PY2021 were via direct install channels. While direct install programs had no income requirements for participation, they sought to reach low- to medium-income customers. Additionally, since programs not explicitly tailored for low-income customers underserve such customers present in the population, our analysis aimed to gauge the effectiveness of smart thermostat programs in reaching these specific customer segments.[41] Given the unavailability of income data, we evaluated participation among hard-to-reach (HTR),[42] disadvantaged community (DAC),[43] and multifamily customers as these segments likely encompass a higher proportion of individuals with lower to moderate incomes, facilitating this assessment. The data show the following:

Direct install programs serve communities that face energy and income burdens in greater proportions. Table 4-2 provides the proportion of participants in DAC, HTR, and non-metro areas by delivery channel and contrast these with the corresponding population proportions in California. The direct install program participation rates underscore that programs

[41] https://www.aceee.org/files/proceedings/2016/data/papers/2_542.pdf.

[42] Hard to reach (HTR): The criteria for residential HTR customers is the combination of a geographic prerequisite plus at least one of the following criteria: primary language, income, or housing type. Commercial HTR customers are defined by a combination of a geographic requirement plus at least one of the following criteria: primary language, business size, or leased or rented facility. Specific details can be found here: Statewide Deemed Workpaper Rulebook.

[43] CPUC, "Disadvantaged Communities," *cpuc.gov*, 2021, https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/infrastructure/disadvantaged-communities.

that seek to serve DAC/HTR/non-metro customers must be intentional in their targeting and outreach to reach such customers.

Table 4-2. Statewide IOU population and program participants in DAC, HTR, and non-metro areas

Participant segment	Total CA population	All DI participants	All rebate participants
DAC	22%	29%	10%
HTR	34%	43%	18%
Non-Metro	56%	57%	51%

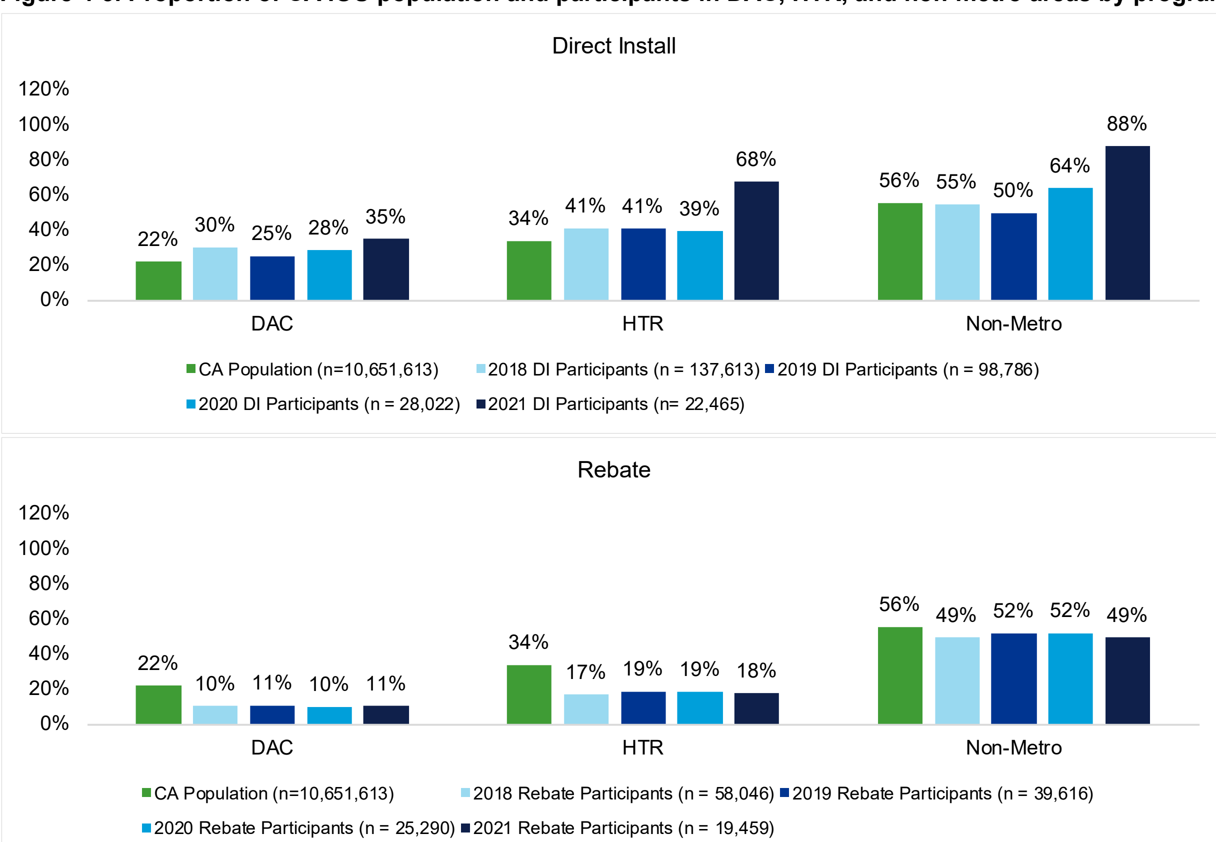
Table 4-3 provides analogous results for CARE participants. As noted previously, while CARE/FERA status is determined strictly on the basis of income, DAC/HTR/non-metro designations are based on different factors including language, geography, and pollution burden. We observed similar results with direct install programs, which reached these vulnerable customer segments.

Table 4-3. Statewide IOU CARE population and program participants in DAC, HTR, and non-metro areas

Participant segment	Total CARE population	DI CARE participants	Rebate CARE participants
DAC	32%	40%	22%
HTR	73%	80%	67%
Non-Metro	63%	71%	59%

Direct install programs have improved DAC, HTR, and non-metro participation over time. Figure 4-3 shows the proportion of direct install participants in DACs, HTR, and non-metro areas has increased over the four-year period from 2018 to 2021, whereas the proportion of rebate participation for three segments has remained the same.

Figure 4-3. Proportion of CA IOU population and participants in DAC, HTR, and non-metro areas by program year



Opportunities exist for targeting desirable customer segments. As Table 4-4 indicates, the proportion of multifamily direct install program participants is twice that of the statewide multifamily population. This reflects direct install programs' focus on serving the multifamily sector to overcome the split incentive barrier to EE by providing EE measures at no cost to multifamily homes. By contrast, the small proportion of multifamily households that participated in rebate programs indicates that property managers and not individual tenants are the decision-makers for program participation. This highlights the necessity of direct install programs to continue serving the multifamily sector effectively.

As seen in other EE programs, like the Home Energy Reports Programs, customers in the top consumption quartile are a desirable target for EE programs. We analyzed the distribution of smart thermostats from PY2018 to PY2021 by consumption level. We observed that participation among households in the top consumption quartile is on par with statewide top consumption quartile for rebate participants and lower than statewide top consumption quartile for direct install participants.

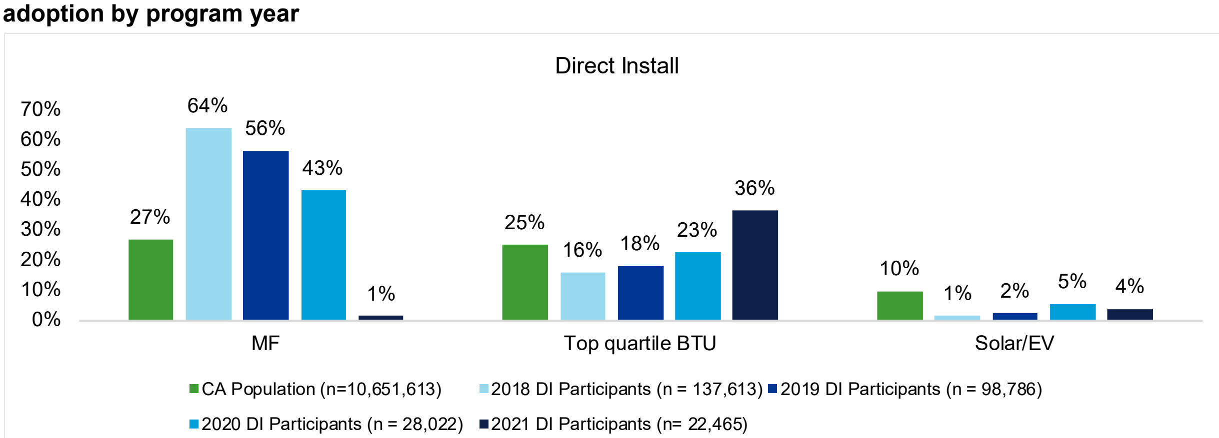
Households with solar or EV are more likely to adopt time-sensitive energy usage behaviors that correspond to periods of high solar energy production during the day or lower EV rates that encourage off-peak charging. Such households hence represent a desirable target for the deployment of smart thermostats and participation in demand response (DR) and virtual power plant programs.

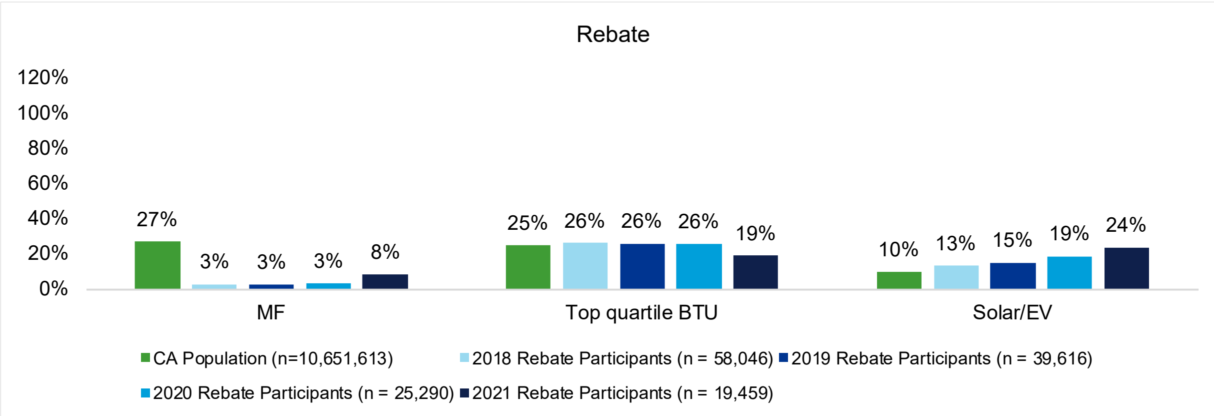
Table 4-4. Statewide IOU population and program participants by dwelling type, consumption, and technology adoption

Participant segment	Total CA Population	All DI Participants	All Rebate Participants
Multifamily	27%	54%	4%
Top quartile BTU	25%	19%	25%
Solar/EV	10%	2%	16%

Positive trend in smart thermostat program participation among solar/EV adopters. Figure 4-4 indicates a steady decline in the proportion of multifamily direct install participants from 2018 to 2021. Implementer and PA interviews for PY2021 indicated that the declines in PY2020 and PY2021 were partly due to the impact of the COVID-19 pandemic, which had greatly restricted access to multifamily buildings. This is reflected in the higher proportion of participants in the top consumption quartile in PY2021. While the proportion of participants that have adopted solar/EV is higher among rebate compared to direct install participants, the proportion has grown over time for both program types. This increase reflects the growing adoption of solar and EV in tandem with participation in energy efficiency programs. As noted above, this is a positive trend for EE programs that deliver smart thermostats.

Figure 4-4. Statewide IOU population and program participants by dwelling type, consumption, and technology adoption by program year





4.1.3 Effective deployment

In the face of potential extreme summer weather, the CPUC has sought to ensure adequate energy resources by authorizing the use of additional supply- and demand-side resources, particularly in the hot climate zones of 9 through 15. For example, the CPUC ordered that all residential customers not currently enrolled in existing supply-side DR programs be considered eligible to participate and automatically enroll in the residential Emergency Load Reduction Program (ELRP) in the summers of 2022 and 2023.[44] It also authorized a thermostat incentive program to improve demand side management in these hot climate zones.[45]

Given the importance of load management in these hot climate zones during resource constraints, DNV examined the deployment of smart thermostats in these regions by PA programs from PY2018 to PY2021. Table 4-5 shows that the proportion of both direct install and rebate participants is higher in this region than in the statewide population. The percent of direct install customers in this region is much higher than the percent of rebate customers indicating PA programs have actively distributed smart thermostats at no-cost to customers in these critical climate zones where this technology can be most effective.

Table 4-5. Statewide IOU population and program participants in ELRP hot climate zones

Participant segment	Total CA Population (n=10,651,613)	All DI Participants (n = 71,722)	All Rebate Participants (n = 35,603)
ELRP CZs (9-15)	45%	77%	50%

Given that low-income customers in the CARE program receive a 20%-35% discount on their electricity and gas rates, managing energy consumption for CARE customers in ELRP climate zones is essential. Smart thermostats enable customers to manage energy consumption. Table 4-6 summarizes the proportion of CARE direct install and rebate participants in ELRP hot climate zones and compares these values to the proportion of the CARE population in these climate zones. Both the direct install and rebate programs have delivered smart thermostats to this customer segment in the ELRP climate zones effectively.

Table 4-6. Statewide IOU CARE population and program participants in ELRP hot climate zones

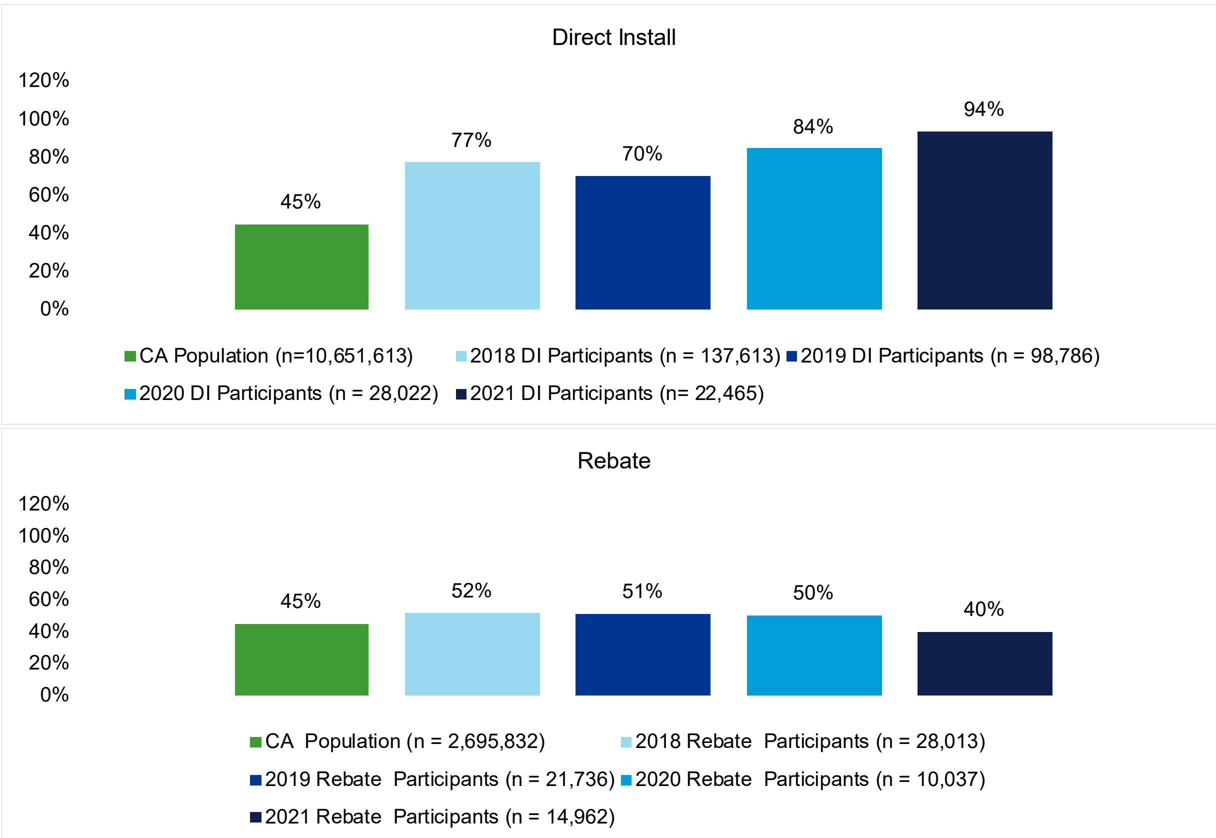
Participant segment	Total CARE Population (n = 2,695,832)	DI CARE Participants (n = 18,687)	Rebate CARE Participants (n = 4,201)
ELRP CZs (9-15)	51%	88%	64%

[44] CPUC, "Phase 2 Decision Directing Pacific Gas and Electric Company, Southern California Edison Company, and San Diego Gas & Electric Company to take actions to prepare for potential extreme weather in the summers of 2022 and 2023," cpuc.ca.gov.https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M428/K821/428821475.PDF

[45] Ibid, p. 79.

Figure 4-5 shows that direct install programs have progressively increased smart thermostat deployment in ELRP climate zones. Program installations in later years are almost all (94%) in ELRP climate zones. The absolute number of smart thermostats installed cumulatively in ELRP climate zones through the PAs' direct install programs from PY2018 through PY2021 are 220,330. This represents 4.6% of the approximately five million households in ELRP climate zones.

Figure 4-5. Statewide IOU population and program participants in ELRP climate zones by program type and year



While installation concentrated in ELRP climate zones is one indicator of effective deployment of smart thermostats, enrollment in DR programs among households receiving this measure is another useful indicator of effective deployment. Table 4-7 shows that over the PY2018 to PY2021 period, on average, the proportion of direct install program participants in demand response programs is notably lower than the proportion of rebate program participants. The proportion of direct install program participants is also lower than that of IOU customers in demand response programs statewide. On average, rebate customers' participation in demand response programs has been higher than overall IOU customers' participation in demand response programs.

