The Best of Both Worlds: Statistics and Engineering Working toward a Good End (Use)

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ABSTRACT

There is often a substantial gulf between energy savings estimates based on engineering calculations and those based on empirical analysis of energy consumption data. Engineering approaches typically involve applying algorithms or building simulations that model energy consumption under different conditions (premise types, climate zones, etc.) to estimate savings after certain efficiency measures are installed. By contrast, consumption data-based approaches involve whole-premise analysis using utility metering data. With the increasing focus on measuring whole premise energy savings performance using Normalized Metered Consumption (NMEC), a new approach that integrates engineering and meter-based methods will reduce the risk for NMEC efforts by allowing for measure-level results and support consistent estimates across these central approaches.

This paper presents findings from a recent evaluation of multiple residential HVAC measures. The analysis integrates engineering and consumption methods and uses statistically adjusted engineering (SAE) models[1] that use a priori savings estimates as inputs to disaggregate whole-home savings into estimates of measure-level savings. In the study, site-specific estimates based on engineering simulation models are used as a priori inputs in place of ex-ante deemed measure savings estimates. The resulting analysis produces both whole-premise savings estimates and an allocation of those estimates across the delivered measures and offers evaluators insights for conducting similar analyses.

Background and Introduction

This paper is based on data from an impact evaluation[2] in which we studied the electricity[3] consumption effect of large-scale deliveries of multiple residential HVAC measures by four California program administrators (PAs) in 2018.[4] Across the 4 PAs, 14 programs delivered the measures to a large number of single-family, multifamily, and mobile homes in different climate zones. Some of the programs targeted specific residential population segments including hard-to-reach mobile home residents and multifamily buildings, while others were open to all residential customers. Participating low-income households received program measures through a direct install delivery mechanism at no cost.

[1] State and Local Energy Efficiency Action Network (2012) provides a definition of SAE models.
[2] DNV (2020a).
[3] Since the intent of the paper is to illustrate the methods we used to estimate measure savings when multiple measures are installed by programs, we present findings based on electricity data to conserve space. Results based on gas data are qualitatively similar.
[4] The four PAs include Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), Southern California Gas (SCG), and San Diego Gas and Electric Company (SDG&E).

Table 1 provides a summary of the number and claimed savings of the HVAC measures the programs installed. The PAs claimed that the installed measures delivered total electric savings of 53 million kWh. Smart thermostats made up the bulk of the total measure electric installations (50%) and claimed savings. Fan controls and refrigerant charge adjustment (RCA) were the next most frequently installed measures and fan controls represented the second highest measure in terms of claimed savings.

Table 1. 2018 direct install programs residential HVAC installations and electric savings claims by measure

Measure Group	Total Claimed kWh Savings	Number of Electric Installations	% Electric Installations
Condenser Coil Cleaning	758,231	28,367	13%
Duct Testing and Sealing	1,694,527	8,592	4%
Fan Controls	11,183,423	32,991	15%
Fan Motor Replacement	5,648,120	13,916	6%
Refrigerant charge adjustment	3,597,868	23,018	10%
Smart Thermostat	30,924,701	114,626	52%
Total	**53,806,870**	**221,510**	**100%**

The direct install programs delivered measures that varied by dwelling type with multifamily homes receiving mostly smart thermostats[5] and limited proportions of other measures (Table 2). Single-family homes, on the other hand, received coil cleaning, control fan, and RCA measures most frequently, followed by smart thermostats. Mobile homes received smart thermostat measures most frequently, followed by RCA and duct sealing, and received the latter measure more frequently than any other premise type.

Table 2. 2018 percent homes with electric saving measures by dwelling type

Dwelling Type	Coil Cleaning	Duct Sealing	Fan Control	Fan Motor	RCA	Smart Thermostat	Lighting	Smart Power Strip	Households
Mobile Home	29%	43%	39%	25%	44%	66%	11%	0%	4,046
Multifamily	5%	0%	14%	5%	2%	95%	9%	0%	21,064
Single Family	75%	9%	69%	28%	59%	45%	21%	11%	17,742
Overall	36%	8%	39%	16%	30%	72%	14%	4%	42,852

The programs also installed different combinations of measures across participating households, most of which included smart thermostats. As an indication of the combinations of measures delivered by the direct install programs and the variation by dwelling type, Figure 1 shows the fraction of other measures installed in homes that received a smart thermostat. As Table 2 indicates, smart thermostats were installed in 66% of mobile homes, 95% of multifamily, and 45% of single-family homes.

[5] In a previous study, we had examined the energy consumption effect of smart thermostats delivered through rebate programs, where they were largely the only measure installed. See DNV (2020b). With only a single measure installed, whole-home energy use changes provide energy savings estimates for smart thermostats. By contrast, when multiple measures are installed, such as with direct install programs that we are examining in this paper, whole-home savings require an additional approach to estimate the contributions of each measure to the overall savings.

