

Trends in the Program Administrator Cost of Saving Electricity for Utility Customer-Funded Energy Efficiency Programs

January 2017

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Overview

This technical brief presents trends in the cost of saved electricity for energy efficiency programs between 2009 and 2013. We collected and analyzed more than 5,400 program years¹ of data collected in 36 states from 78 administrators of programs funded by customers of investor-owned utilities. These administrators provide efficiency programs to customers of investor-owned utilities that serve about half of total U.S. electricity load.

Our key takeaways include:

- We find that the cost to efficiency program administrators of saving a kilowatt-hour (kWh) averaged \$0.028/kWh over the five year period. The average program administrator cost of saved energy (PA CSE) declined from \$0.044/kWh in 2009 to \$0.023/kWh in 2011 and then rebounded slightly to \$0.028/kWh in 2013.
- In the commercial, industrial (C&I) and agricultural market sector, the PA CSE averaged \$0.027/kWh over the five-year period but showed a modest upward trend between 2011 and 2013. In the residential sector, the PA CSE averaged \$0.035/kWh in the residential sector but declined significantly from \$0.071/kWh in 2009 to \$0.030/kWh in 2013.
- A somewhat different picture emerges if we weight the PA CSE values by annual electricity savings, which tends to give more influence to program administrators that are managing larger portfolios of programs. The savings-weighted average CSE increased from \$0.020/kWh in 2009 to \$0.023/kWh in 2013, averaging \$0.022/kWh for the five-year period. These administrators are often quite experienced, have generally been pursuing energy efficiency opportunities longer and are likely to have acquired a larger share of the least costly savings.
- We also examine trends in the PA CSE over time for different types of programs: residential lighting, behavior-based programs, and whole home retrofit, and C&I custom and prescriptive rebate programs.
- The relative share of *spending* for residential sector programs declined somewhat during this time period (35% of total spending in 2009 vs. 29% in 2013), while the relative amounts spent on commercial/industrial sector programs increased somewhat over this period (51% of total spending in 2009 vs. 57% in 2013). Spending for low-income programs accounted for 7-10% of total spending during this period.

Our future work will continue to track trends in the cost performance of efficiency programs by incorporating program data for 2014 and 2015 and will examine potential influences on the cost of acquiring electricity savings in more depth.

¹ A program year is a year's worth of data for each program in the LBNL Demand Side Management Program Database. For example, data covering four years of spending and impacts for a particular program would amount to four program years.

The work described in this technical brief was funded by the U.S. Department of Energy Office of Electricity Delivery and Energy Reliability Transmission Permitting and Technical Assistance Division, and the Office of Energy Policy and Systems Analysis under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231. Any questions or feedback may be directed to Ian Hoffman at IHoffman@lbl.gov or Charles Goldman at CAGoldman@lbl.gov. For more information on the Electricity Markets and Policy Group, visit us at emp.lbl.gov.

Introduction

States and utilities increasingly rely on energy efficiency as a resource as a means of managing utility costs (e.g., potentially deferring generation capacity and possibly distribution system facility investments, and avoiding fuel costs), lowering consumer bills, and reducing emissions. About half of the states have adopted binding energy savings targets, either statewide targets for saving a set percentage of retail sales or targets specific to each state-regulated utility (Barbose et al 2013). Given the increasing role of energy efficiency in utility resource plans and in states with clean energy policies, it is important to track and understand trends in the cost of saving electricity from efficiency programs or measures implemented over multiple years. This is particularly important in light of declining costs of supply-side resource alternatives (e.g., impact of low gas prices and efficiency improvements in combined cycle plants, declining costs for wind and solar)). For example, in 2015, wind and utility-scale solar photovoltaic (PV) developers signed long-term power purchases agreements (PPA) with prices that were often in the \$0.03-0.04/kWh range (Bolinger and Seel 2016; US Department of Energy 2016).²

As savings targets increase, what will happen to the program administrators' cost of efficiency resources? In order to achieve more aggressive savings goals, program administrators typically must convince more customers to participate in their programs (e.g., increase market penetration of high-efficiency measures) or increase savings in customer facilities (e.g., get customers to adopt more measures) or both. These approaches may lead to increases in program administration or incentive costs that then need to be partially or fully offset by greater savings. Program administrators can also leverage technological advances in end use technologies and equipment, as these technologies often offer significant savings at low incremental costs compared to current equipment.

Policymakers and efficiency program administrators can use a metric known as the program administrator cost of saved energy (hereafter, the PA CSE) to assess the typical cost performance of various energy efficiency strategies (Billingsley et al. 2014, Hoffman et al. 2015 and Molina 2014). The PA CSE provides insights on the economic prospects for efficiency to reduce energy supply costs and emissions and save money for consumers.

Analytical Approach

For this technical brief, we identified program administrators of electric efficiency programs that report their costs at the program level and then collected program-level cost and impacts data from regulatory reporting, testimony or similar sources which we compiled in the LBNL Demand Side

² As of 2015, most utility-scale solar PPAs are priced at or below \$0.05/kWh, with some projects coming in at \$0.03/kWh compared to PPA prices of \$0.10/kWh or more in 2011 (136 contracts with ~9000 MW of capacity) (Bolinger and Seel 2016). PPA for wind generation projects with contracts signed in 2015 were ~\$0.03/kWh compared to generation-weighted prices around \$0.06 to \$0.07/kWh in 2009 for wind projects (DOE 2016). Levelized PPA prices for wind and solar projects should not be equated with a project's unsubsidized levelized cost of energy (LCOE) because they currently reflect federal and state tax incentives (e.g., investment tax credit, accelerated depreciation). Solar and wind PPA prices would be 20-40% higher if not for these incentives.

Management (DSM) Program Database.³ Analyses for this study used 5,400 program years of data between 2009 and 2013 from 77 program administrators in 36 states (see Figure 1).

We calculated a levelized cost of saved energy (CSE) for each program administrator for each year that they reported gross savings at the meter and cost information for individual programs and for programs aggregated at the market sector and portfolio level (see Equation 1). The levelized program administrator cost of saved energy is the cost of the electricity saved in an efficiency program when the upfront program costs are spread (i.e. amortized) over the projected lifetime of the measures installed in the program divided by the annual energy saved.

Equation 1.

Levelized Program Administrator Cost of Saved Energy =

$$\frac{\text{Capital Recovery Factor} * \text{Total Program Administrator Costs}}{\text{Gross Annual Energy Savings (in kWh)}}$$

With the *Capital Recovery Factor* = $[A * (1 + A)^B] / [(1 + A)^B - 1]$
 where:

- *A* is the discount rate
- *B* is the estimated program lifetime in years, calculated as the savings-weighted life of measures or actions promoted by a program.

