Show Me the Money: The Role of Energy Efficiency in Energy Affordability

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ABSTRACT

Affordability has become a defining theme in energy policy, reshaping how energy efficiency (EE) programs are evaluated, designed, and communicated. As utilities, regulators, and consumers confront rising energy costs and growing concerns about energy burden, EE programs increasingly must demonstrate its value through direct customer benefits. At the same time, pressure to reduce utility costs creates a risk that the long-recognized benefits of EE as a least-cost resource may be overlooked. This paper examines the role of affordability within contemporary EE policy and practice, with particular attention to Behavioral Energy Efficiency programs. Using empirical data from utility-administered behavioral programs across the United States (U.S.), we estimate customer bill savings directly from observed billing records and randomized controlled trial program designs. The results show that Behavioral EE programs not only produce measurable reductions in customer electricity spending but that bill savings are generally comparable to energy savings. The results also show that even waves that are relative underperformers in energy savings still generate bill savings for the customers receiving treatment. These findings demonstrate that affordability outcomes can be quantified the same way as energy savings, using established evaluation methods. We conclude by discussing how affordability metrics can complement traditional EE objectives and strengthen the case for continued investment in both Behavioral and Structural EE programs.

1. Introduction

In recent years, the number of Americans struggling to pay their utility bills has been growing. This includes households both below and above federal poverty level guidelines. In 2023, 55 million U.S. households (42%) struggled to make ends meet—meaning they were unable to afford the basics such as housing, childcare, food, transportation, healthcare, and technology (United for Alice, n.d.). According to ACEEE, in 2024 a quarter of low-income households spent more than 15% of their income on energy bills (Ayala and Dewey, 2024). Electricity costs have been rising faster than inflation in the U.S. over the past year (Plummer, 2025), and the resulting affordability crisis has become prevalent across all segments of the population. In its 2026 State of the Consumer report, SECC (Smart Energy Consumer Collaborative) found that customers today overwhelmingly prioritize energy affordability:

"Regardless of income level, age, or comfort with technology, saving money on electricity is the dominant driver of consumer concern and action" (SECC 2026, p.18).

Building decarbonization has been considered key to mitigating climate change—avoiding its worst-case-scenario effects. However, because electricity is often more expensive than the natural gas-based space heating systems that decarbonization (electrification) measures often replace (Caputo, 2019), decarbonization can result in higher costs for utility customers—both in upfront capital outlays and in ongoing operational expenses. Air-source heat pump (ASHP) installation is one example of the challenging economics of household electrification: Though most U.S. households can benefit financially from it, many might see energy bill increases. These varying outcomes are determined by many factors, especially the type of fuel and space heating system the ASHP is displacing (e.g., natural gas, propane, heating oil—furnace, boiler) and the relative pricing of those fuels to electricity (Wilson, et al., 2024).

According to a recent ACEEE report, EE has the potential to reduce electricity consumption by 8% and reduce demand by roughly 70 GW by 2040 (Specian and Aquino, 2026). Since the late 1970s, EE has typically been framed within the utility sector as a cheaper alternative to building new power plants—a system-focused approach to aid utility resource planning (Turner and Fane, 2023). A recent ACEEE report confirmed this is still the case, with an average cost of EE at $23.20/MWh in 2024, which is almost 50% lower than the average wholesale price of electricity in summer (Specian and Aquino, 2026). There is now a growing focus on affordability across all sectors of the economy, and utilities are looking at all aspects of ratepayer funding to find places to cut costs for customers. As the cost of maintaining a safe and reliable grid increases at the same time as energy demand, the narrative is now shifting from simply "least cost" (from a utility perspective) to the "ability to pay" (from the customer perspective), implying a more human-centered approach to EE. Due to rising energy costs for consumers, there is an increasing regulatory emphasis on energy burden, or the percentage of income spent on energy, which is particularly high for low-income households.