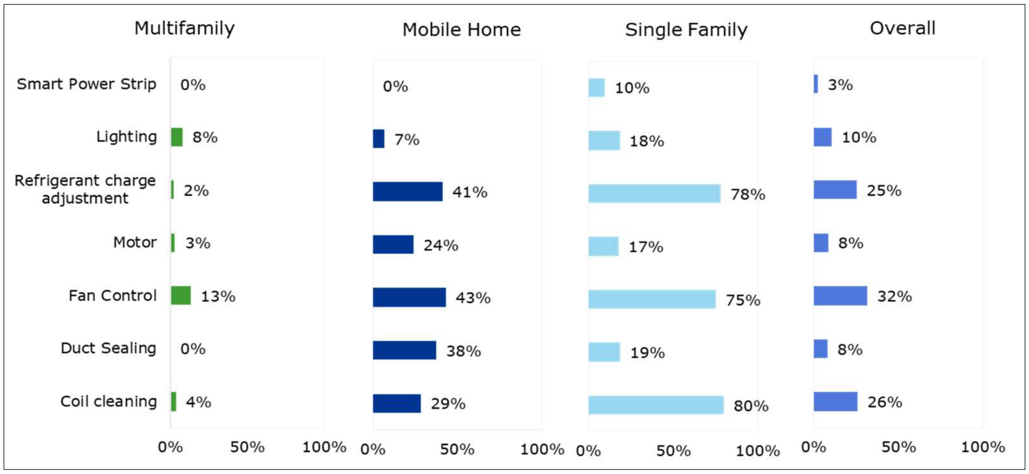

Figure 1. Frequency of direct install programs electric measures installed with smart thermostats by dwelling type

Data

We used the following sources of data for the evaluation:

- Tracking data: We sourced information about program participation from tracking data that the PAs filed with the CPUC in the California Energy Data and Reporting System (CEDARS).
- Energy use data: energy consumption data were obtained from the PAs to analyze energy use changes related to the use of the HVAC measures.
- Customer data: Supplementary information related to demographics and building characteristics for both participating and non-participating customers were sourced from customer information tables obtained from the PAs.
- Weather data: We sourced weather data from the National Oceanic and Atmospheric Administration (NOAA) and climate zone 2018 reference temperature files (CZ2018) to include in regression models to account for weather sensitivity.[6] CZ2018 provides typical meteorological year (TMY) weather data for select California weather stations that are useful for long-term weather normalization. The study also used climate zone information available by zip code from the CEC.[7]

We obtained consumption data from the PAs for electricity at multiple levels of granularity: billing month, daily, and hourly. Billing data were primarily used as a means of identifying customers who did not get any program-sponsored measures (non-participants) and whose energy use patterns could help inform change in energy consumption in the absence of the program. Hourly and daily electric data served to fine-tune the selection of matched comparison non-participants and served as the basis for site-level modeling.

We screened out customers with onsite solar from the analysis since we did not have access to their onsite solar production and, hence, did not know the full amount of electricity they used. We also excluded customers without at least 90% of daily electricity consumption pre-and post-installation in the analysis.[8]

Table 3 presents electric participant data attrition and the number of customers in the study. The table indicates starting household counts from the tracking data considered for use in the study; the number of customers without onsite solar and with daily data available for matching, customers with AMI data and 2018

[6] National Oceanic and Atmospheric Administration Hourly Weather Data; California Energy Commission Title 24. https://www.energy.ca.gov/title24/; http://www.calmac.org/weather.asp.
[7] https://ww2.energy.ca.gov/maps/renewable/building_climate_zones.html
[8] These energy consumption data requirements are in line with CalTrack recommendations. http://docs.caltrack.org/en/latest/methods.html#section-2-data-management

installation dates, and finally customers with AMI data with the requisite pre-and post-data of at least 328 days of data available for the analysis.

Table 3. Electric customer data attrition and counts used in the analysis by PA

Participant Data Attrition	PG&E Electric	SCE Electric	SDG&E Electric
Customers with measures of interest in the 2018 tracking data	27,759	70,281	2,238
Customers for whom data was requested	25,071	69,055	2,033
Customers for whom some data was received	21,760	68,823	2,005
Customers with sufficient pre- and post-period data	13,715	28,948	1,151
Customers without onsite solar and the requisite data for second round matching	13,473	28,727	1,130
Customers with relevant and sufficient data used in the final analysis	13,473	28,727	635

Methodology

We detail approaches we used to estimate savings per household and the disaggregation of these estimates into measure savings in this section. Such disaggregation allows us to obtain savings estimates per installed HVAC measure. The disaggregation method we used is a refinement of standard disaggregation methods that are generally used for this purpose. (Agnew and Goldberg, 2017)

Whole-home Savings

Consumption data analysis formed the foundation of our approach to estimate energy use savings of the multiple residential HVAC measures delivered by the 2018 PA programs discussed earlier. We used all data for each dwelling type from the PAs to estimate a single and consistent savings per household a year post-installation, 2018 through 2019.

