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Comprehensiveness Analysis Report

Phase I

DRAFT REPORT

Prepared for
California Public Utilities Commission

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Executive Summary

Introduction

The research effort described in this report is a foray into developing a program effectiveness metric for all non-residential resource programs called the Depth of Retrofit – Cost-effectiveness (DORCE) metric. Based on data from 163 non-residential resource programs from 2010-2014, this metric directly combines cost-effectiveness indicators of program performance with depth of savings indicators into a single metric. In doing so, the metric serves as a quantitative indicator of how deeply a given program achieves savings with its participants as well as how cost-effectively it achieves those savings.

The purpose of the study is to provide an indicator of program performance that is more aligned than existing quantitative metrics with the state's energy efficiency goals. The Governor's Executive Order B-30-15 pushes the state to establish a California greenhouse gas reduction target of 40 percent below 1990 levels by 2030.[1] As part of that clear and ambitious target, the Executive Order calls for doubling the efficiency savings from existing buildings.

As the state's energy efficiency goals and context have evolved, the metrics used to measure progress toward those goals must also evolve. For example, existing cost-effectiveness tests such as the Total Resource Cost test (TRC) provide important feedback about the balance of program benefits and costs. However, they don't provide quantitative insight into the depth of energy demand and usage reduction for the average participant in a program. TRC and other commonly used cost-effectiveness metrics are indifferent to program delivery mechanisms, such as whether savings are achieved by reaching deeply across energy end uses for participating customers or by focusing on mass delivery and promotion of individual products. Indeed, it is often presumed that higher program cost-effectiveness (as measured through TRC), at least at first pass, comes from this latter, shallower approach to program design.

There is currently an absence of tools that quantitatively measure a program's effectiveness in meeting goals for deep energy demand and usage reductions. The California Long Term Energy Efficiency Strategic Plan (2011)[2], speaks to this need: "The CPUC should integrate the demand-side management (DSM) programs within its jurisdiction – including the harmonization of cost-effectiveness methodologies and metrics – in order to enable offerings of integrated packages that will maximize savings and efficiencies of utility program overhead."

[1] See https://www.gov.ca.gov/news.php?id=18938

[2] http://www.cpuc.ca.gov/General.aspx?id=4125

While the pursuit of deeper savings across multiple end uses is often thought to come with a higher cost, this is a blunt conclusion, and it does not provide a map for how to proceed toward meeting the state's energy efficiency goals. On closer inspection, it may be possible to find subsets of the overall non-residential portfolio that do better than others in terms of both depth of savings and cost-effectiveness simultaneously. These findings may light the way to specific programs and general program design approaches that deserve to be more carefully scrutinized and potentially emulated.

The significance of including both cost-effectiveness and depth of savings indicators in a single metric is unpacked and explored throughout this report. Through the use of this metric, programs naturally rise to the top when their achievements stand out relative to their peers in ways that are consistent with stated policy goals. As such, the metric potentially provides value for reviewing California's very large IOU portfolio through a consistent and well-aligned lens.

As summarized by section below and described more fully in the corresponding sections of the report, we describe three main, complementary research activities that we undertook in this effort and that inform our recommendations to program and portfolio planners in California. The findings and recommendations may also be useful to program and portfolio planners outside of California, since the general principles observed here may carry over to states that lack the rich programming and history needed to perform this kind of analysis.

Primary Research Activities

The main research activities in this study are as follows:

- Development of the DORCE metric, derived as a distillation of 10 separate cost-effectiveness and depth of savings indicators using principal components analysis (PCA) on a comprehensive program dataset.
- Multivariate regression modeling, which serves to draw out patterns in DORCE achievements relative to differences in overall program design, such as degree of targeting on a specific sector, energy end use, customer size, or building type. Separate regression models are developed alongside the DORCE model that focus expressly on cost-effectiveness achievements or on depth of retrofit achievements.
- Ranking of all 163 non-residential programs in the analysis in terms of DORCE score, as well as in terms of component scores specific to depth of retrofit (DOR) and cost-effectiveness (CE).

Data Development

Itron created a single large database with data from multiple sources. First we merged the energy savings claims data from 163 non-residential programs across the 2010-2012 and 2013-2014 program cycles. These data included energy savings claim level information, such as measure name, energy end use, building type, sector, incentive amount, first year savings, and lifecycle savings. We then merged customer billing data, net savings data, Cost-effectiveness Test (CET) outputs, program costs from utility monthly reports, and data from the U.S. Census Bureau to this emerging database. We then used variables in this overarching dataset to define a series of ten metrics that each measured some aspect of a program’s depth of savings or cost-effectiveness. Section 2 describes the data development process in detail.

Program Effectiveness Scoring

To develop a single program metric to reflect both depth of energy savings and cost-effectiveness, we combined ten metrics that each measured some facet of a program’s depth of savings or cost-effectiveness into a single composite metric. As described in Section 3, we used principal components analysis (PCA) and analytical decision making based on PCA outputs to achieve this outcome. PCA is a statistical technique that uses underlying correlations among variables in the dataset to assign weights to each input metric in defining the composite metric. The final DORCE metric is comprised of cost-effectiveness (CE) and depth of retrofit (DOR) components that receive equal weight in the overall DORCE score. The DOR component is further subdivided into indicators of the average number of technologies addressed through a program, as well as the proportion of overall consumption saved.

Modeling Program Effectiveness

Having developed the DORCE metric, the evaluation team could then measure the degree to which various elements of a program’s design, such as its target sector or distribution of customer sizes, for example, correlate with high or low DORCE scores across the IOU portfolio. The team accomplished this using multivariate regression techniques. The final models, described in Section 4, show the specific quantitative DORCE score impacts associated with each significant element of a program’s design. These can be used for a detailed review of how various specific program design elements have historically correlated with effectiveness outcomes.

Notably, in addition to using DORCE score as the dependent variable in regression modeling, the evaluation team built separate, parallel regression models, one of which featured just the cost-effectiveness component of DORCE as the dependent variable and one of which featured just the depth of retrofit component of DORCE as the dependent variable. While the combination of cost-effectiveness and depth of retrofit components is essential to the value and structure of the DORCE score, there is also value in observing and measuring correlations between variations in program design and variations in the cost-effectiveness component and the depth of retrofit component of the overall score separately. By observing model outputs for these separate elements in parallel with the overall DORCE score, the user may track how overall DORCE score may be influenced by the cost-effectiveness and depth of retrofit components in a given context.

Program Rankings

The development of the DORCE metric as a stable scoring system allows each of the 163 programs in the analysis to be scored, and the whole IOU portfolio ranked by DORCE score. This process enables a clear, rank ordered list from 1 to 163 that highlights the highest and lowest overall DORCE scoring programs in the portfolio. Note that in this context, programs can also be assigned rank order 1 to 163 with regard expressly to their score on the cost-effectiveness portion of the metric and with regard expressly to their score on the depth of retrofit portion of the metric. Further, within the depth of retrofit portion of the metric, rankings from 1 to 163 can be provided that separately characterize the average number of technologies addressed and the average proportion of total consumption saved. When the whole portfolio is sorted by overall DORCE score, the associated rankings specifically for cost-effectiveness and for depth of retrofit achievements provide a concise and clear picture of how much a given program's overall DORCE score is driven by cost-effectiveness and depth of retrofit.

Another useful outcome from the rankings exercise is the ability to organize programs into any desired subgroupings, based on one or more shared characteristics, and compare their rankings. For example, one may be interested in comparing the subset of programs that target medium-sized grocery stores, or those programs that target process efficiency at large industrial sites. Simply by focusing on programs with the desired set of characteristics, a user can take note of the relative rankings for these programs on overall DORCE score, as well as the relative role of the key cost-effectiveness and depth of retrofit components in driving that overall score.

