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Authors
Murphy, Sean
Deason, Jeff
Satchwell, Andrew

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ORIGINAL ARTICLE

Timed to save: the added value of accounting for hourly incidence of electricity savings from residential space-conditioning measures

Sean Murphy · **Jeff Deason** · **Andrew Satchwell**

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Abstract Previous research has recognized that the value of measures that reduce electricity usage depends upon the timing of the savings generated, but the lack of hourly savings shapes has limited the demonstration of this concept. We develop empirical hourly savings shapes for residential space-conditioning measures from nearly 18,000 efficiency projects in California and show how they combine with the diurnal and seasonal variation in electricity system costs. We find that these measures (cooling replacements; windows, doors, and skylights; and other envelope measures) tend to save electricity when system costs are highest and that the hourly savings account for 1.4–1.5 times as much value as non-time-sensitive estimates of efficiency would predict. We present these impact multipliers for each measure to quantify the additional value revealed by the time-sensitive approach. We show that this additional value is similar in an evolving electricity grid with storage, rather than natural gas generation, as the marginal resource.

Keywords Energy efficiency · Electricity · Peak demand · Residential buildings · Space-conditioning

S. Murphy (✉) · J. Deason · A. Satchwell
Lawrence Berkeley National Laboratory, Berkeley, USA
e-mail: smurphy@lbl.gov

Introduction

Peak demand in the electricity system creates a cost management problem: a significant share of generation resources are in use for only a limited number of hours. Electricity generation costs during these hours, which typically occur in afternoons and evenings in California but can vary across the country, can be more than an order of magnitude higher than those in average hours (Velocity Suite, 2020). Demand-side resources like energy efficiency can reduce peak demand and decrease these high electricity system costs (Stern, 2013). Accurate estimates of when electric efficiency savings occur, therefore, are important for energy efficiency measure valuation, the selection of demand-side resources, and for resource planning.

The timing of electric efficiency is important when estimating its economic value (Mims Frick & Schwartz, 2019). In cost-effectiveness screens that inform the design of utility ratepayer-funded energy efficiency programs, energy savings estimates combined with avoided costs measure the economic impact of energy efficiency investments (Woolf et al., 2020). Avoided costs delineate the dollar amount that each marginal unit of energy efficiency saves the electricity system under various assumptions about energy markets, policy, and utility operations. They typically include a number of component costs, including energy generation; generation, transmission, and distribution investments; ancillary services; and cap and trade costs. These cost components vary significantly both seasonally and diurnally, but estimates of electric efficiency savings are generally limited in how they address timing. They often measure annual savings and only cover the first year of operation (Schiller et al., 2017). Coincidence factors, which may accompany these annual electricity savings values, translate them into estimates of demand savings in a defined peak period (Schiller et al., 2017). Peak periods vary across the country but generally occur in summer afternoon hours (Mims Frick et al., 2019a). This method does not address the variation in savings outside these peak periods nor does it differentiate between "ordinary" peak periods and the handful of hours that create very high generation costs. If a valuation of efficiency uses only annual energy savings, it misses any hourly variation in avoided costs.

The timing of electric efficiency savings is also essential for understanding how the measures interact with other distributed energy resources, including demand response. When efficiency measures reduce load, they can alter both the need for and availability of demand response resources. The timing of these competing reductions further affects the value of demand response, in particular when renewable energy penetration affects the diurnal profile of electricity system costs (Satchwell et al., 2020). Energy efficiency's passive load reductions can impact multiple demand flexibility modes, including load shifting as well as load shedding (Schiller et al., 2020).

Resource planners benefit from insight into the timing of electric savings as they manage an evolving grid. In California, solar photovoltaics (PV) supply an increasing share of load — for example, reaching 13% of total electricity demand in 2019 (California ISO, 2020). Diurnal variation in PV electricity generation has led to mid-day curtailments and steep generation ramps in the afternoon, which create challenges for resource adequacy (California ISO, 2020) and may shift the timing of peak net load later into the day. At the same time, California is pursuing an expansion of electric vehicles (California Code of Regulations 13.1962.2) and energy storage (California Public Utilities Commission (CPUC) 2013b), both of which will affect the electricity system's peak demand and net load. Many other jurisdictions are facing similar grid evolution challenges or will face them in the near future. Grid planners at ISO-New England (ISO-NE) have already responded to these challenges by including efficiency as a capacity resource in long-term load forecasts (Black & Rojo, 2019). However, these forecasts only make use of on-peak capacity, thereby excluding the capacity provided by efficiency in off-peak hours (Demand Resources Working Group 2019). This disconnect has motivated the development of methods that provide a full accounting of the capacity that efficiency measures provide (Demand Resources Working Group 2019). A lack of utility and efficiency measure performance data currently limits the implementation of these methods. Hourly load and savings shapes generated by building energy simulation models married with detailed building stock data could provide accurate estimates of the non-peak electric efficiency savings (Mims Frick et al., 2019b).[1] However, calibration of these simulations to empirical savings shapes — such as those we estimate here — will be key to their precision, usability, and reliability in utility resource planning and valuation studies.