Table 4-7. Proportion of customers in demand response programs

Customer segment	Total Population (n = 10,651,613)	DI Participants (n = 71,722)	Rebate Participants (n = 35,603)
Customers in DR programs	4%	3%	7%

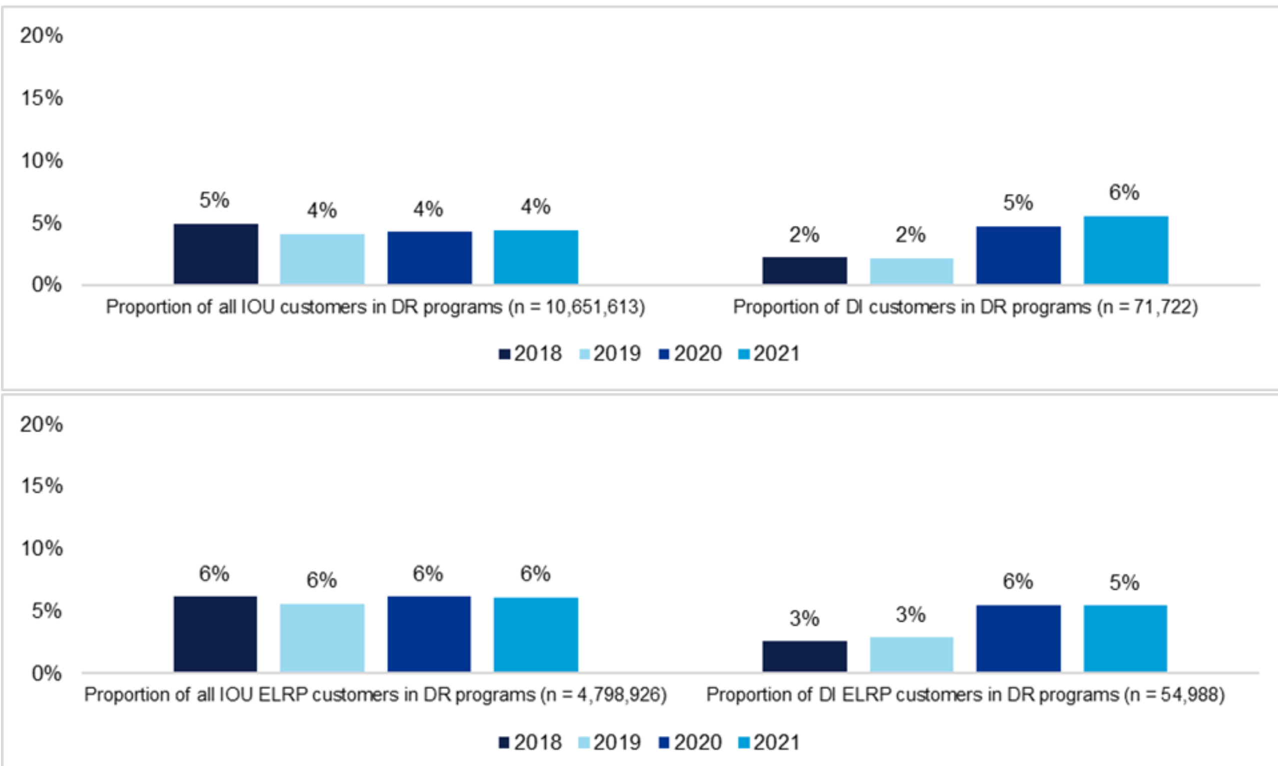
A similar trend is evident for demand response program participation in ELRP climate zones. As Table 4-8 indicates, participation in demand response programs among customers with direct install smart thermostats in ELRP climate zones is lower than participation in demand response programs among customers with rebate program smart thermostats in these hot climate zones.

Table 4-8. Proportion of ELRP climate zone customers in demand response programs

Customer segment	Total Population (n = 4,798,926)	DI Participants (n = 54,988)	Rebate Participants (n = 17,310)
ELRP CZ customers in DR programs	5%	3%	5%

As Figure 4-6 indicates, direct install customer participation in demand response programs has increased over program years PY2018 to PY2021. Such an increase has also occurred among direct install customers in ELRP climate zones. Decision 21-12-015 required enrollment in demand response programs for customers in ELRP climate zones, including those in the CARE or ESA programs, receiving subsidized smart thermostats through new incentive programs.[46] The increasing trend in participation in demand response programs among ELRP direct install participants is a positive development and will aid the effort, reflected in the CPUC decision, to reduce load and grid stress during extreme weather events.

Figure 4-6. Proportion of all and ELRP climate zone customers in demand response programs by year



4.2 Impact Results

This section provides results from the impact evaluation based on the model and savings estimation approaches presented in sections 3.3.3 and 3.3.5 We include a high-level summary of the data used, including a discussion of energy consumption trend over time. We also provide the estimated energy consumption changes based on model estimates. Additionally, we include results for different customer segments that installed smart thermostats in this section. Results from model estimates we used to analyze energy consumptions changes are featured in Appendix 6.1.

[46] https://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M428/K821/428821475.PDF.

4.2.1 Data summary

We provide a summary of the energy consumption data used in the analysis in this section. We start by examining pre-period daily average consumption values for participants and non-participants by delivery channel. As the values in Table 4-9 indicate, the two groups have well-matched pre-period average daily use and rebate participants have higher energy consumption than direct install participants.

Table 4-9. Average pre-period daily use by group and delivery channel

Delivery channel	Group	Electric (kWh)	Gas (therms)
Direct install	Participant	13.19	0.73
	Non-participant	13.20	0.72
Rebate	Participant	18.75	1.02
	Non-participant	18.72	1.02

To examine balance between participants and non-participants, we look at plots that show the distribution of pre-period daily consumption. Figure 4-7 provides violin plots that combine box and density plots of pre-period electric daily consumption annually and by season for participants and non-participants.[47] The figures indicate that both the density and spread of the values for the two groups are identical indicating groups that are well-balanced.

Figure 4-7. Distribution of pre-period electric daily use by year and season for participants and non-participants

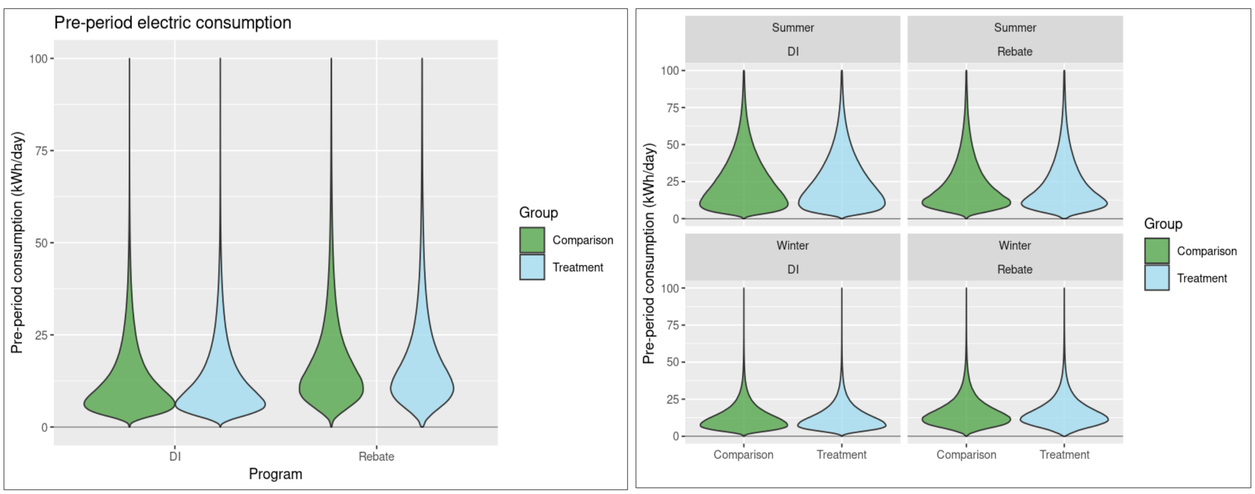
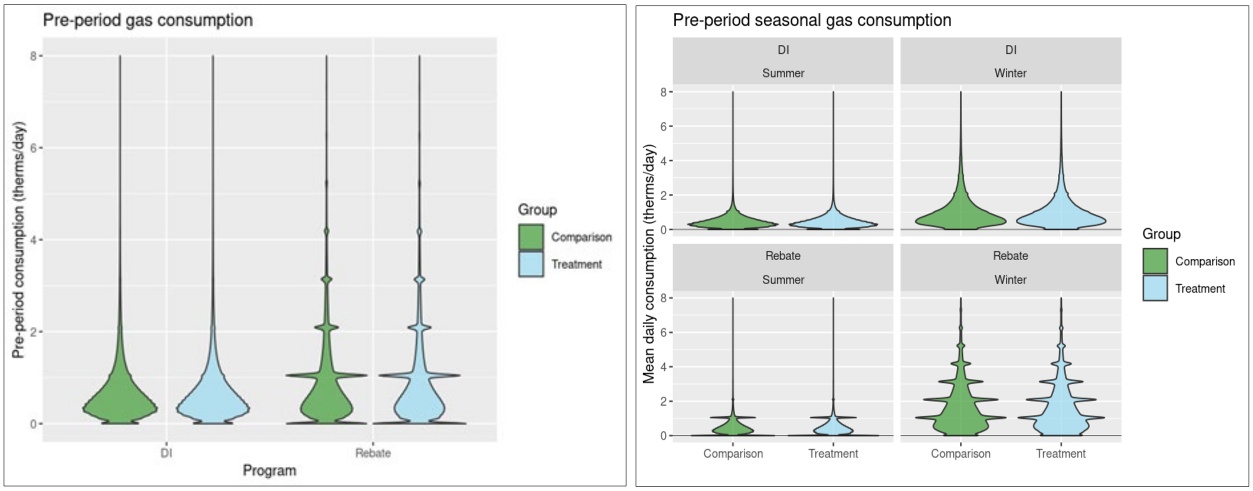


Figure 4-8 provides violin plots for pre-period gas consumption of participants and non-participants by year and by season. This figure also indicates gas data used in the analysis is well balanced. The gas daily density plots have spikes at certain points in the distribution because PG&E’s gas meter reads are integers and not continuous. The figures indicate spikes at similar values in the distribution for both participant and non-participants.

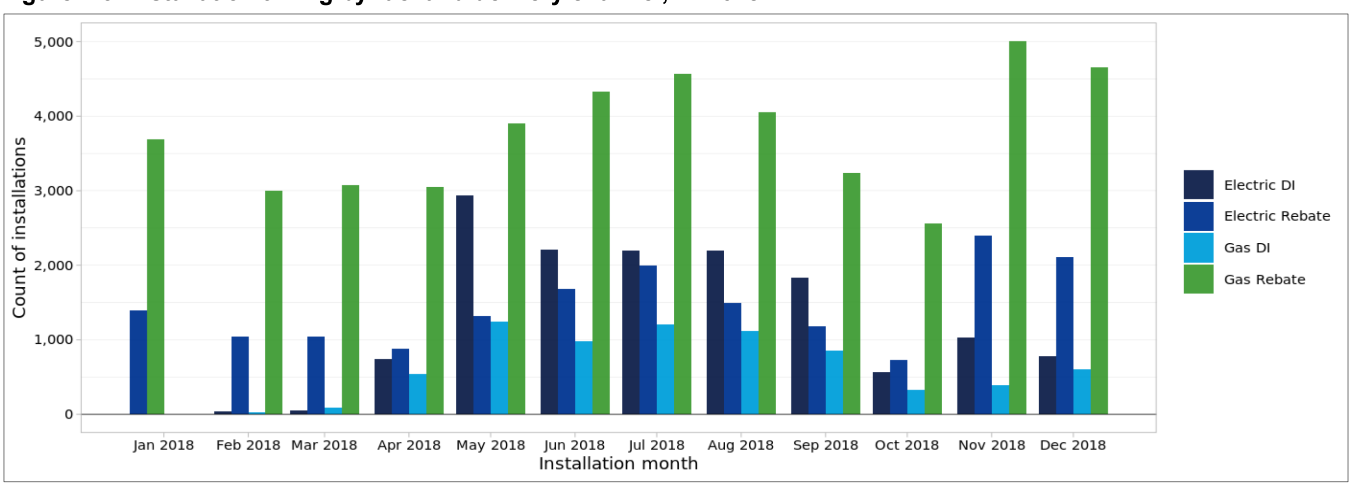
[47] A violin plot is a hybrid of a box plot and a density plot that describes the distribution of a variable by depicting its summary statistics such as 25th, 50th, and 75th percentiles and the probability that it takes on a value within a certain range.

Figure 4-8. Distribution of pre-period gas daily use by year and season for participants and non-participants



We also provide the timing of the installation used in the study. As Figure 4-9 indicates, most of the installations used in the study occurred in the summer, June through September, and winter, December, and January. The number of gas rebate installations is higher than other installations reflecting the large number of rebate smart thermostats provided by SCG. SCG and SCE jointly funded these installations, but SCG ran the program. As a result, the electric identifiers of the participants were not available. We included in the analysis the SCE customers for whom we could identify electric IDs through address matching.

Figure 4-9. Installation timing by fuel and delivery channel, PY2018



Since we use post period data that ends at the end of 2021, we provide a summary of the percent of customers with data in each of the four post years in Table 4-10. The analysis requires that each customer has at least one year of post period data. Thus, all customers included in the analysis have complete first post year data. Over 95% of customers also have complete second post year data. More rebate than direct install customers have complete third post year data, at about 90-95% for rebate customers compared to about 80-85% for direct install customers. This reflects the lower moveout rate (attrition) among single family participants that mostly make up the rebate customer base. The percent of customers with complete year four post period data reflects installations that occurred early in PY2018 rather than attrition. By definition, customers that installed smart thermostats in the middle or the end of 2018 will not have year 4 post data since our analysis data ends in December 2021. The percent of customers with complete post year 4 data is about 10% for direct install and about 25% for rebate customers.

Table 4-10. Summary of the length of the post-period of PY2018 data used in the analysis

Delivery channel	Fuel	Percent of customers with post days			
		1 Year Post	2 Years Post	3 Years Post	4 Years Post
Direct install	Electric	100%	97%	80%	10%
	Gas	100%	97%	86%	11%
Rebate	Electric	100%	96%	89%	22%
	Gas	100%	97%	95%	26%

4.2.2 Energy consumption trend

Figure 4-10 displays the average daily electric and gas consumption of PY2018 rebate program participants and matched non-participants over the analysis period of January 2017 to December 2021. The two panels in the figure demonstrate that the energy consumption of the two groups is well-matched before the installation of smart thermostats. The panels also indicate that electricity and gas consumption of participants grew faster than that of non-participants in the post-period. DNV's PY2018 evaluation demonstrated that the baseload energy consumption of participants was higher than that of non-participants in the post-installation period. Since smart thermostats target the operation of the HVAC system, this difference in baseload energy consumption trend indicates the difference in the energy consumption trend between the two groups. As a result, in a difference-in-difference (DID) analysis, the difference in energy consumption trend between participants and non-participants could suppress savings due to smart thermostat installations. The DNV PY2018 study involved an adjustment to control for the effect of this difference. The current study controls for this effect through a consistent and systematic modeling approach.

Figure 4-10. Average daily electric and consumption for PY2018 rebate customers over time

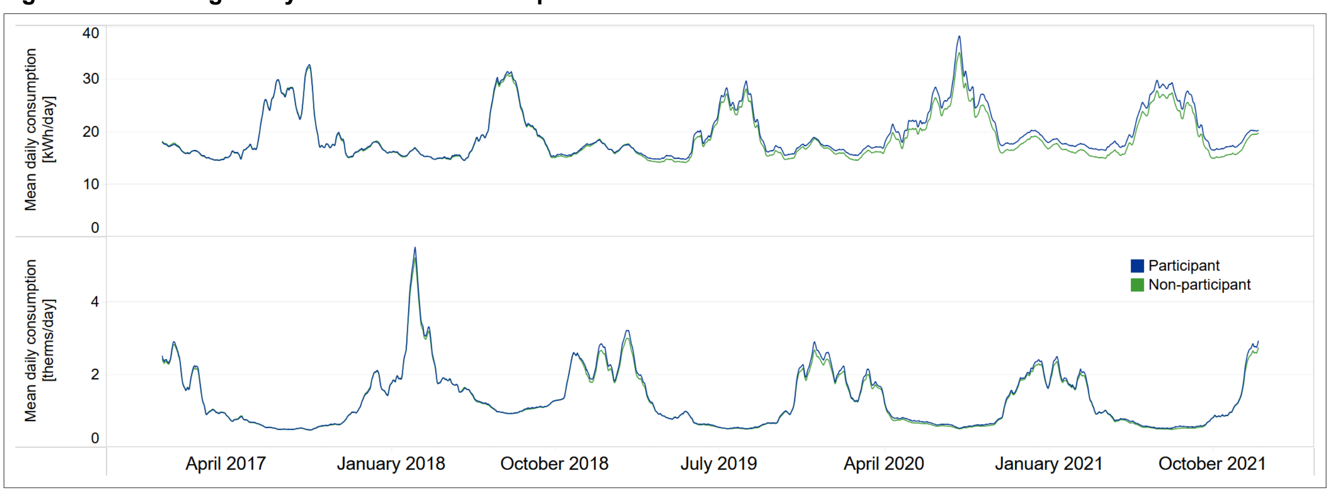
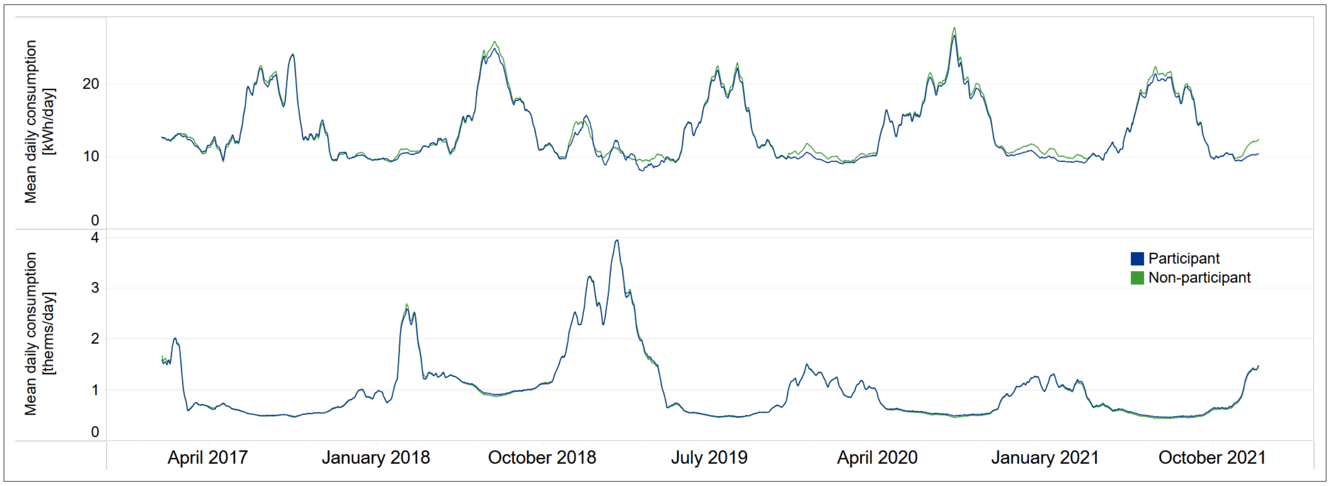


Figure 4-11 provides the same summary as the above figure for direct install participants. The two panels in the figure also indicated well-matched participant and non-participant energy consumption before smart thermostat installation. Further, the electricity consumption of participants appears to grow slower than that of matched non-participants, while there is no evidence of a decrease in participant gas consumption in the post-period.