Programs that Outperform their Predicted Scores

The regression models developed in this study yield the ability to predict a program's DORCE score based on aspects of its target building population and other aspects of its program design. A program's actual DORCE score may fall above, below, or exactly in line with what the model would predict for that program, and the difference between actual and modeled DORCE score is called the residual. As discussed in Section 5, the residual may highlight factors associated with program achievement that are not captured in the regression models, but it also may serve as a useful flag for spotting exceptional programs that complements the overall DORCE score. For example, as with the overall DORCE rankings, programs can be ranked 1 to 163 in terms of their residual, and programs at the top of this ranking would be those that outperform their modeled

DORCE scores by the greatest amount. These programs are scoring notably higher than programs of similar design in the IOU portfolio, and this may serve as a guide for further inquiry into how this success can be characterized and emulated. In particular, high residuals for programs in areas of the portfolio with relatively low DORCE scores may help flag those programs that are outperforming others in cases where high cost-effectiveness and depth of retrofit outcomes are inherently difficult to achieve. Additionally, programs at the bottom of the residuals ranking would be those that have achieved outcomes well below what would be expected for programs with their design elements and may be in need of review and revision. When viewed alongside overall DORCE score rankings, residuals rankings can help provide an especially clear picture of program performance.

Conclusions

Key findings from this study include:

- Generally, an increase in technologies addressed does not necessarily mean either an increase, or a decrease, in savings achieved.
- Tradeoffs are not always necessary between depth of retrofit and cost-effectiveness, as it is only minimally observable that success in depth of retrofit sometimes corresponds with decreases in cost-effectiveness.
- On balance, focus on very small customers yields higher DORCE returns than focusing on large customers.
- A focus on food service and a focus on water heating are both associated with high DORCE scores, driven primarily by their high cost-effectiveness, while programs focused on plug loads perform relatively poorly for both cost-effectiveness and depth of retrofit.
- A relatively high proportion of total program cost toward incentives and, conversely, a low proportion of total program costs toward marketing and outreach correspond with better cost-effectiveness outcomes, without a notable overall impact on depth of retrofit outcomes.
- Colleges (and campus-style buildings generally), offices, and food/liquor stores stand out as building types with high returns on cost-effective, deep savings, while restaurants and public assembly building types give the lowest returns.
- The top-scoring programs in the entire portfolio are highly cost-effective gas programs
- Approximately equal numbers of programs achieve high effectiveness scores (top 20%) via three pathways:
  - Notably high scores on both depth of retrofit and cost-effectiveness
  - Exceptionally strong cost-effectiveness with reasonable depth of retrofit
  - Exceptionally strong depth of retrofit with reasonable cost-effectiveness

- Some particular programs significantly outperform peer programs of similar design.

Recommendations

The evaluation team has distilled a series of recommendations that flow from the research conducted in this report, primarily aimed at program administrators. These recommendations, which are discussed in greater detail in Section 7, range from the general to the specific. They center on using the DORCE metric and other findings from this work to refine program and portfolio planning in service of meeting the state's energy savings goals.

Because DORCE provides a more granular indication of program performance than other quantitative metrics, program administrators should consider incorporating DORCE score and its observed relationships with certain program characteristics when reflecting on past program performance and when anticipating potential future performance. DORCE scores and accompanying component scores may provide useful insight for deciding how to allocate funds, working to enhance current programs, and developing new program concepts. Importantly, statistically significant positive correlations exist between cost-effectiveness and depth of retrofit in various subsections of the portfolio that may offer insight on where and how to pursue cost-effectiveness and depth of retrofit simultaneously.

Because the DORCE score provides a means of more detailed comparison among programs of similar design, consider using DORCE score to help identify standout programs across various segments of the nonresidential portfolio. One particular area of value may come from identifying programs that are performing better than their peers in areas of the portfolio where deep, cost-effective savings are historically challenging.

The DORCE score and associated regression modeling in this study offer detailed information about program performance and trends in performance across different elements of program design and targeting. However, the analysis conducted here does not identify the particular elements of each program's design and implementation that may drive DORCE outcomes. Consider exploring what makes certain programs successful by conducting detailed process evaluation on likely drivers of notably successful and unsuccessful programs. Through interviews with program managers, program implementers, participants, and trade allies, a focused process evaluation would help identify the particular practices and dynamics that appear most responsible for influencing a program's effectiveness score.

Because the DORCE score provides details on the performance of low-scoring programs, consider using DORCE score to help take a closer look at programs that score low on cost-effectiveness, depth of retrofit, or both, to see if outcomes are in line with expectations at the program planning level. In addition to looking at low-scoring programs overall in this regard, it may be instructive to look at low-scoring programs specifically compared against peers that target similar elements of the portfolio. Conspicuously low-scoring programs may represent an inefficient use of program administrator resources or a particularly challenging set of circumstances for generating cost-effective savings, or both. A comparison of outcomes to expectations may help structure program improvements.

Aided by the increased granularity provided by the DORCE score, pursue unrealized energy efficiency potential throughout the state using a targeted approach using DORCE outcomes paired with the most recent potential study.[3] The DORCE score may inform the development of realistic expectations for program outcomes for different segments of the portfolio. However, forward-looking program performance expectations depend sensitively on the remaining technical and economic potential for energy savings. Goals informed by the DORCE score may include increasing the investment in programs or general approaches that have worked well to date, but these should be informed by awareness of remaining achievable savings.

The DORCE score can provide the basis for setting depth of savings goals and cost-effectiveness goals for the whole IOU portfolio, as well as measuring progress toward those goals. Consider setting and working toward portfolio level objectives for DORCE. The study team believes that reaching for high scores on this metric where practicable will also support programs and overall portfolios in moving toward statewide energy efficiency objectives.

Because the DORCE metric provides multiple quantitative measures of the depth of savings achieved, consider using the DORCE metric strategically to reduce the risk of stranded energy efficiency potential. There may be cases where a broad set of measures is cost-effective when these measures are pursued collectively through a confined set of program touch points, but the less cost-effective portion of these measures may become non-cost-effective after “cream skimming” by narrowly focused programs. Using DORCE score as a planning tool may help highlight and minimize this phenomenon.

Because the DORCE score measures energy savings in a standardized way across fuels, it provides a level playing field for optimizing the pursuit of both gas and electricity savings opportunities. Where relevant, program administrators should make a point of exploring and potentially targeting gas savings potential on equal footing with electricity savings potential. Several gas-focused programs performed among the highest of all programs in this study, driven primarily by exceptionally high scores on both the TRC and PAC cost-effectiveness tests. For any comparisons across fuels in this analysis, findings are based on defining electric and gas savings in terms of source energy.

[3] See http://www.cpuc.ca.gov/General.aspx?id=2013

As a newly developed metric, the DORCE score may provide opportunities for iterative program evaluation and improvement that are not yet fully understood. Program administrators should use the tools from this research effort in multifaceted, flexible, and creative ways to help provide insight on the performance of their programs and overall portfolio. If cost-effectiveness is the highest order priority, consider using the tool to maximize depth of retrofit given cost-effectiveness constraints. Consider using the tools to come up with and frame new goals and priorities.

1

Introduction

Energy efficiency programs in California address a wide range of customers using a wide variety of program structures. Focusing on non-residential customers alone, over 160 energy efficiency programs made savings claims in the 2010-2014 timeframe. Programs differ in terms of a wide range of factors in their design, such as the targeted customer segments, program implementer, program measure offerings, and the proportion of total program spending that goes to marketing and other functions, just to name a few sorts of difference.

At the conclusion of the 2013-2014 program cycle, reports from the different research roadmaps (HVAC, Lighting, Residential, and Non-residential) articulated comparative questions about how programs were performing both within and across roadmaps. Several of these questions were framed in terms of how effectively programs were achieving deep savings relative to other programs and how cost effectively they were doing so. The confluence of these questions served to highlight a shared interest across roadmaps and became the genesis of research effort described in this report.

1.1 Why is Depth of Savings an Important Measure of Program Outcomes?

The Governor's Executive Order B-30-15 pushes the state to establish a California greenhouse gas reduction target of 40 percent below 1990 levels by 2030. As part of that clear and ambitious target, the Executive Order calls for doubling the efficiency savings from existing buildings. In addition, the California Energy Efficiency Strategic Plan (2011) and the CA Existing Buildings Energy Efficiency Action Plan (2015), two of the state's central guiding documents for energy efficiency priorities and strategy, both make extensive reference to the need for deep energy savings in both new and existing buildings to achieve ambitious statewide emissions reduction goals. In discussing the goal of getting 50% of existing commercial buildings to zero net energy (ZNE) by 2030, the Strategic Plan notes that deep levels of energy efficiency will be required alongside clean distributed generation to meet this goal. These documents note the overarching need for programs to look holistically at building energy consumption and move away from traditional mass market approaches to individual products. The Strategic Plan notes that achieving potential savings that have been identified in the context of benchmarking and commissioning work necessitates comprehensive improvements in buildings. The overarching thrust of the Strategic Plan is toward a building-as-a-system approach to achieve deep energy savings.