Energy efficiency can be classified into two types: Behavioral and Structural. Behavioral EE (or energy curtailment behavior) focuses on changing how and when people use energy as well as most other energy actions, such as adjusting thermostats or turning lights and electronics off. These behavioral actions are free or low cost and can reach a much larger consumer base. Structural EE, however, involves more permanent physical upgrades to building envelopes or equipment (e.g., insulation and HVAC). These come at a high upfront cost, often subsidized by utility rebates or incentives, but they can provide longer term savings (Kumar, et al., 2022).

Most research on EE for affordability emphasizes weatherization and structural improvements. However, unless the utility significantly subsidizes the upfront costs, these improvements are often out of reach for low- and moderate-income customers. According to research by Kumar et al., low-income households are more likely than energy-efficient high-income households to engage in energy curtailing actions. Therefore, energy policy focusing primarily on Structural EE will exacerbate energy inequities where higher income households are more likely to make Structural EE improvements (Kumar, et al., 2022). Behavioral and Structural EE are highly complementary, and both are needed for a balanced portfolio and optimal outcomes. Behavioral EE programs can be tailored not only to generate direct bill savings from program participation, but also to encourage and accelerate participation in Structural EE programs—further reducing energy usage and therefore further reducing energy burden (Hibbard, et al., 2020).

Behavioral EE provides distributional equity because households can participate regardless of income, homeownership status, or location. This is why utilities need to balance EE portfolios that have an emphasis on Structural programs (Sussman, et al., 2026). For example, a big factor in the persistent access and equity gap in EE uptake and bill savings stems from the fact that most low-income households are also renters (Mateyka and Yoo, 2023). Due to a split incentive to participate in Structural EE (e.g., upgrading an HVAC system), it is technically possible to make Structural EE improvements. However, it requires a high upfront investment, and most low-income customers have neither the cash at hand nor an incentive to make this improvement to a property they do not own.

With a newfound magnifying glass on affordability in the utility sector at a time when inflation is at an all-time high—causing costs to go up for everyone—regulators have put pressure on utilities to find ways to quickly reduce ratepayer costs. This has created a situation wherein policy mechanisms funded on utility bills that are “easy” to cut are at a risk. Targeting EE funds this way creates a significant disconnect between technical progress in EE and the realized benefits to real-world households. The benefits of EE as a least-cost resource are often lost amongst political and economic rhetoric around rate pressure, cost scrutiny, and equity expectations. There is limited empirical evidence for how an affordability-first mindset might change utility strategy and program design, regulatory support and evaluation priorities, as well as customer engagement and participation. As utilities and regulators navigate an affordability-first approach, it is critical to account for EE, and especially Behavioral programs, as an affordability resource in this framework.

In this study, we explore the following research questions:

1. How does an affordability-centered framing alter utility EE strategy?
2. What implications arise for regulators, utilities, and customers?
3. How can Behavioral EE innovations advance affordability?

This paper will contribute by extending the Behavioral EE literature related to affordability-centered policy frames. It will rely on empirical evidence from utilities across the U.S. and will have a novel focus on stakeholder alignment and program design as well as practical guidance for utility program administrators.

2. Methods

The customer benefits of EE programs in general are rather difficult to estimate. This is because these benefits accrue over time in the form of reduced expenditures from energy consumption. It is often said that the least expensive kWh is the kWh not used. The magnitude of that reduction requires estimating the counterfactual for the expenditures that would have occurred in the absence of that consumer’s participation in the program, along with estimates of gains in economic utility that accompany any induced consumption rebound effects (Azevedo, 2014). The monetary value of the reduced energy consumption is the product of the quantity reduced and the corresponding unit costs. The estimation of counterfactual energy consumption, and thus achieved reduction, is inherently uncertain and rightly occupies most of the attention and energies of EE program analysts (Sherwin, et al., 2022).