The consumption data analysis involved a two-stage modeling process that combined variable degree-day PRISM-inspired,[10] site-level models with a matched comparison group, difference-in-difference (DID) framework. This is a well-established and accepted methodology that is appropriate for the evaluation of energy changes at the home level after an energy efficiency intervention. (Agnew and Goldberg, 2017) Moreover, the modeling approach is closely related to all other forms of program analysis that use energy consumption data including time-series, cross-section approaches. It is also consistent with CalTRACK's recent effort to develop agreed-upon steps for the site-level modeling portion of the analysis.[11]

In the first stage, we fit site-level cooling and heating degree models using daily energy consumption pre- and post-installation data separately and calculated normalized annual consumption (NAC). This step puts energy consumption on equal weather footing and isolates the effect of the intervention from weather effects.

In the second stage, we used a quasi-experimental method, the best and only option in the absence of a randomized experimental design, to control for non-program-related changes and estimate savings on a difference-in-difference (DID) basis.[12] The DID approach relies on a comparison group to control for non-program,

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[9] The notable drop in SDG&E electric participant data is due to the removal of accounts with no electric claims.

[10] Princeton Scorekeeping Method or PRISM is a software tool for estimating energy savings from billing data.

[11] CalTRACK specifies a set of empirically tested methods to standardize the way normalized meter-based changes in energy consumption are measured and reported. http://www.caltrack.org

[12] This approach involved selecting non-participants that are similar to participants along with relevant observable characteristics using matching. Matched comparison non-participants or groups were selected in two phases. In phase one, we used monthly billing data to identify 10 comparison candidates and, in phase two, we used interval data to fine-tune the match and select one comparison home for each participant. Details of the matching approach used are provided in DNV (2021).

exogenous change. It assumes that a comparison group is a reasonable proxy for the counterfactual of the participant group.

In the DID model, we regressed NAC on simulation-based percent savings of each home's measure bundle. The model also included a general treatment term as a predictor of pre-post energy use change. Fitted values that combine the estimated model coefficients and percent total simulated savings for each home were used to derive whole-home savings by dwelling type.

Decomposition of Whole-home Savings

Where multiple measures are installed, consumption data analysis can most accurately provide estimates of whole-home savings that occur due to the combination of all the installed measures. The DID model provides average whole-home savings by dwelling type, which is expected to vary depending on which measures were installed. We used multi-measure dummy and statistically adjusted engineering (SAE) models to decompose these savings to measure-specific savings for homes that received the HVAC measures through the direct install programs.

The common multi-measure dummy model (**common dummy model**) provides average measure savings estimates across the different households that only considers the presence of each measure at each participating household. The model is specified to include binary variables that indicate the presence or absence of each measure at each participating household and has the following specification:

$$\Delta NAC_i = \alpha_0 + \sum_k \beta_k I_{ki} + \varepsilon_i$$

where:

ΔNAC_i = change in NAC (normalized annual consumption) for household i, defined as pre-NAC – post-NAC.

α_0 = non-program-related change.

I_{ki} = 0/1 dummy variable, equal to 1 if household i received measure k, 0 if household i is in the comparison group and/or did not receive measure k.

β_k = estimate of mean savings per participant who received measure k.

ε_i = error term.

A more refined approach considers variations in measure savings (for instance, by household type and climate zone) that are possible and can be used to inform model savings estimates. In addition to binary variables that capture the presence of measures at participating households, this approach incorporates ex-ante or other ex-post (collectively a priori) measure savings estimates for each measure that vary based on installation conditions to obtain more informed measure savings estimates. This is the composite SAE model and is specified as:[13]

$$\Delta NAC_i = \alpha_0 + \sum_k \beta_k I_{ki} + \sum_k \gamma_k E_{ki} + \varepsilon_i$$

The terms ΔNAC_i, I_{ki}, α_0, and ε_i are as defined above. The term E_{ki} signifies a priori savings of measure k installed at household i. We provide a discussion of the a priori savings considered and used in our study below.

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[13] A simpler SAE form that omits the participation dummy variable (the common SAE model) has the nominal appeal of the coefficient β_k being interpreted as the "realization rate," the ratio of realized to tracking savings. However, inclusion of the tracking estimate without the corresponding dummy variable can lead to understated estimates of savings due to errors from omitted variables bias (Agnew and Goldberg, 2017).