The Existing Buildings Energy Efficiency Action Plan further notes the importance of building owners pursuing deeper upgrades over time. That document emphasizes the essential importance of deep energy retrofits in achieving the state's goal of roughly 85% emissions reduction from today's levels by 2050. The Plan points to K-12 school efforts at deep retrofits and the Energy Upgrade CA brand focus on deep retrofits and demand-side energy management. It also notes challenges to deep retrofits, such as the reluctance to invest in energy efficiency retrofits with payback periods beyond 6-18 months for small and medium business and beyond 2-3 years for large businesses.

1.2 Why is it Valuable to Have a Metric that Reflects Both Cost Effectiveness and Depth of Retrofit?

The broad-based emphasis on the importance of deep retrofits across the state's key guidance documents, along with the perennial drive for cost-effective savings, serve as dual key drivers for this research effort. Importantly, the historical absence of a metric to quantify and compare program performance with regard to both cost effectiveness and depth of retrofit means there has been little systematic discussion and guidance as to which specific programs, which general areas of the non-residential portfolio, and which particular elements of program design move most effectively in the desired direction of these paired objectives.

Measuring something is often a critical ingredient to improving it. This captures the idea that a metric, when appropriately conceived, may point in a direction of value and improvement, focus attention on identifying and overcoming barriers to improvement, and serve as a feedback mechanism on efforts made to date. In the energy efficiency environment, a form of measurement of program achievements that reflects both cost effectiveness and depth of retrofit provides a mechanism for identifying standout programs and may serve as a useful tool for moving toward state goals at a program and portfolio level. Even in areas of the portfolio where deep energy savings are notoriously challenging, such a metric may help identify programs and approaches that have yielded the best outcomes among all that have been tried.

1.3 The Depth of Retrofit – Cost Effectiveness Metric

This report describes the development of the Depth of Retrofit – Cost Effectiveness (DORCE) metric as an initial foray into developing such as tool. The development of the DORCE metric has been a fundamentally exploratory process and is based directly on data from the 163 non-residential resource programs included in the analysis. Itron, with support from the CPUC, started with the identified interest at the intersection of depth of retrofit and cost effectiveness noted across multiple research roadmaps. We then sought to derive a metric that could meaningfully capture the interaction between cost effectiveness and depth of retrofit at the program level. The evaluation team identified several different views on a program's cost effectiveness that might inform an overall program effectiveness metric:

- Total Resource Cost (TRC)
- Program Administrator Cost Test (PAC)
- Savings (kWh, kW, therms) per incentive dollar
- Savings (kWh, kW, therms) per program dollar

We also identified measurable elements of a program that could serve as indicators of depth of retrofit:

- Number of end uses addressed
- Number of measure classes addressed[4]
- Proportion of overall consumption saved (kWh, therms)

Each of the measurable elements in the above lists represents a positive program outcome. That is, each of these elements has a quantitative value that describes the achievements of a program in some way, and all other things being equal, a higher value for each of these elements can be considered a favorable program outcome. As such, each item in this series of elements can appropriately be regarded as a facet, or component, of a program's effectiveness at achieving deep savings cost effectively. Taken together, these facets can provide a balanced picture of a program's overall effectiveness in this regard.

A key challenge was to combine, or "boil down", these facets into a single composite metric that would meaningfully capture the interaction between cost effectiveness and depth of retrofit at the program level. The central tool we settled on for this purpose was principal components analysis (PCA). The details and outcome of that process are discussed in detail in Section 3. At a high level, PCA uses patterns of covariation in the underlying dataset to put weights on each of the constituent individual metrics of program effectiveness to derive a single, weighted average metric. Hence the essential structure of the scoring tool is based on variations in the data of the programs that are being scored.

1.4 Components of the DORCE Metric

The DORCE metric consists of a cost effectiveness component and a depth of retrofit component. Part of the potential value of the DORCE metric is that, while the overall DORCE score serves as the central indicator of program effectiveness in this study, a program's performance on the distinct

[4] See Section 2.3.1 for the development of Measure Class.

cost effectiveness (CE) and depth of retrofit (DOR) components of the score is also preserved and displayed. This allows the user to note cases where, for example, a particularly high DORCE score is driven primarily by notably high cost effectiveness, high depth of retrofit, or equally by both.

Importantly, the depth of retrofit (DOR) component is derived from indicators of program design, such as the average number of end uses addressed by participants, as well as indicators that are more reflective of program outcomes, such as the proportion of overall consumption saved. The number of end uses and measure classes addressed are indicators of specific elements over which program planners have a large degree of control. That is, a program can be designed to target anywhere from one to many end uses and associated measure classes with its participants. While program designers and administrators don't specifically have control over how many end uses and measure classes a given participant will pursue, the program design goes a long way toward determining these outcomes.

The proportion of overall consumption saved, on the other hand, is quite distinct. It is more of an outcome of program involvement, rather than a lever of program design and control. Hence, the number of end uses and measure classes addressed and the proportion of overall consumption saved can be seen as two sides of a depth of retrofit coin. One is more like the "inputs" and the other is more like the "outputs" from a depth of retrofit standpoint. Throughout this report the evaluation team uses the term "technologies addressed" to refer to depth of retrofit from the program design standpoint of the average number of end uses and measure classes addressed. The team uses the term "savings achieved" to refer to depth of retrofit from the outcomes standpoint of total reduction in energy consumption.

Thus the overall DORCE score is supported by a variety of components that are preserved and displayed alongside the DORCE score to provide additional explanatory power. The DORCE score is comprised of the cost effectiveness (CE) and depth of retrofit (DOR) components, and the depth of retrofit component can be further subdivided into Technologies Addressed and proportion of overall consumption saved (Savings Achieved). When the portfolio is sorted and ranked by DORCE score, the rankings for each of these constituent components can be displayed as well. This yields a clear signal of the degree to which a notable DORCE outcome is driven by one or more distinct portions of the score.

The remainder of this report goes into the details of creating the overarching dataset for this work, deriving the DORCE metric, and evaluating the performance of non-residential programs from 2010-2014 and general program elements with respect to this metric. The evaluation team has put a focus on deriving actionable recommendations from this work. In Phase II of this research effort (expected completion October 2016) we expect to offer an Excel-based planning tool along with the research report for stakeholders to make direct use of the DORCE score in program planning and evaluation. The DORCE metric allows programs that are outperforming their peers in any portion of the portfolio to rise to the top and potentially become the object of closer inspection and emulation. Conversely, the metric identifies programs that are underperforming relative to their peers from both a cost effectiveness and depth of retrofit standpoints that may deserve re-consideration or re-vamping.

1.5 Phase I and Phase II of the Research Effort

This report covers Phase I of the research effort, in which the models and analysis are built on California's non-residential resource programs in the 2010-2014 timeframe. Phase II, to be completed by October 2016, will extend the analysis to include 2015 program data. Also, through engagement with stakeholders, Phase II will refine and add to the scope of the modeling and analysis to maximize the usefulness of the DORCE metric in program- and portfolio planning from the perspective of trying to achieve deep savings cost effectively.

2

Data Development

This section describes the steps taken to develop the master dataset of 2010-2014 non-residential programs and the effectiveness metrics and program characteristics developed for our analysis. The section begins with a discussion of the methods used to select programs for this study. We follow this section with a description of each data source and the methods used to incorporate each data source into a master database. Next, we define the ten metrics developed to measure program effectiveness (six cost effectiveness and four depth of retrofit). Then, we discuss the development of additional program characteristics used to identify common traits and core attributes of each program. These program characteristics were used in the regression models to understand what program attributes are correlated with program effectiveness. The section concludes with an overview of portfolio level programs and savings, to get a sense of the types of program included in our analysis.