Less often analyzed directly is the monetary value of the reduced consumption, and most methods for doing so use prior years' average values, in the form of conversions of energy savings into bill savings using average electricity prices, for example, from EIA data (Clifford, 2022). These methods do not reflect customer benefits accurately but are instead a measure of system or utility benefits. Furthermore, this becomes considerably more challenging for the EE analyst when programs include large customer populations with heterogeneous rate structures.

Such a "back of the envelope" approach may systematically underestimate the EE programs' value to consumers. Reduced consumption is done on the margin, and the marginal kWh of electricity consumption is usually among the most expensive a consumer will consume—especially in the case of volumetrically tiered rate structures or when customers have limited attention to time-of-use (TOU) rates with high price ratios. Additionally, the last unit of energy consumed (and the first to be conserved because of an EE program) is the least valuable to the consumer, following textbook theory on marginal returns to utility from consumption.

A more robust approach to estimating the monetary values associated with electricity bills can be done by rate modeling: matching the charges utilities assess on consumers for each unit of energy consumed. Rate modeling is remarkably challenging, though, and is often not plausibly done for the purpose of assessing benefits associated with an EE program. Some of the complexities presented by rate modeling are the variety of rate schedules for residential rate classes, not least of which includes rates that change by season. Examples of these complications include: TOU rates that include different cost values based on times that (often roughly) correspond to peak demand periods, hybrid rates combining tiered rates with TOU rates, complex tariffs structures having both volumetric and fixed components, change to a household's rate plan part-way through an analysis period, and the challenge of reconciling smart meter (advanced metering infrastructure, or AMI) data with billing data when not perfectly aligned in the final totals. Compounding this, the computation load of assigning service territory-wide rate values across an AMI data set with high time resolution can be overwhelming for a standard desk analysis.

We sidestep this complexity by observing monthly customer bills directly. This avoids the need to separately model complex rate structures, and it removes any inaccuracies that can be generated in doing so—focusing instead on the actual bill charge confronting the customer. Behavioral EE programs are well positioned (possibly uniquely so due to the opt-out nature of many of these programs, compared to Structural EE programs that are necessarily opt-in) to generate accurate estimates of programmatic improvements in customer affordability. This is because most residential Behavioral EE programs are in the form of Home Energy Reports (HERs) deployed using a randomized control trial (RCT) (Illume, 2022). RCTs are the "gold standard" for causal inference (SEE Action, 2012) where the counterfactual is estimated directly by a control group that is statistically equivalent to the treatment group, prior to the start of treatment. We then use the same modeling framework that is routinely used to estimate energy savings (kWh) to estimate the bill impacts (in dollars, $) that customers realize because of the

HER program. This approach has the advantage of obviating the need for complex rate modeling, while improving the accuracy of the resulting bill savings estimate.

Note that the resulting estimates should not be interpreted as a sum of total social benefits. These values exclude many of the value streams EE gains provide to a social welfare calculation. Instead, these estimates provide a more accurate representation of the monetary value that behavioral programs can contribute to one part of the social welfare calculus, namely a reduction in consumer expenditure to receive useful energy services.

Data Preparation

Raw billing records have arbitrary start and end dates, can have non-uniform durations, and may contain some fraction of estimated reads which do not represent actual energy consumption for the period. Each of these requires manipulation to transform the records into a consistent panel dataset:

- **True-up for estimated reads.** First, we combine all estimated billing reads with the next actual read in the series, creating a single billing period with the sum of consumption over the two (or more) time periods. Where there is an estimated read at the end of the billing record, those records are dropped, so only actual reads remain. Similarly, we drop records from our dataset where the start of our observation of billing records for a given household may contain an actual read with a "true-up" value associated with an unobserved preceding estimated read.
- **Calendarization.** Next, we transform the series of billing records into a panel of calendar month records. This is accomplished by calculating a daily consumption rate for each billing record and attributing a weighted average of observed consumption for the number of days in the calendar month attributable to each bill. For example, if a customer has a billing period that typically runs monthly from the 20th of the month, then a given month will contain 20 days of one bill's average daily consumption rate as well as the next bill rate for the remaining days in that month. Similarly, this process is applied if there are more than two bills in a calendar month (which may happen infrequently) or for records spanning periods longer than a month (e.g., for a true-up period originally containing an estimated read value).
- **Data trimming.** Finally, data are trimmed following a consistent set of rules that apply to all HER waves that Oracle administers. Usage that occurs after a customer moves out of the premises (or after the account termination date) is removed; records with daily consumption rates with an absolute value exceeding 300 kWh are removed (to exclude erroneously classified commercial customers); and records associated with consumption that occurred more than 12 months prior to the start of the Behavioral EE program are dropped.