Figure 4-11. Average daily electric and gas consumption for PY2018 direct install customers over time



4.2.3 Comparison with past impact estimates

As noted earlier, smart thermostats have been delivered through both direct install and rebate channels. In our prior evaluations on the impact of smart thermostat installations, we used a difference-in-difference (DID) framework with a matched comparison group to estimate the effect of smart thermostats delivered through both channels. This is a widely used and accepted methodology to evaluate EE programs. It is the correct methodology to estimate the household-level impact of a program if it is reasonable to assume that the comparison group change is a representation of the participant group change over time, absent the measure or program.

Participant populations all reflect external- and self-selection processes that lead to differences from the general population in observable and unobservable characteristics. The matching process is designed to select a comparison group that best matches the participant group but, in practice, this is challenging. Some observable characteristics are difficult to represent with available data. Unobservable characteristics can only be represented through other correlated variables, and only if those other variables can be identified and are available. As a result, matching algorithms tend to be heavily weighted toward consumption data parameters that provide good pre-period balance on consumption but incorporate limited information on other possible characteristics. Of particular importance is the impact of characteristics on trends in consumption over time. Consumption data matching on a single pre-period year of data is unable to meaningfully capture trends over time. Yet a fully representative comparison group should have consumption that tracks with what the participant group’s consumption would have been over multiple years.

It is impossible to directly compare trends over time once the program effect is present, and the obvious alternatives, multiple years of pre-data, are difficult to access and would further constrict the analysis population. As a result, the potential for trend differential is hypothesized based on the difference of the participant population from identified potential matches based largely on the nature of the selection process. In general, direct install programs work within identified (thus identifiable) target populations and the free offerings are easy to accept. These two aspects of direct install programs, the identifiable program target populations and free program offerings, make it easier to assume that there are limited trend differences in energy consumption between participants and matched non-participants.

Thermostat rebate programs present a different challenge. The eligible population is unconstrained and, while the rebates are sufficient to motivate substantial participation, participants will generally spend at least $100 dollars out of pocket above the provided incentive. The matched comparison group process must draw from the full residential population and does so without any way to target the limited subset of customers who might be willing and able to spend $100 on a new thermostat.[48] To the extent that the characteristics of those purchasing rebate program thermostats are correlated with a consumption trend over time that is different from that of the general population, a matched comparison group created under these circumstances cannot intentionally avoid the bias associated with a trend differential. For example, it is not unreasonable to imagine that those willing and able to spend that $100 are more likely to add an EV during the evaluation period than those who are not. In this case, a self-report survey after the fact could support a simplistic adjustment.

For the PY2018 rebate program impact evaluation, we devised a more comprehensive adjustment to address differences in trends over time. Because thermostats are expected to impact only heating and cooling consumption, the difference between participant and comparison group pre-to-post baseload consumption provided a proxy estimate of the trend differential. We used the participant group's percent change in baseload to adjust the percent change in the group's heating and cooling load. This adjustment involved the simplifying assumption that the baseload trend was a good proxy for the overall trend.

The models used for the current analysis follow similar logic but within an explicit regression framework. The panel models used effectively incorporate this approach into the structural equation with some subtle differences. A single trend is estimated across all three consumption components: baseload, heating, and cooling. The only flexibility for the model to capture program-related change is through a shifting degree-day base. This model structure-enforced relationship is consistent with the understanding that a smart thermostat causes a decrease in summer reference temperature values and an increase in winter reference temperature values. The shared trend over the three components, baseload, heating, and cooling, makes the panel regression non-linear in parameters, but the underlying structure is a linear model that quantifies the reference temperature-related shift due to a smart thermostat installation while controlling for differences across participant and comparison groups and trend over time.

In contrast, the original PY2018 and PY2019 results used two-stage site-level models. Pre- and post-installation data were modeled independently at the site-level and the second stage effectively aggregated the annualized, weather normalized results from those site-level models. The new specification is a panel model that includes all customers' and pre- and post-installation interval data in a single model structure. This model does, in fact, incorporate information from the pre-installation models as the pre-installation degree-day bases provide the customer-specific baseline against which change in degree-day base can occur because of the program. It is the combination of site-level information from site-level models and a panel model specification that structurally separates program-related effects from a simple linear trend over time that makes this approach so unique and compelling.

A nice attribute of the panel specification is that we can estimate it with and without the trend component. This quality allows structurally consistent results and comparisons between the no-trend panel model and the PY2018 and PY2019 unadjusted two-stage DID model results and the panel model with trend and the PY2018 and PY2019 adjusted results.

The panel model results support the conclusion that energy consumption trend differential caused a downward bias of first-year unadjusted PY2018 rebate program savings estimates. They indicate the need to account for such differential between participant and comparison group households, which DNV undertook in the PY2018 rebate evaluation. The PY2019 direct install evaluation assumed no similar differential and did not apply an adjustment in the study. The current results indicate that it may have also been appropriate to include the adjustment in the PY2019 direct install analysis.

Table 4-11 compares savings estimated based on smart thermostats delivered through PY2018 direct install programs used to evaluate PY2019 claims, and PY2018 rebate programs used to assess PY2018 claims.

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[48] While it is possible to develop data correlated with being "able" to afford a new rebated thermostat, it will be far more challenging to do the same for being "willing" to spend money on the technology.

Rebate program smart thermostat electric savings change from negative to positive and are significant when we account for trend differences. The trend estimates for participants and non-participants in the panel models (Table 6-1, Appendix A) are different and statistically significant, indicating the need to control for trend differences. The panel model results reveal that the prior PY2018 ad hoc corrections somewhat overstated rebate electric savings. There are also gas consumption trend differences for rebate program smart thermostats. The panel model indicates that gas consumption trend estimates are different and statistically significant for participants and non-participants (Table 6-3, Appendix A). The panel results suggest that the prior PY2018 adjusted gas savings are also overstated.

Direct install electric savings estimates from the unadjusted PY2019 DID and the current panel approaches are similar. Panel model savings estimates that account for trend differences indicate that the PY2019 electric direct install evaluation may have overstated savings. Direct install smart thermostat gas savings based on panel models are higher than the two-stage DID results. However, similar to the rebate program gas smart thermostat savings, accounting for trend differences does not appear to affect these gas savings.

Overall, the DID and panel data approaches indicate electric and gas savings are well below claimed levels.

Table 4-11. Comparison of PY2018 and PY2019 evaluated and current model savings per household[49]

Delivery type	Model type	Models[50]	Electric savings (kWh)	Gas savings (therm)
Rebate	No trend	Current panel	-106	-6
		Prior two-stage PY2018 DID	-104	-4
	Trend	Current panel	29	-10
		Prior two-stage PY2018 DID	64	2
Direct Install	No trend	Current panel	44	5
		Prior two-stage PY2019 DID	43	0
	Trend	Current panel	-13	5

The current panel model also allows for the inclusion of multiple years of post-installation data. Table 4-12 provides a summary of the results based one- and four post-year data. It indicates that average annual savings based on four post-year data are higher for both electricity and gas.

Table 4-12. Comparison of current model annual savings per household: one-year and four year-post results

Delivery type	Model type	Models	Electric savings (kWh)	Gas savings (therm)
Rebate	Trend	One post-year panel	29	-10
		All-post-years panel	45	-2
Direct Install		One post-year panel	-13	5
		All-post-years panel	4	9

The four-year trends are perhaps misleading because by the second post-year, the COVID pandemic effects are present in the data. By the third post-year almost all the data is from the pandemic period. The pandemic saw a general increase in residential energy consumption though impacts varied across the population depending on location and occupation. Despite the possible COVID-induced reductions in energy savings, in general, it appears that energy savings from smart thermostats installed in PY2018 have increased over time.

[49] Negative values in all tables indicate dissavings.

[50] The two-stage DID results in this table are participant weighted per site savings. The table does not include two-stage PY2019 DID result for direct install programs since DNV did not adjust the PY2019 DID results for any possible trend differences.

4.2.4 Energy impact across all customers

We obtained the overall impact of smart thermostat installations on energy consumption by combining panel model coefficients (provided in Appendix A) with pre-period reference temperature values using the approach detailed in section 3.3.5. Estimated electric and gas savings reflect both the global reference temperature estimates and the participant group's incremental reference temperature shifts and the participant group's estimated slope and trend coefficients, as specified in (Equation 3).

In general, the electric model results indicate either limited difference between the cooling reference temperature estimates of participants and non-participants or lower cooling reference temperature estimates for participants in the post period indicating higher cooling load post-installation. They also reflect electric heating reference temperature estimates that are generally lower among participants in the post period indicating lower electric heating load. Table 4-13 summarizes the electric cooling and heating results. It indicates electric cooling increases (negative values) and electric heating savings (positive values) post smart thermostat installations based on the estimated incremental reference temperature changes. For rebate participants, cooling increases are lower and heating savings are higher when we account for energy consumption trend differential between participants and matched non-participants—that is, for the models that include the trend terms.

Table 4-13. PY2018 smart thermostat electric cooling and heating savings per household

Delivery type	Models	Cooling electric savings			Heating electric savings		
		kWh	p-value	RP	kWh	p-value	RP
Rebate	Trend, All-post-years	-13	0.01	0.02	59	0.00	0.00
	Trend, One year-post	-19	0.01	0.02	47	0.00	0.01
	No trend, All-post-years	-90	0.00	0.00	-16	0.01	0.04
Direct install	Trend, All-post-years	-30	0.00	0.00	34	0.00	0.00
	Trend, One year-post	-39	0.00	0.01	26	0.00	0.00
	No trend, All-post-years	-1	0.91	11.46	44	0.00	0.00

The estimated overall electric (kWh) and gas (therm) impacts along with their significance and relative precisions (RP) are provided in Table 4-14 for the trend and no-trend models. The overall electric impacts reflect the combined effect of electric cooling and heating savings. All estimated electric savings are statistically significant and have a relative precision of at least 0.20, with most models indicating more precisely estimated values.

Rebate program thermostats exhibit electric savings only when we account for differences in energy consumption trends between participants and non-participants. Accounting for trend differences does not affect the gas savings of rebate program thermostats, which do not provide gas savings. Controlling for trend differences also matters for direct install smart thermostat electric savings. Without such accounting, the electric savings of direct-install smart thermostats appear to be overstated. Accounting for trend differences does not affect direct install gas savings. In all cases, there is evidence of improvements in smart thermostat savings over time.

Table 4-14. PY2018 smart thermostat savings per household

Delivery type	Model type	Electric impact			Gas impact		
		kWh	p-value	RP	Therm	p-value	RP
Rebate	Trend, All-post-years	45	0.00	0.01	-1.5	0.20	0.54
	Trend, One year-post	29	0.01	0.01	-10.0	0.01	0.02
	No trend, All-post-years	-106	0.00	0.01	-6.0	0.01	0.03
Direct install	Trend, All-post-years	4	0.02	0.05	9.1	0.01	0.02
	Trend, One year-post	-13	0.01	0.02	5.1	0.04	0.09
	No trend, All-post-years	44	0.06	0.14	5.0	0.03	0.07

We calculated savings from the annual shift models to gauge savings relative to baseline over time.[51] Table 4-15 provides the estimated savings based on these models. Rebate smart thermostat electric savings are positive in all years, and gas savings are positive in most years. Direct install electric savings are low or negative in all years, and gas savings are positive and similar in all post years. The models do not exhibit systematic trends over time, fuel, or program, but results from post years 2 onwards are likely to reflect the COVID pandemic effects.

Table 4-15. PY2018 smart thermostat savings per household and by year

Delivery type	Period	Electric impact			Gas impact		
		kWh	p-value	RP	Therm	p-value	RP
Rebate	Post year 1	53	0.00	0.00	-11.5	0.00	0.01
	Post year 2	43	0.00	0.01	9.5	0.01	0.03
	Post year 3	25	0.01	0.03	11.8	0.01	0.02
	Post year 4	60	0.01	0.01	10.2	0.02	0.04
Direct install	Post year 1	7	0.01	0.02	7.2	0.01	0.03
	Post year 2	-12	0.01	0.02	10.2	0.01	0.02
	Post year 3	-49	0.00	0.00	8.9	0.01	0.04
	Post year 4	-16	0.01	0.02	6.0	0.05	0.13

4.2.5 Energy impact by customer segment

The preceding section provided the impact of smart thermostats from all the models we estimated across all customer segments. In this section, we provide the impact of smart thermostats on overall energy consumption by customer segment based on **all-post-years** models, which include up to four years of post-period data and incremental reference temperature shift terms for participants. Model coefficient estimates for customer segment models are provided in Appendix 6.2.

We sought to understand if smart thermostat savings varied by participant demographic segments, levels of energy consumption, household characteristics, rates, and smart thermostat brand. Particularly, we explored smart thermostat savings differences by:

- Demographic segments (HTR, DAC status)
- Consumption level and household characteristics (consumption quartile, dwelling type, climate zone)
- Rate, demand response and technology brand (TOU, DR, smart thermostat brand)

We explored the impact of smart thermostats for all the customer segments listed above, but report on results for only those segments where matching between participants and non-participants was well-balanced. We were able to estimate the impact of smart thermostats on HTR but not DAC status for this reason. Since participants were matched to non-participants by location (climate zone) and housing type, it was possible to determine impact by HTR status, which partly reflects geographic status and renters in multifamily and mobile homes. In some cases, we also had data from only a limited number of customers within a particular segment, which did not make it possible to report the energy impact of smart thermostats among such customers. For example, we had data from about 300 rebate and 28 direct install customers on demand response, which did not enable us to determine smart thermostat impact by demand response status.

Table 4-16 provides electric and gas impacts of smart thermostats by household characteristics, including dwelling type, HTR status, consumption level, and technology type.

The electric impact of smart thermostats differs by HTR status and dwelling type. Both rebate and direct install non-HTR participants have electric smart thermostat savings and non-HTR participants have electric dissavings. Participants in

[51] Model coefficients for these models are provided in Table 6-1 to Table 6-4 in Appendix A.

multifamily dwelling units also have higher electricity use post-installation than those in single-family and mobile homes.[52] There is considerable overlap between HTR status and multifamily residence since being a multifamily renter is one of the criteria used to define the former. The electricity dissavings of HTR and multifamily participants is likely higher due to customer takeback. Participants in these two groups likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy deprivation. A technology that promises to regulate and reduce energy use and cost could lead such participants to increase their comfort and use more energy inadvertently. This pattern holds for gas rebates participants. Customer responses from participant surveys conducted for DNV's impact evaluations of the PAs' PY2018, 2019, and 2020 rebate and direct install programs indicate a significant increase in customer comfort post smart thermostat installation, which could be indications of takeback.[53]

We also note higher electricity and gas savings for rebate participants in the top consumption quartile than in the other consumption quartiles. It appears that smart thermostats enable a reduction in energy use among the consumption quartile that can most readily accomplish this.

Table 4-16. PY2018 all post years annual savings by household characteristics and technology type

Delivery type	Segment value	Electric impact			Gas impact		
		kWh	p-value	RP	Therm	p-value	RP
Rebate	HTR	-54	0.02	0.02	-9.6	0.01	0.03
	Non-HTR	43	0.00	0.03	-1.2	0.38	1.12
	Top Btu Quartile	151	0.00	0.00	11.8	0.01	0.02
	Other Quartile	3	0.00	0.07	-5.8	0.01	0.03
	Technology 1	55	0.00	0.03	-1.5	0.22	0.60
	Technology 2	17	0.00	0.02	2.6	0.26	0.72
Direct install	HTR	-15	0.00	0.02	10.2	0.01	0.03
	Non-HTR	17	0.00	0.07	7.5	0.02	0.06
	Top Btu Quartile	-119	0.00	0.00	8.9	0.05	0.14
	Other Quartile	-8	0.00	0.02	8.8	0.01	0.01
	SF/MH	123	0.00	0.02	7.3	0.03	0.07
	MF	-15	0.00	0.01	11.0	0.01	0.02

Table 4-17 provides electric and gas savings estimates by time of use (TOU) rate and location. Being on a TOU rate appears to have a significant effect on overall smart thermostat electric savings. Rebate participants on TOU rates have robust smart thermostat electric savings while those not on TOU rates have a small increase in electric consumption. This pattern does not hold for direct install participants on TOU.

Both rebate and direct install participants outside of ELRP climate zones have significant electric savings but those in the hot ELRP climate zones either have limited electric savings or have electric dissavings. The significant cooling needs in the hot climate zones are the likely reason for this outcome. We noted overall gas savings among direct install and gas consumption increases among rebate participants earlier and note the presence of significant gas savings in both ELRP and non-ELRP climate zones for direct install participants. Rebate participants outside of the ELRP climate zones have gas savings but not those in the ELRP climate zones, which indicates location matters for savings among rebate participants.

[52] Unlike multifamily homes, single-family and mobile homes have their own walls and roofs, and energy consumption is unaffected by adjacent homes. However, single-family and mobile homes may have different insulation levels and, thus, leakiness. We grouped these two home types in the analysis because the PAs' CIS data often only distinguishes attached and detached homes, which made it challenging to identify mobile homes for matching.

[53] The following links include DNV's impact evaluations of the PAs for PY2018, 2019, 2020:
https://www.calmac.org/publications/CPUC_Group_A_Report_Smart_Thermostat_PY_2018_CALMAC.pdf (Table 4-9),
https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf (Table 4-9),
https://www.calmac.org/publications/Group_A_Residential_PY2020_RES_HVAC_Final_Report_CALMAC.pdf (Table 5-8).