2.1 Program Selection

This study includes non-residential programs from PG&E, SDG&E, SCE, and SCG from the 2010-2014[5] program years. The evaluation team identified 163 programs for inclusion in this study, including 76 PG&E programs, 64 SCE programs, 11 SCG programs, and 12 SDG&E programs. Since some program IDs changed from the 2010-2012 program cycle (1012) to the 2013-2014 (1314) program cycle, we needed to identify which programs were continuations across cycles. In some cases programs were split, merged, or discontinued. We contacted each IOU to get a mapping of the 1012 program IDs to the 1314 program IDs and created our own program ID for each unique program (accounting for merges and splits) in the study. The full list of programs, including the mapping of Itron program ID to the 1012 and 1314 program IDs is found in Table 8-1 of the appendix. Of the 163 programs included in this study 12 are new in 1314 (5 PG&E, 5 SCE, and 2 SCG) and 20 were discontinued after 1012 (10 PG&E, 9 SCE, and 1 SDG&E).

Our main criterion for selecting programs to include in the study was the presence of non-residential claims in the program tracking data. In most cases, a program's claims were entirely in the non-residential sector. However, there were 25 programs where some claims were non-

5 The 2015 finalized program tracking data was not available at the time of this report. We anticipate incorporating 2015 in Phase II.

residential and some claims were residential (7 programs had less than 50% non-residential claims[6]). In these cases, we only included the non-residential claims in the study. Program costs were allocated to these programs on an avoided cost basis (weights developed from the reported gas benefits and reported electric benefits from the CPUC's Cost Effectiveness Tool (CET)) to assign an appropriate proportion of costs to the non-residential claims. This approach is consistent with how costs are allocated for the TRC and PAC tests per the CET. The avoided cost weight development is described in Section 2.2.3 below.

From the set of non-residential programs, we also excluded primary upstream lighting programs, codes and standards programs, and energy advisor programs. Upstream lighting programs are primarily residential programs from which a small proportion of installations are allocated to the non-residential sector. Since there is no participant information and they're not designed as non-residential programs they were excluded from analysis. Codes and standards (C&S) programs claim savings due to legislative changes so there is no participant information involved. Similarly, Energy Advisor programs claim savings based on recommendations made to the participant, however no physical measures were incentivized or installed. Since this evaluation is focused on the effectiveness of downstream participant-based resource programs these types of programs were excluded.

2.2 Data Sources

We created the master dataset of 163 programs with data combined from six separate sources:

- Program tracking data
- Program cost tables
- Program evaluation tables
- Cost effectiveness data
- Customer information system (CIS) and billing data
- U.S. Census Bureau's American Community Survey (ACS)

We first compiled information from the six sources into a claim level dataset, then we created a program level dataset with effectiveness metrics (cost effectiveness and depth of retrofit) and program characteristics. The program level dataset was used as the basis for the principal component analysis (PCA), regression, and rankings discussed in later sections.

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[6] The seven programs with less than 50% non-residential claims included in the study are (from most to least non-residential claims): PGE211013 Marin County, PGE211011 Kern, SCE-13-L-002J Desert Cities Energy Leadership Partnership, PGE21037 Light Exchange Program, PGE211007 Association of Monterey Bay Area Governments (AMBAG), PGE211016 Redwood Coast, and SCE-13-SW-005B Lighting Innovation Program.

2.2.1 Program Tracking Data

For this study, we used the 2010-12 and 2013-14 CPUC standardized program tracking databases managed and maintained by the Data Management and Reporting team at Itron. These databases include program claim level information such as: measure name, measure group, end use, building type, sector, gross incentive amount, incentive structure (i.e., Custom or Deemed), gross ex ante first year savings (kWh and therms), and gross ex ante lifecycle savings (kWh and therms). Since the 1012 and 1314 databases were developed and maintained separately, there were some differences in the set of variables present in each database. In order to cleanly merge the two datasets, the variables of interest were updated and standardly defined across databases.

We added or changed the following variables in the 1012 database in order to match the logic of the 1314 database: end use, measure group, sector, and building type. End use is defined as one of eleven classifications: appliance, food service, HVAC, indoor lighting, outdoor lighting, plug loads, process, refrigeration, water heating, whole building, or other. The full list of 219 measure groups can be found in Table 8-2 in the appendix. Sector can be Agricultural, Commercial, or Industrial. The full list of 51 building types can be found in Table 8-3 in the appendix.

After the 1012 and 1314 datasets were merged, we created five new classification variables for the purposes of this study. In later sections we will discuss the development of those variables; Measure class will be discussed in Section 2.3.1, building group, gross program group (GPG), and program status in Section 2.4, and target fuel below.

MMBtu Conversion

Savings were reported in the program tracking database separately for electricity (kWh) and gas (therms). Some programs only save electricity, some only save gas, and some save a combination. For this reason, a uniform unit of energy savings was necessary to compare savings across all programs. Instead of analyzing electricity savings in kWh and gas savings in therms, we converted all energy savings and consumption in both fuel types to millions of British Thermal Units (MMBtu).

KWh, therms, and MMBtu are all units of energy measurement. The equation below illustrates the unit conversion of 1 gigajoule (joule is the SI unit for energy) to kWh, therms, and MMBtu. From these conversions we can estimate that one therm is equivalent to approximately 29.3 kWh.

$$1\,GJ \approx 277.8\,kWh \approx 9.48\,therms \approx 0.947817\,MMBtu$$ [7]

Using the 1:29.3 unit conversion ratio would successfully quantify the reported amount of energy saved at the meter. These savings, often called site savings, quantify a decrease in the amount of

[7] Energy unit conversions from www.wolframalpha.com

energy delivered to and used by the customer. However, some fuel types require more energy at generation to deliver 1 unit of useful energy to the customer. Thus savings by the customer end up delivering more overall grid energy savings from the standpoint of avoided power generation inputs. We refer to these increased savings at generation as source energy savings.

For this analysis, we converted all reported electricity and gas savings and consumption to source energy expressed in MMBtus. We used the approach described in ENERGY STAR's Portfolio Manager Technical Reference document to calculate appropriate site to source energy savings conversion ratios for electricity and gas.[8] Data from the EIA's annual energy flow diagrams were used to calculate the site to source ratio for each year from 2010 through 2014.[9] We took the average across the five years as the site to source ratio used in our analysis. Table 2-1 shows the site energy unit conversion to MMBtu and the site to source ratio for electricity and gas.

Table 2-1: Savings Conversion to MMBtu

Fuel	Site Energy Unit Conversion to MMBtu	Site to Source Ratio
kWh	0.003412	3.0235
therms	0.1	1.05

The site energy unit conversion ratio is multiplied by the site to source ratio to determine the ultimate conversion ratio of site electricity or gas savings to source energy savings in MMBtus. The final conversion ratios are presented in the below equation. Note that the kWh to therms ratio is now roughly 1:10.

$$MMBtu = 0.0103 * kWh + 0.105 * therms$$

Target Fuel

Sometimes, a program claimed savings in a fuel source that was not necessarily the targeted fuel source. When evaluating a program's depth of savings, or savings expressed as a proportion of annual consumption, we wanted to be sure programs were not penalized by large consumption among program participants in a non-targeted fuel source. In effect, the task was to exclude a non-targeted fuel source from the denominator of total energy consumption when expressing program savings as a proportion of annual consumption. For this reason we developed the target fuel source program classification. This field denotes whether a program targeted electricity savings, gas savings, or both. A program targets savings from a fuel source if at least 20% of its ex ante gross first year MMBtu savings came from that fuel source. Out of 163 programs, 20 targeted gas

8 ENERGY STAR Portfolio Manager Technical Reference: https://portfoliomanager.energystar.gov/pdf/reference/Source%20Energy.pdf

9 EIA energy flow diagrams: http://www.eia.gov/totalenergy/data/annual/archive/energyflow.cfm

savings, 112 targeted electricity savings, and 31 targeted savings from both fuel sources. When we created the savings achieved metric (see Section 2.3.2), only the savings and consumption from the targeted fuel(s) were considered for each program.

2.2.2 Ex Post Data

Claim level evaluation results, managed and maintained by the Data Management and Reporting team, from 2010-2013 were merged to the master claim level data set. This data allowed us to incorporate ex post savings into our analysis. At the time of this analysis, evaluation results were not finalized for the 2014 program year. Therefore, we substituted ex ante savings in place of ex post for all 2014 claims. We anticipate incorporating 2014 ex post savings in the Phase II report.