In the composite SAE model, the coefficient estimates of γ_k are adjustment factors of a priori measure savings, akin to a realization rate, and the treatment dummy coefficient, β_k, are estimates of the average change in NAC across customers with each respective measure. This model allows for the possibility that empirical savings are correlated with a priori savings estimates but are not strictly proportional to it. Total savings for each measure installed in different households for this model is calculated using:

$$S_k = \hat{\beta}_k \sum_i I_i + \hat{\gamma}_k \sum_i E_i$$

Unit savings per measure is then calculated as this total, divided by the number of customers that installed the measure.

The size of participant households and the associated energy consumption vary substantially. In order to avoid the savings estimates from being driven by large homes with high energy consumption, we also estimated a third SAE model that took initial household energy consumption into account. In this model, we normalized the change in NAC by the pre-installation NAC (which is the percent change in NAC) and a priori measure savings by each home's initial energy consumption (which are the percent a priori measure savings). This refined approach (the **scaled SAE model**), thus, takes the size of each participating household into consideration when decomposing whole-home savings into measure savings.

The **scaled SAE model** specifies percent change in NAC as a function of binary variables that reflect the presence of installed measures and a priori measure savings as a percent of initial energy consumption for each participating household. This model is specified as:

$$\%\Delta NAC_i = \alpha_0 + \sum_k \beta_k I_{ki} + \sum_k \gamma_k \%E_{ki} + \varepsilon_i$$

where:

$\%\Delta NAC_i$ = percent change in NAC for individual i, defined as (preNAC – postNAC)/preNAC.

$\%E_{ki}$ = a priori percent savings of measure k, for the climate zone and building type of household i that received the measure, where percent measure savings are measured as a priori measure savings relative to consumption of household i.

γ_k = an adjustment factor of measure k's a priori percent savings.

α_0 = non-program related percent change.

β_k = estimate of mean percent savings per participant who received measure k.

ε_i = error term.

Total savings for measure k for the **scaled SAE model** is given by:

$$S_k = \sum_i PreNAC_i * (\hat{\beta}_k I_{ki} + \hat{\gamma}_k \%E_{ki})$$

where the summation is over all customers with the measure. Unit savings per measure then is this estimated total savings divided by the number of customers with the measure.

In this study, we considered two sources of a priori measure savings that are used in the **composite** and **scaled** SAE models (defined above). One source was ex-ante deemed measure savings data, which provides unit savings for each measure that program providers use for their claims. These values are derived from engineering calculations or simulations that use various assumptions to derive the unit savings for each measure installed under different circumstances, including location and dwelling type. The second source was ex-post engineering simulation results we conducted using key measure inputs from recent evaluations to derive savings estimates for measures installed individually and simultaneously.

We based our scaled SAE models on ex-post engineering simulated values rather than ex-ante deemed measure savings estimates in order to use the most consistent and accurate dwelling type and climate zone-level estimates of savings as a percent of baseline consumption. We conducted the simulation using DEER prototypes in eQUEST, a well-established simulation engine, which incorporated the best data available from previous studies and evaluation findings. We developed savings estimates by building type and climate zone for each of the residential HVAC measures under study for the combinations that were installed by the programs.

For instance, some households might have implemented duct sealing and testing, refrigeration charge adjustment, and fan control measures; others might have implemented only duct sealing and testing, and still, others might have implemented other measure combinations. For each of these combinations, we ran a “last-in” simulation to determine the incremental savings contribution of that measure to that combination. Therefore, this approach attempts to account for interactive effects of the multiple HVAC measures and provides a more realistic estimate of the marginal contribution of each measure in the combination. For installed measures where engineering simulation estimates were not developed (lighting and smart power strips), we used ex-ante deemed savings in the SAE models.

Results

We will first discuss whole-home electric savings before focusing on the decomposition of these savings into measure savings.

Whole-home Savings

The starting point for our evaluation of direct install programs was estimating weather-normalized energy consumption changes among participant homes that received direct install measures as compared to similar homes that had no such intervention. We find that average electric savings per home, which includes the savings for all technologies installed at the same time, are 115 kWh, 70 kWh, and 132 kWh for mobile homes, multifamily homes, and single-family homes respectively (see Figure 2). The figure also provides claimed whole-home savings for each dwelling type, calculated by dividing total claimed electric savings by the total number of participating sites.