Table 4-17. PY2018 all post years annual savings by TOU rate and location

Delivery type	Segment value	Electric impact			Gas impact		
		kWh	p-value	RP	Therm	p-value	RP
Rebate	TOU	54	0.00	0.01	-9.5	0.02	0.06
	No TOU	-3	0.00	0.09	-0.6	0.73	3.58
	ELRP CZ	2	0.00	0.23	-6.4	0.01	0.03
	Non-ELRP CZ	69	0.00	0.05	4.5	0.04	0.12
Direct install	TOU	-35	0.88	0.23	33.6*	0.03	0.03
	No TOU	-33	0.00	0.01	7.9	0.01	0.03
	ELRP CZ	-29	0.00	0.01	10.4	0.01	0.02
	Non-ELRP CZ	71	0.00	0.00	6.1	0.03	0.08

*Estimate based on only 35 customers

4.3 Device data results

This research is motivated to address the challenge of quantifying thermostat-related savings using household level consumption data when those savings may amount to just 1-2% of household consumption. The specific challenge is the potential presence of bias due to self-selection manifesting in differential trends in consumption between participants and the comparison group. This bias could be of similar magnitude to the expected savings and could be the reason for the consistently modest estimates of savings. The pandemic, an extreme example of an exogenous effect, makes the effort of estimating savings that much more challenging. In requesting device data from thermostat manufacturers, we sought evidence for one of the base assumptions of process – that there is evidence of consumption reduction in the available HVAC system data.

The aggregate device data for a set of thermostats activated during the last 6 months of 2019 and all of 2020 provide a unique view into HVAC usage before and during the pandemic. These average runtime data reflect demand for cooling or heating as reflected in the number of minutes per hour the system was running.[54] Runtime is the primary source of energy consumption that a thermostat controls.[55] The runtime data illustrate how demand for heating and cooling changed over the first years of the pandemic. Because the aggregated population continues to grow through 2020, observed changes may also reflect changing underlying characteristics of thermostat acquirers. As the potential for this conflating factor is difficult to assess (we did not receive data reflecting the growing counts), we had to consider the data as if this was not a factor.

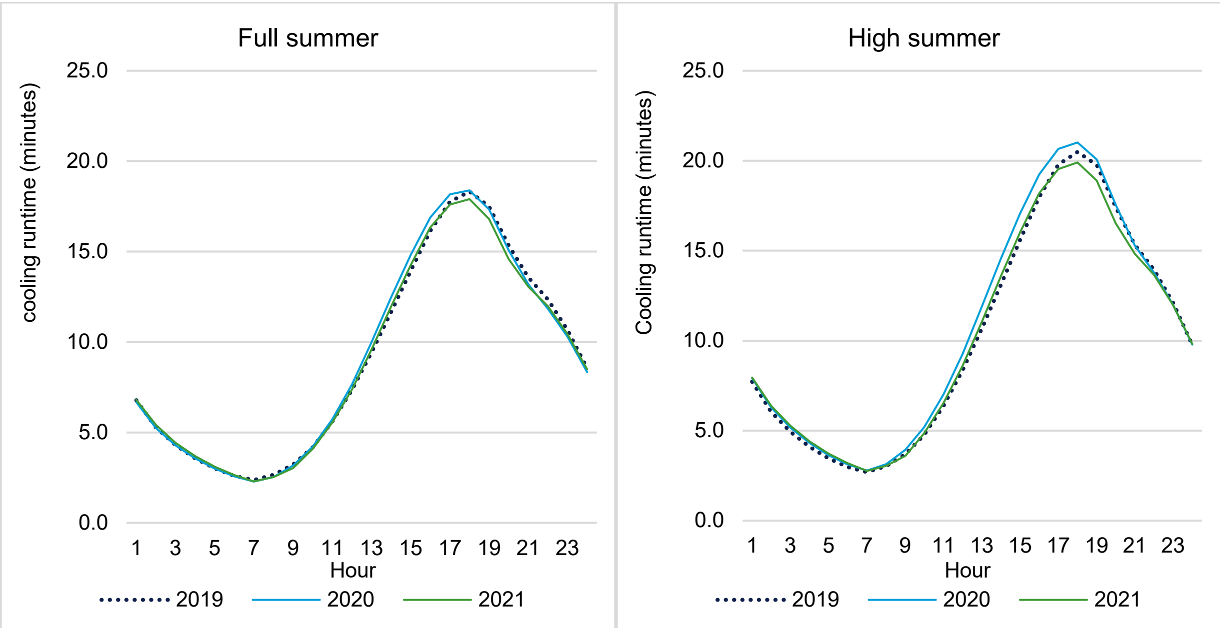
Figure 4-12 provides plots of the hourly runtime for 2019, 2020, and 2021 normalized to 2020 weather conditions. The left panel plots the three average normalized runtimes across the four months June through September (full summer) while the right panel shows just the hotter months of July and August (high summer). Both plots illustrate the substantial increase in daytime runtime in 2020, the first year of the pandemic, relative to the baseline year of 2019. Looking at actual weather, non-normalized shapes, the increase in 2020 is even more dramatic because 2020 was substantially hotter than the other two years.[56] This increase is consistent with increased daytime occupancy due to shutdowns. Cooling runtime in 2020 is higher across all hours during July and August, while during the full summer, the increased cooling during the day appears to lead to lower runtimes later in the evening.

[54] Runtime is roughly analogous to electric consumption, though system connected load (the load required by the systems to run at any moment) changes with current outdoor temperature. For example, when in cooling mode, AC connected load generally increases by about one percent for each degree increase in the temperature.

[55] Thermostats also control fan usage and may, in fact, make increased fan usage easier via convenient scheduling, etc.

[56] We pursued a similar analysis for the heating runtimes. Because of the timespan of the data, only two winters, one pre- and one post-COVID, were available for consideration. The 2020-2021 heating runtime plot demonstrated a substantial shift in runtime, increasing the morning peak, pushing it an hour later, and with heating runtime remaining well above winter 2019-2020 runtime throughout the morning hours. Across the whole day, heating runtime decreased by an average of 3% in the winter of 2020-21 compared to the pre-COVID winter of 2019-2020. One possible explanation of this slight reduction in average runtime even under the apparent increased daytime occupancy is that the thermostats were decreasing customers' demand for heating.

Figure 4-12. Average weather normalized hourly cooling runtime (in minutes) by year



Due to the pandemic-related changes in runtime, and the potentially conflating factor of the growing underlying population, it is difficult to determine whether smart thermostats had any effect on HVAC usage levels based on these year-over-year comparisons. The 2021 runtime shapes do appear to show modest reductions in overall and peak runtime relative to the 2019 baseline. The weather-normalized runtime in 2021 continues to show evidence of increased daytime occupancy but demonstrates a lower peak runtime. Across the whole day, 2021 runtime was lower by 1% for the whole summer. Load during hour 18, a proxy for peak load, was lower by 2% and 3% for the whole summer and high summer (hot) months, respectively.

A reduction of 1% in runtime, where cooling consumption is approximately 25% of household consumption across the state's geographically dispersed population, would represent a decrease in household consumption of just 0.3%.[57] As noted above, this is a reduction that can be difficult to distinguish from natural variation in the billing analysis context. These data indicate that demand for cooling had modest reduction for this cohort by 2021 despite obvious upward pressure from pandemic-related changes in household occupancy. Without data from a comparison group of non-smart thermostats for comparison, it is impossible to say confidently that this is, indeed, an effect caused by the thermostat and not just a subtle change in cooling behavior that reflected wider trends.

While these data may establish the feasibility of smart thermostat-related reduction in consumption, we need to consider several caveats in this analysis. The data provide no information on the number of smart thermostats aggregated in each climate zone, and it is unclear how those thermostats accrued over the second half of 2019 into 2020. As a result, the summer 2019 baseline is an incomplete baseline for the later years. Furthermore, even if the 2019 baseline were reliable, other dynamics could explain lower runtimes unrelated to smart thermostat-specific operations. For example, in 2021, some pandemic-related relief programs ended with possible economic effects on individuals. Alternatively, with the return to travelling, aggregate 2021 numbers include an increasing number of vacation days with associated setbacks. While it is impossible to disentangle these kinds of year-over-year impacts using these device data, it is possible to address them in

[57] Even if we could measure a higher reduction in runtime based on baseline thermostat use or comparison group data, the percent of reduction in household consumption is unlikely to exceed 2%-3% since average cooling load makes up about a quarterly of total energy consumption.

the primary analysis of this study, which uses a comparison group and the novel approach of addressing differential trends over time.

5 CONCLUSIONS AND RECOMMENDATIONS

In this study, we used data from the large installed base of smart thermostats delivered from PY2018 through PY2020 via rebate and direct install programs to gain insights regarding program participation. We also used one year of pre- and four years of post-installation data from PY2018 installed rebate and direct install programs to understand savings variability. The study enabled us to validate and strengthen our understanding of the following:

- **Matching of participant and non-participant data.** The panel model results validated the matching and the balance achieved between participant and non-participant energy consumption data, not only in overall energy use but also in the coefficients that characterize base, heating, and cooling patterns.
- **Energy consumption trends are different between the two groups.** While we achieved a close match between participants and non-participants pre-installation, the two groups exhibit different underlying trends unrelated to smart thermostat installations.
- **Savings, to the extent they exist, are small.** While our study illuminates the variability by various demographic and geographic customer segments, evaluated gross savings estimates are still significantly and uniformly lower than expected savings.

The findings from this study and resulting recommendations and implications for programs that will include or employ smart thermostats are summarized in Table 5-1 below.

Table 5-1. Key findings and recommendations

Key findings	Implications and recommendations
1. Our analysis indicates that the proportion of vulnerable customers (DAC, HTR, and non-metro area customers) receiving smart thermostats via direct install programs has increased significantly from PY2018 through PY2021, even as the participation of customers from these segments in smart thermostat rebate programs has remained flat. Participation of multifamily customers in direct install programs has also been significantly high at 57% over this period.[58] These findings indicate improved targeting of these populations.	Direct install programs should continue serving the state's vulnerable customers, given this customer segment's limited resources to take advantage of rebate programs' EE offerings. Direct install programs should also continue serving the multifamily sector, which makes up one-third of the state's residential population since this is the primary channel for multifamily households to access IOU EE program offerings.
2. Top-quartile energy consumption rebate program participants achieved significantly higher electric and gas savings than customers in lower energy consumption quartiles, at 151 versus 3 kWh per household and 12 versus -6 therms per household, respectively.	Smart thermostat savings may be improved by factoring in household energy consumption levels in program targeting. Rebate programs should consider using the level of energy consumption as a key targeting variable.
3. The single consistent modeling approach we used in the study addresses the self-selection bias identified in previous evaluations. Model estimates indicate that the energy consumption trends of participants and non-	When feasible, evaluations should identify and correct for these possible biases when estimating the effect of opt-in programs using consumption data analysis.

[58] In contrast, rebate participation among multifamily customers is low at 4%, which reflects that property managers and not individual tenants are the decision-makers for program participation in this sector.

Key findings	Implications and recommendations
participants are different and statistically significant. These differences affect estimated electric rebate and direct install smart thermostat savings but have limited effect on gas savings. When moving from a model that does not account for trend differences to one that does, rebate smart thermostat electric savings go from negative to positive, and direct install smart thermostat electric savings go from positive to a small negative number.	
4. The evidence suggests that energy savings from smart thermostats installed in PY2018, while small, increased over time despite the possibility that COVID-related increased occupancy eroded the saving potential for thermostats. DNV's new model results, presented in Table 4-12, show that electric and gas savings from both the rebate and direct install channels are higher when estimated using data from all post-years compared to the pre-COVID first post-year. Device information DNV received also indicates that average HVAC cooling runtimes decreased in 2021 compared to 2019.	Thermostat optimization could improve smart thermostat energy savings performance. Additional studies that track smart thermostat savings over time are needed to strengthen this finding.
5. Previous smart thermostat savings may have been overstated. The current panel and previous DID evaluation results indicate similar findings when neither corrects for trend differences (Table 4-11). However, the current model results reveal that the prior PY2018 ad hoc corrections somewhat overstated rebate electric and gas savings. They also indicate that the PY2019 electric direct install evaluation may have overstated savings.	We recommend continued evaluation of new installations to confirm the results identified in this study.
6. Both rebate and direct install non-HTR participants have electric savings, while HTR and multifamily participants do not. Participants in the latter two groups likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy deprivation. Customer responses from participant surveys conducted for DNV's impact evaluations of the PAs' PY2018, 2019, and 2020 rebate and direct install programs indicate a significant increase in customer comfort post smart thermostat installation.[59] Smart thermostats' promise to	There is higher energy consumption post-installation among some customer segments. Given this, we recommend improved customer education on how smart thermostats work and how they provide energy and cost savings. The PAs cannot require "eco" settings on these program-provided thermostats, but they need to find a way to encourage more participants to adopt those settings.

[59] https://www.calmac.org/publications/CPUC_Group_A_Report_Smart_Thermostat_PY_2018_CALMAC.pdf (Table 4-9), https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf (Table 4-9), https://www.calmac.org/publications/Group_A_Residential_PY2020_RES_HVAC_Final_Report_CALMAC.pdf (Table 5-8)

Key findings	Implications and recommendations
regulate and reduce energy use and cost could have led some of these participants to increase their comfort and use more energy inadvertently.	
7. Unlike direct install programs that delivered largely the same smart thermostat technology type to participants, rebate program participants purchased different smart thermostat types. Using these data, DNV estimated the electric savings of one vendor's device (Technology 1) to be 55 kWh per household and another vendor's device (Technology 2) to be 17 kWh per household. Neither technology type provided statistically significant gas savings.	The savings potential of smart thermostats continues to change even after installation due to software updates. Programs should factor in variations in technology and evolving algorithms that result in notably different outcomes when considering this measure for programs. PAs should assess savings by specific technologies periodically to understand if there are differences and calibrate technology/measure package recommendations accordingly.
8. CPUC D. 21-12-015 (in Rulemaking R.20-11-003), adopted in December 2021, is designed to reduce load in hot climate zones 9-15 and directs PAs to subsidize smart thermostats for customers in these climate zones. The absolute number of smart thermostats installed cumulatively in these climate zones through the PAs' direct install programs from PY2018 through PY2021 is approximately 286,000. The total installed base of smart thermostats in these climate zones is more than 286,000 since it will also include those provided at low to no cost by other energy efficiency programs like Energy Savings Assistance (ESA) and non-program adoption of smart thermostats. Assuming a non-program smart thermostat adoption rate of 25%[60] and a statewide average annual ESA program footprint of 260,000,[61] the smart thermostat installed base is likely lower than the estimated 3.5 million of five million households that use air-conditioning[62] in these specific climate zones. Households with air-conditioning contribute to grid stress from increased cooling demand during peak	There are program opportunities to increase smart thermostat penetration in households with air-conditioning in hot climate zones. Programs should aim to expand the penetration of smart thermostats that can operate as part of a "fleet" serve as virtual power plants (VPPs) to provide direct relief to the overloaded parts of the grid.[63]

60 The prevalence of smart thermostats among non-participant households is estimated in the CPUC Group A PY2019 Smart Thermostat Evaluation. https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf
The prevalence of smart thermostats among non-participant households is estimated in the CPUC Group A PY2019 Smart Thermostat Evaluation. https://www.calmac.org/publications/CPUC_Group_A_Residential_PY2019_SCT_Final_Report_CALMAC.pdf

61 The PY2015-2017 ESA Program Impact Evaluation indicated the statewide average annual footprint of the program. 2015-2017_ESA_Impact_Evaluation_-_FINAL_-_CALMAC_Posting.pdf

62 The EIA's RECS survey estimates that 70% of CA households have air-conditioning. Applying this penetration to the five million households in climate zones 9-15 results in an estimated 3.5 million households with air-conditioning. https://www.eia.gov/consumption/residential/data/2020/state/pdf/State%20Air%20Conditioning.pdf
The EIA's RECS survey estimates that 70% of CA households have air-conditioning. Applying this penetration to the five million households in climate zones 9-15 results in an estimated 3.5 million households with air-conditioning. https://www.eia.gov/consumption/residential/data/2020/state/pdf/State%20Air%20Conditioning.pdf

63 VPPs adjust the power use of a fleet of electric devices and appliances like smart thermostats, heat pumps, and induction stoves to reduce stress on the grid.

Key findings	Implications and recommendations
periods from May through October. These households represent ideal targets for energy efficiency and demand response programs that deploy smart thermostats.	
9. Smart thermostats' peak load reduction potential makes them suitable for use in DR programs. However, DR program enrollment among smart thermostat program participants has been modest at 7% for rebate program participants and no more than 6% for direct install participants.	Programs delivering free or subsidized smart thermostats should consider automatically enrolling direct install program participants in DR programs with an opt-out option and providing information on DR programs for rebate program participants to maximize peak load savings.[64]

[64] Smart thermostat program participants could be enrolled in PA and other DR programs such as Power Saver Rewards, OhmConnect, SmartRate Plan, Summer Discount Plan, Smart Energy Program, AC Saver (Summer Saver) Program, and AC Saver Thermostat Program. SCE's PY2021 Residential Direct Install Program that leveraged SCE's smart thermostat DR program is an example of a successful application of such an integrated demand side management (IDSM) approach. The initiative has yielded success in its first year of operation. Survey results showed a higher proportion of participants became aware of and enrolled in the smart thermostat DR program due to the IDSM campaign.

6 APPENDICES

6.1 Appendix A: Panel model results across all customers

In this section, we provide coefficient estimates and discussions of the results for models estimated across all customers. Table 6-1 provides estimates from the panel electric rebate models, including those based on one year of pre- and up to four years of post-installation period. It also provides estimates from the model based on one year of pre- and only one year of post-installation data, the annual thermostat shift model, and the model with no trend terms.