2.2.3 Cost Effectiveness Data

Claim level cost effectiveness data from 1012 and 1314, developed and maintained by the Data Management and Reporting team using the Cost Effectiveness Tool (CET), were merged to the master claim level dataset. The cost effectiveness data includes the reported electric benefits, the reported gas benefits, the reported Total Resource Cost (TRC) test costs, and the reported Program Administrator Cost (PAC) test costs associated with each claim. These fields were used to calculate the TRC and PAC on the non-residential claims of each program from 2010-2014, based on the methods found in the California Standard Practice Manual.

Since some programs had both residential and non-residential claims, we used the electric and gas benefits to establish a weighting scheme to apply program level costs at the claim level. Since we only analyzed non-residential claims, we needed a method to select an appropriate portion of the program level costs to associate with the non-residential claims. The weight applied to each claim was developed for each cycle and program separately, per the below equation. In program p and cycle c, W_i is the weight applied to claim i, E_i is the electric benefits for claim i and G_i is the gas benefits for claim i. Note that W_i will sum to one for all the claims in a given program and cycle. If a program has neither gas nor electric benefits in that cycle, then program costs distribute evenly across all claims in that program and cycle.

$$W_i = \frac{E_i + G_i}{\sum_{i \in p,c} E_i + G_i}$$

2.2.4 Expense Data

The program cost data for each cycle, managed and maintained by the Data Management and Reporting team, was merged to the master claim level data, so that each claim was assigned the costs from the associated program and cycle. To allocate the program cost to the claim level, the program level cost was multiplied by the weighted benefits field for each claim (see Section 2.2.3). Expenses in the program costs table were divided into the following five categories: administration costs in overhead and G&A, other administration costs, marketing and outreach, direct implementation activity, and rebates and incentives not calculated on a per unit basis (this last category was only used in 1012 programs).

2.2.5 CIS/Billing Data

In order to include information such as participant annual consumption and size in the analysis, customer information system (CIS) and billing data was incorporated into the master claim level data. The group of accounts corresponding to a single site had been determined by the Data Management and Reporting team for PG&E, SCE, and SDG&E. For those three program administrators (PAs), the CIS and billing data had been aggregated and summarized by the Data Management and Reporting team to the site level, and each claim in the program tracking data was mapped to its associated site. The CIS and billing data was summarized by site with key fields such as customer name, address, latitude and longitude, phone number, and annual consumption.

The SCG billing data needed to be summarized in order to acquire the annual gas consumption in each year from 2010 through 2014. Before that could take place, SCG accounts needed to be aggregated into individual sites and joined to existing PG&E, SCE, and SDG&E accounts where necessary. We followed the same site aggregation process as the data team used for the other PA's to aggregate SCG accounts to sites, based on address, phone number, and customer name -. In cases where multiple existing PG&E/SCE/SDG&E sites were matched to a single SCG site, then those sites were combined to create a single new site. Similarly, if a single PG&E/SCE/SDG&E site was matched to multiple SCG sites, then those SCG sites were combined to a single site. Once the final site aggregation had taken place, the new site ID was mapped onto the master claim level data. Once SCG sites were created, a new summary table was created of each site's annual consumption. Finally, the site level annual consumption were merged to the master claim level data by site ID.

Sometimes claims from the program tracking data could not be matched to the CIS data. For these cases, any site-dependent program effectiveness metric or characteristic was calculated excluding the claims not matched to CIS. These cases are mentioned below when they occur.

Savings Achieved Threshold

As a screen to identify sites with potential data issues (that could in turn drive inaccurate program effectiveness scores), we reviewed claimed savings at the site level in proportion to annual consumption. We flagged all sites where ex post gross first year savings were greater than 30% of annual consumption for a single program in a single claim year. There are a few reasons that could drive higher savings in relation to consumption: overstated savings (e.g., anecdotally greenhouses tend to claim savings that are about five times their annual consumption), a bias towards under aggregation in the site development process, the fact that some programs are not evaluated for ex post, and the fact that 2014 ex post is not yet included in the analysis. For cases where ex post gross first year savings were greater than 30% of annual consumption for a single program in a single claim year, any site-dependent program effectiveness metric or characteristic was calculated excluding the claims not matched to CIS. Within any program, only the targeted fuel source savings and consumption were included in these calculations (see Section 2.3.1 for definition of target fuel).

We performed sensitivity analysis around establishing a threshold for percent of annual consumption saved above which claims not matched to CIS would be excluded from site-dependent program effectiveness metrics. We reviewed a number of options for savings as a percentage of annual consumption, including either 30% or 50% cut-off points and whether to use ex ante or ex post savings. We performed two main activities to determine which threshold is most appropriate. First, we compared the impact of using either ex ante or ex post savings to calculate the threshold metric. Table 2-2 shows the percentage of claims in each program, averaged across all analyzed programs, which exceed a particular threshold and would be excluded from analysis. In all cases, moving from ex ante savings to ex post results in excluding an average additional 3% of claims. Ultimately, we chose to use an ex post threshold to minimize the risk of excluding sites due to potentially inflated ex ante savings.

We also considered whether to use 50% or 30% as a cut-off point. It seemed unlikely in most cases for a site to reduce more than 30% of its energy demands as a result of participation in a single program. However, we evaluated against a more lenient cut-off point of 50% for sensitivity analysis. With both ex ante or ex post savings, moving from 50% to 30% excludes an average additional 8% of claims. To explore this idea further, we calculated the 75th percentile ex post savings achieved within each program, to get a sense of the range of savings achieved values, while excluding potential outliers. Across individual programs the 75th percentile savings achieved exceeded 50% in 12 programs, and exceeded 30% in 39 programs. Overall, the 75th percentile ex post savings achieved within each program, averaged across all programs, was 23%, meaning that on average only 25% of claims within each program achieved savings above 23%. These findings support our choice of 30% ex post threshold, since it is above a reasonable range for ex post savings achieved.

Table 2-2: Sensitivity of Average % of Claims Exceeding Threshold

> 50% Ex Ante	> 50% Ex Post	> 30% Ex Ante	> 30% Ex Post
14%	11%	22%	19%

2.2.6 Census Data

The U.S. Census Bureau's 2013 American Community Survey (ACS) was used to identify regions where English is not the primary spoken language.[10] This information was necessary to develop a hard-to-reach site classification for each site (Section 2.4.3). The 2013 ACS provides 5-year average (2009-2013) estimates of English speaking ability by census block group. We anticipate incorporating the 2014 ACS 5-year averages in the phase II report.

To merge the ACS data to the master claim level data, we first determined the census block group of each site in the master claim level data. The latitude and longitude of each site was taken from the CIS data and read into QGIS.[11] The 2013 census block group shape files[12] were then read into QGIS and used to map each site to the correct census block group. Once the census block group was identified for each site, the ACS data was merged to the master claim level data by census block group.

2.3 Success Metrics

Upon creation of the master claim level data, we summarized key statistics for each program. Based on the objectives of the project, we needed sensible indicators of depth of retrofit and cost effectiveness that could be woven into an overall effectiveness score.

We identified two facets of depth of retrofit characterized by technologies addressed and savings achieved. Technologies addressed was measured by two metrics: number of end uses per site and number of measure classes per site. Savings achieved was also measured by two metrics: ex ante and ex post gross MMBtu savings as a proportion of annual consumption. Cost effectiveness was measured by TRC, PAC, ex ante and ex post gross MMBtu savings per total program cost, and ex ante and ex post gross MMBtu savings per gross incentive.

2.3.1 End Use and Measure Class per Site

We decided that the number of end uses addressed by the average participant in a given program could serve as one clear indicator of depth of retrofit. In other words, all other things being equal, programs that went after a higher number of end uses achieved greater depth of retrofit. We also decided that a more granular indicator would serve to reflect the range of technologies implemented by a program, so we created a new way to categorize measures which we called measure class.

