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Energy efficiency lifetimes: How reported savings of electric and gas energy efficiency programs change over time

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Economic analysis of energy efficiency programs, utility resource planning, and procurement require estimating how long energy savings last. We analyzed program-level gas and electric efficiency data reported by more than 100 utilities and other program administrators in 41 states to produce distributions of program lifetimes and active savings curves. We find that most gas and electricity savings expire within 15 years of initial program investment, with the trajectory varying by fuel and market sector. Program design and the technologies addressed by programs drive these differences. In particular, residential electricity savings decline more quickly than commercial and industrial (C&I) savings due to the expiration of behavioral and lighting measures. We also find that gas savings are longer lived than electricity savings for all sectors but C&I. Finally, we consider the relevance of active savings curves and program lifetime distributions to resource planning and assessing energy efficiency program performance.

Introduction

Estimates of savings lifetimes are important for assessing the economic impact of energy efficiency and its role in resource planning and procurement. For integrated resource plans (IRPs), utilities may use lifetimes to calculate levelized costs and develop energy efficiency supply curves for capacity expansion modeling (Pacificorp 2019; Frick et al. 2021). Similarly, regional grid operators use estimates of savings lifetimes in load forecasts (ISO New England 2016). Long-term decisions on resource procurement, then, can depend on estimates of efficiency lifetimes.

Lifetimes are also important in assessing the performance of efficiency programs funded by utility customers, both for calculating benefits for cost-effectiveness tests and lifetime savings for utility performance incentive mechanisms (Gold and Nowak 2019). For example, the performance incentive mechanism for gas and electric efficiency programs in Michigan is largely based on lifetime savings (Michigan Public Service Commission 2018).

At the *measure* level, program administrators often track effective useful life (EUL) of measures, which is the median number of years that a device is operational. EULs may incorporate estimates of savings persistence: changes in savings performance over time (Hoffman et al. 2016). EULs vary due to site and climate characteristics, project type (retrofit vs. new construction), and required caps on

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lifetimes (Hoffman et al. 2016). At the *program* level, program administrators typically report the savings-weighted¹ average of these EULs. Since 2014, Berkeley Lab has published studies on the program administrator cost of saving energy using these program average measure lifetimes. We use a levelized cost metric that amortizes costs over the lifetime of a program and discounts them to the year of implementation (Hoffman et al. 2018).

In this brief, we build on the characterization of energy efficiency lifetimes in Hoffman et al. (2015) by presenting distributions of reported gas and electric efficiency program lifetimes. We render these distributions as active savings curves, which show how savings decline over time by market sector. We find that the significant majority of gas and electricity savings expire within 15 years of program investment. Active savings curves, however, are not linear. Expiration rates reflect characteristics of particular technologies and program designs, especially for residential behavioral and lighting programs.

Data and Methodology

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This analysis draws on Berkeley Lab's Cost of Saved Energy database,² which tracks program spending, savings, and lifetimes for customer-funded efficiency programs. Data primarily are from publicly available utility filings, with supplemental information collected from data requests to utilities and public utility commissions. The savings values we use in this analysis are ex-ante estimates of gross savings claimed by program administrators. They do not include the results of any evaluation, measurement, and verification activities that occur following the initial claims.

To reflect more recent program design and equipment efficiency, we use the last six years of data we collected for electric (2014-2019) and gas (2012-2017) efficiency programs operated by investor-owned utilities, third-party administrators (e.g., Efficiency Vermont), and state administrators (e.g., NYSERDA). Our dataset for this study contains more than 7,500 program-years³ of electricity data and 1,800 program-years of gas data. Because some program administrators do not report lifetimes, our final electric sample size includes about 2,900 program-years from 32 states and 71 program administrators. The electric sample size exceeds that used in our previous study of lifetimes of programs operated by electric investor-owned utilities (Hoffman et al. 2015) by more than 1,200 program years. Programs in the Northeast account for the plurality of electric and gas savings in our datasets, with somewhat smaller shares of savings coming from the West and Midwest. In both the electric and gas datasets, less than 10% of savings are from programs in the South (Table 1).⁴

¹ Efficiency programs can contain a mix of measures that each have their own EULs and provide lifetime savings equal to those EULs multiplied (weighted) by their annual savings. Dividing the sum of these measure-level lifetime savings by the sum of the measure-level annual savings yields the savings-weighted average lifetime for the program.