This paper builds on existing research on the timing of electric efficiency savings. Mims Frick et al. (2019b) identified the importance of end-use load profiles for understanding the time-sensitive value of efficiency and the dependence of that value on location and utility operations. It also documented how the limited availability of these shapes has hindered analysis of the time-sensitive value of efficiency. Mims Frick and Schwartz (2019) differentiated between two categories of end-use load profiles, load shapes and savings shapes, and comments on their use. The paper demonstrated how efficiency measures can introduce technological changes that lead to savings shapes that differ substantially from load shapes. For example, a reduction in lamp wattage scales a load shape down, which changes the peak demand but not its timing or the overall shape of load. The introduction of a measure with controls, on the other hand, can change when a measure uses energy, resulting in a shape that peaks both at different values and times.

Our analysis recognizes the importance of interval metering data and builds upon similar efforts to use them in efficiency measure valuation. Interval metering data reveal load patterns and are more accurate than engineering algorithms and building simulations (Stern, 2013). Boomhower and Davis (2020), for example, used interval

[1] ResStock (see Wilson et. al 2017) and ComStock, tools developed and maintained by the National Renewable Energy Laboratory, will be able to generate modeled hourly load for specific regions of the country in this fashion by late 2021.

metering data to develop empirical savings shapes for a Southern California Edison air conditioning program. They found that electricity savings from upgraded air conditioning systems were concentrated in summer months between 4 and 8PM, when avoided capacity and energy costs are high. They compared the value of the program using both annual and hourly energy savings and found that the hourly approach yields a "premium" on the annual value estimation. Similarly, analyses of Pacific Gas and Electric's Advanced Home Upgrade Program (AHUP) demonstrated that energy savings are concentrated in evenings and coincided with high avoided costs in summer evenings to create significant value (California Efficiency Demand Management Council, 2019).

In this study, we provide additional evidence of the time-sensitive value of energy efficiency measures. We leverage a dataset of energy efficiency projects installed through residential Property Assessed Clean Energy (R-PACE) programs in California between 2009 and 2017.[2] Using weather-normalized metered energy consumption methods, detailed project information, and interval metering data from households that implemented R-PACE projects, we produce empirical electricity savings shapes for several efficiency measure categories and demonstrate how evening savings drive their value.

While we present metrics similar to those in Boomhower and Davis (2020), we cover more than twice as many projects over three California investor-owned utility service territories and provide results for multiple space-conditioning measures. We also compare the value of efficiency using two avoided cost models. The first model assumes gas turbines as the marginal generation unit, which reflects current grid conditions in California, and the second uses battery storage as the marginal generation unit, which represents future grid conditions. With this approach, we are able to determine in which hours and seasons space-conditioning measures reduce electricity usage and provide the most value in California. We compare these savings profiles to annual estimates of energy savings to illustrate the importance of time-sensitive valuations of energy efficiency. The use of two avoided cost models further addresses how the value of efficiency may change in an evolving electricity grid, in and outside California. We also compare our results to those in Boomhower and Davis (2020) and discuss the implications of the study on energy efficiency cost-effectiveness screening, building modeling, and resource planning.

Data and methodology

To estimate hourly electric savings for the projects in our study, we follow a common approach in the energy efficiency industry that compares pre- and post-project household usage to estimate savings (Fels, 1986). The method first fits models of pre- and post-project electricity usage regressed on actual weather over those periods. We then feed both models "typical" weather year data and estimate savings by taking the difference in usage predicted by the pre- and post-project models. Since weather varies annually, estimates of energy savings based on a single year of observed temperature do not necessarily reflect expected performance in future years. For example, if the observed year is atypically cool, savings estimates for measures that likely save more in warm weather (like air conditioning retrofits) would be biased downwards and under-predict savings in warmer years. Typical weather data, such as the TMY3 maintained by the Renewable Energy Laboratory,[3] mitigate this issue by constructing a year of data that reflects median historical weather. A savings estimate based on a typical weather year is, therefore, "normalized" to weather.[4]

We use the time-of-week and temperature (TOWT) model, which builds on Fels (1986) in its use of hourly

[2] R-PACE is a mechanism for financing residential energy-related upgrades through property taxes that is most commonly used in California and Florida. Several previous papers have studied the impacts of R-PACE programs. A series of analyses (Ameli et al., 2017; Deason and Murphy 2018; Kirkpatrick and Bennear 2014) have studied the impact of R-PACE programs on solar PV installation, generally finding that the presence of R-PACE programs has been associated with, and may have driven, increased deployment. Goodman and Zhu (2016) study home value impacts of R-PACE programs, while Rose and Wei (2019) review their macroeconomic impacts.