A *Capital Recovery Factor* (CRF) converts a present value into a stream of equal annual payments over a specified time at a specified discount rate.

To explore trends in the PA CSE over time, we tested several statistical regression models of the CSE and report statistically significant results for the model with the “best fit in the Results section.”⁴ We also provide the results of all statistical tests at each level of analysis in Appendix A. Linear regression models impose an interpretation of the data as a straight line with a single slope. Non-linear models (e.g., quadratic) can allow for changes in the rate at which the cost of saved energy changes over time.

We applied a panel regression with fixed effects at the level of the program administrator because we recognize that multi-year observations from the same program administrator over time are not independent from each other.⁵ Moreover, we have an unbalanced panel because we do not have CSE values for each program administrator for the entire study period (2009-2013).⁶ Some program administrators started programs in the middle of our study period, while, in other cases,

³ Program costs include all costs of administering, marketing, implementing and evaluating the program, as well as any incentives paid to any party, including program participants, manufacturers, retailers and contractors. See Billingsley et al. (2014) and Hoffman et al. (2015) for information on data sources and information included in the LBNL DSM Program Database and discussion of LBNL’s efforts to establish more consistent data definitions and reporting of energy efficiency program results, given state practices and regulatory policies.

⁴ Measurements of statistical significance and “fit” can indicate which model approximates the data most closely.

⁵ By controlling for program administrator fixed effects, we are controlling for everything about a given program administrator that does not change over time.

⁶ One to five yearly values for the CSE are available for each program administrator at each level of analysis (i.e., portfolio-level, market sector, or individual program).

data from a program administrator were not available for a given year due to a change in policy or reporting practice.⁷

Linear and quadratic regression models are presented in Equations 2 and 3, respectively.

Equation 2.

Levelized Program Administrator Cost of Saved Electricity $_{it} = \alpha + \beta_1 (Year_t) + \gamma_i + \varepsilon_{it}$

where:

- i is an index over program administrators
- t is an index for program years
- $Year_t$ is the time variable, expressed as a numeral (e.g., 1 for 2009, 2 for 2010, and so on);
- β_1 is the coefficient on the time variable; and
- α is the intercept
- γ_i represent a set of program administrator fixed effects
- ε_{it} is an error term

Equation 3.

Levelized Program Administrator Cost of Saved Electricity $_{it} = \alpha + \beta_1 (Year) + \beta_2 (Year\ of\ Program_t)^2 + \gamma_i + \varepsilon_{it}$

where:

- $Year_t$ is the time variable, expressed as a numeral (e.g., 1 for 2009, 2 for 2010, and so on);
- β_1 is the coefficient on the linear term of time;
- β_2 is the coefficient on the quadratic term of the time variable;
- α is the intercept;
- γ_i represent a set of program administrator fixed effects
- ε_{it} is an error term

CSE values for each administrator over a multi-year period are fairly likely to be inherently correlated because at least some influences, such as the maturity of the efficiency market in their service territory or their relative experience, are likely to be similar for that administrator. If not accounted for, autocorrelation can lead to inaccurate estimates of the standard errors.⁸ To correct for autocorrelation, we clustered the standard errors in the regression at the level of each program administrator.

At most levels of analysis, we also encountered a few cases of distant outlier values for the CSE. Typically, these outliers involved programs that incurred significant start-up costs but may have started late in a year and thus had minimal savings. We excluded outlier values in our regressions

⁷ In a few states, program spending or savings data that had been available in previous years was not available in one or more subsequent years.

⁸ If we did not account for autocorrelation, we would get smaller standard error values, which can result in a parameter estimate appearing significantly different from zero at a higher degree of confidence than is appropriate.

by screening out data points that are at least two standard deviations outside of the mean levelized cost of saved energy at each level of analysis.

Results: Trends in the Program Administrator Cost of Saved Electricity

National Trends in EE Portfolios of Program Administrators

Figure 1 provides a geographic representation of the 36 states in which we have program-level efficiency data that are reported by program administrators. Program administrators in a number of states do not report program-level data to their state regulators.

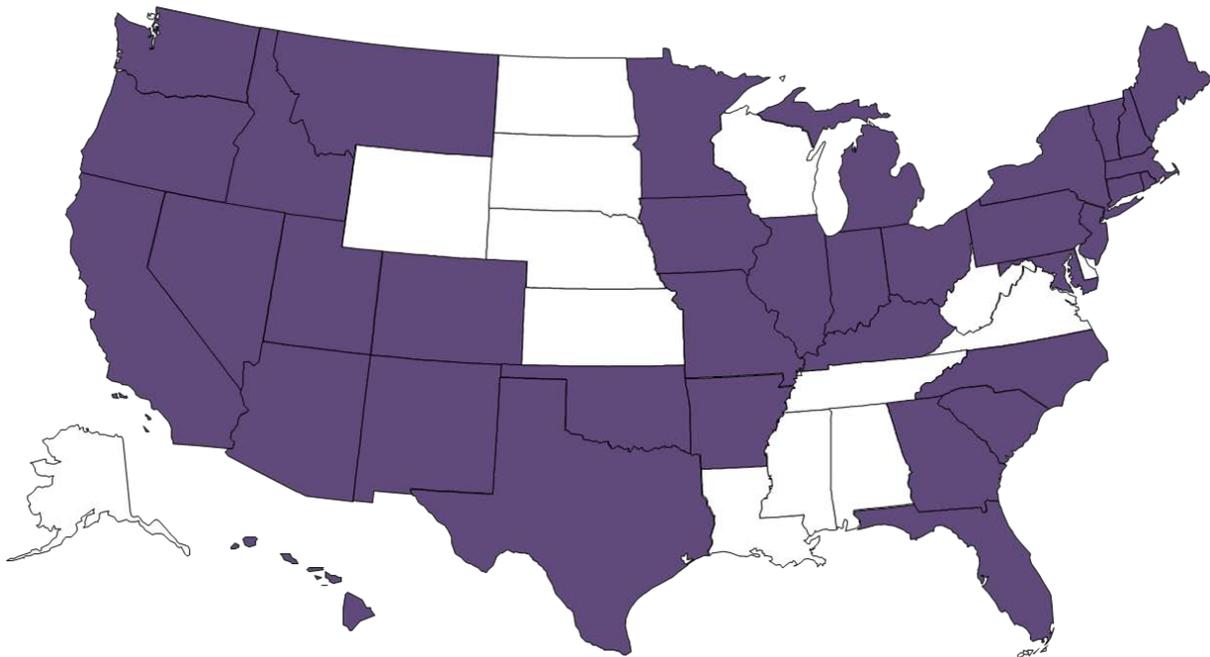


Figure 1. States with electric energy efficiency programs funded by customers of investor-owned utilities that are included in this study

Figure 2 shows both the cost of saved electricity for individual program administrators (PA) over time (2009-2013) and the number of program administrators for which we have reported data in that year. Each data point represents the levelized cost of saved electricity for the portfolio of efficiency programs managed by an individual program administrator in that year. Our sample size generally increases over time because states are expanding their energy efficiency efforts and more state PUCs are adopting annual reporting requirements. In calculating the levelized PA CSE at the portfolio level, we include all reported program costs and gross savings, including support and planning costs as well as programs for which no savings are claimed. Such programs may include audits or energy assessments, pilot programs, financing programs, and other planning or implementation support activities that are listed in annual reporting as “programs.” Rules or practices regarding claims of savings for these programs vary from state to state.