[10] ACS data: https://www.census.gov/programs-surveys/acs

[11] QGIS is free and open source Geographic Information System (GIS) software: http://www.qgis.org/en/site/

[12] 2013 census block group shape files located here: https://www.census.gov/geo/maps-data/data/tiger-line.html

Measure class was defined to classify technologies at a level falling between end use and measure group. We felt that a more granular classification than end use would help portray a program's depth of retrofit and serve as a complementary indicator to the number of end uses addressed, but that measure group was too granular and too arbitrary for this purpose. To generate the measure class categorization, each measure group was mapped to a single measure class (see Table 8-2 in the appendix). Where measure group has 219 unique designations and end use has 11, the measure class variable has 35.

For each site that participated in a program, we calculated the number of distinct end uses and measure classes addressed. Program averages were calculated as the straight average of end uses per site and measure classes per site, respectively, across all program participant sites.

As discussed in Section 2.2.5 above, if a site was flagged as not matching to CIS or had greater than 30% of consumption in ex post savings, it was not included in the program's calculation of average end uses per site and average measure classes per site.

2.3.2 Savings Achieved

A key and complementary indicator of depth of retrofit, in addition to the number of technologies addressed, is the amount of energy savings achieved. This was expressed as the average percentage of total consumption each participant saved through the program.

The following steps were taken to calculate the savings as a percentage of consumption metrics. At the claim level, a variable was created for the annual MMBtu consumption in the year of the claim, from targeted fuel sources only. Ex ante and ex post gross MMBtu savings as a percent of consumption were calculated for each program and site. As described above (Section 2.2.5), claims that were not matched to CIS or that had been flagged with ex post gross first year savings greater than 30% of consumption were not included in these calculations. The average savings as a percent of consumption was taken across sites within each program to calculate the final savings as a percent of consumption metric.

Through the remainder of this report we will refer to ex ante gross first-year MMBtu savings as a percent of consumption as Ex Ante Savings Achieved. We will refer to ex post gross first-year MMBtu savings as a percent of consumption as Ex Post Savings Achieved.

2.3.3 TRC and PAC

"The Total Resource Cost Test measures the net costs of a demand-side management program as a resource option based on the total costs of the program, including both the participants' and the utility's costs."[13]

"The Program Administrator Cost (PAC) Test measures the net costs of a demand-side management program as a resource option based on the costs incurred by the program administrator (including incentive costs) and excluding any net costs incurred by the participant. The benefits are similar to the TRC benefits. Costs are defined more narrowly."[14]

Both of these tests are used by the CPUC to evaluate program cost effectiveness.

Program level TRC and PAC were calculated from the master claim level dataset. The cost effectiveness data output from the CET was the ultimate source of the claim level inputs for program level TRC and PAC. For each program, we calculated TRC as the sum of the claim level electric and gas benefits divided by the sum of the claim level TRC costs. Similarly, we calculated PAC as the sum of the claim level electric and gas benefits divided by the sum of the claim level PAC costs.

2.3.4 Savings per Program Cost and Gross Incentive

Along with the TRC and PAC, we developed two other simpler metrics measuring cost effectiveness. They are lifecycle gross MMBtu savings per total program cost and lifecycle gross MMBtu savings per total program gross incentive. Total program cost is the sum of the five program cost components from the program cost table (Section 2.2.4) and the claim level gross incentives field. Total program gross incentive is comprised only of the claim level gross incentives field. Two versions of each metric were developed, one using ex ante savings and one using ex post.

2.4 Descriptive Metrics

In addition to the program success metrics described above, we developed program level characteristics to describe various attributes of the program. Upon development, the descriptive metrics were used to highlight any correlations between program characteristics and program effectiveness.

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[13] http://www.cpuc.ca.gov/uploadedFiles/CPUC_Public_Website/Content/Utilities_and_Industries/Energy_-_Electricity_and_Natural_Gas/CPUC_STANDARD_PRACTICE_MANUAL.pdf

[14] http://www.cpuc.ca.gov/uploadedFiles/CPUC_Public_Website/Content/Utilities_and_Industries/Energy_-_Electricity_and_Natural_Gas/CPUC_STANDARD_PRACTICE_MANUAL.pdf

Program classification metrics include: Program sector, program gross program group (GPG), program administrator, program status (defined below), and program direct install (DI) flag.

Gross Program Group

As part of the gross impact evaluations done for the Efficiency Savings and Performance Incentive (ESPI) evaluations, gross program group was developed as a way to identify program with similar delivery mechanisms. GPG had only been developed by the Data Management and Reporting team for the 1314 programs, so we utilized the program mapping to assign GPG to the 1012 data as well. We also simplified the GPG definition to four general areas: core/statewide, local government partnership (LGP), third/local party implementer (3P), and state institutional partnership (SIP).

Program Cycle

We created a program classification to identify programs that were discontinued after 1012, continued from 1012 through 1314, or new in 1314.

2.4.2 Percent of Sites Attributes

Site Size

The evaluation team characterized the percent of sites in each program that are very small, small, medium, and large. A site's size was defined based on its 2014 annual consumption from the CIS/billing data. If the site had kWh consumption in 2014 then the kWh criteria were used, otherwise the therms criteria were used. Each site was tested against the size criteria in Table 2-3 in sequential order from very small to large until a size bucket was matched. For example, if a site did not meet the threshold for very small it was then tested against the small criteria. If at that point the size was determined to be a small site no further criteria testing took place.

Table 2-3: Site Size Criteria

Size	kWh Criteria	Therms Criteria
Very Small	<= 40,000 kWh	<= 8,478,507 therms
Small	<=300,000 kWh	<= 149,927,361 therms
Medium	<= 1,750,000 kWh	<= 245,060,234 therms
Large	> 1,750,000 kWh	> 245,060,234 therms

If a site could not be matched to CIS/billing data, then the size of the site was defined as "unknown".

End Use

Another proportion metric we developed was the percent of sites in each program that installed a particular end use including: appliances, food service, HVAC, indoor lighting, outdoor lighting, plug loads, process, refrigeration, whole building, water heating, and other.

Building Group

The building type classifications in the tracking data were too granular for the purposes of this study, with 51 different building types. For instance, there were separate building types for fast food and sit down restaurants. We consolidated some of these building types and created a new variable, called building group, with just 19 different classifications. Building groups were created so that each group would have a significant amount of savings (at least 1% of portfolio).

The building group metric is defined as the percent of sites in each program that include accounts in one of the following building groups: assembly, colleges, food/liquor, health, lodging, manufacturing, office, retail, restaurant, school, transportation, communication, and utilities (TCU), and warehouse.

DG and DR

We developed a statistic for the percent of sites in each program that participated in a distributed generation (DG) program in the past. Percent of sites in each program that participated in a demand response (DR) program in the past. This data came from the CIS/billing data.

Incentive Structure

Another proportion metric we developed was the percent of sites in each program with a deemed incentive structure and the percent of sites with a custom incentive structure.

2.4.3 Hard To Reach

We created a definition of whether a site is Hard to Reach (HTR). This classification is used to determine whether a program is able to recruit customers that are on the edges of normal program participation. Guided by criteria used by utilities to define HTR customers for use of deemed ex ante NTG ratios specific for direct install hard to reach customers in program year 2013[15], we used three[16] points to determine whether a site is HTR, they are:

[15] Resolution G-3497, Attachment 3

[16] One criterion not included was whether a facility was leased or owned, as the evaluation team had no method of determining this at the outset.

1. Business Size – very small businesses (sites with annual demand less than 20kW or annual gas consumption less than 10,000 therms)
2. Language – English not the primary spoken language (based on the prevalent language spoken in the site's census block group)
3. Geography – sites in areas other than the metropolitan regions associate with the San Francisco Bay Area, the Greater Los Angeles Area, the Greater Sacramento Area, or San Diego County.

A site is HTR if it is rural or not English speaking, and very small.

Language and Geography are defined in their own sections below. Site size was determined to be very small if either the 2014 max kW was less than 20 kW or the 2014 annual therms was less than 10,000 therms.

We also classified sites as HTR if the program tracking data indicated (based on a field in the program tracking data that classifies the NTG ratio) the use of a NTG ratio that was characterized as a HTR ratio. The special HTR NTG ratio was only implemented in 1314 and only for some programs, for this reason we had to create our own definition of HTR as well for all participating sites. The HTR NTG ratio allowed us to identify a few more sites that were HTR that would have been overlooked, since we do not have data on the actual language spoken on site or whether buildings are owned or leased.