[3] https://nsrdb.nrel.gov/about/tmy.html

[4] Typical weather data, importantly, do not account for expected increases in temperature due to climate change. Indeed, the TMY3 only represents weather between 1991 and 2005. Given that California air temperatures have risen since 2005 and recent modeling indicates continued increases (He et al., 2018; *Hydroclimate Report Water Year 2015* 2016), the TMY3 may systematically underestimate savings from cooling measures. Still, TMY3 datasets have an advantage over a single year's worth of more recent data in that it is possible to evaluate their bias relative to climate models (Murphy 2017) and modify them to incorporate expected temperature changes (Belcher et al., 2005).

data to estimate occupancy and to construct monthly piecewise-linear models of electricity usage and temperature (Mathieu et al., 2011; Price, 2010; Price et al., 2011). We include a year of electricity and weather data in both the pre- and post-project models. To define weather for each household, we selected the nearest weather station within 200 km that provided both observational and TMY3 data during the baseline and reporting periods. Our implementation of TOWT is consistent with CalTRACK,[5] a set of standardized methods for metered energy analysis in California, used in particular for pay-for-performance programs.[6]

PACE households and electricity usage data

We identified households for this study from a dataset maintained by the California Advanced Energy and Alternative Transportation Financing Authority (CAEATFA), a state agency that provides a loan loss reserve for R-PACE programs. R-PACE programs have financed energy efficiency measures and solar photovoltaic panels in more than 200,000 houses between 2009 and 2019. We worked with 120,000 of these households, all of which participated between 2009 and 2017. We connected the majority of them with interval electricity metering data obtained from the three California investor-owned electric utilities: Southern California Edison (SCE), Pacific Gas & Electric (PG&E), and San Diego Gas & Electric (SDG&E). We applied several data sufficiency screens on the metering data informed by CalTRACK methods and Uniform Methods Project recommendations (Agnew & Goldberg, 2017). The primary screen, which required that no more than 10% of metering reads be missing in any month in the baseline or reporting period, led us to discard a significant share of meters for some utilities and resulted in a sample for this analysis of about 18,000 households with electric meters that implemented energy efficiency projects.[7]

Five R-PACE program providers[8] provided us with data on measures installed in their projects in disparate levels of details. For this analysis, we set aside projects that included solar PV (24% of projects) as well as those that include only water consumption-related measures (5%) to focus on those that relate chiefly to energy consumption.[9] We standardized the measure data into three common efficiency measure categories, HVAC; windows, doors, and skylights; and other envelope measures, which includes reflective roofs and insulation. Either standalone or in combination, these measures accounted for 95% of efficiency projects. A small share of projects (5%) contained efficiency measures such as water heating that did not fall in these categories. Our analysis does not present the impact of these miscellaneous measures in isolation but does include them in the "combined measures" category detailed below.

The measure data generally did not specify whether HVAC measures heated or cooled homes, used electricity or gas as the primary energy source, or were new installations[10] or replacements (retrofits). Our HVAC category, therefore, covers a range of measures, from heat pumps and duct sealing to furnaces and air conditioners. To address the uncertainty within this general HVAC category, we separated replacements from new installations by evaluating

[5] See https://www.caltrack.org/

[6] Following CalTRACK methods, we estimate two sets of piecewise-linear relationships for each temperature interval, one for an "occupied" building state and one for an "unoccupied" state. These states are defined by examining the residuals of a preliminary fixed balance point regression of usage on temperature during the model baseline period in the presence of indicator variables for 168-h-of-week intervals. The model considers hours of the week that have more than 65% positive residuals in the baseline period as "occupied" and the remaining hours as "unoccupied." Again following CalTRACK methods, we estimate a separate TOWT model on each calendar month in a project's baseline and reporting period.

[7] For additional details on our data and our data screening process, see Deason et al. (forthcoming), which estimate non-time-dependent electricity and gas impacts of R-PACE projects.

[8] These programs cover more than 99% of all R-PACE projects through mid-2017 that are tracked by CAEATFA.

[9] We do include projects that contain energy efficiency measures as well as water savings measures.

[10] R-PACE programs support efficient HVAC measures regardless of whether they replace existing equipment. We use the term "installations" to refer to HVAC measures that we believe represent new air conditioning equipment where none was previously present and "replacements" to refer to HVAC measures that we believe replace existing air conditioning equipment with more efficient equipment. In this paper, we emphasize the subset of projects that do not include installations, as installations would not generally be considered energy efficiency projects.

Table 1 Components of CPUC avoided cost calculator

Avoided cost component	Definition
Energy	Wholesale market energy prices
Capacity	Levelized cost of new generation capacity
Transmission and distribution	Cost for expanding transmission and distribution systems
Ancillary services	Procurement of up- and down-regulation, spinning reserves, and non-spinning reserves
Greenhouse gases	Compliance cost (cap and trade) and remaining economic cost for meeting emissions targets (GHG adder)

project performance in hours when cooling demand tends to be higher. If we observed a project increased energy usage by more than 15% in summer months (July to September) between noon and midnight, we categorized it as a new cooling installation. If we observed a reduction in energy usage greater than 10%, we categorized it as a cooling replacement. We include the remaining HVAC projects — those that were not categorized as installations or replacements by this method — as part of a combined non-installation category that also includes the windows, doors, skylight, and other envelope measures.