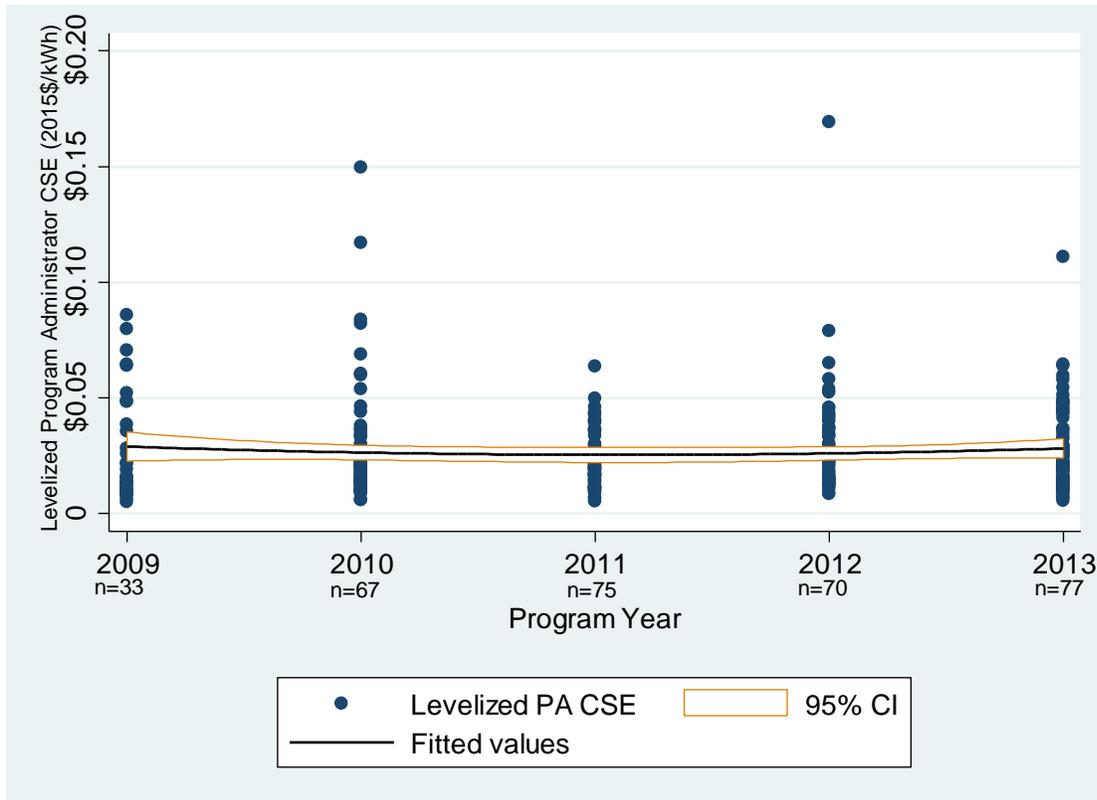


Figure 2. Portfolio-level results: Trends in the program administrator cost of saved energy for each program administrator between 2009 and 2013

Source: LBNL DSM Program Database, 2009-2013

A quadratic function has the best fit overall (shown by the black line in Figure 2). The PA CSE averaged \$0.028/kilowatt-hour (kWh) over the five-year period.⁹ The PA CSE declined from \$0.044/kWh in 2009 to \$0.023/kWh in 2011 and then increased slightly to \$0.028/kWh in 2013. This result is significant at the 90% level, meaning the likelihood that the null hypothesis is true—that the data do not fit the specified time trend—is less than 10%.

The orange lines in this figure (and all subsequent charts) denote the 95% confidence interval for the quadratic fit. The 95% confidence interval for the fitted values indicates that there is a 95% chance of the defined range containing the true mean for the quadratic fit.

In interpreting this result, it is important to note that each program administrator’s CSE is treated the same in this regression analysis, irrespective of the relative size (and budget) of their efficiency programs, their experience administering programs or the relative maturity of the energy efficiency services market in their service territory. During this time period, a number of states expanded their efficiency efforts, meaning that customers in more service territories were exposed to program offerings and a number of administrators offered pilot programs that were ramping up over time.¹⁰

⁹ We performed non-parametric regressions as a check for robustness of the non-linear (quadratic) regressions. Those regressions confirmed that the time trends observed do follow a concave shape, and thus a quadratic form is appropriate. Full statistical results for linear and quadratic forms, as well as the non-parametric tests may be found in Appendix A.

A somewhat different picture emerges if we weight the PA CSE values by annual electricity savings, which tends to give more influence to program administrators that are managing larger portfolios of programs.¹¹ With this approach, the savings-weighted average CSE increased from \$0.020/kWh in 2009 to \$0.023/kWh in 2013, averaging \$0.022/kWh for the five-year period. These administrators are often quite experienced, have generally been pursuing energy efficiency opportunities longer and are likely to have acquired a larger share of the least costly savings.

We also examined trends in sector-level spending and savings to assess whether there were meaningful changes in the composition of efficiency portfolios during this time period. As shown in Figure 3a, the relative share of spending for residential sector programs declined somewhat during this time period (36% of total spending in 2009 vs. 29% in 2013), while the relative amounts spent on commercial/industrial (C&I) sector programs increased somewhat over time (51% of total spending in 2009 vs. 56% in 2013). Market shares for savings for residential programs accounted for 43% of savings in 2009 and 41% in 2013, while savings from commercial and industrial programs accounted for 50%-54% of total spending in all years except for 2010 (see Figure 3b).