Table 6-1. Electric rebate model results

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	14.66	0.00	15.16	0.00	14.99	0.00	14.96	0.00
α_{p}	14.72	0.00	15.15	0.00	15.03	0.00	15.68	0.00
$1000\lambda_{np}$[65]	0.028	0.00	-0.071	0.00	0.008	0.10		
$1000\lambda_{p}$	0.090	0.00	-0.024	0.04	0.070	0.00		
β_{np}	0.22	0.00	0.25	0.00	0.21	0.00	0.22	0.00
β_{p}	0.19	0.00	0.21	0.00	0.18	0.00	0.18	0.00
γ_{np}	1.46	0.00	1.55	0.00	1.47	0.00	1.48	0.00
γ_{p}	1.44	0.00	1.57	0.00	1.45	0.00	1.51	0.00
δ_{H}	-0.57	0.05	1.41	0.00			0.48	0.08
δ_{C}	0.24	0.00	-0.20	0.01			-0.04	0.44
δ_{pH}	-2.34	0.00	-1.36	0.01			0.52	0.24
δ_{pC}	-0.11	0.16	-0.13	0.22			-0.66	0.00
δ_{H1}					-0.99	0.00		
δ_{H2}					-0.43	0.24		
δ_{H3}					0.82	0.08		
δ_{H4}					0.76	0.26		
δ_{pH1}					-3.07	0.00		
δ_{pH2}					-2.58	0.00		
δ_{pH3}					-1.24	0.09		
δ_{pH4}					-1.48	0.14		
δ_{C1}					0.45	0.00		
δ_{C2}					0.29	0.00		
δ_{C3}					-0.34	0.00		
δ_{C4}					-0.17	0.27		
δ_{pC1}					-0.12	0.08		
δ_{pC2}					-0.15	0.11		
δ_{pC3}					-0.08	0.55		
δ_{pC4}					0.14	0.53		

For all the models, except the No trend model, similarity in the estimated responses to weather, captured by beta and gamma coefficients, and baseload, captured by alpha, indicate that our matching produced participant and non-participant groups with well-balanced consumption characteristics. As expected, for the No trend model, beta and gamma coefficients are similar, but the baseload coefficient, alpha, is quite different. That the models balance across participants and non-

[65] We multiplied the estimated trend terms by 1000 for ease of interpretation. The original estimates reflected average change in daily consumption over the analysis period covered in each model.

participants separately for baseload, heating, and cooling is one of the novel improvements of the current approach over a basic two-stage DID approach.

The lambda estimates for the electric rebate models support the PY2018 and PY2020 study findings that rebate participants have higher trends than the matched comparison homes but control for them in an internally consistent and comprehensive way. These estimates indicate a faster increase in energy consumption for participants over time.

In the models, the delta terms capture the effect of smart thermostats. These terms capture general reference temperature shifts in the post period for all customers and incremental reference temperature shifts for participants. Estimates of the cooling reference temperature parameter (δ_C) capture overall cooling reference temperature shifts across all customers, while the heating reference temperature parameter (δ_H) captures general heating reference temperature shifts across all customers. The incremental shifts in cooling and heating estimates for participants include p subscripts in the delta terms.

- In the All-post-years model:
  - The negative estimate for δ_H indicates a lower electric heating reference temperature for all customers in the post period, while the negative estimate for δ_{pH} shows an additional decrease in electric heating reference temperature for participants in the post period
  - A positive estimate for δ_C indicates a higher electric cooling reference temperature for all customers but the insignificant estimate for δ_{pC} indicates no additional increase in the cooling reference temperature for participants
  - The estimates indicate significant electric heating load decrease but no cooling load reductions due to smart thermostats for rebate participants
  - The decrease in electric heating reference temperature values apply only to proportion of the participating population that has electric heating
- In the One post-year model:
  - Consistent with All-post-years model, the incremental heating delta (δ_{pH}) estimate for participants shows heating savings, but the incremental cooling delta (δ_{pC}) estimate for participants fails to show cooling savings
  - The electric heating savings are not as high as the savings in the model using all the data and as noted above, apply only to a subset of the participating population that has electric heating
- In the Annual shift model:
  - The participant electric heating reference temperature increments (δ_{pH1}- δ_{pH4}), which are statistically significant for the first 3 post years, indicate that electric heating savings exist but decline over time
  - There are increases in electric setpoints across the population, particularly in the first two post years, but the electric cooling reference temperature increments (δ_{pC1} - δ_{pC4}) become less negative over time and positive, though not significant, in the last post year providing directional evidence of improvements in participant electric cooling savings
- In the No trend model:
  - Where we don't control for differential energy consumption trends between participants and non-participants, we observe no electric heating savings (with a statistically insignificant positive heating

reference temperature estimate for δ_{pH}) and cooling dissavings (with a statistically significant negative value for δ_{pC})

- In general, in electric rebate models:
  - The similarity of the baseload (α) and weather response (β, γ) terms between participants and non-participants indicate good matches
  - We observe electric heating savings but no statistically significant cooling savings, except when there is no trend term where we observe no electric heating savings and electric cooling dissavings, which demonstrate the importance of allowing for the differential trends
  - Trend estimates are highly statistically significant and participant minus non-participant trend terms are positive indicating faster energy consumption increase (or slower decrease) among participants, unrelated to reference temperature shifts

Table 6-2 provides estimates from panel models based on electric direct install data. We used data from direct install programs where smart thermostats were the only installed measure by the programs.

Table 6-2. Electric direct install model results

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	9.47	0.00	9.50	0.00	9.70	0.00	9.44	0.00
α_p	9.70	0.00	9.86	0.00	9.95	0.00	9.49	0.00
$1000\lambda_{np}$	-0.005	0.12	-0.058	0.00	-0.012	0.01		
$1000\lambda_p$	-0.030	0.00	-0.102	0.00	-0.044	0.00		
β_{np}	0.20	0.00	0.23	0.00	0.19	0.00	0.20	0.00
β_p	0.11	0.00	0.13	0.00	0.11	0.00	0.11	0.00
γ_{np}	0.92	0.00	0.97	0.00	0.92	0.00	0.92	0.00
γ_p	0.88	0.00	0.93	0.00	0.88	0.00	0.86	0.00
δ_H	2.90	0.00	3.13	0.00			2.77	0.00
δ_C	-0.34	0.00	-0.52	0.00			-0.29	0.00
δ_{pH}	-2.82	0.00	-1.82	0.00			-3.97	0.00
δ_{pC}	-0.29	0.00	-0.34	0.01			-0.01	0.93
δ_{H1}					1.55	0.00		
δ_{H2}					2.87	0.00		
δ_{H3}					2.67	0.00		
δ_{H4}					4.53	0.00		
δ_{pH1}					-3.20	0.00		
δ_{pH2}					-2.47	0.00		
δ_{pH3}					-1.63	0.04		
δ_{pH4}					-2.07	0.04		
δ_{C1}					-0.02	0.71		
δ_{C2}					-0.46	0.00		
δ_{C3}					-0.67	0.00		
δ_{C4}					0.58	0.00		
δ_{pC1}					-0.23	0.00		
δ_{pC2}					-0.37	0.00		
δ_{pC3}					-0.61	0.00		

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
$\boldsymbol{\delta_{pC4}}$					-0.45	0.06		

In the PY2018 and PY2020 direct install evaluations, there was no clear evidence of consistent trend differential in the energy consumption of participants and non-participants. Thus, we did not apply an adjustment. The panel models that include trend terms indicate a trend differential but in the opposite direction from the rebate programs. This differential suggests that prior direct install evaluations may have overestimated savings due to unaddressed self-selection among participants. There was no way to identify this using the original DID specifications and, thus, no way to develop an adjustment.

- In the All-post-years model:
  - The electric coefficients are not perfectly matched; electric heating coefficients in particular indicate different electric heating levels between participants and non-participants, possibly related to the presence of space heating
  - However, because the models allow participants and non-participants to have separate slopes, they provide estimates of heating and cooling reference temperature shifts for participants given baseload, and heating and cooling loads for the two groups
  - We observe the energy consumption of all customers trending down over time with that of participants decreasing faster than non-participant (the λ_p estimate is more negative than the λ_{np} estimate)
  - Reference temperature baseline estimates indicate shifts towards more heating (as indicated by the positive δ_H estimate) and cooling (as indicated by the negative δ_C estimate) across all participants
  - We see participant heating savings (statistically significant negative estimates for δ_{pH}), but cooling dissavings (statistically significant negative estimates for δ_{pC})
- In the One post-year model:
  - Indicates similar energy consumption trends and reference temperature baseline shifts as the All-post-years model
  - There are savings from electric heating, but not as high as in the model using all the post data
  - We observe statistically significant cooling dissavings
- In the Annual shift model:
  - We see significant heating savings for participants that decline in magnitude over time
  - There are significant cooling dissavings for participants in all post years
- In the No trend model:
  - Heating savings are higher than in models that include trend terms indicating that differential energy consumption trends are being estimated as heating savings when we don’t control for these differentials
  - There are no cooling dissavings when we don't control for differential trend indicating that differential energy consumption trends mask cooling load increases
- In general, in electric direct install models:

- Differences in heating and cooling responses for the two (participant and non-participant) groups show the value of models that allow for different slope (beta and gamma) estimates between the two groups
- Indicate strong electric heating savings and no cooling savings. Since these customers had low cooling usage compared to otherwise matched counterparts, and compared to the rebate customers, they may have had little savings opportunity
- Show significant trend estimates, where participant energy consumption trend is lower than non-participant trend, which suggests analyses that includes trend terms is useful for direct install participants as well

Table 6-3 provides estimates from the panel gas models for the rebate program. The table includes estimates from the model that includes data for all four post years, only from the one post-year period data, the Annual shift model, and the No trend model.

Table 6-3. Gas rebate model results

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.65	0.00	0.63	0.00	0.70	0.00	0.62	0.00
α_{p}	0.68	0.00	0.64	0.00	0.72	0.00	0.65	0.00
$1000\lambda_{np}$	-0.083	0.00	-0.077	0.00	-0.101	-0.083		
$1000\lambda_{p}$	-0.064	0.00	-0.057	0.00	-0.057	-0.064		
β_{np}	0.12	0.00	0.13	0.00	0.13	0.00	0.12	0.00
β_{p}	0.13	0.00	0.14	0.00	0.14	0.00	0.13	0.00
δ_{H}	2.31	0.00	1.84	0.00			1.76	0.00
δ_{pH}	0.05	0.26	0.30	0.00			0.20	0.00
δ_{H1}					2.11	0.00		
δ_{H2}					2.97	0.00		
δ_{H3}					2.73	0.00		
δ_{H4}					2.06	0.00		
δ_{pH1}					0.35	0.00		
δ_{pH2}					-0.28	0.00		
δ_{pH3}					-0.35	0.00		
δ_{pH4}					-0.31	0.03		

- In the All-post-years model:
  - The similarity in baseload (α) and heating load (β) estimates of participants and non-participants indicates that these groups are well matched
  - The estimates on the lambda (λ) term indicate energy consumption of all customers trended downwards, with the decrease for participants being slower than for non-participants
  - Heating reference temperature estimates across all customers are positive indicating increasing heating in the post-period compared to the pre-period
  - And the incremental heating reference temperature shift (δ_{pH}) indicates no statistically significant average heating savings for participants over the four-post year period
- In the One post-year model:

- Model estimates indicate outcomes similar to those of the All-post-years model with well-balanced participant and non-participant consumption data, decreasing consumption trend for all customers but slower decrease for participants, and heating load increase across customers
- The estimate of incremental heating reference temperature shift is also positive and statistically significant indicating increasing heating load among participants in the first post-year

- In the Annual shift model:
  - Estimates are based on a randomly selected 50% matched pairs since it was not feasible to run the rebate gas model using all the data, which involved data from over 80,000 participants and non-participants[66]
  - Baseline heating reference temperature shifts are higher in all four post years compared to the pre-period indicating higher heating load across all customers in the model
  - Incremental heating reference temperature shift estimates indicate that participants have heating dissavings in post-year one, but have savings in the remaining 3 post-installation years
- In the No trend model:
  - We observe positive and statistically significant incremental heating reference temperature estimates
  - Heating dissavings are apparent when we don't control for the trend differential in energy consumption between the two groups
- In general, rebate gas models:
  - There is similarity in baseload (α) and heating load (β) terms for participants and non-participants that indicates consumption data is well-balanced
  - The estimates of the trend terms are highly significant and indicate differential energy consumption trend between participants and non-participants
  - Indicated no heating savings across all years with modest heating reference temperature increases indicating heating savings in post years 2, 3, and 4

Table 6-4 provides estimates from gas direct install models estimated using participants that received only smart thermostats from the programs.

Table 6-4. Gas direct install model results

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.56	0.00	0.45	0.00	0.54	0.00	0.53	0.00
α_p	0.56	0.00	0.44	0.00	0.53	0.00	0.54	0.00
$1000\lambda_{np}$	-0.075	0.00	0.367	0.00	-0.008	0.32		
$1000\lambda_p$	-0.048	0.00	0.411	0.00	0.027	0.00		
β_{np}	0.04	0.00	0.04	0.00	0.04	0.00	0.04	0.00
β_p	0.04	0.00	0.04	0.00	0.04	0.00	0.04	0.00
δ_H	4.47	0.00	0.95	0.00			3.66	0.00

[66] The second smallest analysis data used in the study has less than one-third of the observations of the gas rebate data set. The randomly selected 50% of rebate gas pairs for the Annual shift model reflect the distribution of climate zones in the full data.

Term	All-post-years model		One post-year model		Annual shift model		No trend model	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
δ_{pH}	-0.71	0.00	-0.49	0.03			-0.41	0.00
δ_{H1}					4.21	0.00		
δ_{H2}					4.63	0.00		
δ_{H3}					1.86	0.00		
δ_{H4}					-0.20	0.56		
δ_{pH1}					-0.59	0.00		
δ_{pH2}					-0.83	0.00		
δ_{pH3}					-0.82	0.00		
δ_{pH4}					-0.63	0.18		

- In the All-post-years model:
    - The similarity of baseload (α) and heating load (β) estimates between participants and non-participants indicate well-matched groups
    - The trend term estimates indicate energy consumption decreases less rapidly for participants than for non-participants
    - Incremental heating reference temperature shifts are negative indicating heating savings for participants compared to non-participants
- In the One Post-Yeas Model:
    - Baseload and heating load estimates as well trend estimate terms indicate similar outcomes to the All-post-years model
    - Negative incremental heating reference temperature estimates also indicate heating savings, which is lower than that based on all post-installation data
- In the Annual shift model:
    - Negative incremental heating savings indicate consistent savings across all four post years, although the estimated decrease in year four is not statistically significant
- In the No trend model:
    - Negative heating reference temperature shifts for participants indicate the presence of heating savings, which are statistically significant but lower in magnitude than when we control for the energy consumption trend differential
- In general, in all gas direct install models:
    - There is high similarity in baseload (α) and heating load (β) between participants and non-participants indicating good balance between the two groups
    - Coefficient estimates of trend terms indicate the difference in energy consumption trend between participants and non-participants is positive, with slower gas decrease or faster increase for participants compared to non-participants
    - Estimated heating reference temperature shifts are negative and indicate heating savings across all four post-installation years

Comparison between rebate and direct install electric models:

- Faster increase in energy consumption among participants compared to non-participants in rebate programs and the opposite in direct install programs
- Incremental electric heating reference temperature reductions among participants in both rebate and direct install programs (of similar magnitude of about 2 degrees) indicating electric heating savings associated with smart thermostats
- No incremental electric cooling reference temperature increases among participants in both rebate and direct install programs indicating either the absence of electric cooling savings or electric dissavings associated with smart thermostat installations
- We observe electric heating and cooling dissavings for rebate and greater electric heating or lower electric cooling dissavings for direct install participants when we do not account for trend differential

6.2 Appendix B: Panel model results by customer segment

In this section, we provide coefficient estimates and discussions of the results for models estimated by different customer segments.

6.2.1 High-level panel model results by customer segment

To investigate smart thermostat savings by different participant segments, we estimated All-post-years models that include one pre- and up to four years of post-installation data for all customers.

We include model estimates for each customer segment in section 6.2.2 that provide estimates of all model coefficients. We provide estimates of incremental reference temperature shifts that are indicate smart thermostat impact on load in Table 6-5.

Table 6-5. Estimates of incremental reference temperature shifts by customer segment

Segment	Term	Electric rebate		Electric DI		Gas rebate		Gas DI	
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
TOU	δ_{pH}	0.11	0.37	0.05	0.58	0.29	0.06	-1.35	0.28
	δ_{pC}	0.13	0.42	-0.31	0.01				
No TOU	δ_{pH}	0.05	0.58	-2.98	0.00	0.02	0.68	-0.67	0.00
	δ_{pC}	-0.31	0.01	-0.44	0.00				
SF/MH	δ_{pH}			-5.23	0.00			-0.29	0.09
	δ_{pC}			0.07	0.79				
MF	δ_{pH}			-2.62	0.00			-1.18	0.00
	δ_{pC}			-0.30	0.00				
Technology 1	δ_{pH}	-2.01	0.00			0.05	0.31		
	δ_{pC}	-0.02	0.83						
Technology 2	δ_{pH}	-2.31	0.03			-0.08	0.60		
	δ_{pC}	-0.39	0.03						
Top Btu Quartile	δ_{pH}	-2.63	0.00	-1.70	0.06	-0.26	0.00	-0.30	0.42
	δ_{pC}	0.33	0.01	-0.73	0.00				
Other Quartile	δ_{pH}	-1.27	0.00	-2.26	0.00	0.25	0.00	-0.93	0.00
	δ_{pC}	-0.43	0.00	-0.31	0.00				
HTR	δ_{pH}	-0.64	0.48	-2.42	0.01	0.44	0.01	-1.06	0.00
	δ_{pC}	-0.58	0.01	-0.31	0.02				

Segment	Term	Electric rebate		Electric DI		Gas rebate		Gas DI	
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Non-HTR	δ_{pH}	-2.38	0.00	-2.72	0.02	0.03	0.50	-0.46	0.02
	δ_{pC}	-0.04	0.74	-0.07	0.62				
ELRP CZ	δ_{pH}	-2.06	0.00	-2.42	0.01	0.22	0.00	-0.95	0.00
	δ_{pC}	-0.20	0.09	-0.31	0.02				
Non-ELRP CZ	δ_{pH}	-2.56	0.00	-2.72	0.02	-0.13	0.05	-0.42	0.04
	δ_{pC}	0.01	0.93	-0.07	0.62				

Differences in incremental cooling reference temperature estimates are evident by segment among rebate customers and are more limited among direct install participants. Such cooling reference temperature estimates are positive, although insignificant, for rebate participants on TOU rates and positive and statistically significant for rebate participants in the top consumption quartile. These estimates are negative for rebate participants not on TOU rates and in the other consumption quartiles. Participants in the top consumption quartile can most readily reduce their energy use, and the statistically significantly positive incremental cooling reference temperature estimates reflect how smart thermostat enable these customers to trim their consumption. However, the same patterns are not evident among direct install customers, which probably indicates the relatively slower trend in energy consumption among such participants compared to non-participants that results in energy consumption increases once the models account for these trend differences.

Both rebate and direct install participants that are HTR and in ELRP climate zones have negative incremental cooling reference temperature estimates, while non-HTR and non-ELRP climate zone participants do not have statistically significant changes in cooling reference temperature estimates. Higher cooling loads post installation for HTR customers could reflect takeback and for participants in ELRP climate zones cooling for comfort during hot summers.