Model Form

For estimating bill impacts, we use a model form that is like the model used to evaluate savings, modified by changing the dependent variable from consumption (kWh/day) to the value of the bill the customer received ($/day). We use a post-only lagged dependent variable (LDV) model form (following Allcot and Rodgers 2014), and the lagged terms are similarly modified to match the units of the dependent variable. This model form, for estimating energy savings, is consistent with guidance from the U.S. Department of Energy's Uniform Methods Project (UMP, Stewart and Todd 2017) and has been validated via many third-party evaluations over the course of more than 15 years (see, e.g., Illume, 2022, for a relevant meta-analysis). The LDV model form is preferred over a fixed-effects (FE) model due to its improved econometric efficiency (Burlig, et al., 2017; see especially footnote 35 and equation 11; McKenzie, 2011, see "Implication 2"). This approach, using household-level billing data, is in line with "Option C" of the International Performance Measurement and Verification Protocol (IPMVP 2022). Our model for estimating the effect of HER treatment on a customer's bill is as follows: $daily\_cost_{i,t} = \alpha + \beta treatment_i + \gamma \boldsymbol{Y_{o,i}} + mm_t + (\gamma \boldsymbol{Y_{o,i}} * mm_t) + \varepsilon_{i,t}$

Where:

- $daily\_cost_{i,t}$ is the average daily bill charge for month, *t*, and household, *i,* in the post-treatment period;
- $treatment_i$ is a variable indicating treatment group assignment for household, *i*;
- $\boldsymbol{Y_{o,i}}$ is a vector of three LDV terms, including:
    - $average\_preusage_i$, the average daily charge for household, *i*, in the 12 months immediately prior to the start of treatment,
    - $average\_preusage\_winter_i$, the average daily charge for household, *i*, in the winter months (December-March) immediately prior to the start of treatment, and,
    - $average\_preusage\_summer_i$, the average daily charge for household, *i*, in the summer months (June-September) immediately prior to the start of treatment;
- mm_t is a set of indicators for each month-year, *t*, in the treatment period and;
- $\varepsilon_{i,t}$ is an idiosyncratic error term.

The estimated coefficient, β, is the effect of treatment (using an opt-out, intent-to-treat basis) in units of the dependent variable, dollars per household per day. We generate our estimate of wave- or program-level impacts on customer affordability by scaling this estimate by the number of household days (sometimes called "data days") of the treatment group in the period of analysis (accounting for mid-bill account closure events). The resulting quantity is a reduction in household expenditure on electricity bills as a direct causal consequence of the HER program. This can be used to support the argument that EE programs help alleviate energy burden.

3. Results

We use an example program as a first demonstration of the nature of the results before providing a broader set of results from across EE programs in the U.S. This program—at a large West Coast utility—is selected for a clean mapping of wave-level RCT savings to results evaluated by a third-party evaluation firm. This allows us to compare three quantities of relevance to this analysis: our measurements of energy savings, independently evaluated energy savings, and our measurements of bill savings using the econometrically similar approach as is used for energy savings. In this way, we hope to demonstrate the logical chain that leads from our measurement of energy savings, through a trusted (unbiased) measurement verification, to a measure of bill savings that is caused by the Behavioral EE program. Table 1 shows that the waves (all constructed using RCT) are broadly consistent with the external evaluation results. Wave names show the year in which the RCT was first launched, and all results reflect program (and calendar) year 2025. The variation that exists provides some context to the variability in results generally: Even within a single program and utility, individual waves differ in maturity, customer composition, and, ultimately, realized savings performance. There are also often reasonable differences in analytic choices related to data cleaning procedures and estimation models between (and among) implementors and evaluation firms, so final savings point estimate values usually vary within the statistical margin of error that implementors report. For a broad review of many Behavioral EE program evaluations, see the meta-analysis completed by Illume in 2022, which is listed in the references at the end of this paper.