Avoided costs

To estimate the time-dependent value of the electricity usage impacts of our projects in different grid conditions, we used two versions of the California Public Utilities Commission (CPUC)'s avoided cost model (Energy and Environmental Economics 2020; Horii et al., 2019).[11] These avoided costs represent the marginal costs the electric system would incur if electricity usage reductions did not occur. The model estimates hour-of-year (8760) nominal avoided costs for 30 years for the electricity cost components listed in Table 1 by utility service territory.[12]

The CPUC made a significant update to its avoided cost model in 2020 (Energy and Environmental Economics 2020). The primary modeling difference between the 2019 and 2020 avoided cost models is the use of a 4-hour battery storage as the cost of new capacity in the 2020 model, as opposed to a gas combustion turbine in the 2019 model (Horii et al., 2019). The 2020 avoided cost model, therefore, reflects an electricity system with high levels of renewables and storage that can absorb mid-day solar production and avoid evening ramps. Neither model includes non-energy impacts that can be part of energy efficiency cost-effectiveness tests (Woolf et al., 2020) nor impacts on reliability (Horii et al., 2019). We also exclude the methane avoided costs introduced in the 2020 model for the sake of symmetry in comparing the results generated by the two models.

For both models, we deflate the nominal avoided costs and calculate their net present value in 2019 dollars with inflation and discount rates from 2019 avoided cost model.[13] We then calculate hourly dollar savings by multiplying our estimated hourly electricity savings by the hourly avoided costs. The sum of these hourly savings is the time-sensitive project dollar savings.

In parallel, we calculate a "naïve" estimate of project dollar savings by multiplying annual average avoided costs by the project's annual energy savings. This estimate ignores the time dependence of

[11] See CPUC's website to access the avoided cost model and associated documentation: https://www.cpuc.ca.gov/General.aspx?id=5267

[12] Some avoided costs also vary by climate zone within a utility. The 2019 model generates each avoided cost component by climate zone and utility, but the 2020 model only breaks distribution costs out by climate zone.

[13] The inflation and discount rates in the 2019 avoided costs model are 2.33% and 5%, respectively. In the 2020 model, the inflation varies between 2 and 2.5%, and the real discount rate ranges from 5.2 to 5.5% depending on the utility.

electricity usage changes, instead assuming they are equally distributed over the year. We then calculate the ratio of time-sensitive project dollar savings to the naïve estimate of project dollar savings. We conceptualize this ratio as an "impact multiplier" that describes how much more valuable (or costly) projects are to the electricity system due to their timing:

$$Multiplier = \frac{ProjectDollarImpacts_{hourlyestimate}}{ProjectDollarImpacts_{annualestimate}}$$

Results

Hourly demand shapes provide visibility into diurnal and seasonal patterns in building load and energy efficiency measure savings. They also show how savings, avoided costs, and load align with each other. In hours when savings coincide with large avoided costs, efficiency measures create significant value. We present these demand shapes by measure for two seasons, summer (June through September) and non-summer (October through May).[14] As discussed earlier, our sample includes some projects with inferred new cooling installations. We first consider the savings shapes and multipliers for non-installations, which includes inferred cooling replacements, windows and doors, and other envelope projects, before addressing the inferred new cooling installations.[15]

Efficiency (non-installations) projects

Figure 1 shows three demand shapes for all efficiency measures in our dataset, excluding inferred new cooling installations. The top panels show baseline (pre-project) and post-project usage. The line in the bottom panel shows the savings, which is the difference between the baseline and post-project usage. In general, we find that peak savings from these non-installation measures are well-correlated with peak load and peak avoided costs, which occur at 6PM in non-summer and 5PM in summer for the 2019 avoided cost model and at 6PM for both seasons in the 2020 avoided cost model.

We find that summer peak savings for efficiency measures tend to be larger than non-summer peak savings. This observation is not surprising given that most California homes use natural gas, not electricity, as the primary heating fuel, so we would expect most HVAC impacts on electricity usage to be cooling-related (Palmgren et al., 2010). Peak demand savings from projects that are not new installations are two and a half times as large in summer as they are in non-summer (see Fig. 1). Summer savings are near zero in the mornings, rise rapidly in early afternoon, and remain near their maximum from 4 to 8PM, before declining throughout the night. This profile is consistent with expected residential space cooling-related reductions. In non-summer, we see small savings in the morning and early afternoon, peaking at 1PM before declining until 5PM. We see a larger peak in the evening hours, again consistent with space-conditioning-related savings. As electricity prices tend to be highest in the summer, the summer peak savings have an outsized impact on measure valuation relative to savings in other hours of the year.

The variation in the diurnal and seasonal timing of peak savings is even more significant at the measure level. Inferred cooling replacement savings are largest in the afternoon and evening in both seasons, though savings are several times higher in the summer (see Fig. 2). Inferred cooling replacement savings are also well-aligned with the peak summer avoided costs in both the 2019 and 2020 peak avoided cost models, which occur at 5PM and 6PM, respectively.

In households that implemented windows and door measures, we observe small morning load increases (negative savings) in both seasons, accompanied by more significant load reductions in the afternoon and evening, especially in the summer. The savings from these measures are also generally well-aligned with peak avoided costs.