English Speaking Status

In order to determine whether a site is hard to reach, we needed to determine the language status of the site. Since we cannot know the language spoken at each individual site, we decided to use a proxy based on census data. At the census block level, we know from the 2013 5-year American Community Survey, the percentage of the population the speak English only, very well, well, not well, or not at all. We classified a census block as non-English speaking if greater than 2/3 of the population speaks English either not well or not at all.

Rural

Each site had a zip code indicated in the CIS data. The zip codes were cleaned and validated to ensure they were located within California. A mapping of zip codes to rural/urban was applied to the sites based on a map created by the Data Team. Zip codes not located in major cities in California (San Francisco, Los Angeles, San Diego, or Sacramento) are denoted as rural.

2.4.4 Programs per Site

The number of programs each site participated in was calculated. Then within each program, the average number of programs per site was taken across all sites within that program to create the average program statistic. The statistics are calculated only sites that matched to CIS or have less than 30% of ex post savings as percent of annual consumption.

2.4.5 Percent of Total Program Cost

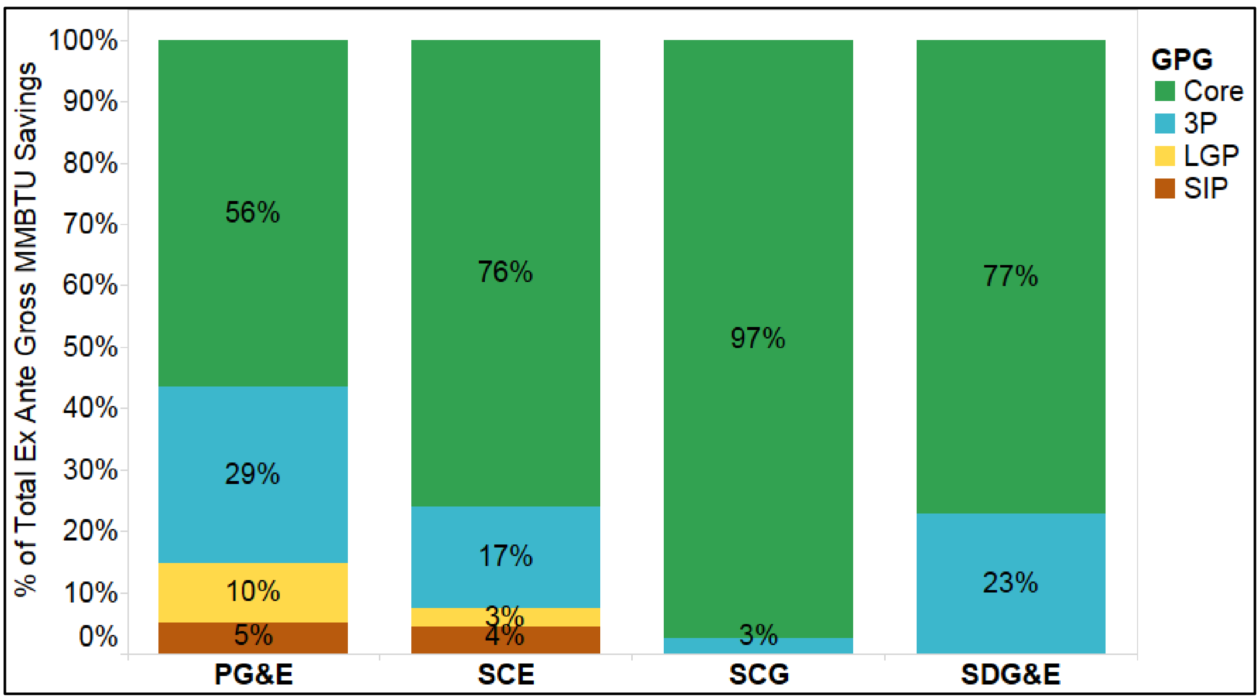
Total program cost was split into five categories: Administration costs – overhead and G&A, administration costs – other, DI activity, marketing/ outreach, and incentives. For each program, the proportion of total program cost spent in each of these individual categories was calculated.

2.5 Portfolio Overview

Upon creation of the final claim level and program level datasets, we are able to make high level observations regarding the non-residential portfolio.

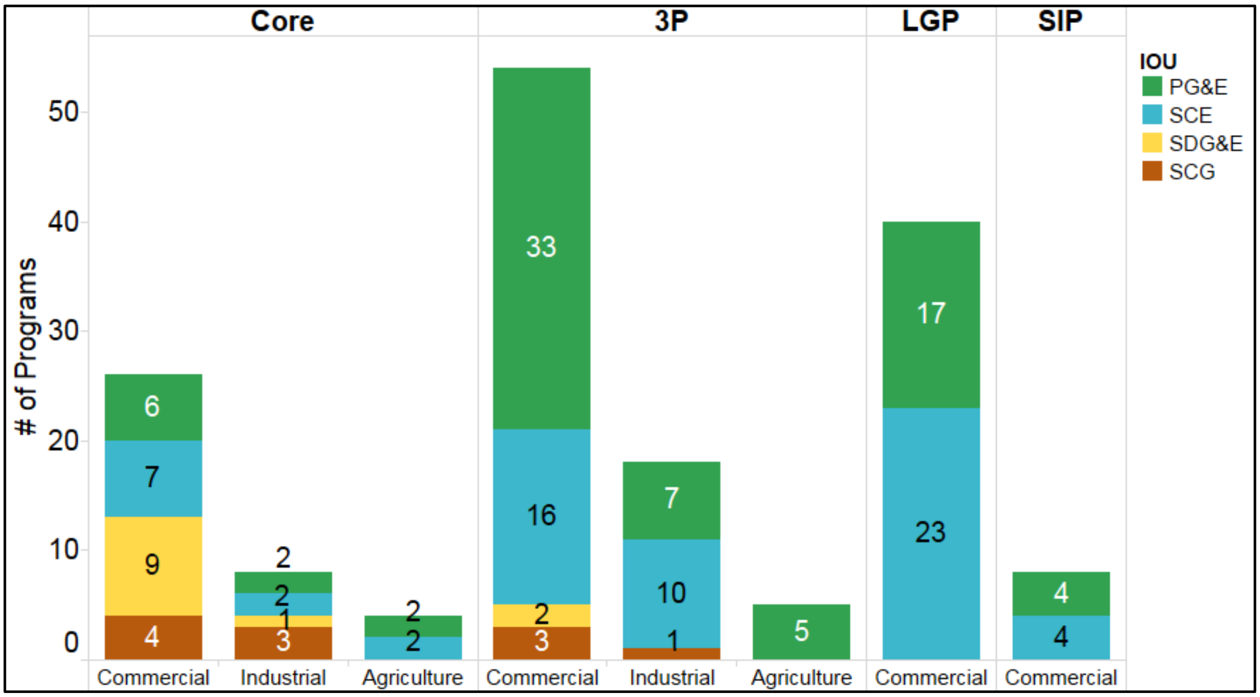
In Figure 2-1 the proportion of savings from each gross program group is presented by PA. We see that core/statewide programs are the predominant source of savings within each PA, constituting 97% of SCG's savings, 77% of SDG&E's savings, 76% of SCE's savings and 56% of PG&E's savings. Third party programs are the second largest contributor to program savings within each PA. PG&E and SCE are the only PA's with local government partnership and state institutional partnership programs. For PG&E they make up 15% of savings and for SCE they contribute to just 7% of savings.

Figure 2-1: Proportion of Total PA Ex ante Gross MMBTU Savings by GPG



In Figure 2-2, the number of programs in each IOU is presented by GPG and sector. Within the non-residential portfolio, the majority of programs target the commercial sector, followed with a significant gap by the industrial, and agricultural sectors, respectively. Local government partnerships and state institutional partnerships consist solely of commercial sector programs. Within each sector, the largest number of programs are third party, followed by local government partnerships (commercial sector only), then core/ statewide, then state institutional partnerships (commercial sector only).