Table 1. 2025 comparison of evaluated savings for West Coast behavioral program waves

Wave name[1]	Treatment households[2]	Savings rate (kWh/HH-day)	Opower savings estimate (MWh)	Evaluated savings estimate (MWh)	Evaluated / Reported[3]
Wave 2014	40,757	0.154	2,245	2,995	129%
Wave 2015	85,614	0.277	8,516	7,958	95%
Wave 2016	113,318	0.394	15,972	14,834	95%
Wave 2017	278,793	0.112	11,144	10,344	89%

[1] Wave labels indicate the launch year for each RCT. 2025a-c are newer waves whose results reflect partial-year results for 2025 and therefore should be interpreted separately from mature waves.
[2] Treatment households shown in this column are a snapshot of the number of active treatment households in June 2025: The number of treatment households declines over time from launch due to attrition (e.g., move-outs).
[3] This value differs slightly from the ratio of two preceding columns because the “Reported” value differs from “Opower Savings Estimate.” “Opower Savings Estimate” is the most up-to-date estimate of savings for the wave, while “Reported” is the value that was reported at the time of the evaluation. Small numbers of updated billing records routinely are missing and later updated, causing small differences over time.

Wave 2018a	253,775	0.156	14,115	12,640	87%
Wave 2018b	160,822	0.058	3,314	3,587	112%
Wave 2019	436,815	0.110	17,142	19,154	109%
Wave 2025a	467,991	0.056	7,015	7,317	99%
Wave 2025b	482,485	0.020	2,215	2,141	111%
Wave 2025c	149,043	0.131	4,686	4,755	101%
Totals	2,469,413	0.113	86,364	85,724	98%

Next, Table 2 compares energy savings rates with bill savings rates for this program's waves. Here, the Table 1 energy savings value is converted to an energy savings rate (in %) and compared to the bill savings rate for the 2025 wave. We prefer reporting in percentage terms due to heterogeneity in wave-level RCT construction. This is because, while households are randomly allocated to treatment or control groups within each wave, the population from which each wave is drawn is not a random representation of the utility population: Some waves have greater pre-treatment usage, are targeted for low-income households, or have other characteristics that meet various EE program goals for the utility. Percentage values allow us to present results across waves (and, later, programs) with more relevant comparisons, though important differences will still exist. Finally, the last column in Table 2 shows each wave's ratio of bill savings rate to energy savings rate, which we call "affordability performance." There is notable heterogeneity among the waves on this metric, but the weighted average is very near to a one-to-one ratio. An exploration of hypotheses for the observed heterogeneity in this ratio is beyond the scope of this paper but is one of several avenues for future research that we find.

Table 2. 2025 energy and bill savings rates by program wave for West Coast utility

Wave name	Treatment households	Energy savings rate	Bill savings rate	Affordability performance (%$/%kWh)
Wave 2014	40,757	0.91%	0.51%	0.56x
Wave 2015	85,614	1.54%	1.60%	1.04x
Wave 2016	113,318	1.59%	1.39%	0.87x
Wave 2017	278,793	0.60%	1.10%	1.84x

Wave 2018a	253,775	1.00%	1.06%	1.07x
Wave 2018b	160,822	0.49%	0.18%	0.36x
Wave 2019	436,815	0.62%	0.44%	0.71x
Wave 2025a	467,991	0.20%	0.30%	1.50x
Wave 2025b	482,485	0.14%	0.15%	1.09x
Wave 2025c	149,043	1.41%	0.49%	0.35x
Totals	2,469,413	0.62%	0.65%	1.06x