Peak savings from other envelope measures occur in the late evening in both summer (9PM) and non-summer (10PM). In the summer, as indicated by the negative savings, other envelope upgrades increase mid-day usage, likely by allowing less heat to escape the household in the mornings, causing

[14] PG&E and SCE both used this definition of summer in their electricity tariffs as of July 2020, and SDG&E defines summer as June through October (Pacific Gas and Electric, 2020; San Diego Gas and Electric, 2020; Southern California Edison, 2018).

[15] Eighty percent of non-installations projects contain measures from a single measure category (HVAC, windows and doors, other envelope). The remainder includes multiple measures or less common measure such as water heating.

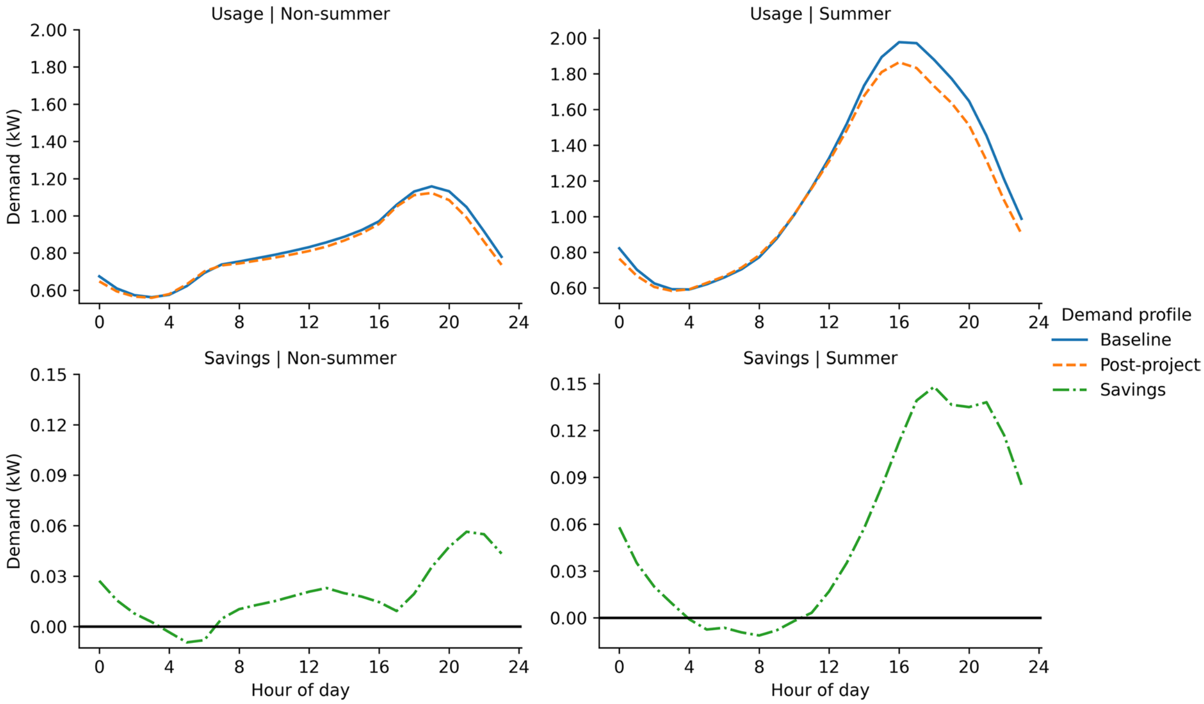

Fig. 1 Hourly non-installation measure baseline and post-project usage and savings shapes by season

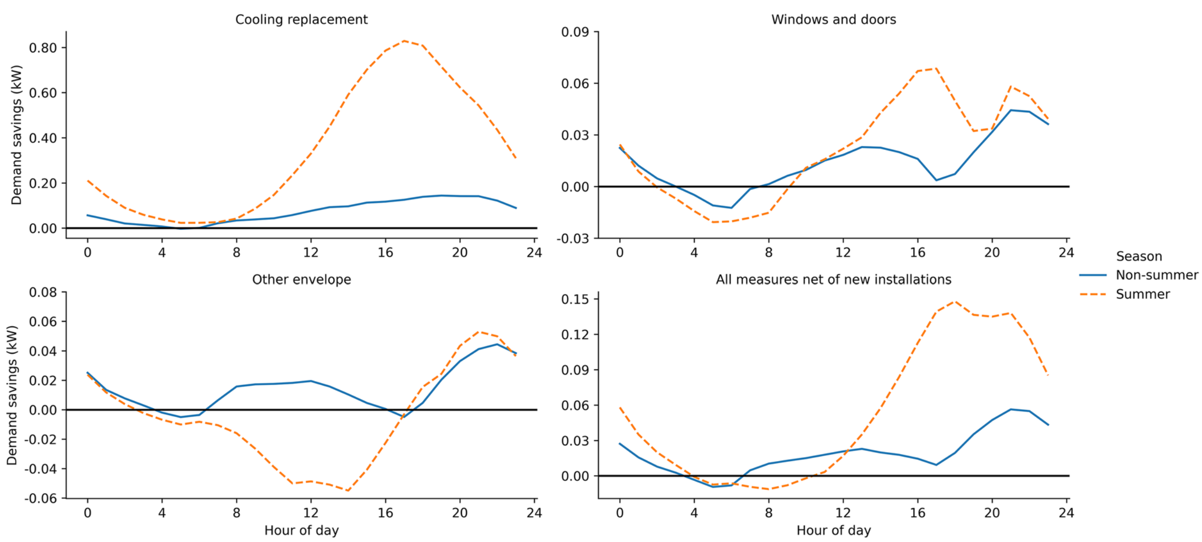

Fig. 2 Seasonal demand savings by efficiency measure category

space-conditioning usage to begin earlier. In non-summer, the late evening peak may correspond to better electric heating efficiency. While their peak savings do not coincide with the peak avoided costs hours in either season, other envelope measures still provide significant value because both savings and avoided costs remain high throughout the evening.