² The database includes data from 2009 to 2019. See <u>https://emp.lbl.gov/projects/what-it-costs-save-energy</u> for additional worked based on the database, including the cost of saved energy in public power utilities (Schwartz et al. 2019).

³ A *program year* is a year's worth of data for each program. For example, data covering four years of spending and impacts for a particular program represent four program years.

⁴ See the U.S. Census for a mapping of states to regions: <u>https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf</u>

	Electric		Gas	
Region	Share of kWh savings	Sample Size (program-years)	Share of therm savings	Sample Size (program-years)
Northeast	41.8%	797	40.9%	355
Midwest	17.3%	426	27.6%	154
South	9.6%	477	5.5%	89
West	31.3%	1181	26.0%	208

Table 1. Share of savings and sample size by Census region

To facilitate the comparison of spending and savings across program administrators, we categorize efficiency programs with a standard typology that includes four market sectors: residential, C&I, low income, and cross-cutting (Hoffman et al. 2013). This final category includes programs such as codes and standards and market transformation that are not specific to any of the other three sectors. We also exclude any reported lifetimes above 30 years, which we consider unrealistic (Schwartz et al. 2019). Such values are not common in our dataset.

The lifetime values that program administrators report are savings-weighted averages of the measures installed in a given program. We bin each lifetime by rounding it down to the nearest whole number and then calculate the share of savings in each bin (1-30 years) relative to all reported program savings in a sector and all sectors combined. Each bin represents the share of savings that expires after a number of years. Savings, then, expire immediately after the reported lifetime.⁵ Finally, we calculate the savings active in each lifetime bin by subtracting the cumulative expirations from 100%.

Active
$$Savings_n = 100\% - \sum_{y=1}^n Share of savings_y$$
 for lifetime bins y to n

As the lifetime bin increases, the active savings decline until reaching 0% at the maximum lifetime bin of 30 years.

Results

We summarize the distribution of electric efficiency program lifetimes in Figure 1. Bar height indicates the number of programs and color indicates sector. Overall, we find that 10-to 15-year lifetimes are common throughout electric efficiency programs. C&I and cross-cutting program lifetimes are particularly concentrated in this five-year range. In contrast, residential and low-income programs show a more even

⁵ Technologies supported by a given program—let alone installations of a given technology—will not all fail at exactly the same number of years post-installation. In reality, each program has a distribution of lifetimes. Measure-level installation records would be necessary to estimate such a distribution. In the absence of these data, we assume all program savings expire after the reported lifetime.

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distribution of programs across lifetime bins. Distributions reflect the underlying differences in technologies addressed in each sector. For example, among programs with a measure life less than five years, residential behavioral programs are the most common.⁶ Few C&I or cross-cutting programs have one-year lifetimes. After reaching a peak at 15 years, the number of programs declines as claimed lifetime bins increase. After 20 years, we find few programs for any sector claiming savings.

These results are consistent with econometric estimates of lifetimes for utility efficiency programs (Arimura et al. 2012). Results also align well with the electric efficiency program lifetimes reported in our earlier study (Hoffman et al. 2015), except for the residential sector. We find a weighted average lifetime for residential programs of about nine years, whereas Hoffman et al. reports a simple average of 13 years. Differences in the scale of residential behavioral programs and weighting may explain the longer lifetime we found in our current study. Between 2014 and 2018, behavioral programs account for 2.8%-4.7% of annual savings in our cost of saved energy database, in contrast to 0.6%-2.3% between 2010 and 2013.