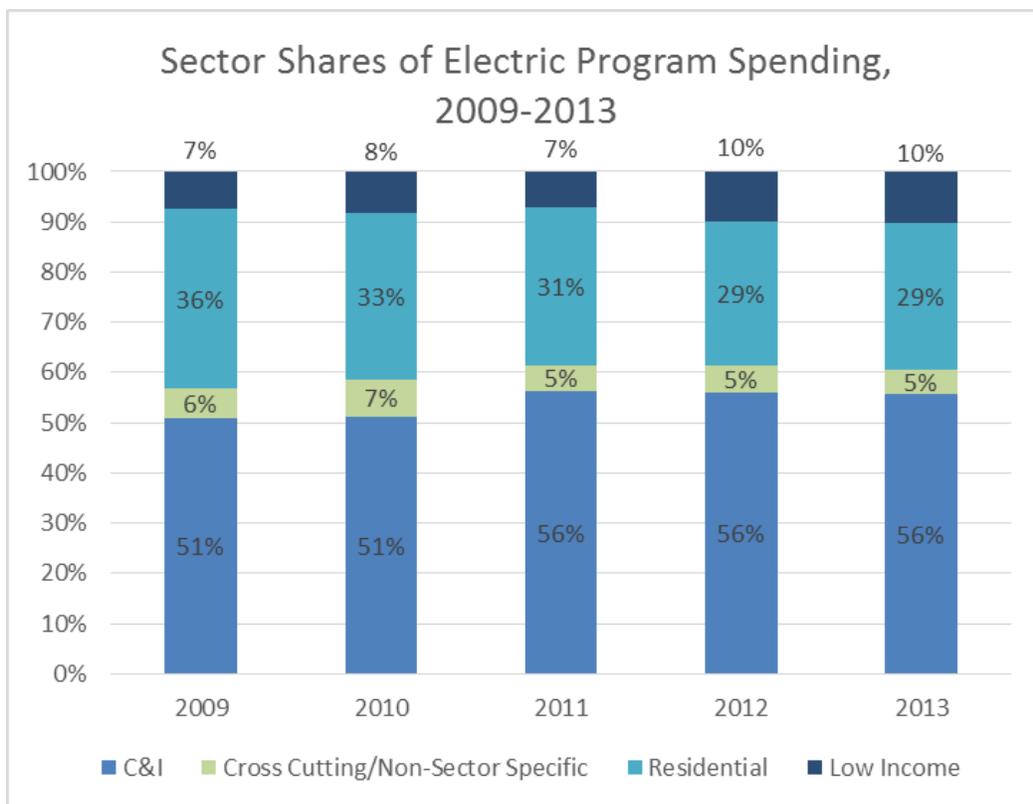


Figure 3a. Electric energy efficiency program spending by sector

Source: LBNL DSM Program Database, 2009-2013

¹⁰ In pilot programs, administrators often incurred significant upfront administrative costs and modest savings.

¹¹ Program administrators that manage larger EE portfolios typically face more scrutiny on evaluation, measurement and verification (EM&V) of savings. This often leads to more conservative estimates of first-year savings (e.g., because there are more disaggregated estimates of hours of operation of lighting and/or equipment by market sector) and shorter program-average measure lifetimes (as evaluators account for remodeling/renovation of the building stock). More conservative estimates of first-year savings and shorter lifetime assumptions will tend to result in higher values for the PA CSE.

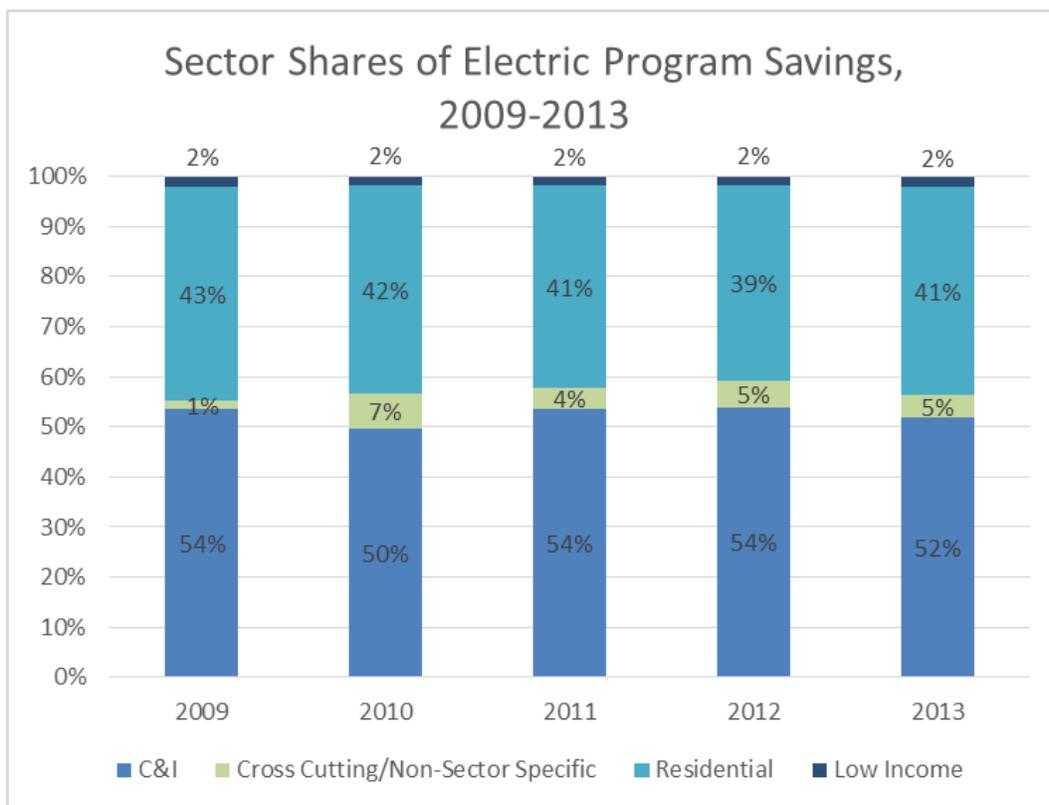


Figure 3b. Electric energy efficiency program savings by sector

Source: LBNL DSM Program Database, 2009-2013

As noted above in Figure 2, the number of program administrators for which we have data varies over time. However, we identified 48 administrators for which program data were available for every year between 2010 and 2013 (see Figure 4).

The best fit regression for this sample of program administrators also takes a quadratic form with the PA CSE averaging \$0.023/kWh between 2010 and 2013 (see black line in Figure 4). The yearly values followed a similar pattern as our larger data set of program administrators (e.g., \$0.024/kWh in 2010, dropping to \$0.022/kWh in 2011 and then increasing to \$0.024/kWh in 2013).

In the following sections, we present PA CSE results at the market sector and program level; unless otherwise noted, we report simple average values for the PA CSE, which reflect the experience of all program administrators, regardless of program budget, program administrator experience and relative maturity of the efficiency services market in a utility’s service territory.