Table 2 Impact multipliers for efficiency measures

Measure category	2019 model		2020 model	
	Impact multiplier	Effect on valuation	Impact multiplier	Effect on valuation
Inferred cooling replacement	1.43	Increase	1.26	Increase
Windows and doors	1.62	Increase	1.35	Increase
Other envelope	1.41	Increase	1.63	Increase
All measures exclusive of inferred new cooling installations	1.53	Increase	1.37	Increase

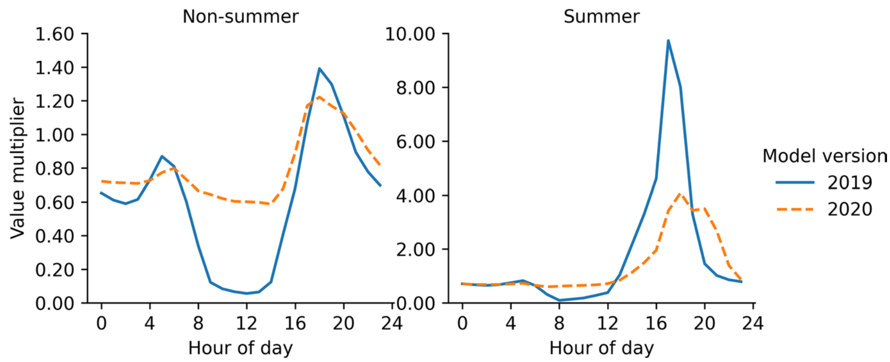

Fig. 3 Average hourly avoided cost multipliers by season for 2019 and 2020 avoided cost model versions

Table 2 presents the impact multipliers for each efficiency measure category using both the 2019 and 2020 avoided cost models. The multipliers are the ratio of project dollar impacts estimated with hourly energy savings to project dollar impacts estimated with annual energy savings. Multipliers do not rank measures by their absolute impacts; they measure the share of extra impact revealed through a time-sensitive valuation. Inferred cooling replacements, for example, have the highest demand savings (see Fig. 2) but do not have the largest multiplier.

In general, we find that impact multipliers for load decreasing measures are greater than one, which means that estimates of electric savings that ignore their timing would undercount the value that they provide to the electricity system. The time-sensitive valuation reveals that, when considered together, these measures provide substantially more value than a naïve valuation would estimate: 53% more using the 2019 model and 37% more using the 2020 model.

The impact multipliers differ across measures and avoided cost models. As we discussed earlier in this section, efficiency measures have distinct savings shapes that combine with avoided costs in different ways. To help explain the differences in impact multipliers, we present avoided cost multipliers for each season and hour across our entire project sample using both the 2019 and 2020 avoided cost models in Fig. 3. We calculate these as the ratio of the average avoided cost in an hour of the day to the average avoided costs across the whole year.

The primary difference occurs in early summer evenings (5PM to 6PM), when the 2019 avoided costs, in particular capacity costs, are much higher than those in the 2020 model.[16] This disparity stems from the use of gas turbines as the marginal resource in the 2019 model, in contrast to battery storage in the 2020 model. Measures that have peak savings between 4 and 6PM (e.g., inferred cooling replacements), therefore, provide *less* value using the 2020 avoided cost model relative to the 2019 model. After 7PM, this pattern changes as the 2020 model's avoided costs taper more slowly than the 2019 model's and extend higher valued savings out to 9PM. For envelope measures, this increase in late evening value results in a higher multiplier with the 2020 avoided cost model.

[16] The avoided capacity costs at 6PM in summers are about 31 times higher than the average annual capacity avoided costs in the 2019 model but only 15 times higher in the 2020 model.

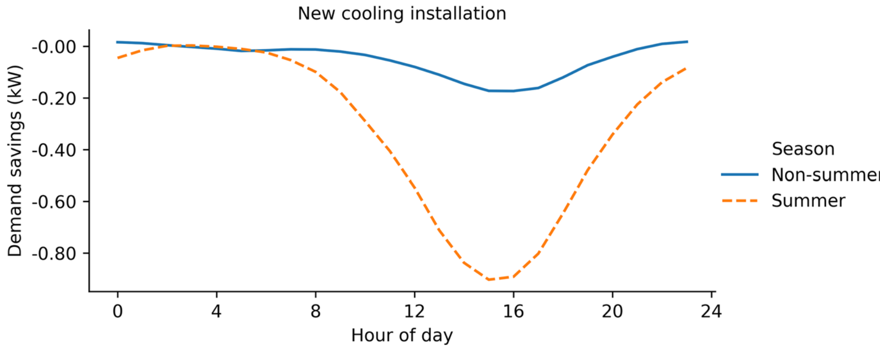

Fig. 4 Seasonal demand savings for inferred new cooling installations

Table 3 Impact multipliers for inferred new cooling installations

	2019 model		2020 model	
Measure category	**Impact multiplier**	**Effect on valuation**	**Impact multiplier**	**Effect on valuation**
Inferred new cooling installation	1.50	Decrease (costs increase)	1.20	Decrease (costs increase)