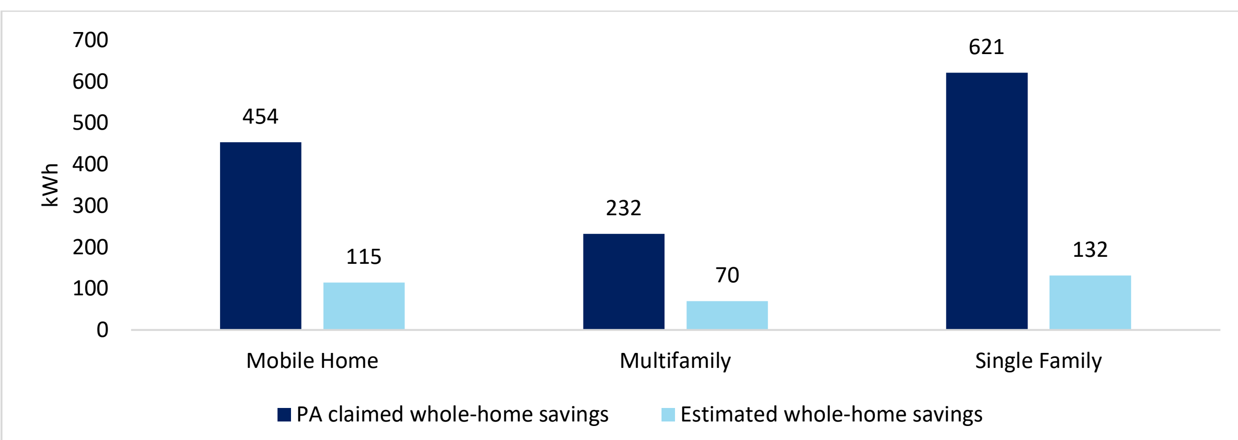

Figure 2. Average claimed and estimated electric whole-home savings from 2018 residential from multi-measure installations

Whole-home claimed electric savings were highest for single-family homes that installed measures with relatively high claimed savings (e.g., fan motor replacements and fan controls). The next highest claimed savings were for mobile homes, and for similar reasons. Moreover, the energy consumption of single-family homes is generally high, which provides greater opportunities for energy savings. Multifamily homes largely installed smart thermostats alone and had the lowest claimed whole-home savings. The actual savings achieved per home roughly followed the patterns of claimed or reported savings, although the realization rates (estimated savings as a fraction of claimed savings) were 30% for multifamily homes and about 20-25% for single-family and mobile homes.

Engineering Simulation Estimates

Values from engineering simulation models formed an important foundation of both the models used to estimate whole-home energy use changes and the decomposition of these changes into measure-level estimates. The engineering estimates used a simulation engine to produce prototype models based on certain parameters that reflect multiple scenarios, including dwelling type, climate zone, and retrofits. Figure 3 provides the average estimated percent electric savings for installed HVAC measures based on engineering simulation models and PA-provided tracking data for the non-HVAC measures by dwelling type. In the figure, DMO signifies mobile homes, MFM multifamily homes, and SFM single-family homes.

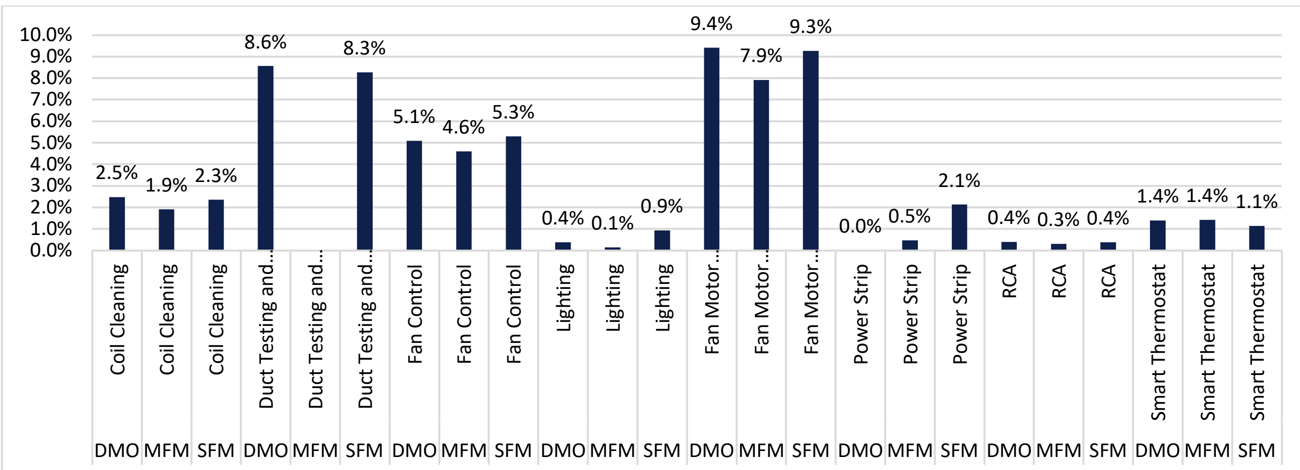

Figure 3. Average simulated percent electric savings per measure for 2018 direct install programs

Decomposition of Whole-home Savings

We decomposed whole-home savings into measure-level savings using each of the three second-stage models outlined above. We provide our findings from these models including measure savings estimates and their statistical significance, the number of households used in the models and the average baseline consumption among the homes in this section.[14]

Table 4 provides the results from full models that feature all installed measures by dwelling type. The measure savings estimates are qualitatively similar across all the models for each dwelling type. While model estimates from the common dummy model reflect average measure savings across all climate zones and installations for each dwelling type, the estimates from the other two methods are informed by a priori variation in measure savings based on location and housing type. In addition, measure savings estimates from the third (scaled SAE) model also reflect variation in scale or energy consumption that exists across homes receiving the measures. These refinements were undertaken to produce more realistic and better-determined model estimates and to overcome any limitations that may arise from the common dummy model.