Incremental cooling reference temperature estimates are not statistically significantly different from zero for single-family direct install participants but are negative and statistically significant for multifamily direct install participants. These reference temperature estimates are insignificant for rebate customers with Technology 1 but negative and statistically significant for rebate customers with Technology 2.

There is less distinction in incremental electric and gas heating reference temperature estimates by segment among rebate and direct install participants. Being on a TOU rate does not provide heating load savings advantages. While the magnitudes differ, participants in all housing types have both electric and gas heating savings. Additionally, electric and gas heating savings do not vary by technology type. Participant heating reference temperature estimates also generally indicate heating load reductions regardless of consumption level, except for gas rebate participant dissavings in the bottom consumption quartiles. Similarly, heating reference temperature changes are mostly not dependent on HTR status and climate zone.

6.2.2 Detailed panel model results by customer segments

We provide estimates of the panel models we estimated by customer segment in this section. Table 6-6 provides electric model estimates by HTR status.

Table 6-6. Electric model results by HTR status

Term	Rebate				Direct install			
	Hard to reach		Not hard to reach		Hard to reach		Not hard to reach	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	12.67	0.00	15.76	0.00	9.62	0.00	9.53	0.00
α_p	12.47	0.00	15.81	0.00	9.91	0.00	9.59	0.00
$1000\lambda_{np}$	0.06	0.00	0.02	0.00	0.00	0.47	-0.01	0.31
$1000\lambda_p$	0.14	0.00	0.07	0.00	-0.04	0.00	-0.02	0.00
β_{np}	0.26	0.00	0.19	0.00	0.20	0.00	0.16	0.00

Term	Rebate				Direct install			
	Hard to reach		Not hard to reach		Hard to reach		Not hard to reach	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
β_p	0.21	0.00	0.16	0.00	0.12	0.00	0.08	0.00
γ_{np}	1.43	0.00	1.51	0.00	0.91	0.00	0.99	0.00
γ_p	1.44	0.00	1.47	0.00	0.86	0.00	0.98	0.00
δ_H	-2.04	0.00	-1.03	0.03	2.55	0.00	3.50	0.00
δ_C	1.08	0.00	0.17	0.03	-0.82	0.00	0.28	0.00
δ_{pH}	-0.64	0.48	-2.38	0.00	-2.42	0.01	-2.72	0.02
δ_{pC}	-0.58	0.01	-0.04	0.74	-0.31	0.02	-0.07	0.62

Table 6-7 provides electric model estimates by consumption quartile. It provides estimates for customers in the top consumption quartile and customers in other consumption quartiles.

Table 6-7. Electric model results by consumption quartile

Term	Rebate				Direct install			
	Top quartile		Other quartiles		Top quartile		Other quartiles	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	24.58	0.00	11.13	0.00	19.96	0.00	8.43	0.00
α_p	24.63	0.00	11.02	0.00	20.30	0.00	8.60	0.00
$1000\lambda_{np}$	-0.02	0.00	0.06	0.00	-0.10	0.00	0.01	0.00
$1000\lambda_p$	0.02	0.01	0.15	0.00	-0.13	0.00	-0.01	0.00
β_{np}	0.42	0.00	0.21	0.00	0.37	0.00	0.17	0.00
β_p	0.35	0.00	0.19	0.00	0.43	0.00	0.10	0.00
γ_{np}	1.81	0.00	0.99	0.00	1.41	0.00	0.78	0.00
γ_p	1.78	0.00	0.98	0.00	1.34	0.00	0.74	0.00
δ_H	-1.49	0.00	-0.28	0.17	5.01	0.00	3.23	0.00
δ_C	-0.17	0.06	0.17	0.00	-1.68	0.00	-0.64	0.00
δ_{pH}	-2.63	0.00	-1.27	0.00	-1.70	0.06	-2.26	0.00
δ_{pC}	0.33	0.01	-0.43	0.00	-0.73	0.00	-0.31	0.00

Table 6-8 provides electric model results by technology type for rebate and by dwelling type for direct install participants. Over 90% of rebate customers are single family participants and, thus, it is not possible to breakout results by dwelling type for rebate participants.

Table 6-8. Electric model results by dwelling and technology type

Term	Rebate				Direct install			
	Technology 1		Technology 2		SF and MH		MF	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
alpha_0	14.65	0.00	14.48	0.00	12.67	0.00	9.31	0.00
α_{np}	14.57	0.00	14.23	0.00	12.35	0.00	9.56	0.00
α_p	0.03	0.00	0.03	0.00	0.01	0.68	-0.01	0.05
$1000\lambda_{np}$	0.09	0.00	0.11	0.00	0.02	0.06	-0.04	0.00
$1000\lambda_p$	0.22	0.00	0.22	0.00	0.20	0.00	0.18	0.00
β_{np}	0.21	0.00	0.19	0.00	0.18	0.00	0.08	0.00
β_p	1.46	0.00	1.42	0.00	1.38	0.00	0.88	0.00
γ_{np}	1.46	0.00	1.44	0.00	1.47	0.00	0.83	0.00
γ_p	-0.88	0.02	-1.11	0.14	1.42	0.19	3.08	0.00
δ_H	0.21	0.00	0.69	0.00	0.19	0.36	-0.52	0.00
δ_C	-2.01	0.00	-2.31	0.03	-5.23	0.00	-2.62	0.00

Term	Rebate				Direct install			
	Technology 1		Technology 2		SF and MH		MF	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
δ_{pH}	-0.02	0.83	-0.39	0.03	0.07	0.79	-0.30	0.00

Table 6-9 provides electric model results by time of use (TOU) rates. Customers who were on TOU rates at any point during the analysis period were considered TOU customers in the evaluation.

Table 6-9. Electric model results by TOU status

Term	Rebate				Direct install			
	TOU		No TOU		TOU		No TOU	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	15.03	0.00	14.50	0.00	14.50	0.00	9.90	0.00
α_{p}	14.90	0.00	14.70	0.00	14.70	0.00	10.15	0.00
$1000\lambda_{np}$	0.03	0.00	0.03	0.00	0.03	0.00	-0.02	0.00
$1000\lambda_{p}$	0.09	0.00	0.08	0.00	0.08	0.00	-0.05	0.00
β_{np}	0.18	0.00	0.23	0.00	0.23	0.00	0.19	0.00
β_{p}	0.16	0.00	0.21	0.00	0.21	0.00	0.11	0.00
γ_{np}	-0.03	0.97	-1.40	0.00	-1.40	0.00	0.95	0.00
γ_{p}	-1.66	0.12	-1.95	0.00	-1.95	0.00	0.89	0.00
δ_{H}	1.34	0.00	1.46	0.00	1.46	0.00	2.67	0.00
δ_{C}	1.39	0.00	1.43	0.00	1.43	0.00	-0.92	0.00
δ_{pH}	0.11	0.37	0.05	0.58	0.05	0.58	-2.98	0.00
δ_{pC}	0.13	0.42	-0.31	0.01	-0.31	0.01	-0.44	0.00

Table 6-10 provides electric model estimates by climate region. In particular, the table provides model estimates for customers in both hot or emergency load reduction program (ELRP) and non-ELRP or mild climate zones.

Table 6-10. Electric model results by climate region

Term	Rebate				Direct install			
	Hot climate zone		Not hot climate zone		Hot climate zone		Not hot climate zone	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	15.93	0.00	14.12	0.00	9.80	0.00	9.20	0.00
α_{p}	16.08	0.00	13.99	0.00	10.13	0.00	9.12	0.00
$1000\lambda_{np}$	0.01	0.00	0.02	0.00	-0.02	0.00	0.00	0.45
$1000\lambda_{p}$	0.07	0.00	0.10	0.00	-0.04	0.00	-0.01	0.05
β_{np}	0.22	0.00	0.20	0.00	0.20	0.00	0.20	0.00
β_{p}	0.19	0.00	0.17	0.00	0.12	0.00	0.10	0.00
γ_{np}	1.49	0.00	1.18	0.00	0.93	0.00	0.77	0.00
γ_{p}	1.46	0.00	1.18	0.00	0.87	0.00	0.83	0.00
δ_{H}	-0.65	0.16	0.13	0.76	2.58	0.00	3.60	0.00
δ_{C}	-0.40	0.00	0.13	0.05	-0.95	0.00	-0.30	0.00
δ_{pH}	-2.06	0.00	-2.56	0.00	-3.31	0.00	-1.70	0.05
δ_{pC}	-0.20	0.09	0.01	0.93	-0.47	0.00	0.51	0.00

The next set of tables provide the analogous results for gas models. Table 6-11 provides gas model estimates by HTR status.

Table 6-11. Gas model results by HTR status

Term	Rebate				Direct install			
	Hard to reach		Not hard to reach		Hard to reach		Not hard to reach	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.57	0.00	0.68	0.00	0.54	0.00	0.56	0.00
α_p	0.59	0.00	0.71	0.00	0.55	0.00	0.57	0.00
$1000\lambda_{np}$	-0.09	0.00	-0.07	0.00	-0.11	0.00	0.01	0.32
$1000\lambda_p$	-0.07	0.00	-0.06	0.00	-0.10	0.00	0.04	0.00
β_{np}	0.08	0.00	0.15	0.00	0.03	0.00	0.07	0.00
β_p	0.09	0.00	0.15	0.00	0.04	0.00	0.07	0.00
δ_H	2.89	0.00	1.98	0.00	6.05	0.00	1.94	0.00
δ_{pH}	0.44	0.01	0.03	0.50	-1.06	0.00	-0.46	0.02

Table 6-12 provides gas model estimates by consumption quartile. It provides estimates for customers in the top consumption quartile and customers in other consumption quartiles.

Table 6-12. Gas model results by consumption quartile

Term	Rebate				Direct install			
	Top quartile		Other quartiles		Top quartile		Other quartiles	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	1.13	0.00	0.47	0.00	1.34	0.00	0.47	0.00
α_p	1.18	0.00	0.49	0.00	1.38	0.00	0.46	0.00
$1000\lambda_{np}$	-0.10	0.00	-0.07	0.00	-0.14	0.00	-0.08	0.00
$1000\lambda_p$	-0.08	0.00	-0.05	0.00	-0.12	0.00	-0.05	0.00
β_{np}	0.18	0.00	0.09	0.00	0.12	0.00	0.03	0.00
β_p	0.19	0.00	0.10	0.00	0.12	0.00	0.03	0.00
δ_H	1.98	0.00	3.19	0.00	3.71	0.00	5.49	0.00
δ_{pH}	-0.26	0.00	0.25	0.00	-0.30	0.42	-0.93	0.00

Table 6-13 provides gas model results by technology type for rebate participants and by dwelling type for direct install participants. Over 90% of rebate customers were single family participants and it was not possible to breakout results by dwelling type for rebate participants.

Table 6-13. Gas model results by technology and dwelling type

Term	Rebate				Direct install			
	Technology 1		Technology 2		SF and MH		MF	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.66	0.00	0.59	0.00	0.65	0.00	0.54	0.00
α_p	0.69	0.00	0.61	0.00	0.66	0.00	0.54	0.00
$1000\lambda_{np}$	-0.09	0.00	-0.08	0.00	-0.06	0.00	-0.13	0.00
$1000\lambda_p$	-0.06	0.00	-0.08	0.00	-0.04	0.00	-0.09	0.00
β_{np}	0.13	0.00	0.12	0.00	0.11	0.00	0.03	0.00
β_p	0.14	0.00	0.13	0.00	0.11	0.00	0.03	0.00
δ_H	2.35	0.00	2.25	0.00	2.36	0.00	6.52	0.00
δ_{pH}	0.05	0.31	-0.08	0.60	-0.29	0.09	-1.18	0.00

Table 6-14 provides gas model estimates by TOU rate. Customers who were on TOU rates at any point during the analysis period were considered TOU customers in the evaluation.

Table 6-14. Gas model results by TOU status

Term	Rebate				Direct install			
	TOU		No TOU		TOU		No TOU	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.58	0.00	0.67	0.00	0.48	0.00	0.56	0.00
α_p	0.58	0.00	0.70	0.00	0.41	0.00	0.56	0.00
$1000\lambda_{np}$	-0.09	0.00	-0.09	0.00	-0.06	0.28	-0.07	0.00
$1000\lambda_p$	-0.08	0.00	-0.07	0.00	-0.13	0.00	-0.05	0.00
β_{np}	0.11	0.00	0.13	0.00	0.08	0.00	0.04	0.00
β_p	0.12	0.00	0.14	0.00	0.10	0.00	0.04	0.00
δ_H	1.96	0.00	2.59	0.00	2.68	0.01	4.50	0.00
δ_{pH}	0.29	0.06	0.02	0.68	-1.35	0.28	-0.67	0.00

Table 6-15 provides gas model estimates by climate region. In particular, the table provides model estimates for customers in both hot or emergency load reduction program (ELRP) and non-ELRP or mild climate zones.

Table 6-15. Gas model results by climate region

Term	Rebate				Direct install			
	Hot climate zone		Not hot climate zone		Hot climate zone		Not hot climate zone	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_{np}	0.68	0.00	0.61	0.00	0.54	0.00	0.60	0.00
α_p	0.71	0.00	0.63	0.00	0.54	0.00	0.60	0.00
$1000\lambda_{np}$	-0.09	0.00	-0.08	0.00	-0.07	0.00	-0.07	0.00
$1000\lambda_p$	-0.07	0.00	-0.06	0.00	-0.04	0.00	-0.04	0.00
β_{np}	0.13	0.00	0.12	0.00	0.04	0.00	0.05	0.00
β_p	0.13	0.00	0.13	0.00	0.04	0.00	0.05	0.00
δ_H	2.74	0.00	1.92	0.00	4.18	0.00	4.02	0.00
δ_{pH}	0.22	0.00	-0.13	0.05	-0.95	0.00	-0.42	0.04

6.3 Appendix C: Response to comments

Comment #	Commenter	Topic/Section	Comment	Response to comment
1	SCE	1.1; Page 1	Please be specific and explicit as which specific climate zones recommendations are being provided for. When referring to hot climate zones, please clarify which specific climates zone the report is referring to, e.g., CZ11, CZ13, CZ15, etc.	Climate zones 9-15 are hot climate zones. The rest are mild climate zones. We indicate in several parts of the report the definition of hot climate zones, such as in Section 1.2.3 of the Executive Summary and Section 4.1.3 of the main body of the report. To make the definition more explicit, we have now also added a definition for the hot climate zone in a footnote where it is first mentioned on the first page of the Executive Summary.
2	SCE	1.2; Page 2	Did the study evaluate and/or validate technology's savings potential on other features including fan-delayed control? Please clarify and expand as needed.	The study uses site-level consumption data so all savings are included but there is no ability to specify whether savings come from one feature or another.
3	SCE	1.2.1; Page2	"Continue targeting key underserved demographic customer segments in direct install programs" – Please clarify the basis for this recommendation. Is the recommendation based on savings potential opportunities? Why should the measure be implemented for underserved customers if there are marginal savings and/or it can induce higher energy consumption? Please clarify. Consider updating recommendation to include critical EE offerings that are likely to improve space comfort with weatherization EE treatments first in addition to fuel substitution EE treatments, etc. To the study's point…"…HTR and multifamily participants likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy deprivation."	CA PAs' EE programs provide smart thermostats via direct install and rebate programs. The results from the program participation analysis in this report show that this segment has relatively lower participation in rebate programs for smart thermostats relative to participation in direct install programs. Direct install programs provide and install energy-efficient electric appliances, energy efficiency measures, and related upgrades directly to consumers at minimal or no cost. These programs serve low to middle-income households, a significant proportion of which are MF customers. These segments have been shown to be underserved and participate at lower rates in EE programs. The report recommends that programs continue to target these segments given the known financial barriers to acquiring thermostats without any rebates or subsidies and the aforementioned lower participation in rebate programs.
4	SCE	1.2.1; 1.2.2; Table 1-1; Figure 1-1; Page 2	To support the update of EE deemed measure packages, savings potentials should be documented for each applicable residential building type, ALL climate zones, and segmentation (and program type). Please include comparative analysis and documentation on kWh, kW, and Therms for all evaluated program years to understand variation on savings potentials due to improvement on evaluation methods and/or assisted by the smart thermostat learning AI algorithm.	This is not an impact evaluation and documenting the savings potential of smart thermostats by residential type, climate zones, and program type is beyond the scope of the study. A comparative analysis and documentation of savings by different segments were done as part of the PY2018 to PY2020 impact evaluations.
5	SCE	1.2.2; Figure 1-1; Page 3	"The model estimated different energy consumption trends between participants and matched non-participants and captured shifts in smart thermostat setpoints among participants" per the previous comment, for transparency of the analysis, please document specific temperature setpoint reductions per building type and all climate zones. Additionally,	As indicated in the response to the previous questions, estimating these shifts by the subgroups listed in the question was not in the scope of this study. The temperature setpoint shifts estimated by the model are captured by the parameter estimates associated with the incremental delta terms in the model. These estimates indicate both modest increases and modest decreases that are no different than 2 degrees (and

Comment #	Commenter	Topic/Section	Comment	Response to comment
			can you specify how they compare with RASS temperature setpoints? If different, why is that the case?	often no different than a half degree). These are provided in appendix section 6.1 in Tables 6-1 to 6-4.
6	SCE	1.2.2; Page 4	“Given the evidence of possible improvements in smart thermostat savings over time, we recommend continued evaluation of new installations and additional years of existing installations to ascertain if the improved later-year results found here are borne out.” Given (a) limited, marginal, or negative (in some cases) savings potentials of the measure; (b) resource optimization on evaluation activities; (c) measure has been evaluated several times - consider updating recommendation to NOT to support additional evaluation of the measure for the short term.	This evaluation indicates that applying first-year savings to later years may not be appropriate given increased savings in later years compared to year 1, as shown in the report. We make the recommendation to evaluate additional years of existing installations in order to establish longitudinal savings trends for smart thermostats and consequently estimate lifetime savings and assess cost-benefit for the measure more accurately.
7	SCE	1.2.3; Page 6	“There are program opportunities to increase smart thermostat penetration in households with air-conditioning in hot climate zones” – per previous comments, which specific CZs is the report referring to? Please clarify.	Please see the response to comment #1.
8	SCE	2.1; Page 7	Particularly for “equity” customers, did the study evaluate potential WiFi connectivity issues that may prevent the use of technology’s full functionality, e.g., fencing, learning, etc.? How do savings realization compare between WiFi connected and disconnected devices, particularly for equity customers?	While this evaluation does not study Wi-Fi connectivity issues, survey data from past evaluations indicate that lower income/equity customers do not make full use of smart thermostat features relative to their higher income counterparts, which could be a contributor to lower realized savings for this segment.
9	SCE	2.2; Page 8	Please elaborate on technology’s occupant learning and vendor-operated optimization features. What are these? How are these driving savings realizations?	Occupancy or motion sensors enable smart thermostats to adjust temperatures based on real-time occupancy data and learn occupancy patterns to optimize heating and cooling setpoints. By optimizing heating or cooling only when needed, smart thermostats enhance energy efficiency, leading to significant cost savings and reduced environmental impact. Manufacturers often push software updates to installed smart thermostats to enhance energy efficiency and user experience. These updates may include improved algorithms for learning user preferences, enhanced scheduling features, setpoint refinements, and compatibility with the latest smart home technologies. By continually optimizing the thermostat's functionality, these updates contribute to ongoing energy savings by ensuring more accurate temperature control and better adaptation to user behavior.
10	SCE	3.1; Page 9	Please clarify weather data source, e.g., CALMAC?	We sourced actual weather data from NOAA and typical meteorological year (TMY) data from CALMAC. We have added a description of the weather data sources in a footnote in Table 3-1.
11	SCE	3.1; Page 9	Please clarify which specific device data was collected and provided by vendors. Additionally, please clarify and provide data characterization on data provided by NEST/google to support evaluation.	The device data used in this study is described in Section 3.4. Google/Nest provided aggregate zip code level smart thermostat/HVAC operation data including runtime for installed Nest smart thermostats (not just PA program participants) among CA IOU customers.