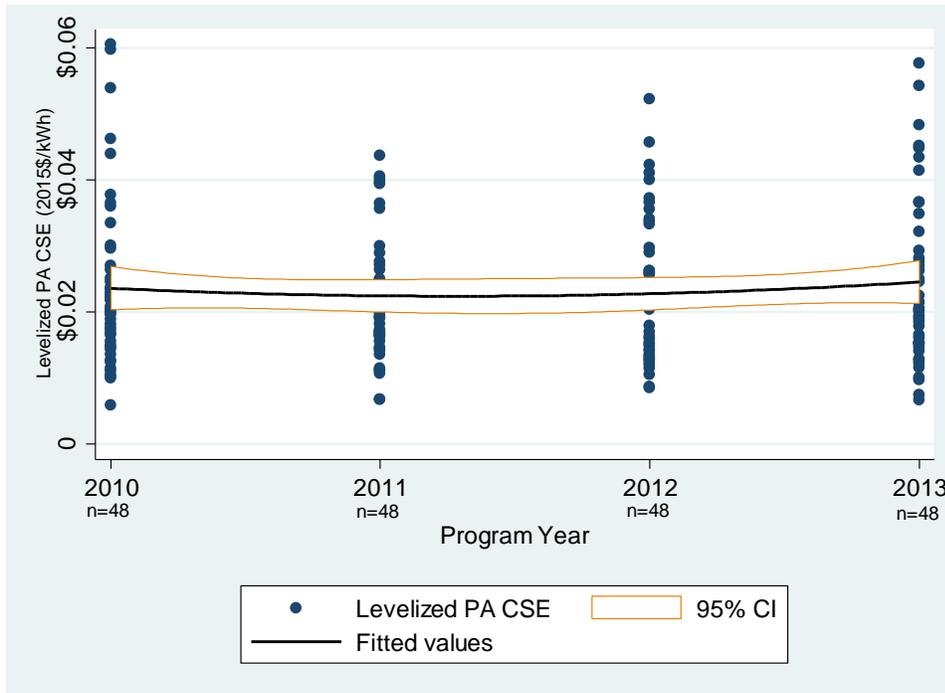


Figure 4. Trends in the program administrator cost of saved electricity among all electric efficiency programs offered by 48 program administrators between 2010 and 2013

Source: LBNL DSM Program Database, 2009-2013

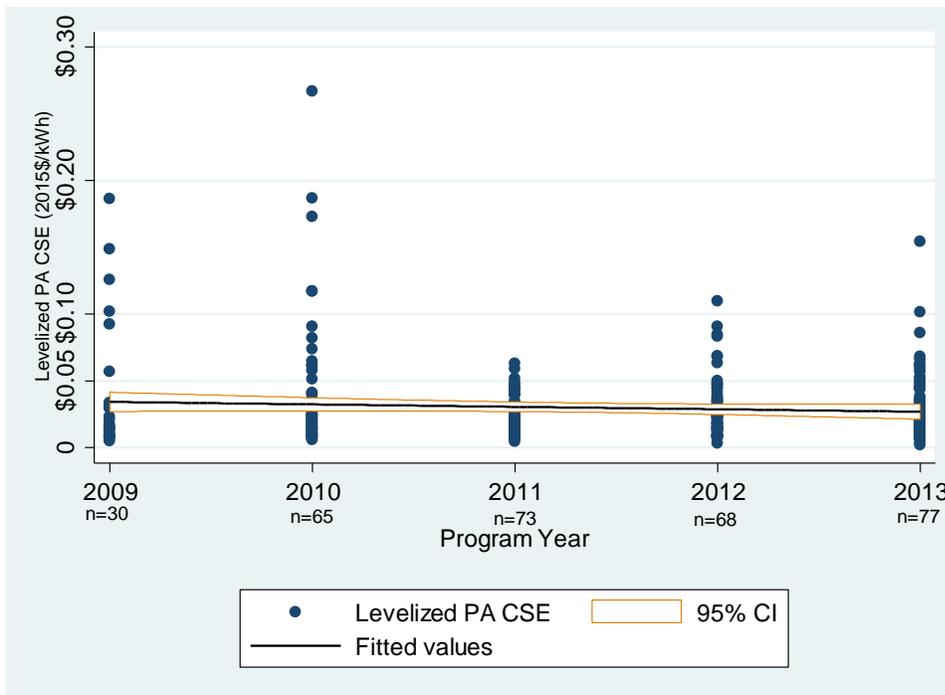


Figure 5. Residential sector programs: Trends in the program administrator cost of saved electricity between 2009 and 2013

Source: LBNL DSM Program Database, 2009-2013

Note: The maximum y-axis value on this graph has been truncated at \$0.30/kWh; the regression analysis includes all data except outliers screened as described above.

Residential Sector: Trends in Cost of Saved Electricity

The PA CSE in the residential sector programs averaged \$0.035/kWh between 2009 and 2013 (see Figure 5) and declined over time (\$0.071/kWh in 2009 to \$0.03/kWh in 2013). This analysis included all programs in the residential sector, including those that reported costs but no savings.¹² The best fit trend for the residential sector was linear and significant at the 90% level.

Residential Lighting Programs

We also looked at trends in the PA CSE at the program level. For example, the average PA CSE for residential lighting programs was quite low (\$0.015/kWh), although CSE values increased somewhat from 2009 to \$0.017/kWh in 2013 (see black line in Figure 6). A quadratic regression is the “best fit” that reflects a small increase in the PA CSE for residential lighting programs between 2011 and 2013. Several technological and market changes may explain at least some of this trend. In 2012, a first phase of new federal lighting standards increased the minimum efficiency of incandescent bulbs, which would increase the baseline for calculating savings for compact fluorescent light bulbs (CFLs) and light-emitting diodes (LEDs).¹³