[14] The number of households used in models and average baseline consumption vary among the models slightly due to small differences in the number of outliers excluded from model runs. DID models were used to determine and exclude outliers based on statistical tests; DID values exceeding pre-defined DFITS or studentized residual limits were considered outliers and excluded from model estimates presented in this paper. No more than 2-4% of observations were excluded based on such tests.

Table 4. Household counts, baseline use (kWh), and estimated whole-home and measure savings (kWh per measure) from full SAE models

Variables	Common Dummy Model			Composite SAE Model			Scaled SAE Model		
	DMO	MFM	SFM	DMO	MFM	SFM	DMO	MFM	SFM
Households Counts	3,866	20,928	17,425	3,866	20,928	17,425	3,869	20,803	17,604
Baseline Use	6,280	4,858	8,228	6,280	4,858	8,228	6,360	4,905	8,354
Whole-home	107	76	111	107	76	111	109	78	129
Coil cleaning (CC)	84	54	**-60	*106	462	**-86	***158	39	-33
Duct Sealing	**83		***123	**82		**112	29		***166
Fan Control (FC)	-24	-16	***114	-34	10	***121	-20	-5	***93
Fan Motors	***130	***114	***123	***129	**565	69	***172	**68	***139
Lighting	62	***110	***115	61	***109	31	15	*8	***115
Smart Power Strips (SPS)			**-66			-39			**-58
RCA	-16	-57	28	-37	-14	58	*-87	-5	20
Smart Thermostat (SCT)	38	***61	-30	*45	***39	***-78	**62	***62	-16

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Results in the table indicate relatively consistent savings estimates across the models, particularly for those that are statistically significant. The results also show that savings estimates for some measures are statistically insignificant, which is plausible. However, there are some negative and statistically significant measure savings estimates, which are not plausible, and suggest the presence of multicollinearity. The composite and enhanced models do not appear to provide additional information to overcome these challenges.

Looking at the overlap of installed measures could explain these outcomes.[15] We use a heatmap of installed measure overlaps to illustrate this point. Figure 4 provides a heatmap of all measures installed among single-family homes; similar figures for multifamily and mobile homes are not presented to conserve space. Each row in the heatmap provides the proportion with which a particular measure (measure x) coincides with the remaining measures. For example, the smart thermostat row indicates that 74% of smart thermostats were installed with coil cleaning while the coil cleaning row indicates that 49% of coil cleanings were done in premises with smart thermostat installations.

[15] We should note that the overlap in measure installations (and the resulting multicollinearity) alone do not necessarily explain the inconsistent and implausible measure savings estimates. For example, in cases where there are strong interactive effects, including overlapping functions between or among the measures, the estimated measure savings could be imprecise and, in some instances, even negative. For example, one of the patterns to emerge from these models is the interactive effects between fan controls and smart thermostats, two measures that perform some similar functions. Savings estimates for fan controls and smart thermostats have opposite signs across all models and dwelling types reflecting this overlapping function: delaying fan turn-off. Similar to what fan controls do, smart thermostats use the HVAC fan to spread the cool air remaining in the coils through a home after switching off the air conditioner compressor.

Figure 4. Single-family heatmap of measure installation overlaps

The figure indicates that smart thermostats were installed most commonly with fan controls (for 69% of homes), RCA (for 73% of homes) and coil cleaning (for 74% of homes). The extensive overlap of smart thermostat installations with these three measures explains the common dummy model's inability to provide a well-defined marginal savings estimate for this measure in the single-family model.[16]

Similarly, the coil cleaning measure overlaps with RCA and fan controls measures in 76% and 83% of single-family home installations, respectively. High measure installations overlaps could also explain the common dummy model's inability to assign meaningful marginal savings estimates to the coil cleaning and RCA measures, which is exacerbated by relatively low overall whole-home savings.

The additional information that the SAE models incorporate is used to overcome the noted limitation faced by the common dummy model by providing an external source of measure savings variations that can be used to inform the decomposition of whole-home savings into measure savings. However, despite the extra information incorporated by the two SAE models, the challenges observed for the common dummy model estimates are still evident. While the measure savings estimates are more significant, the negative estimates that plague the common dummy models persist. Thus, the extra information embedded within these models does not appear to overcome the multicollinearity problems caused by the multi-measure installations noted above.