Comment #	Commenter	Topic/Section	Comment	Response to comment
12	SCE	3.2; Page 9	Did customer segmentation include customers with PV or EV? If so, were there adjustments made to the base load to account for these load conditions? Please clarify where appropriate.	The data analysis excluded customers with PV. We used data from a large installed base of smart thermostats delivered in PY2018 for the consumption data analysis. We could only use the rate code available in the billing data to identify customers with EV. This data indicated no more than 3.5% of program participants had EV. Given the small proportion of customers with known EV data, both in participant and non-participant groups, the impact of EV on the results is likely minimal. Moreover, only changes in EV during the analysis period matter. The modeling framework explicitly specifies and estimates the different energy consumption trends of the participants and comparison group customers and controls for any small differential in EV adoption trends between the two groups.
13	SCE	3.3.1; Page 11	Did the study track distribution and characterization of HVAC equipment controlled by the smart thermostat, e.g., central DX/GAS vs central HP vs other?	The only source of HVAC equipment type is the tracking data for participants and utility customer information system (CIS) data for both participants and non-participants. The tracking data included a column on HVAC equipment type but did not provide the specific HVAC type for most participants. Most entries were rWtd, a generic weighted residential HVAC type that reflects 50% DXGF, 25% HP, and 25% electric baseboard. The CIS did not provide this information, and additional data requests DNV made while conducting the PY2018 to PY2020 impact analysis did not yield this information. While it was impossible to account for the specific HVAC type in the analysis, DNV matched participants and non-participants based on seasonal loads, such as summer-to-winter period ratios, to account for the extent of gas and electric heating and electric cooling.
14	SCE	Table 3-4; Page 16	"Table 3-4. Winter and summer average smart thermostat operations by year" how does NEST data compare with that of RASS? As I understand NEST data may not be fully representative of statewide stock and/or consistent with that in RASS. Was there any attempt to align and/or adjust the NEST data with that in RASS? On a related note, the study points out that non-equity customers users of smart thermostat technology may naturally use more energy.	Table 3-4 summarizes the key operation metrics of all Nest smart thermostats activated in California from mid-2019 to late 2020 that DNV received. It is population-level data and not an estimate based on a subset of activated Nest thermostats. RASS provides data based on survey samples. Any comparisons between the two would not be an apples-to-apples comparison. Moreover, as detailed in the report, DNV used the Nest data to compare changes in the operation (runtime) of these activated thermostats over time to glean insights on possible improvements in smart thermostat operations. RASS provides summary data at a given time, which would not make it possible to estimate such changes year-over-year. As indicated in an earlier response, Nest provided aggregate data at the zip code level, which does not make it possible to analyze data by customer segment (including equity customers).

Comment #	Commenter	Topic/Section	Comment	Response to comment
15	SCE	Figure 4-1; Page 18	Figure 4-1. Number and proportion of installations from PY2018 to PY2021 by delivery channel. Savings potential should be documented for each applicable residential building type, climate zone, program and segmentation so that values can be used for updating EE deemed measure package values.	Please see the response to comment #4.
16	SCE	Figure 4-1; Page 18	From the electric claims, is there a way to desegregate central DX vs HP? This would be useful for adequately updating deemed measure package values per technology type.	Please see the response to comment #13.
17	SCE	Table 4.11; Page 30	The comparison needs to be made among all CZs, BTs, and sectors or program types. Per previous comment, it would be valuable to include comparative analysis and documentation on kWh, kW, and Therms for all evaluated program years (per specific CZ, BTs, and program type and segmentation) to understand variation on savings potential due to improvement on evaluation methods and/or assisted by the smart thermostat learning AI algorithm.	Please see the response to comment #4.
18	SCE	5; Page 37	“Savings, to the extent they exist, are small. While our study illuminates the variability by various demographic and geographic customer segments, evaluated gross savings estimates are still significantly and uniformly lower than expected savings.” Given that the measure yields marginal savings (if any), and per previous comments, consider recommending for the measure NOT to be re-evaluated in the near future.	Please see the response to comment #6.
19	SCE	5; Page 40	“The peak load reduction potential of smart thermostats makes them suitable for use in DR programs” …what level of peak demand savings potential are you referring to? Although these are currently not claimed under EE, please report peak demand savings potential per climate zone, building type, and segmentation. It would be useful to gauge the potential demand savings from technology.	The DR potential of smart thermostats is established in many places and was not the focus of this study.
20	SDG&E	Recommendation 7; Page 39	DNV states "PAs should assess savings by specific technologies periodically to understand if there are differences and calibrate technology/measure package recommendations." Due to the fact the smart thermostats are deemed measures, SDG&E confirms that savings per technology or brand of thermostat is not tracked. The favoring or separating of one thermostat brand over the other goes against historical deemed offerings where brand neutrality must be maintained.	DNV understands that the smart thermostat is a deemed measure whose savings are not tracked by brand. DNV's recommendation does not call for evaluation or assessment by brand. It is an implementation recommendation to consider savings by brand and technology from time to time based on our findings of different savings potential, which likely evolve, of different smart thermostat types.
21	SDG&E	Recommendation 9; Page 40	DNV states "Programs providing free or subsidized smart thermostats should consider automatic enrollment with the ability for customers to opt-out" in regard to DR programs. As auto-enrolling customers into DR programs is not always feasible, SDG&E recommends the evaluator clearly define	This recommendation aligns with the CPUC decision (Energy Efficiency: R.13-11-005) to install smart thermostats in hot climate zones and incentivize customers to participate in demand response programs. The PAs' existing EE programs that disburse smart thermostats can engage customers in

Comment #	Commenter	Topic/Section	Comment	Response to comment
			which program types they are referring to for these auto-enrollments.	demand response by 1) providing information encouraging customers to participate in demand response programs when they avail of rebated smart thermostats and 2) auto-enrolling and providing information about how to engage in demand response programs to customers who receive free smart thermostats. Programs can provide information either at or after the point of purchase/installation. This recommendation is especially applicable to customers residing in hot climate zones 9-15.
22	SoCalREN	Device data analysis	Beyond the statement about technology one and two for the non-NEST thermostats, was much done to evaluate the other thermostats to the same level of detail?	Both rebate and direct install programs offered mostly Nest and, to a lesser extent, Ecobee thermostats. While the percentage of Nest thermostats installed through the PA programs has declined over time (with PY2021 direct install programs mainly offering Honeywell thermostats), on average, from PY2018 to PY2021, 88% of installed smart thermostats were Nest. The average percent of Ecobee thermostats over the same timeframe was 5%. Since DNV based the consumption data analysis on the large installed base of PY2018 installations, where 94% of installed thermostats were Nest, 5% were Ecobee, and only 1% were other smart thermostats, there was only sufficient data to analyze by brand for these two technologies.
23	SoCalREN	Device data analysis	Were occupants who turned their HVAC off for significant periods (as would be seen in Southern California) analyzed separately as part of this effort? The Tobit analysis would have adjusted annually, but it seems the impact on runtime is seasonal?	DNV conducted the Tobit analysis using the aggregate climate zone smart thermostat operation data received for Nest smart thermostats. Since the analysis reflects aggregate data, any changes in HVAC or smart thermostat operations at the customer level cannot be observed. Any HVAC operation changes will affect DNV's energy consumption analysis, which relies on customer-level data. However, the purpose of including matched comparison households in the study is to control for such non-program-related changes. Any HVAC shutdowns on the participant side are also happening among matched participants, which makes it possible to control for this effect and isolate the impact of the smart thermostat.
24	SoCalREN	Energy Savings	For the panel approach, wouldn't other changes (e.g., other EE program participation post the initial effort, renovation, occupancy changes, etc.) during the four-year evaluation period have a significant impact? How were these accounted for in selecting the participant and non-participant groups? The panel model implies adjustments were made and the groups align at an overall usage level, but do they address these other factors?	The study design involved the inclusion of participants that only installed smart thermostats. Additionally, we selected non-participants who did not participate in any utility EE or DR programs. Both participants and non-participants can have all types of non-program-related changes. As we indicated in responses to the previous comments, the purpose of including matched comparison households in the study is to control for such non-program-related changes. Any changes on the participant side are also happening among matched participants, making it possible to control for these changes and isolate the impact of the smart thermostat.

Comment #	Commenter	Topic/Section	Comment	Response to comment
25	SoCalREN	Energy Savings	The report implies that there were some participants without AC. Was that true, and if so, would it have lowered the savings impacts significantly?	It is unclear where the report implied that some participants did not have AC. DNV evaluated electric savings for all customers with kWh savings claims, which indicates that the customers had cooling systems, and gas savings for all customers with therm savings claims, which signifies that the customers had gas heating systems.
26	SoCalREN	Energy Savings	The report concluded that high energy consumers should be targeted. However, SoCalREN's understanding of prior studies (including Impact Evaluation of Smart Thermostats Residential Sector - Program Year 2018) was that the users who actively manage their thermostats tend to save little. Was that factor considered as part of the opt in participant bias?	Active management of smart thermostats does not necessarily mean customers have high energy consumption. High energy consumption could be motivated by a desire for comfort. Our evaluation indicates that customers with high energy consumption realize higher savings and, thus, are a desirable target for EE programs.
27	SoCalREN	Energy Savings	Please provide more clarification on the trend adjustment approach and how it differs from prior approaches used to evaluate the smart thermostats.	As detailed in our PY2018 and PY2020 evaluations, we used the identified baseload trend differences between participants and matched non-participants to adjust heating and cooling savings estimates. We adjusted the percent change in estimated heating and cooling savings by the percent increase in baseload among participants compared to non-participants. The current evaluation formalizes our approach to account for trend differentials in a modeling framework. Sections 3.3.3 to 3.3.5 of the report provide the details. As indicated in those sections, we interact trend terms with baseload and heating and cooling load separately for participants and matched non-participants to control trend differences between the two groups and estimate smart thermostat impacts through shifts in temperature reference points associated with smart thermostat setpoints.
28	SoCalREN	Energy Savings	The conclusions emphasize targeting DI customers (page 2). However, the results tend to indicate that the DI customers do not yield much electric savings (Table 1-1). While the drivers are different for each conclusion, as written, this seems somewhat contradictory. Can this be reconciled?	Please see the response to comment #3.
29	SoCalREN	Energy Savings; Page 3	Per page 3 of the draft report, "The evidence suggests that energy savings from smart thermostats installed in PY2018, while small, increased over time despite the possibility that COVID-related increased occupancy eroded the saving potential for thermostats. These savings would occur due to thermostat optimization over time." Shouldn't the COVID period be analyzed separately from non-COVID periods for the reason noted? Also, our understanding is that the learning mechanism of the thermostat is over the course of weeks not several years. Can you explain why the savings would increase over time if the smart thermostats algorithms only require 1-2 weeks to predict the occupant usage patterns? Is this related to software updates that are noted elsewhere or additional factors?	The study's purpose was not to investigate savings differences between COVID and non-COVID periods. However, we did use aggregate data on smart thermostat operations to understand HVAC runtime differences during COVID and non-COVID periods. While smart thermostat learning algorithms require a relatively short period to learn occupant usage patterns, the increased savings from smart thermostats over time the study discussed is related to smart thermostat optimization (a process designed to save more energy through additional setpoint adjustments that balance each home's response to weather conditions and energy use habits) through continual software updates pushed by manufacturers well after installation/in later years.

Comment #	Commenter	Topic/Section	Comment	Response to comment
30	SoCalREN	Energy Savings; Page 4	Per page 4 of the draft report, "HTR and multifamily participants likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy deprivation." Wouldn't lower efficiency homes realize more savings from the thermostats?	As noted in section 4.2.5 of the report, the HTR/MF participants could also be motivated by comfort and have takeback which reduces the level of savings realized. Individuals in these categories likely live in less energy-efficient homes compared to non-HTR and single-family participants, leading to increased energy deprivation. The installation of a technology aimed at regulating and reducing energy consumption and costs could potentially encourage participants in these groups to enhance their comfort levels, resulting in higher energy usage.
31	SoCalREN	Energy Savings; Page 4-5	Per pages 4-5 of the draft report: "Generally thermostats produce savings by reducing consumption in ways that do not undermine comfort." This seems to contradict the following which makes sense: "Smart thermostats cannot generally improve comfort while also reducing consumption. It is possible that smart thermostats' promise to regulate and reduce energy use and cost could have led some of these participants to inadvertently increase their comfort and use more energy." If their thermostats were set up to better control for occupant usage, it could improve comfort and maybe save energy vs a single set point that is turned on /off. Was this level of data collected?	Smart thermostats deliver savings by optimizing heating and cooling schedules and setpoints based on occupancy patterns, learning guided by user preferences, and remote control via mobile apps. Baseline energy consumption appears lower for customers experiencing energy deprivation. These customers could specify higher comfort preferences post-installation, which translates to higher consumption (i.e., takeback), thus reducing the potential savings. The second statement the comment cites describes such takeback and does not contradict the first cited statement.
32	SoCalREN	Energy Savings	DR is mentioned as a recommendation and in terms of overall participation. Did the data savings analysis account for those participating in DR and EE separately?	DNV attempted to estimate impact separately for those on DR and EE from those only in the EE program. However, since the original study design did not stratify by DR participation, there were not sufficient numbers of participants in DR programs matched to non-participants also in DR to make this analysis possible.
33	SoCalREN	Software Update Impacts	Interesting observation about the software changes. Was any effort made to see if those impacted savings significantly?	The longitudinal savings trend indicates that savings post installation increased (i.e. savings in later years were greater than first year savings) and that this increase was significant.
34	SoCalREN	Access to Program Benefits	Is "non-metro" meaning not in a census defined metropolitan area? The reported 56% of California seems high for this.	As indicated in footnote 30 of the report, we used the U.S. Office of Management and Budget (OMB's) core-based statistical areas (CBSAs) definition of metro areas, which include the San Francisco Bay area, San Diego, Greater Los Angeles (Los Angeles, Orange, San Bernardino, Riverside, and Ventura counties), and Sacramento. Non-metro is a county-level variable that includes those outside the CBSA metro regions.
35	SoCalREN	Access to Program Benefits	n=10,651,613 for CA population. Is this value CA population or customer accounts? SoCalREN assumes the context is within IOU territory. This seems low if population.	This number refers to the size of the CA IOU population. We have now updated the titles of tables and figures to indicate this.