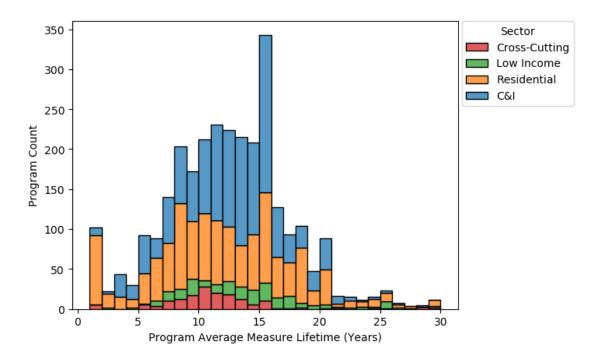


Figure 2. Electric program lifetimes by sector

In Figure 2, we show the distribution of lifetimes for the five most common residential electric efficiency programs in our dataset. Residential lighting programs have a range of lifetimes, but are concentrated between five and 10 years. This span corresponds to the expected useful life of installed lamps, which can include light-emitting diodes (LEDs) and compact fluorescent lamps (CFLs). In the five years of data we analyzed, we found some evidence of a transition towards longer-lived technologies like LEDs in residential lighting programs. In California, for example, lighting program lifetimes increased over this period from about eight to 15 years.

⁶ Program administrators typically assume a one-year lifetime for these programs (Dougherty and Van de Grift 2016), but as of its 2020 annual report, Public Service Company of Colorado assumed a three year lifetime for its residential behavior program savings (Public Service Company of Colorado 2020). Empirical estimates suggest that savings from behavioral programs likely persist for more than one year (Allcott and Rogers 2014).



Lifetimes of programs that address multiple technologies in a home, such as whole home retrofits, multifamily, and new construction, are less concentrated. The diversity of technologies that these program types could address may explain this finding. We also note the prevalence of electric new construction programs with average measure lifetimes beyond 20 years.

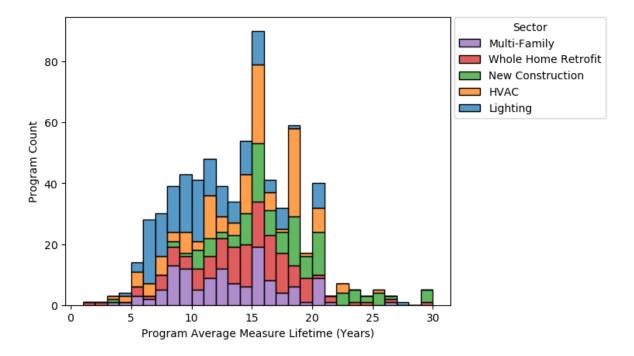


Figure 3. Program lifetimes for the five most common electric residential program types

The lifetimes of the five most common C&I electric programs (Figure 3), consistent with the sector results in Figure 1, are concentrated between 10 and 15 years. Differences in the approach to estimating lifetimes for prescriptive and custom programs may explain some of the inter-program type differences in Figure 3. Programs that serve commercial customers or governments; nonprofit organizations; and municipal, university, school, and hospital (MUSH) markets can include a range of measures and are typically prescriptive. Program administrators, therefore, may reference predefined lifetime estimates for an established set of measures. In contrast, industrial process and C&I custom program projects are site-specific, so the measures and their expected lifetimes are more varied.

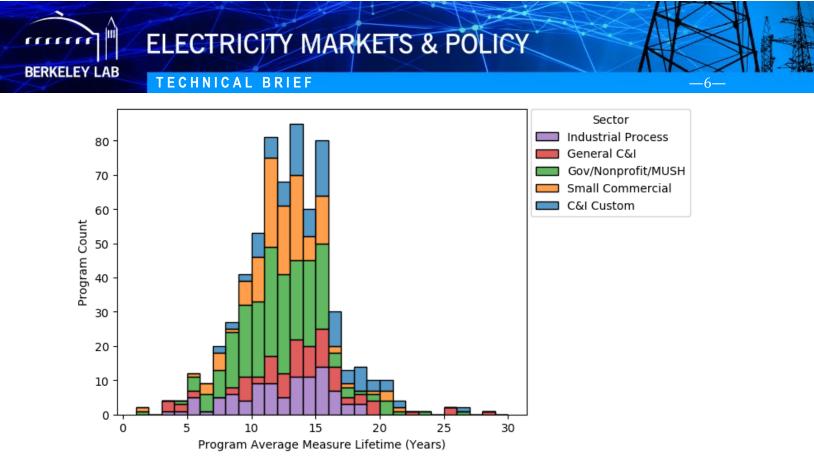


Figure 4. Program lifetimes for the five most common electric commercial program types