The 2019 and 2020 avoided cost models also diverge in morning and mid-day non-summer hours, when solar PV generation is high and residential loads are low. The 2020 avoided cost model multipliers in this period are about five times higher than the 2019 avoided cost model multipliers. Measures with non-summer mid-day savings, such as windows and doors, therefore deliver more value with the 2020 avoided cost model in those hours. Battery storage as the marginal resource also explains this difference because batteries can charge with low-cost solar during the middle of the day, effectively redirecting solar generation to times when it is more valuable and thereby raising the avoided cost of generation during those hours. Despite this increase in the value of mid-day savings, the multiplier for windows and doors decreases with the 2020 avoided cost model due to the reduction in early evening value.

As we discussed earlier, our sample contained some inferred new cooling installations, which increase load in all hours. As with energy savings, the timing and magnitude of avoided costs that coincide with a load increase also matter for a measure's valuation. We address cooling installations in the next section.

Results that include inferred new cooling installations

In Fig. 4, we show the savings profiles for cooling installations. We find that load begins to increase in the late morning and reaches a maximum at 4PM — slightly earlier than the maximum load reduction from inferred cooling replacements. The summer load increase, which is approximately equal in magnitude to the inferred cooling replacement savings, is about five times higher than the non-summer increase. These load increases come at times when grid costs are higher than average, particularly in summer (see Fig. 3). Since the inferred new cooling installations increase load (negative savings), the category's impact multiplier (Table 3) is a ratio of cost *increases*, not savings. A multiplier above one, therefore, indicates that costs are greater than the naïve estimate of energy savings would suggest. With both avoided cost models, we find that time-sensitive valuation reveals additional costs, yielding multipliers of 1.50 and 1.20 (Table 3).

Finally, we consider the savings profiles of all measures combined, including cooling installations, in Fig. 5. This savings profile displays a diurnal profile similar to that of all measures net of installations, as shown in Fig. 2. The inclusion of the installations, however, creates a net load increase in the morning and early- and mid-afternoon in summer and reduces maximum summer energy savings by about one third — from about 0.15 to 0.10 kW. Overall, we find that net impacts from all R-PACE projects are still coincident with peak demand, despite the load increases from the installations.

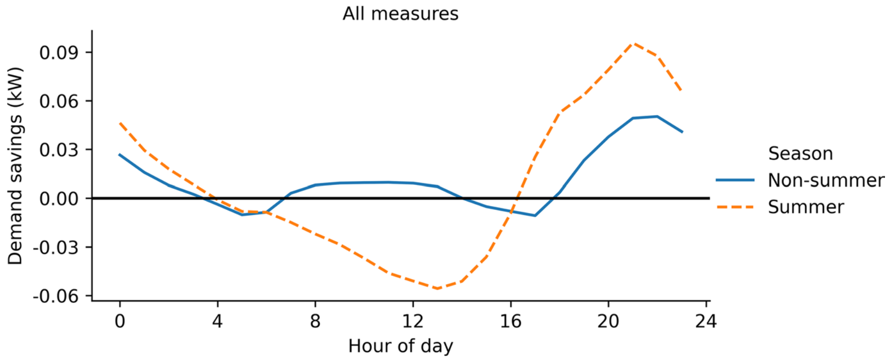

Fig. 5 Seasonal demand savings for all measures, including installations

Impact multipliers of 1.55 and 1.69 (Table 4) underscore this alignment.

Discussion

Our results are generally consistent with similar studies (Boomhower & Davis, 2020; California Efficiency Demand Management Council, 2019) and uphold their conclusions that electric efficiency measures can provide savings that coincide well with electricity system needs.

California's Advanced Home Upgrade Program (AHUP), implemented by each of the large California investor-owned utilities, supports whole home retrofits that address a building's shell and its space-conditioning devices (DNVGL, 2019). A typical R-PACE project tends to be less comprehensive in terms of the number of measures installed than an AHUP project, but the mix of measures is generally aligned. The AHUP program, therefore, is a useful comparison to our combined non-installation measure results. PG&E has found that AHUP's energy savings were concentrated in summer evenings, which overlapped with peak avoided costs, in particular capacity and transmission and distribution (California Efficiency Demand Management Council, 2019). AHUP's summer savings peak later than the R-PACE non-installations do.