Comment #	Commenter	Topic/Section	Comment	Response to comment
36	SoCalREN	Energy Consumption Trend	In selecting participants to analyze (through the Panel method), was there any discretion when grouping participants based on occupancy, or schedule (work from home vs. leave home to work)?	We based the data analysis on PY2018 participants and their matches, some of whom may have worked from home and others who may have worked outside of the home once the pandemic began. In other words, we used customers in the study selected before the pandemic. While there is no readily available variable to capture daytime occupancy during the pandemic, future st+F48udies that include data from this period could construct such variables based on the percent of daytime energy consumption relative to total daily consumption outside of heating and cooling seasons to account for such occupancy differentials.
37	SoCalREN	Energy Consumption Trend	In multifamily cases, was change in occupancy (tenants leaving and new tenants coming in) accounted for? This could increase/decrease energy usage drastically as the behavior of the pre-existing tenant may be different to the newer tenant.	We used person and premise identifiers to construct a unique customer in the analysis. We included only customers (participants and their selected matches) residing at a premise at least one year before and one year after installation in the study. We did not include data from locations (premises) where occupants changed during this period. Since this was a longitudinal analysis, we did not use data from a particular premise if the occupant (participant or matched non-participant) left 12 months post-installation. This condition applied to single and multifamily participants.
38	SoCalREN	Energy Consumption Trend	Was climate zone and/or weather data factored into the analysis as some climates may use more or less heating/cooling and could impact the participant groups energy savings if not accounted for?	Yes. The model we specified included cooling and heating degree days (HDD and CDD) to account for the impact of weather. We estimated impact based on model parameter estimates evaluated at typical meteorological year (TMY) weather data.
39	SoCalREN	Energy Consumption Trend	Did the analysis include factoring in additional measures that may have been installed along with the thermostat (such as duct sealing, insulation replacements, HVAC upgrades, etc.) or do the participant groups have homes with only thermostat installs? This would impact multifamily as there could be renovations to tenant units that could impact savings/usage.	As section 3.3.1 of the report indicates, the study included participants who installed only smart thermostats. We would expect any participant post-installation changes, including participation in other programs or renovations, to be mirrored by similar changes among matched non-participants. As we stated in response to prior comments, the purpose of including matched non-participants is to control for non-program-related changes.
40	SoCalREN	Energy Consumption Trend	To the point above, does the multi-year study factor in/account for upgrades that may have occurred during the years after the thermostat was installed that could impact HVAC energy usage? If so, how?	We do not return to participants to capture any changes in the household in later years/post-program participation that may impact savings. The matched comparison group is assumed to have changes in similar proportions and hence an explicit consideration of these changes is not necessary. The comparison group combined with the adjustment for the trend differential addresses any such changes comprehensively. Please see the response to comment #30 for additional details.
41	SoCalREN	Energy Impact by Customer	Per page 4 of draft report: If “HTR and multifamily participants likely reside in less efficient homes than non-HTR and single-family participants and experience higher levels of energy	The report points to less efficient homes to underscore lower savings due to factors such as a leaky building envelope or inefficient HVAC equipment. Less efficient homes combined

DNV

Comment #	Commenter	Topic/Section	Comment	Response to comment
		Segment; Page 4	deprivation", wouldn't the savings still exist between both groups, but those with the less efficient homes would "lose" the savings through their less efficient homes, maybe through single pane windows or though lower insulation levels as compared to non-HTR/single family participants?	with any potential takeback, result in lower savings for HTR and MF customers.
42	PG&E	Device data, 1.2; Page 2	Can the evaluation team clarify why data was only collected for Google on Nest and no other smart thermostat devices, such as Ecobee and Emerson devices? PG&E believes it would be useful to conduct similar analyses using aggregate thermostat data in order to offer insights on the energy savings potential of smart thermostats as well as on impact on load management.	DNV had exploratory conversations with Google, Ecobee, and Resideo to receive smart thermostat operations data in November 2019. We included Nest data in the analysis since we made more progress receiving data from Google. Nest thermostats comprise over 88% of EE program installations across PY2018 to PY2021.The findings based on device data analysis generally reflect the outcomes of the installed base of smart thermostats disbursed via the CA PAs' EE programs.
43	PG&E	Device data results, 4.3; Page 34	Can the evaluation team offer any insights or suggestions from its research about how participant behaviors related to controlling smart thermostats (e.g., optimal temperature set points) can influence load management metrics (e.g., maximize load reduction)?	The evaluation includes a participant survey to determine program attribution. The surveys also capture smart thermostat user behavior such as remote control via thermostat apps, precooling, etc. Since participants completing the survey are a small subset of program participants, the respondent sample does not support consumption analysis to estimate savings by smart thermostat user behavior-defined customer segments.
44	Google	Overarching	**The Study should analyze the causes for the sharp decline in smart thermostat installations by investigating program design and enrollment issues.** Households with smart thermostats are poised to play a critical role in meeting California's ambitious climate targets. Not only do smart thermostats provide immediate value to customers in reducing energy consumption, but they can also prime the home for future participation in demand response or other demand flexibility programs. This secondary use of smart thermostats is particularly important as the Commission examines how to roll out demand flexibility rates that will rely on technology to respond to these rates and shift customer load. However, the Smart Thermostat Study shows that installations both by direct install and rebate are declining, with direct install showing the most acute drop-off.[67] We appreciate the Study's narrative that identifies the negative implications of this trend: direct install programs primarily serve communities that face energy and income burdens in greater proportions (and thus a decline in smart thermostat deployment exacerbates inequity), and smart thermostats can support California's resource adequacy needs via the ELRP (and thus a decline in smart thermostat deployment exacerbates reliability issues). But what	While the past smart thermostat evaluations conducted by DNV have included customer and contractor research to gather insights on user behavior and program attribution to inform the estimation of gross and net impacts, they have not focused on broader program design and delivery elements. These are outside the scope of this and prior impact evaluations and are usually covered in depth in a process evaluation. Additionally, customer education on the use of smart thermostats to ensure and encourage energy savings should be conducted by program implementers, as DNV has recommended in past evaluation studies, and by manufacturers.

67 Forward-looking Smart Thermostat Study, at p. 18.

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			we did not see in the Study, and what we strongly encourage DNV-GL and the Commission to further explore, are the underpinning causes for these declines. Google Nest believes that the Study should evaluate the Direct Install program designs and implementations. It is not clear how Direct Install customers learn about and use their smart thermostats, especially when they may have been installed without their knowledge or interest. Research questions could include: 1. How are thermostats installed in multifamily units? Can tenants object? How do they connect to WiFi? 2. How do customers use the thermostats and how does it vary with WiFi connection, program design or implementor practices, or other factors? 3. What customer education is provided upon install? What education on maximizing energy savings might still be needed? 4. Do some programs, or contractors within programs, provide better support for customers and education on how to use smart thermostats effectively? These questions are essential to answer because there is still a significant potential for smart thermostat deployment throughout California. Based on available RECS data, approximately 1.7 million California homes currently have smart thermostats and 5.6 million homes with central A/C do not yet have smart thermostats representing a large potential for meaningful load reductions, particularly during periods of peak demand. Programs with enabling technology like thermostats have proven to be extremely effective in generating demand flexibility. The latest IOU load impact protocol ("LIP") reports for residential thermostat demand response programs show load reductions of 0.9 kW per household.[68] OhmConnect has additionally demonstrated that households with participating devices have over four times the load reduction per event as compared to households without a device.[69] In summary, the decline in smart thermostat deployments impacts more than just California's energy efficiency goals. It also has significant bearing on California's ability to meet its demand flexibility aspirations. For these reasons, we believe it is crucial to assess program designs to inform future smart thermostat deployments.	

[68] See March 2023 "SCE 2022 Demand Response Executive Summary", available at https://docs.cpuc.ca.gov/PublishedDocs/Efile/G000/M505/K462/505462861.PDF.

[69] See May 10, 2023 "OhmConnect 2022 LIP Evaluation", at Slide 8, available at https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/demand-response/ demand-response-workshops/2023-load-impact-protocol-workshops/ohmconnect_2022_lip_presentat ion.pdf.

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45	Google	Overarching - Methodology	**Using Reference Temperature Estimates as Explanatory Variables** One of the major changes in the new statistical modeling approach is that it represents all smart thermostat energy savings as occurring through changes in the heating and cooling reference temperatures. These reference temperatures are themselves statistical estimates from modeling each customer's energy use separately in the pre- and post-periods. This approach creates several significant problems: a) The use of statistically estimated reference temperatures on the right hand side of the model will bias the impact estimates low. A key assumption in regression modeling is that the explanatory variables are fixed values and not statistical estimates or measured with error. This problem is known as attenuation bias (a.k.a. regression dilution) because it leads to systematic underestimation of the regression coefficients. The attenuation bias is expected to be especially large in this application due to high uncertainty in reference temperatures estimates, which will cause underestimation of impacts. b) The reference temperatures are treated as estimates of thermostat setpoints, but there is only a weak relationship between reference temperature estimates and actual thermostat setpoints[70], [71] – especially for electricity with many seasonal end uses. Cooling reference temperatures are especially suspect due to summer seasonal load changes (school schedules, pool pumps, refrigerators, etc.). c) The fitting of the reference temperatures in a separate regression also means that the main panel data regression fit can't properly account for the correlation between parameters or the variance in the reference temperatures. d) The model assumes that smart thermostats have no impact on energy use other than through temperature setpoints. But smart thermostats can affect energy use in ways that don't involve setpoints – such as HVAC fan overrun to harvest cooling at end of cycles (e.g. Nest's Airwave feature), optimized staging of multistage systems and heat pump aux heat, and fan scheduling for customers who run fan-only. It is unclear how these savings would be accounted for in the model.	First, the study does not claim the approach is flawless. There is no perfect model. All models are approximations of complicated realities. Our model controls for trend differential and provides information on how it affects smart thermostat impacts. The model provides value by indicating how the device shifts tau, the outdoor temperature at which heating or cooling begins. We have clarified the role of the models we use to estimate smart thermostat effects and included appropriate caveats about possible limitations. i.e. while degree day shifts affect thermostat setpoints, additional activities and changes in the home could also affect the setpoints. More importantly, the main takeaways from prior evaluations remain the same. All attempts to adjust for possible selection bias have not provided savings at the claimed levels. As DNV has stated in response to previous comments, the current quasi-experimental modeling framework is the best approach to estimate EE intervention impacts. We welcome any credible and industry-vetted approaches to account for selection issues likely to affect EE impacts. Some have suggested using smart thermostat operations rather than energy consumption data as a possible solution. However, without baseline information, these data don't provide the information necessary to estimate impact. a) Our model included pre-estimated baseline reference temperatures (tau). It then estimated shifts from these baseline reference temperatures in the post-period for everyone and incrementally for the participant group. The model allowed for post-period reference temperatures to be different from pre-period reference temperature values by the amount of the shift term. While attenuation bias may be present in the estimated degree day slopes (the only parameters incorporating tau), it is unclear whether the bias would affect the shift above or below tau, which is the actual basis of the impact estimate. b) Our analysis does not presume that tau estimates setpoints. It assumes that shifts in setpoints result in shifts in

[70] The seminal paper on variable reference temperature energy modeling cautioned against assuming that changes in reference temperatures can be tied to changes in thermostat setpoints. See p.11 in PRISM: An Introduction, M. Fels, Energy and Buildings 1986. Available at https://www.sciencedirect.com/science/article/abs/pii/0378778886900034.

[71] An Oak Ridge National Lab study (https://www.osti.gov/servlets/purl/5129762) looked at changes in reference temperatures vs. monitored indoor temperatures and found "Often changes in the base reference temperature have been attributed to a change in the thermostatic set point. However, the indoor temperature data collected from the monitoring does not indicate substantial changes between the two periods in the temperatures maintained." (p.28)

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				tau by the same amount, which is what basic PRISM theory states. For HVAC savings to occur, average setpoints must have shifted, and those shifts will be evident in a reference temperature shift, tau. The model estimates these shifts to evaluate the impact of smart thermostats. Seasonal end-uses certainly have the potential to affect the relationship between thermostat setpoints and reference temperatures. However, for this to substantially bias the impact estimates, these seasonal end-uses would have to vary year over year within participants and/or differ from the comparison group year-over-year differences. The DID structure does not entirely avoid this potential concern but limits the magnitude. c) This is true to an extent. The variability of the estimated energy impact reflects the variability of all model parameter estimates. However, it takes the proportion of days with heating and cooling degree days, which are functions of the pre-estimated baseline temperatures as a given. Thus, we may not have fully accounted for all cross-correlations and properly entrained the variability of the pre-estimated baseline temperature values. The likely effect of such accounting is additional variability in the estimated energy impact. However, given the large number of data points and the high precision of all variable estimates, it may not have a material impact on the variability of the estimated savings estimates. d) The additional effects of smart thermostats, including fan control delays and fan scheduling, are likely to impact savings in both positive and negative directions. Moreover, the Nest Airwave feature, which increases fan runtimes but decreases AC (compressor) usage, is weather-correlated and, thus, related to temperature reference point shifts, which our model estimates. Additionally, all estimates happen in a DID context where we include the same treatment for the comparison group, which mitigates the noted effects.
46	Google	Overarching - Methodology	**Selection Bias Adjustment** Prior California evaluations found a significant (and initially unexpected) increase in baseload electric use for rebate participants relative to the carefully matched comparison group. Customer surveys revealed that participants reported significantly more household changes that increased energy use than the comparison group – such as adding an EV (9% for participants vs 3% for comparison group), increased household size (net 5% more), and increased living space (net 4% more). Significant selection bias among smart thermostat program	a) The net changes noted in the comment come from prior DNV evaluations. These changes partially (occupants and living space increases) or wholly (EVs and refrigerators) increase baseload. In the current study, DNV accounted for the different energy consumption trends precipitated by such changes through baseload trend adjustments. To the extent these life changes are associated with smart thermostats, these changes do not coincide with smart thermostat installations but happen over time. They are more diffuse. In other words, these are not step changes that occur all at once at the same time as smart thermostat installations. Thus, the trend terms in our models provide first-order

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			participants has also been found in other studies[72] and is further supported by the EIA RECS 2020 mentioned later in these comments. The prior evaluations recognized and attempted to adjust for this bias by assuming that any changes in baseload use provide a direct estimate of the baseload bias (i.e., estimated baseload use is unaffected by the thermostat) and that the heating and cooling loads experienced the exact same percentage bias. The prior evaluations adjusted the results using the average change in baseload use from individual weather normalization models. The new study analysis makes the same assumptions but attempts to improve on it by estimating a linear trend as part of a panel data regression model. There are several concerns with this approach: a) The model assumes that the bias is a linear trend. But research on the timing of the biasing activities has shown that most changes occur after thermostat installation[73] – particularly for households having a baby (perhaps the largest potential change on HVAC use) – and so the trend isn't linear. The pandemic makes this linear trend assumption even less realistic (see later comments). b) The approach still assumes that changes in baseload usage can be accurately estimated from meter data even though many baseload uses (lighting, refrigerators, pools) have seasonal patterns that bias this allocation of load components. In addition, the timing of new baseloads can make them appear as partly heating or cooling (e.g., an EV added in May will increase the estimated cooling load in year 1). c) The approach still assumes that smart thermostats have no impact on estimated baseload use. But smart thermostats provide scheduling features (vs simple on/off provided by standard thermostats) that could reduce HVAC fan-only runtime that is sometimes used for air quality or comfort/circulation reasons. Fan runtimes for Nest thermostat customers averaged significantly lower than published data from Wisconsin (38% fewer hours) and Minnesota (55% fewer hours). Google Nest is not aware of any California-specific studies but it stands to reason that some reduction is certainly conceivable which would reduce baseload use and cause too small a bias adjustment. d) The approach still assumes that heating and cooling biases	approximations of these changes. b) The seasonality effect is a recognized limitation of the degree day analysis. Some seasonal biases are unaccounted for (particularly where there is change over time, as in the EV example). However, these are also unaccounted for among the matched comparison group. The purpose of including matched comparison households in the study is to control for these types of non-program effects. To the extent there is a mismatch between treatment and comparison, these are the kinds of differences that will cause selection-related bias. However, bias due to differential non-heating and cooling seasonality between participant and comparison group households is a second-order effect. c) A study on the fan runtime effect of Nest would be valuable to determine the claim that Nest's effect on baseload is in a direction that saves energy. Such a study should include baseline fan runtimes to accurately estimate the impact of the Nest thermostat on baseload. DNV has pointed out in the past that the relative ease of scheduling regular fan time via the Nest app, a non-binary capability not present in programmable or dial thermostats, could easily increase average fan load. The studies cited (the same as with previous report comments) do not prove the alternative. d) As stated earlier, the approach DNV used in the current study is a reasonable solution to address selection bias. In previous evaluations, DNV assumed a structure to approximate the level of bias and provided an adjustment based on it. This study takes that structure and formalizes it in a modeling framework. The model is informative and a good way of looking at the data. Our model does not assume the "bias" is the same in heating/cooling and baseload but considers the trends between them to be similar. Additionally, without investigating and quantifying the bias or trend differences that exist between baseload and heating/cooling load, the current adjustment is a reasonable one. For example, it may be valuable to investigate the extent to which percentage change in baseload and heating/cooling load differ based on data from non-participating homes. In

[72] For example, https://neea.org/resources/northwest-smart-thermostat-research-study with key finding "Major home and life changes occurring in a similar timeframe to thermostats impacted energy savings substantially"

[73] The NEEA study (prior footnote) found that two thirds of the changes occurred during or after thermostat installation vs one third before. For increases in household size (e.g., having a baby), the skew was even larger with 78% born at the same time or after (14% of thermostat households had a baby during or after thermostat installation vs 4% before).

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			are the same percentage as the baseload change. But this assumption has no basis and, given that having a new baby is a major source of the bias (found in California and elsewhere), it is easy to imagine heating and cooling biases being much larger than baseload – especially in California's mild climates where small changes in set points result in large relative changes in heating and cooling loads (often 10% or more per degree F). This untested assumption can have a significant impact on overall savings estimates. It would be easier to adjust for the major biases affecting smart thermostat impact estimates if changes in estimated baseload energy use accurately captured the large selection bias present in these studies and if the percent bias were the same for heating and cooling. But we believe these assumptions are not very realistic and the true bias could differ to the extent of having a meaningful impact on overall conclusions.	terms of the magnification of this problem in mild climate zones, while this could be the case in percentage terms, given the relatively low cooling load, the impact on the estimated cooling load is likely small.
47	Google	Overarching - Methodology	**Pandemic Impacts** The multi-year analysis contained in the Study is interesting, but the overlap with the Covid-19 pandemic adds more sources of bias and risks drawing conclusions based on extraordinary times. The EIA RECS 2020 survey added questions about work-from-home to assess impacts of the pandemic (RECS deployed in late 2020 /early 2021). RECS includes 1,152 California households, with 14% having smart thermostats. California households with smart thermostats were 78% more likely to have been working from home than other households (64% vs 36%), implying that the pandemic had a greater impact on smart thermostat homes. This difference would be expected to have a major biasing impact on energy use and thermostat setpoint changes over the period and thwart any attempts to assess how thermostat impacts shifted across 2020 and 2021. RECS also provides a wealth of data showing major differences between households that have or don't have a smart thermostat. California smart thermostat households were 4.6 times more likely to have EV charging (11.1% vs 2.4%), 34% more likely to have children in the home, 37% less likely to have a senior citizen, and 55% more likely to be employed full time. Smart thermostat households had 3.6x as many smart speakers, 1.6x as many video game consoles, 3.3x as many home theater systems, 1.5x as many laptops and desktop computers and were 1.9x as likely to have multiple refrigerators. These differences illustrate the large and wide-ranging self-selection biases at work and makes any attempted statistical adjustment speculative at best and potentially quite misleading.	The analysis presented in this report uses data from PY2018 participants and their matches. Year 1 (2019) impacts are unaffected by the pandemic. Only the second post-installation year outcome is affected by the pandemic directly. The effect on the rest of the post-installation years is diffuse. Additionally, while the pandemic may impact subsequent years (2020 and beyond), as we indicate above, the comparison group mitigates these effects to some extent. Furthermore, as noted previously, while our model may not capture every possible source of selection bias, the trend differential adjustment accounts for the remainder of the effects.

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48	Google	Overarching - Methodology	**Statistical Model Errors/Typos in report** Google Nest identified multiple errors in the description of the main regression model, perhaps a reflection of the complexity of the specification. ● On page 14, the descriptions of δ_H and δ_C are both inaccurate in claiming that the shifts are "due to smart thermostats" when they are instead the average change in post period. ● On page 15, equation 3 and also the text in the bullet below both erroneously use δ_H in the cooling term when they should have used δ_C. We recommend examining the model and analysis to ensure that errors were just in the text and not the calculations.	Thank you. We have edited the explanations for the reference temperature parameters on page 14. The actual model as specified on page 15 was fitted correctly. We have fixed the typos in the equations on page 15.

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