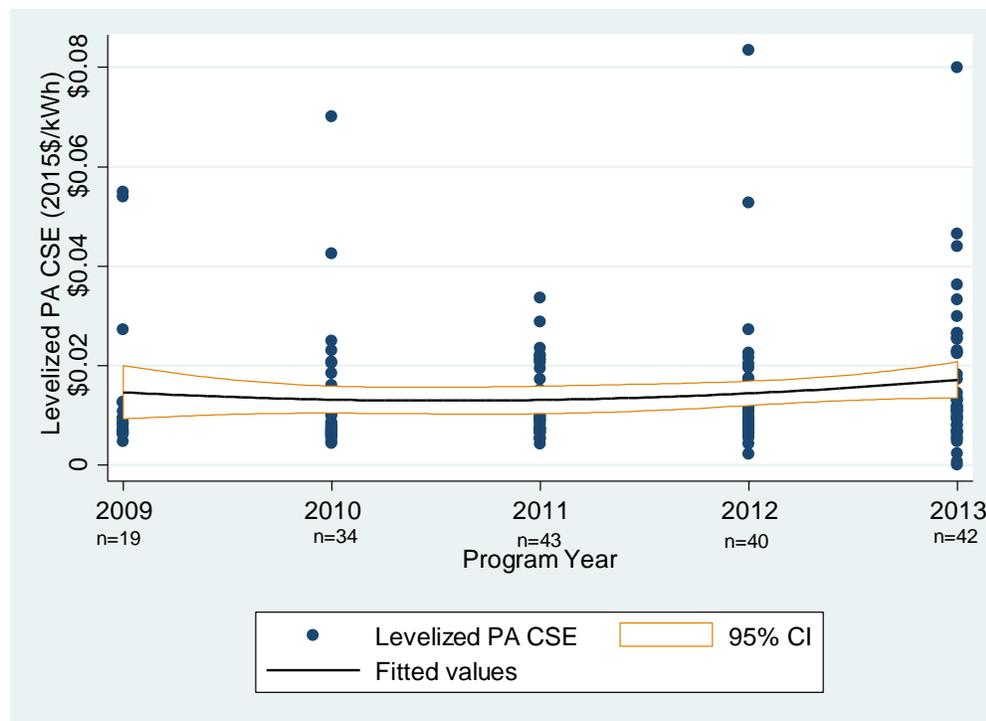


Figure 6. Residential lighting programs: Trends in the program administrator cost of saved electricity between 2009 and 2013

Source: LBNL DSM Program Database, 2009-2013

¹² Such programs may include audits or energy assessments, pilot programs, financing programs, and other planning or implementation support activities that are listed in annual reporting as “programs.” Rules or practices regarding claims of savings for these programs vary from state to state.

¹³ Over the study period, the cost of LEDs—while still higher than CFLs—declined considerably, and sales increased. Because LEDs last considerably longer than incandescent lights and CFLs, the overall market volume for residential light bulbs began to decline, which may leave less volume for programs to incentivize.

Residential Behavioral Feedback Programs

Behavioral feedback or “home energy report” programs have grown rapidly in recent years from a handful of small pilots (e.g., 8 programs in 2011) to more than 25 behavior-based programs by 2013. These programs employ normative messaging about energy use to promote energy conservation activities, such as turning off lights in unoccupied rooms and turning up thermostats. Some behavioral programs today propose to deliver first year electricity savings that in some cases rival or exceed those from residential lighting programs.¹⁴

During our study period, many behavior-based programs were pilots and some program administrators did not claim savings. Our sample of behavior-based programs includes only those for which savings are claimed. As Figure 7 shows, the number and size of behavioral programs increased dramatically between 2010 and 2013, with more program administrators launching programs and expanding those programs to include more residential customers. We found that the PA CSE for behavioral-based programs averaged \$0.068/kWh between 2010 and 2013. A quadratic regression provided the “best fit” (black line in Figure 7). PA CSE values declined significantly from 2010 to 2011 and then increased to \$0.077/kWh in 2013. This result is significant at the 99% level.

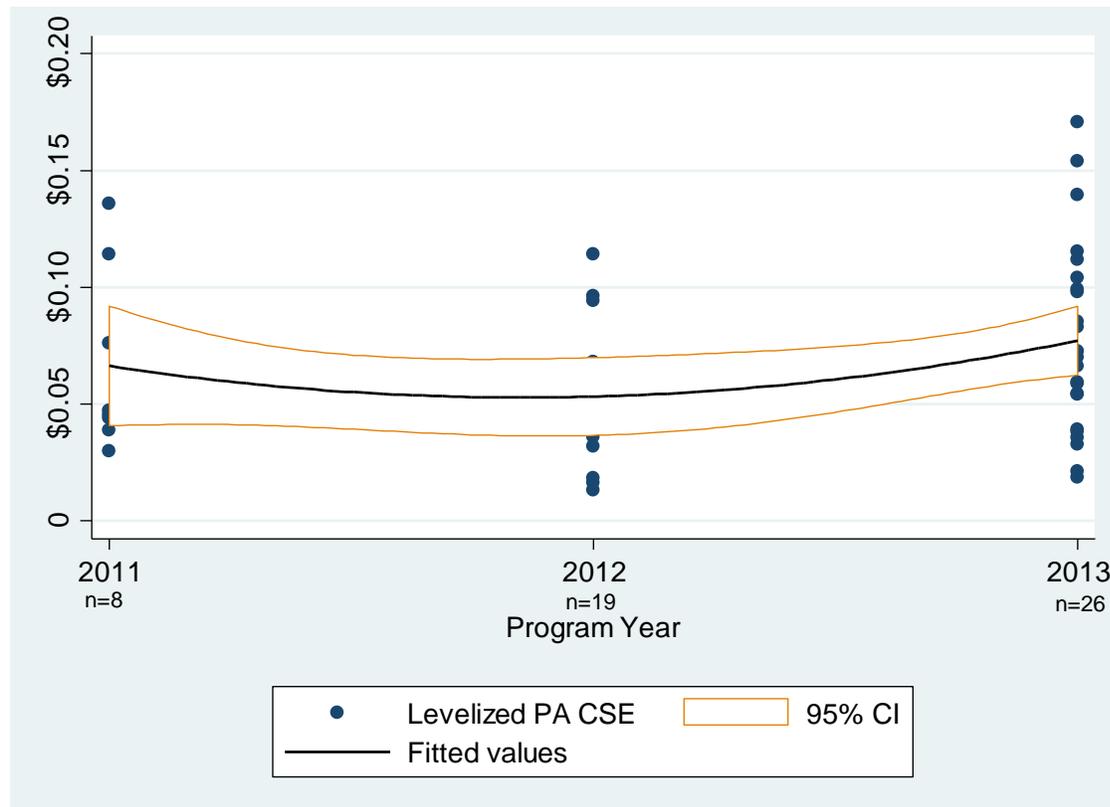


Figure 7. Residential behavior feedback (or home energy report programs): Trend in the program administrator cost of saved electricity between 2011 and 2013

Source: LBNL DSM Program Database, 2009-2013

¹⁴ For example, see program plans for program administrators in Massachusetts where one large utility was counting on 38% of 2015 portfolio annual savings from its behavioral feedback program.

Program administrators (and state regulators) assumed that savings from behavioral-based programs lasted for one year, which significantly impacts the estimated PA CSE. For example, the savings-weighted average PA CSE for all behavior-based programs is \$0.063/kWh, using a one-year measure life. If we assume that savings from behavior-based programs persist for two years, then the PA CSE decreases to of \$0.033/kWh. If first-year savings persist for three years, then the PA CSE would only be \$0.022/kWh. Thus, if program administrators demonstrate and regulators decide that behavioral program savings persist for longer than a year, then the cost of saved electricity for these programs could drop significantly.