Figure 4 presents the distribution of lifetimes for gas efficiency programs. The granularity of our gas program lifetimes is limited by the smaller sample size of our gas dataset. We address this issue by aggregating the gas programs data at the sector-level. Whereas each data point in Figures 1-3 is a program-year, each data point in Figure 4 is a sector-year, which represents all programs in a market sector offered by a single program administrator in a single year. A sector-year can include a number of program-years, so its lifetime bin is weighted by the savings and lifetimes of its constituent programs.

Gas C&I program lifetimes, as with their electric counterparts, are concentrated between 10 and 15 years. Low-income and cross-cutting program lifetimes, however, are generally longer than their electric counterparts. Relative to electric efficiency, gas efficiency programs are less likely to have lifetimes less than 10 years, largely due to the absence of gas measures equivalent to efficient lighting in its contribution to overall savings.

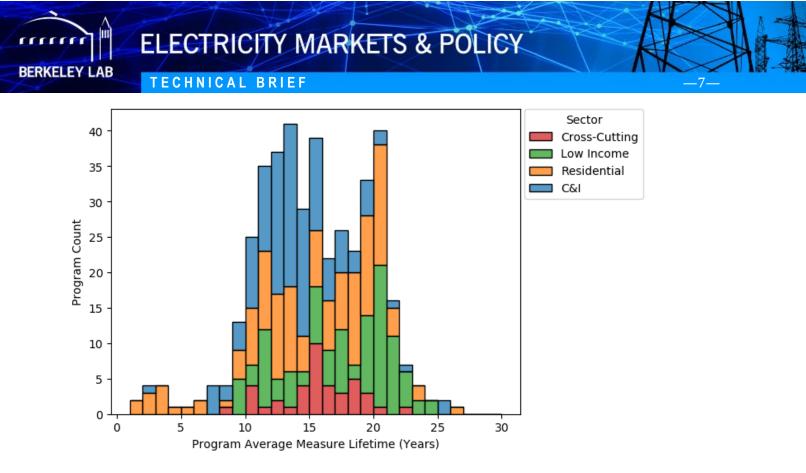


Figure 5. Gas program lifetimes by sector

Thus far, we have only considered the number of programs in each lifetime bin, not the programs' energy savings. Figure 5 shows the share of savings active each year after initial investments by fuel and sector. We do not present active savings for the cross-cutting sector due to its smaller sample size and the sensitivity of the results to a few large programs. We do, however, include the cross-cutting programs in the overall results in the top panel of Figure 5. Both electric and gas savings follow a similar trend: gradual declines up to year 10, followed by significant decreases between years 10 and 15. By year 20, only a small amount of gas (2.9%) and electric (1.5%) savings remain active. The rate of decline in active savings is not uniform across fuels, with electric savings expiring somewhat more quickly than gas savings in the first 10 years, and gas savings remain active than do electric savings for 20 years after investment. This trend is consistent with the savings-weighted lifetime of gas programs (13.5 years) exceeding that of electric programs (11.4 years).