Table 3 shows the same affordability performance metric by season for 2025. At this utility, TOU rates have a steeper on/off peak price ratio in the summer months compared to the winter months (the spring and fall months straddle the rates change-over). Observing a higher affordability performance metric in the summer months is consistent with the *a priori* hypothesis that greater relative bill savings are driven by cases in which the marginal unit of energy consumption avoided is more expensive than the average unit of energy consumed. More research is needed to confirm this result's consistency across utility territories and rate structures.

Table 3. 2025 seasonal energy and bill savings rates for West Coast utility

Season (2025)	Treatment household-months[4]	Energy savings rate	Affordability impact	Affordability performance (%$/%kWh)
Winter	5,188,200	0.72%	0.49%	0.68x
Spring	5,716,605	0.75%	0.73%	0.97x
Summer	7,357,687	0.47%	0.65%	1.39x
Fall	7,261,039	0.66%	0.72%	1.09x

Table 4 shows a measure of affordability performance across a much broader swath of waves and programs in the U.S. for 2025. The table shows counts of waves by a similarity comparison of bill savings rate to energy savings rate, where "similar" is defined as within 0.25 percentage points. It shows that most waves (weighted by the number of treatment households) have similar energy and bill savings rates, but there are meaningful dissimilarities among included Behavioral EE waves. A key finding from this view of the data is in the row in which bill savings are materially higher than energy savings. For those waves, the affordability performance looks significantly higher than the other waves, but this is driven by a lower energy savings rate instead of a lower bill savings rate. In fact, the bill savings rate (affordability impact) is reasonably consistent across all three categories of waves in this table.

[4] The winter and spring counts of treatment household-months are lower than summer and fall due to the in-year launch of three new waves in 2025.

Table 4. Affordability performance in 2025[5]

Relationship category[6]	Wave count	Treatment households[7]	Share of treatment households	Opower savings rate (%kWh)	Affordability impact (%$)	Affordability performance (%$/%kWh)
Energy savings higher	68	4,059,609	13%	1.02%	0.58%	0.57x
Similar bill and energy	310	24,127,166	80%	0.72%	0.67%	0.93x
Bill savings higher	28	2,143,895	7%	0.10%	0.55%	5.48x
Total 2025	406	30,330,670	100%	0.72%	0.65%	0.91x

4. Discussion

The results from the West Coast Behavioral EE program example highlight that, while measured bill savings are closely related to measured energy savings, they are not identical: Important heterogeneity exists, pointing to a promising avenue of future research work in understanding the covariates associated with greater or lesser affordability performance in EE programs. The results from a larger swath of HER programs in the U.S. show that even waves that are relative underperformers in energy savings still generate bill savings for the customers receiving treatment. Understanding this dynamic is a priority for future research on this subject.

Taken together, these results show that Behavioral EE programs can produce measurable customer bill savings, verified using the same RCT framework already used to estimate energy savings. Across the 2025 electric sample, bill savings are broadly comparable to energy savings, and the bill savings remained positive across each of the three relationship categories described in Table 4. For utilities, this means affordability claims need not rely only on modeled rates or assumed bill impacts; they can be measured directly from customer bills.

The results also suggest that Behavioral EE programs can support affordability goals because traditional energy savings metrics sometimes do not tell the full story. In the 2025 sample, waves where bill savings materially exceeded energy savings had an average bill savings

[5] Data in this table are taken from all Opower electric waves with full data for 2025. The data are limited by the following: Only waves with sufficient pre-treatment data for estimation via LDV model are included; only electric waves are included (gas waves excluded); and a winsorization 1/99 percentile rule has been applied to exclude extreme outliers.
[6] "Similar" means the two rates are within 0.25 percentage points of each other.
[7] June 2025 is used for household counts. All percentages and totals are weighted by the number of treatment households.

rate of 0.55%, despite relatively low measured energy savings. In the West Coast utility example, summer bill savings exceeded energy savings, consistent with the possibility that consumption avoided during higher-cost (summer) periods can create disproportionate customer bill relief. These findings point to a broader role for Behavioral EE programs as scalable opt-out affordability tools that can reach large customer populations without requiring equipment purchases or customer out-of-pocket expense.