Residential Whole Home Retrofit Programs

The cost of saved energy for home retrofit programs—including both home performance programs that address multiple measures throughout the home and more limited direct-install retrofit programs—averaged \$0.15/kwh between 2009 and 2013 (see Figure 8).¹⁵ A linear specification provided the best fit, and the time trend for the PA CSE was significant at the 90% level (Figure 8).

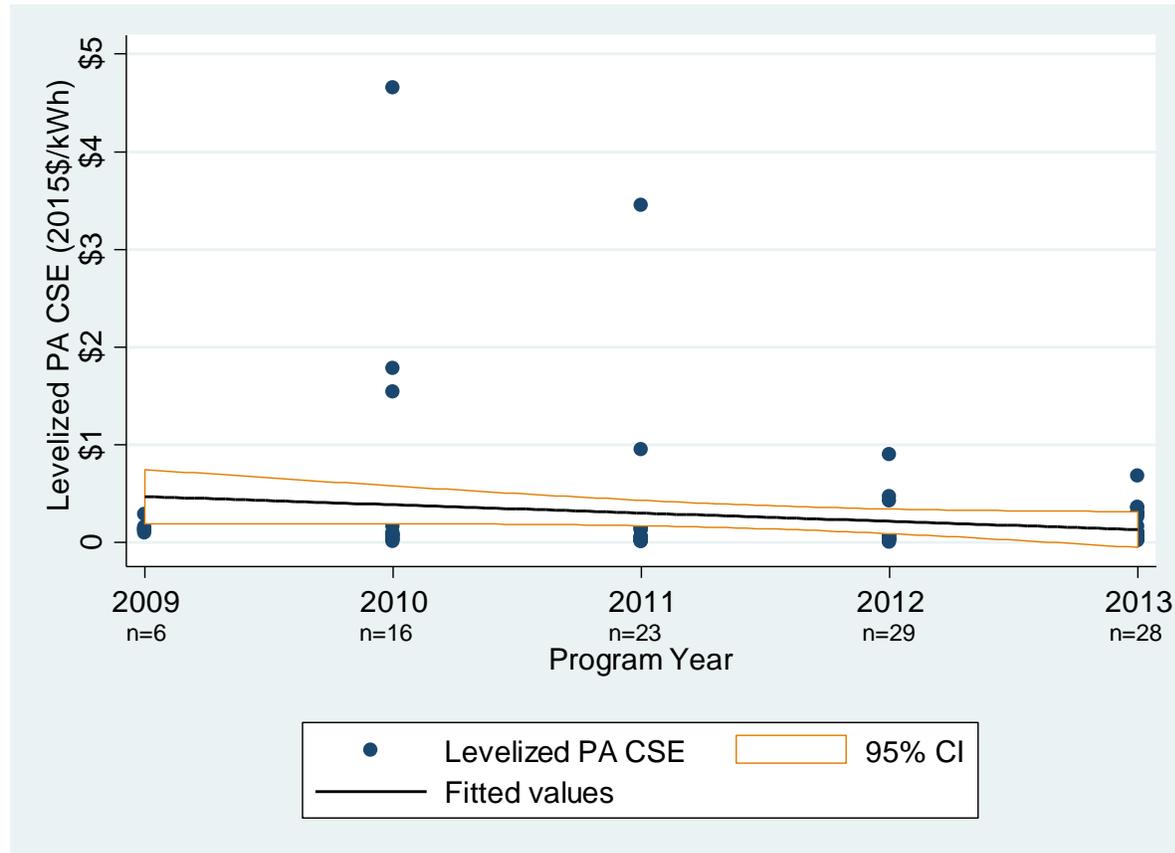


Figure 8. Residential whole-home retrofit programs: Trends in the program administrator cost of saved electricity between 2009 and 2013

Source: LBNL DSM Program Database, 2009-2013

¹⁵ There were a significant number of pilot whole home retrofit programs. In these pilot programs, program administrators often had few completed projects but typically incurred high upfront costs to develop program guidelines and working relationships with contractors as well as marketing expenses. We therefore excluded whole home retrofit programs that spent less than \$1 million in a year under the rationale that these are likely to be pilot programs.

We also examined the savings-weighted average PA CSE for all whole home retrofit programs, which tends to reflect the influence of larger programs and found that the PA CSE was \$0.066/kWh for the five-year period. It is also important to note that a significant number of these home retrofit programs are designed to save energy across multiple fuels (e.g., electric, gas, fuel oil); however our reported PA CSE values are strictly for the acquisition of electricity savings.

Low-Income Programs

The PA CSE simple average for low-income programs from 2009 to 2013 was \$0.15/kWh. The cost of saved energy for low income programs also appeared to decline over our study period, but we found no trend that was statistically significant.

Commercial, Industrial and Agricultural Sector: Trends in Cost of Saved Electricity

The cost of saving electricity in the commercial, industrial and agricultural sector averaged \$0.027 between 2009 and 2013, starting at \$0.27 in 2009, fluctuating in the interim years to reach \$0.028 in 2013. Our regression results are significant at the 85% level for this quadratic relationship (see black line in Figure 9).