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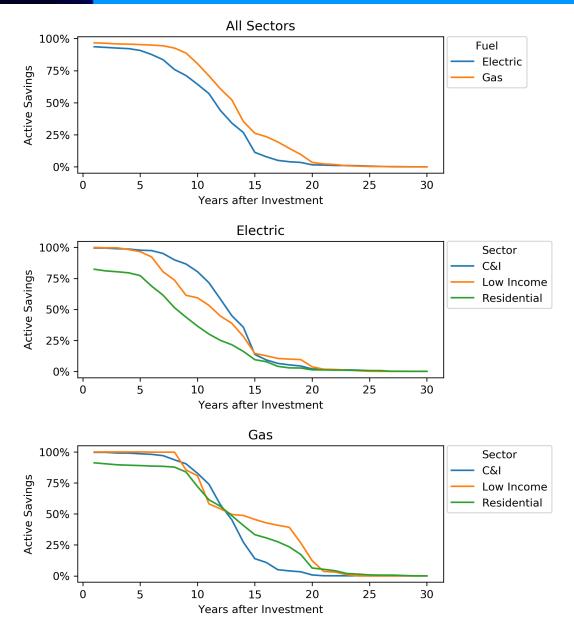


Figure 6. Active efficiency savings by fuel and sector

For electricity programs, the share of active residential savings diverges from other sectors soon after investment. Nearly 18% of residential electric savings expire before the second year due to the assumed short lifetime of most behavioral programs. The expiration of lighting savings after year five further accelerates the decline in residential savings. By year 10, only about 40% of residential savings remain. These continuing savings, however, expire more gradually than in other sectors. That pattern of savings expiration does not hold for low-income programs, where only a small portion of savings expires before five years.⁷ Additionally, the share of active low-income savings is relatively stable between 15 and 20 years, indicating the presence of more long-lived measures relative to other sectors. Consistent with the

⁷ Behavioral programs may serve low-income customers as well as other customers, but savings generally are not attributed to low-income programs.

distribution of C&I programs in Figure 1, C&I electricity savings decline quickly after 10 years. Indeed, 50% of C&I savings expire between years 10 and 15.

We also find early declines in residential gas savings due to behavioral programs, but only by 9%, or about half the impact of the programs on electricity savings. Between years 13 and 15, the share of active residential and low-income gas savings diverges from the share of active C&I savings. Between these two years, about 40% of C&I gas savings expire. This gap remains until year 20, at which point 12% and 15% of residential and low-income gas savings remain, well above the 1.5% of C&I savings still active. These gas residential and low-income savings levels exceed the share of electricity savings still active in those sectors after the same amount of time.

Discussion

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The active savings curves demonstrate how average lifetimes can obfuscate how energy efficiency savings change over time. Whether at the sector, program, or measure level, savings are not constant up until some end point after which they expire completely. This approach would both undercount savings that extend beyond the average lifetime and overcount savings that precede it. For example, at the savings-weighted average lifetime of 11.4 years for the electric programs in our dataset, 57% percent of electric efficiency savings are still active. If savings were treated as fully expiring at this average lifetime, that would miss the majority of savings that are still active. In the time leading up to 11.4 years, savings would be over-counted because 43% of savings expire at some point over this time period. Using a performance curve will result in significantly more accurate forecasting of savings over time.

It is important to recognize that the active savings curves are sensitive to the efficiency measures that provide the most savings. Energy efficiency opportunities, however, are not static. Evolving program designs and measure mixes influence the shape of the curves. For example, if in the future lighting programs provide a smaller share of savings, we would expect active residential electric savings to decline less quickly between five and 10 years.⁸ An increased focus on low-income programs would result in a larger share of gas savings active after 20 years. Further, electrification of gas space and water heating equipment would likely increase the share of electric savings that last beyond 10 years.

In the context of utility resource planning, accurate measurements of EULs and program average measure lifetimes are important inputs into IRPs, in particular as parameters of capacity expansion models. Estimates of when efficiency savings expire help utility planners determine when re-investment in efficiency may be needed within a planning horizon (e.g., 20 years). Active savings curves can help support the full use of energy efficiency as a resource.

In any of these applications, accurate estimates of measure EULs and program lifetimes are critical. Additional research on how long efficiency savings last can support efficiency's role as a resource and better define its benefits.

⁸ Here, we assume that the measures that substitute for lighting programs do not all have EULs in the 5-10 year range.

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