However, these models do hold some promise over the common dummy model that is worth investigating further in future studies. In particular, the scaled SAE model appears to have the ability to provide more reasonable savings estimates by scaling engineering simulated measure savings used to decompose whole-home savings. For example, multifamily sites that received relatively few coil cleaning and fan motors (see Table 2) have outsized savings estimates for these measures in the composite SAE model, reflecting the fact that almost all measures were installed with smart thermostats in these homes and the model is based on a priori savings estimates that only vary by climate zone. The savings estimates for these two measures, however, are more reasonable in the scaled SEA model where a priori savings used to inform model estimates are calibrated to reflect each participant's energy use, which provides more variation. The latter model shows the improvement in savings estimates this approach makes possible.

[16] Comparatively, smart thermostats do not coincide with any other measure more than in 7% of multifamily homes.

Given the challenges that each of the full models had in decomposing whole-home savings outlined above, we bundled measures that appeared to be correlated and estimated additional (reduced) models using the scaled SAE modeling approach. Table 5 provides savings estimates that are based on various measure bundles.

Table 5. Household counts, baseline use (kWh), and estimated measure savings (kWh per measure) from reduced SAE models

	Scaled SAE Reduced Model 1			Scaled SAE Reduced Model 2			Scaled SAE Reduced Model 3		
Variables	DMO	MFM	SFM	DMO	MFM	SFM	DMO	MFM	SFM
Household counts	3,859	20,775	17,602	3,859	20,775	17,602	3,859	20,775	17,602
Baseline Use	6,350	4,895	8,354	6,350	4,895	8,354	6,350	4,895	8,354
CC, RCA	**66	37	-30						
CC, RCA, FC				14	-1	***59	*40	***26	***49
Duct Sealing	20		***158	37		171	33		***161
FC		-6							
Fan Motors	***159	**67	***155	***153	***86	***148	***149	**53	***155
Lighting, SPS	***67	17	***52	**61	17	***56	***63	17	***53
SCT, FC	9		***78						
SCT		***62		**62	***62	-17			

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

In the first reduced model, we bundled measures that were most commonly installed together. The bundling did not resolve the problem of negative savings estimates that still appeared to reflect the effect of remaining measure overlaps. Additional bundling in the second reduced model did not provide much improvement. The third reduced model provided plausibly signed and significant savings estimates for the specified bundles.

However, it was not clear how these estimates could be used to evaluate installed measures given that such bundles were not always installed together. The savings for the estimated bundles still required disaggregation of the savings from each bundle into individual measure savings in order to use these values in the calculation of overall program savings. In the face of these difficulties, we undertook a different approach to disaggregate whole-home savings that we discuss below.

Alternative Decomposition of Whole-home Savings

Given the foregoing limitations, instead of estimating a scaled SAE model that is specified to include separate terms for all the installed measures, we estimated a collapsed scaled SAE model based on the sum of the engineering simulation measure savings of all the installed measures as a percent energy consumption for each site. In this model, the percent change in NAC is explained by the informed engineering percent savings of the total measure bundle installed at each site along with a treatment dummy, which accounts for constant savings associated with the program installations. This collapsed scaled SAE model is specified as:

$$\%\Delta NAC_i = \alpha_0 + \beta I_i + \gamma \% E_i + \varepsilon_i$$

where:

$\%\Delta NAC_i$ is percent change in NAC for individual i, defined as (pre-NAC – post-NAC)/pre-NAC.

$\%E_i$ is savings of the total measure bundle that participant i received estimated by the engineering model as a percent of typical energy consumption.

I_i is a treatment indicator variable, which is 1 if i is a participant, 0 otherwise.

In this model, the coefficient associated with total engineering percent savings estimate, γ, is an adjustment factor of these savings and the treatment dummy coefficient, β, is an estimate of the constant percent change in NAC across customers with any measure bundle.

Total savings for a home receiving a given measure bundle is estimated using:

$$S_i = (\hat{\beta} + \hat{\gamma}\%E) * PreNAC_i$$

These estimated savings are converted into measure savings for each participant i based on the relative engineering savings proportions of each measure for that participant. Total measure savings are averages of the measure savings across all participants that received the measure.

Table 6 provides measure savings estimates based on the disaggregation of whole-home savings estimates using engineering savings proportions by dwelling type. The table also provides the number of homes where data were included in the models and the average annual baseline electricity consumption.

Table 6. Disaggregation of whole-home savings using engineering savings proportions

Variables	DMO	MFM	SFM
Household counts	3,976	20,813	17,514
Baseline Consumption (kWh)	6,290	4,878	8,349
Coil cleaning	30	32	32
Duct Sealing	93		100
Fan Controls	57	66	71
Fan Motors	94	69	121
Lighting	14	26	14
Smart Power Strips			28
RCA	6	5	5
Smart Thermostat	24	56	15
Whole-home savings	115	70	132

$p < 0.01$ for all savings estimates except lighting for mobile homes

A comparison of measure savings estimates for multifamily home installations illustrates our attempts to decompose whole-home savings using different statistical approaches.[17] The bar chart highlights both the promise and limitations of our attempts at statistical decomposition of whole-home savings and the challenges of estimating measure savings from multi-installation projects. The two (SAE) statistical approaches provided savings estimates for some measures (coil cleaning and smart thermostats) that are higher than those apportioned using engineering savings proportions. They also resulted in implausible negative savings estimates for other measures (fan controls and RCA) partly due to considerable overlap in installations of these measures.