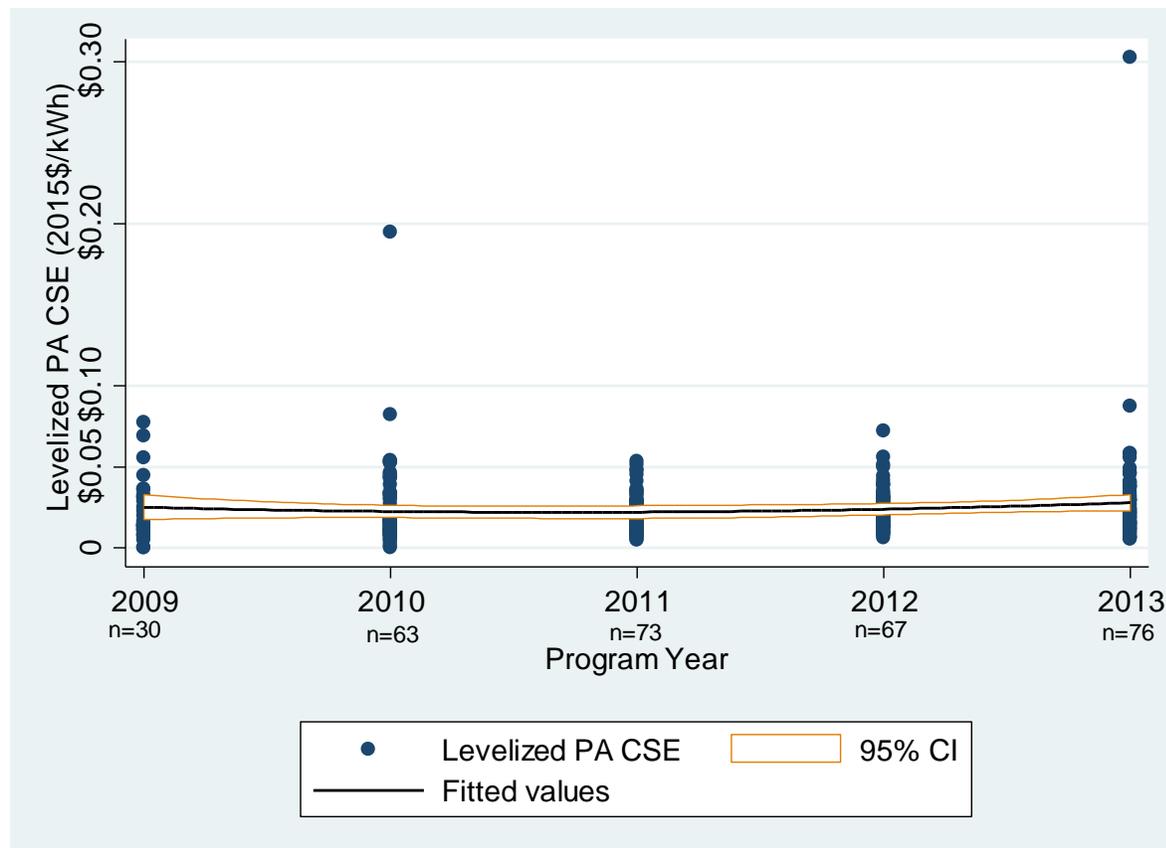


Figure 9. Commercial, industrial and agricultural sector programs: Trends in the cost of saved electricity between 2009 and 2013

Source: LBNL DSM Program Database, 2009-2013

Savings in the C&I sector are concentrated primarily in two types of programs: C/I custom and prescriptive rebate programs. Custom C&I programs account for about one-third of the total savings in the C/I sector in our sample of program administrators. Custom programs had an average PA CSE of \$0.029/kWh between 2009 and 2013. C/I prescriptive programs offer rebates on lighting; heating, air conditioning and ventilation (HVAC) systems; air compressors; motors and pumps; and other common appliances and equipment. These C&I prescriptive rebate programs also account for about one-third of electricity savings in the C&I sector and had an average PA CSE of \$0.021/kWh between 2009 and 2013, reaching \$0.023/kWh (see Figure 9). The PA CSE for these C&I prescriptive rebate programs appeared to increase somewhat for the 2009 to 2013 period, but we did not find statistically significant results for time trends for these program types.

Conclusion

The program administrator cost of saved electricity can be a valuable metric for assessing efficiency program performance and for weighing strategies – and associated costs – for saving energy, reducing emissions and saving consumers' money. Trends in the PA CSE can thus serve as an indication of the role that efficiency may play in meeting energy and environmental policy objectives.

Statistical analyses of program-level spending and savings data for efficiency programs in 36 states indicates that the national cost of saving electricity across those programs, on average, was relatively flat or slightly declining for the period 2009 to 2013. Regression analysis shows the trend in the cost of saved electricity among all program types for those years took a non-linear form. The PA CSE declined at a gradually decreasing rate from 2009 to 2011 (from \$0.044/kWh to \$0.023/kWh) and then began a shallow climb to a 2013 level of \$0.028/kWh, which is lower than the cost of savings at the start of the study period.

Analyses at the sector level suggest that the cost of saved electricity fluctuated somewhat in the commercial, industrial and agricultural sector but ended the period at about \$0.028/kWh, close to its 2009 level of \$0.027/kWh. In contrast, in the residential sector, the PA CSE averaged \$0.035/kWh, declining from an average of \$0.071/kWh in 2009 to \$0.03/kWh in 2013.

We plan to continue tracking trends in the cost performance of efficiency programs, including program data for 2014 and 2015; future work will also take a more expansive look at factors that potentially influence the cost of achieving electricity savings.

Acknowledgements

We thank Caitlin Callaghan, Caitlin Smith, Carla Frisch and John Agan (DOE), Maggie Molina (ACEEE), Fred Gordon, Snu Price, Kenji Takahashi, Frank Ackerman, and Peter Fox-Penner for helpful comments on a draft of this brief. We are especially grateful to Anna Spurlock (LBNL) for her technical assistance with the statistical analysis and its interpretation and to Dana Robson (LBNL) for her help with formatting this document.

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Appendix A

In this appendix, we describe our approach to statistical testing of longitudinal trends in the cost of saved electricity. In analyzing regression results, we reviewed statistical significance first and then looked at the R-squared value. Specifications with coefficients that had the lowest P values and the largest R-squared value were deemed to have the “best fit.” P values are commonly used as an indicator of statistical significance. They are calculated probabilities that measure the chance that the specified model is incompatible with the data. A low value indicates a low probability of a poor fit between the model and the underlying data. At most levels of our analysis, the best fit was a quadratic with concave form, generally with a minimum value, or inflection point, in 2011.

A polynomial regression allows the shape of the relationship to assume a curved form. Applying such a regression to a relatively small number of years of data with fluctuating values can bias the specification toward a curved form. To assess whether a quadratic form was appropriate, we used a non-parametric test for this five-year dataset. This robustness check involved a linear multi-variate regression on binned dummy time variables for each year of efficiency program data. We regressed the leveled cost of saved electricity for all efficiency portfolios on each year on either side of the observed minimum in 2011. Our full dataset is an unbalanced panel with a different number of years of data for some program administrators. These non-parametric test regressions showed positive coefficients for the binned variables for program years 2009, 2010, 2012 and 2013 versus the 2011 mean. These coefficients for the time variables in our non-parametric test generally had P values of 0.10 or lower. Those values indicate a level of statistical significance of 90% or better, signifying that the y-axis difference between the PA CSE mean for 2011 and each mean for the remaining years was positive and thus meaningfully higher than the minimum value in 2011.

The results of linear and quadratic regressions on the portfolio-level PA CSE and the non-parametric robustness check are summarized in Table A-1.

Table A-1. Results for portfolio-level regressions over study period (2009-2013)

Panel and Regression	Time Variable	Coefficient	P Value
Unbalanced Panel			
Linear	program year	-0.003	0.124
Quadratic	program year	-0.021	0.060
	program year squared	0.003	0.056
Non-parametric test	2009 bin	0.021	0.082
	2010 bin	0.006	0.037
	2012 bin	0.002	0.152
	2013 bin	0.004	0.012
Balanced Panel			
Linear	program year	0.001	0.468
Quadratic	program year	-0.008	0.059
	program year squared	0.001	0.037
Non-parametric test	2010 bin	0.006	0.075
	2012 bin	0.001	0.039
	2013 bin	0.004	0.021