5. Conclusion and Recommendations

Behavioral EE remains one of the most valuable tools in utilities' EE toolkit. According to ACEEE, HERs—the most common form of Behavioral EE—have continued to change behavior at roughly the same rate as when they were first introduced more than 15 years ago (Sussman, et al., 2026). The 2022 Illume meta-analysis of 111 research and evaluation reports of HER programs found that behavioral programs deliver significant energy savings (up to 1.21% on average for cohorts treated for 2-5 years) that remain consistent over long treatment periods. While performance can vary by program providers for numerous reasons, the study showed that savings outcomes remain robust across all studied vendors and designs (1.16% average savings rate for electric cohorts, 0.87% average savings rate for gas cohorts) (Illume, 2022). Similarly, ACEEE finds that HER programs continue to deliver reliable savings for as long as reports continue to be delivered (Sussman, et al., 2026). The costs of these programs per household are also lower than Structural programs ($5.42 per dollar of avoided damage, vs. $22.82 for Structural programs) and the savings are cheaper when averaged across full measure life than from many other efficiency measures (Hibbard, et al., 2020), making Behavioral EE programs a highly cost-effective and reliable solution to rapid load growth (Specian and Aquino, 2026).

In the current context of intensified financial pressures on customers, increasing emphasis on affordability offers an opportunity to reframe how we should value EE—and, by extension, Behavioral programs. Utilities, legislators, and regulators are under immense pressure to figure out what should be funded via utility bills, and how to balance grid needs to ensure reliable service with growing demand, while trying to manage energy affordability expectations (SECC, 2026). There is already some evidence of Behavioral EE's impact on customer bill savings. In California the CPUC's 2021-2023 Report on Demand-Side Management Programs found that Behavioral programs in the state had helped save up to $28.61 per household each year (CPUC, 2025). Our data analysis reinforces that argument by showing that Behavioral EE programs not only deliver financial savings for customers, but they have also done so historically at a rate like energy savings. This finding sheds new light on the value of Behavioral EE for energy affordability and for helping reduce energy burden, beyond the traditional realm of demand-side management. In fact, it is a multi-purpose tool for utilities delivering reliable and scalable energy savings, while providing immediate bill savings to customers.

Within program portfolios, Behavioral EE has also unlocked new recruitment channels for Structural programs. In addition to driving savings at scale, measures such as HERs are proven accelerators of customers' participation in other EE programs (Olig and Wong, 2024). Some independent program evaluations have shown 17% higher participation in EE programs among HER recipients than among non-HER recipients (ADM Associates, 2024). In our current affordability context, Behavioral programs can help connect customers (especially low-income customers) to energy support services and tools (Sussman, et al., 2026). Such tools may take the form of bill assistance programs, time-varying rates, peak energy savings credits, or other measures. Behavioral programs offer effective channels to raise customers' awareness of these tools, educate them about their available options, and reinforce their impact via consistent and regular engagement. This is especially true for HERs. Over the years, while delivering consistent bill savings, HER programs have made a lasting impact on customers and their relationship with their utility. Independent evaluations repeatedly find that HERs improve customers' sentiment and strengthen daily habits that support utilities' decarbonization and grid modernization efforts (Dougherty, et al., 2015; Guidehouse, 2025).