Table 4 Impact multipliers for all measures

	2019 model		2020 model	
Measure category	**Impact multiplier**	**Effect on valuation**	**Impact multiplier**	**Effect on valuation**
Combined measures	1.55	Increase	1.69	Increase

Our impact multiplier of 1.43 generated with the 2019 avoided cost model for the inferred cooling replacements is consistent with the "premium" of 50% for the air conditioning program in Boomhower and Davis (2020). The 2020 avoided cost model, however, differs from the 2019 model and the historical wholesale market data used by Boomhower and Davis (2020) in its use of battery storage for the cost of new capacity. The 2020 inferred cooling replacement multiplier, therefore, is not an appropriate comparison. The divergence in the multipliers between the two avoided cost models, however, illustrates the sensitivity of the value of energy efficiency to capacity prices, which the findings in Boomhower and Davis (2020) also support.

While impact multipliers illustrate the sensitivity of energy efficiency measure value to the timing of savings, they do not speak to overall impact or cost-effectiveness. A multiplier of one does not mean that a measure provides little value, only that it provides equivalent value in all hours. The impact multipliers demonstrate how significant the timing of efficiency can be to its economic impact and underscore the importance of accurately accounting for timing in cost-effectiveness tests. For program implementers who have not actively considered the timing of the savings provided by different measures, multipliers above one may indicate potentials areas for increased investment, while multipliers below one might suggest the opposite.

Empirical hourly savings shapes such as those we derive here can provide accurate estimates of value (Mims Frick et al., 2019b). Where these shapes are not available, coincidence factors and peak period avoided costs can mitigate the issues of naïve annual estimates of energy savings. We find that for all efficiency measures combined, energy savings between 4 and 8PM in the summer generate 47% and 32% of total annual value from the studied measures when using the 2019 and 2020 avoided cost models, respectively. This concentration of value in a few hours underscores the importance of accurate coincidence factors when hourly savings shapes are not available. This approach may not account for the time-sensitive value of efficiency outside peak periods, but it does address the most valuable hours in a year. Policy makers should prioritize estimates of hourly savings, or (as a second-best alternative) peak demand reduction and coincidence factors, as part of on-going evaluation, measurement, and verification of customer-funded efficiency programs implemented by utilities. While non-peak savings are less valuable than peak savings, we do find that they vary throughout the day and year, which supports recent efforts by ISO-NE market participants to estimate savings provided by energy efficiency measures in all hours (Demand Resources Working Group 2019).

The hourly savings shapes presented here demonstrate that residential energy efficiency space-conditioning measures can help support an evolving electricity grid. The space-conditioning measures we studied provide electricity savings that remain high from the late afternoon to the evening. Even if peak avoided costs in summer evenings decline with the switch from gas turbines to battery storage as the marginal resource, our 2020 avoided cost results demonstrate that these measures still provide significant value and help mitigate peak system costs. Efficiency measures that reduce usage in the late evening perform well in this context and may be increasingly valuable if solar production pushes peak net load later into the evening. Policy makers and efficiency program implementers should consider how to adapt program design and measure mix to meet these evolving grid needs. Cost-effectiveness tests that account for the value of savings in a future grid may suggest investments in the short-run different from those most preferred in existing grid conditions. Since electric efficiency savings on average persist for more than 10 years (Murphy & Deason, 2021), attention to the evolving grid is warranted when making these investments.

Conclusion

We quantify the value of residential space-conditioning energy efficiency projects in California using hourly estimates of electricity savings combined with hourly avoided electricity system avoided costs. We compare these values to naïve estimates of energy efficiency value, which assume constant savings in all hours and take their ratio to create impact multipliers.

We find that the timing of electricity savings is important to their valuation. A time-sensitive valuation of savings generally reveals extra value from these measures that naïve estimates miss. For the space-conditioning efficiency measures that we study, hourly savings that coincide with high avoided capacity costs in peak load hours increase value by 40–50%. Programs that support these measures, by extension provide more value than standard estimates recognize. Program implementers and policy makers should consider the time-sensitive value of efficiency when designing programs and prioritizing investments.

Weather-normalized metered energy consumption methods are well-established, and software implementing these methods is readily available. Utilities have access to the electricity load data and measure installation data necessary for developing savings shapes and to the information necessary to develop avoided cost estimates. Program implementers can follow the method we have presented here to identify which efficiency investments are most valuable in their grid context and structure their programs accordingly.

While we study efficiency performance in California, the time-sensitive value of efficiency has broader geographic relevance. Other jurisdictions that have summer-peaking systems would likely find impact multipliers above one for space-conditioning measures. Furthermore, our comparison of these multipliers using two avoided cost models provides insight into how an evolving grid affects the value of energy efficiency measures. Our results suggest that if battery storage replaces gas turbines as the marginal resource and decrease peak summer system costs, energy savings from residential space-conditioning energy efficiency measures will still coincide with high avoided costs, in particular in late evenings, and therefore continue to provide more value than standard estimates recognize.

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Data availability The avoided cost models we used were developed by the Energy and Environmental Economics, Inc. (E3) for the California Public Utilities Commission (CPUC). Both E3 and the CPUC publish these models on their websites.

Project and electricity usage data were acquired under non-disclosure agreements with program providers and California electric utilities and are not available for request.

Declarations

Conflict of interest The authors declare no competing interests.

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