[17] Estimates for single-family and mobile homes that provide similar insights are not presented here to conserve space.

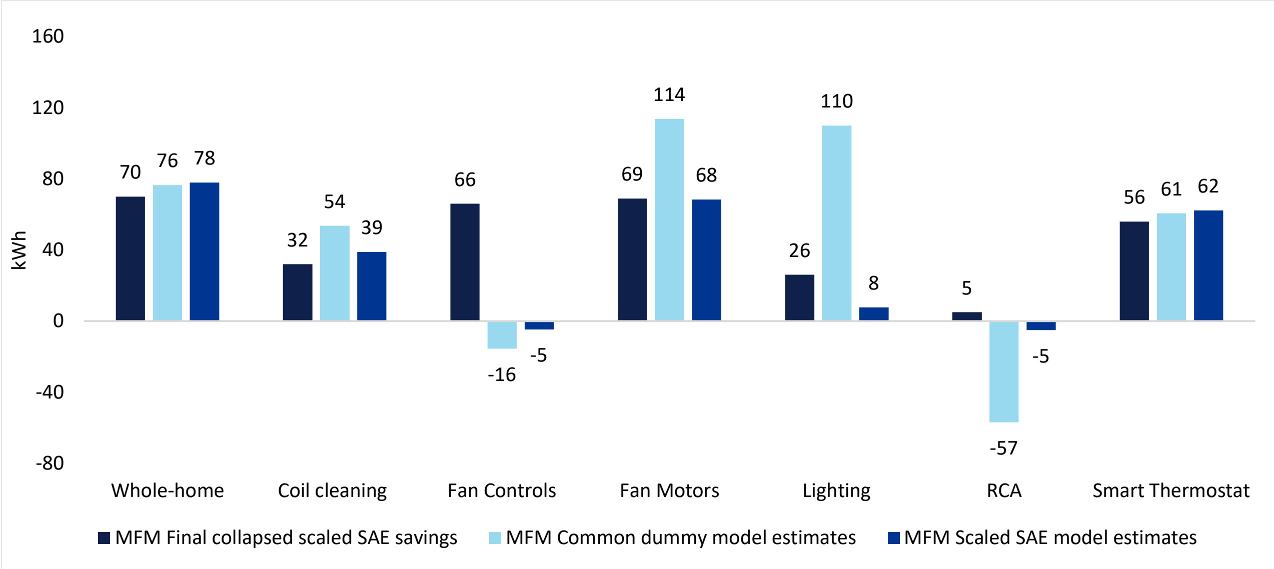

Figure 5. Comparison of measure savings estimates for multifamily installations

Concluding Remarks

We used data from California direct install programs that delivered a large number of HVAC measures to single-family, multifamily, and mobile home participants across the state to estimate individual measure savings. The installation of multiple measures in different combinations poses challenges for estimating individual measure savings, particularly because of interactive and overlapping measure effects and relatively low whole-home savings.

We used a modified form of a statistically-adjusted engineering model (the scaled SAE model) as an improvement over existing approaches to overcome these challenges as well as those posed by variations in home size. In particular, this approach was meant to provide estimates that are better informed than those obtained from the common dummy variable and composite SAE models. The common dummy variable model provides average measure savings across all installation locations (climate zones) and settings (housing type and consumption levels) while the composite SAE models incorporate a priori savings estimates that reflect variations along certain dimensions, such as housing type and location.

The scaled SAE model extends this approach one more step by incorporating varying measure savings relative to consumption, which also vary by home size, and attempts to weight measure savings so they can be better estimated relative to each other. It moves away from the naïve a priori used by the composite SAE model to more informed a priori savings estimates that reflect variations in savings across customers. Each step from the common dummy variable model to the scaled SAE model introduces more customer-specific data and uses additional sources of savings variation in an attempt to produce better measure savings estimates.

Obtaining separate realization rates by measure has always been a challenge. Informing consumption data analysis is always useful and the current application that uses these estimates scaled by home size holds promise as it mitigates the effects of variation of home size on savings estimates.

The efforts we undertook to disaggregate whole-home savings suggest that it could be useful to assess measure installation overlaps prior to estimating measure-specific savings estimates. Such analysis would reveal the extent of overlap in installed measures and suggest ways to combine either similar or highly overlapping measures prior to attempting to disaggregate whole-home savings into measure-specific savings.

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