To realize the affordability benefits of Behavioral EE programs, we must consider the implications and pathways to approval for utilities and regulators. Twenty-six states plus the District of Columbia currently have an energy efficiency resource standard (EERS) in place, which requires utilities to achieve multiyear EE savings (Mah, Nadel, and Subramanian, 2025). These policies have been the foundation to support EE programs over the past several decades. Within these states, regulators may consider additional features to expand the scope of what EE programs are set to achieve. Examples include greenhouse gas (GHG) reductions, low-income targets, and other goals related to electrification (Mah, Nadel, and Subramanian, op. cit.). Regulators and utilities in these states may consider energy affordability targets as additional scope to an EERS. This would expand the scope of bill savings related to EE beyond traditional low-income targets to service all customers with energy affordability solutions.

Behavioral programs would be able to leverage the methods discussed in this paper to measure bill savings. For Structural EE programs, bills savings could be quantified using the same methods used to estimate energy savings but would suffer from the same complications in causal inference associated with any non-RCT measurement (e.g., Sherwin, et al., 2022). Including this type of metric to measure the impact of EE programs on energy affordability by reducing customer bills helps solidify their cost-effectiveness and supports the need for ratepayer-funded EE programs with reconciling mechanisms on ratepayer energy bills. In addition to the long-term benefits of EE programs, this quantifies the direct near-term benefits to customers. In states with EERS policies in place where energy affordability is being scrutinized, it is critical for regulators and public stakeholders to work with state legislators to ensure the value of EE funding is understood and protected as utility bill funding mechanisms are being reevaluated and, in some cases, legislation is being considered to advance energy affordability.

In states without EERS policies in place, this type of metric plays an even bigger role in getting EE programs approved. Alternative regulatory frameworks may be leveraged, such as integrated resource planning (IRP), rate cases, performance-based regulation (PBR), and grid modernization proceedings. Customer benefits are often included in benefit-cost analyses, and customer bill savings should be identified as a benefit where appropriate. In PBR proceedings, utilities are provided financial incentives and/or penalties for achieving or exceeding certain program goals (Rosenbach, et al., 2024). With a growing focus on equity and energy affordability, regulators may consider performance incentive mechanisms (PIMs) to incentivize utilities to achieve energy affordability outcomes, such as PIMs related to EE spending and savings targets for LMI households (Mah, Nadel, and Subramanian, op. cit.). The savings target may be energy savings or bill savings targets.

As another pathway identified for non-EERS states, Behavioral EE programs should be considered part of the customer's benefits of rate cases considering low-income discount rates, time-varying rates, or any complex base rate for residential customers. As we have identified in this paper, HERs provide direct customer bill savings, and they do so by providing personalized and targeted insights into how customers use energy in their homes. Complementing Behavioral EE programs with rate design can help reduce energy burden across residential customers, and utilities may consider limiting energy burden to a specific percentage to measure this. Next generation HERs can integrate rate modeling to better connect energy savings in the home to bill savings reflective of the specific rate a household is enrolled in. This may be targeted at time-varying rates to show bill savings achieved during different pricing periods, or peak-focused HERs that specifically call out savings during peak events (Sussman, et al., 2026).

Grid modernization and IRPs have also been identified as potential pathways to enable cost recovery for EE programs that directly support grid planning efforts. Via grid modernization, Behavioral EE can leverage AMI data to provide more personalized data insights in HERs and enable weekly and triggered alerts to customers. These programs help deliver customer benefits when large capital investments are being considered. IRPs should allow EE as the least-cost resource to be considered for managing increased demand and should include energy affordability metrics associated with these plans.

While we've seen cost-cutting pressures undermine utilities' investments in EE, we also remain hopeful: Utilities and regulators across the country have renewed their commitments to advancing EE to ensure reliable and affordable energy for their customers (PECO, 2026). "Energy Efficiency is one of the original affordability strategies," was heard on stage at the AESP Northeast conference. In this paper, we set to prove that, based on empirical evidence from utilities across the U.S. and using RCT gold standards, Behavioral EE has significant affordability value and, therefore, a role to play as utilities and regulators navigate a new affordability-first approach.

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