Figure 2-2: Number of Programs by IOU, GPG, and Sector



3

Program Effectiveness Scoring

Program comparison and ranking, requires a single metric to measure against, driving the search for a method to combine all of the program level effectiveness metrics. Inherent in their creation, the ten effectiveness metrics discussed in the previous section often measured similar ideas. Therefore, high correlation is expected across some of these variables. The evaluation team decided to use a statistical tool called principal components analysis (PCA) to combine the metrics mathematically into a single effectiveness metric. PCA is a variable reduction technique that combines highly correlated variables. The analysis process drove the determination that there were three distinct effectiveness groups, necessitating a separate PCA for each of three groups. Weighting the three PCA metrics allowed for the creation of a single program effectiveness score.

This section begins with an introduction to PCA concepts and analysis. A review of the metrics chosen to measure various aspects of program success follows. Next is a discussion of the analytical basis for three separate PCA models and the results of those PCAs, followed by a description of the weighting scheme used to combine the three PCA models.

3.1 Methods

Principal Component Analysis is a statistical method used for variable reduction. In analytical cases with many variables that are highly correlated and are likely measuring the same thing, PCA can be used to reduce the number of variables. PCA uses an orthogonal linear transformation to execute a change of basis and obtain a set of the same number of variables as inputted. Whereas prior to PCA the input variables might have had high correlations, the variables output from PCA are linearly uncorrelated. Closely related to factor analysis, PCA is a purely mathematical, data-driven approach for variable reduction.

3.1.1 Concept

The basic concept of PCA begins with a set of n variables fed into the PCA procedure.[17] PCA produces a set of n principal components (PC) representing the same information as the inputted variables. The n principal components are linearly orthogonal (statistically independent) and ordered from the PC representing the most variability in the data to the least. Each PC represents

[17] The evaluation team used SAS to carry out the principal component analysis

a different facet or type of activity in the n-dimensional space that is completely different and uncorrelated with the other PCs.

Essentially, PCA identifies which variables measure the same activity and groups those variables together into a single PC. The following example illustrates this idea. Imagine a single variable, x1. Now imagine defining four other variables as exact copies of the original variable (x1 = x2 = x3 = x4 = x5). If those five variables are input into a PCA the output includes a set of five PCs. The first PC represents all of the variability in the data (eigenvalue[18] = 5) and the remaining four PCs represent zero of the variability. This is because PCA recognized that the five input variables measured the same thing and therefore mapped all into a single PC. For variable reduction one would select only the first PC for analysis.

The previous example extends to cases where the input variables measure closely related activities. PCA identifies commonalities across the input variables and maps to the PCs accordingly. The researcher identifies which PCs represent the activities of interest and discards the leftovers. SAS[19] produces three main useful output tables and graphics to aid this selection process, they are the eigenvalue table, the scree plot, and the factor pattern (discussed in Section 3.1.2). The eigenvalue table and the scree plot guide the PC selection process and the factor pattern allows for PC interpretation.

3.1.2 Analysis

A number of approaches exist to determine how many PCs to keep. The Kaiser criterion – whether an eigenvalue is greater than one – is one such approach. An eigenvalue represents the amount of variance in the data accounted for by a given PC. The SAS PCA procedure standardizes input variables to have a mean of zero and variance of one. Therefore, a PC with an eigenvalue less than one accounts for less variance than one original input variable. The eigenvalue of each PC is presented in an eigenvalue table (see Table 3-1 for example) outputted from the PCA procedure. One concern with this approach is that Kaiser criterion can be overzealous in excluding PCs.

Another PC selection criteria is to set a minimum threshold for the variance accounted for by the selected PCs. For example, in our analysis we chose to select the minimum number of PCs that make up at least 70% of the variance. The eigenvalue output table also presents this information as the proportion and cumulative total of variance accounted for by each PC.

[18] Eigenvalue represents the amount of variance in the data accounted for by a given principal component (see 3.1.2)

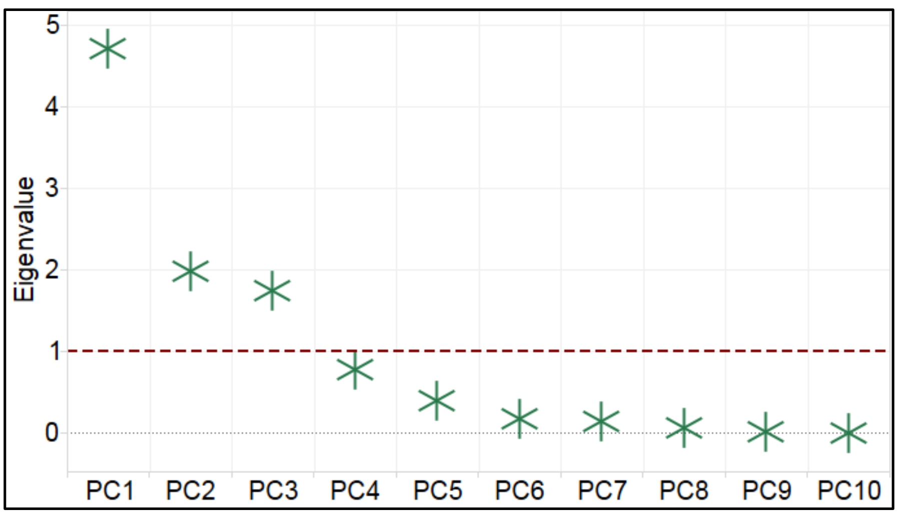
[19] SAS is statistical software developed by the SAS Institute, often used for data management and statistical analysis.

Table 3-1: Example Eigenvalue Table

PC	Eigenvalue	Proportion	Cumulative
PC1	4.7	47.1%	47%
PC2	2.0	19.9%	67%
PC3	1.7	17.4%	84%
PC4	0.8	7.8%	92%
PC5	0.4	4.0%	96%
PC6	0.2	1.8%	98%
PC7	0.1	1.4%	99%
PC8	0.1	0.6%	100%
PC9	0.0	0.2%	100%
PC10	0.0	0.0%	100%

A third PC selection approach is the Scree test. In a scree plot (see Figure 3-1 for example) eigenvalues are plotted against each principal component, ordered left to right from highest eigenvalue to lowest. We then visually determine at what point there is a large drop in the eigenvalues. The PC immediately prior to the cliff is the last PC kept for analysis. The ambiguity of this approach raises some concern with researchers, so it is often used in conjunction with other methods.

Figure 3-1: Example Scree Plot



Alongside the eigenvalues, the factor pattern provides another lens to judge the quality of PCA results. The factor pattern table (see example in Table 3-2) displays the correlations between the input variables and the principal components. This table provides a sense of how each principal component is defined. When reviewing the factor pattern consider whether the variables which are highly correlated with an individual PC (or "load on a PC") share the same conceptual meaning.

Similarly, consider whether variables that load on difference PCs measure different concepts. This final step provides confidence in the overall PCA and the PCs that are kept.

Table 3-2: Example Factor Pattern

Input Variables	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
Variable 1	**-0.4**	**0.6**	**0.6**	0.1	0.0	0.2	-0.2	0.0	0.0	0.0
Variable 2	-0.3	**0.5**	**0.8**	0.1	0.0	-0.2	0.2	0.0	0.0	0.0
Variable 3	-0.3	**0.8**	**-0.5**	-0.1	0.1	0.2	0.1	0.0	0.0	0.0
Variable 4	-0.1	**0.8**	**-0.6**	0.1	-0.2	-0.3	-0.1	0.0	0.0	0.0
Variable 5	**0.8**	0.2	-0.1	-0.2	**0.6**	-0.1	0.0	0.1	0.0	0.0
Variable 6	**0.9**	0.2	0.1	-0.3	0.0	0.1	0.0	-0.2	0.0	0.0
Variable 7	**0.9**	0.2	0.1	-0.2	-0.3	0.1	0.0	0.1	-0.1	0.0
Variable 8	**0.9**	0.1	0.1	-0.2	-0.3	0.0	0.0	0.1	0.1	0.0
Variable 9	**0.9**	0.1	0.0	**0.5**	0.0	0.1	0.0	0.0	-0.1	0.0
Variable 10	**0.9**	0.0	0.0	**0.5**	0.0	0.0	0.0	0.0	0.1	0.0

3.2 Findings

This section presents a brief discussion of the metrics chosen to measure program effectiveness and other metrics also considered but not included in the final set of effectiveness metrics. The section goes on to review the relationships between the ten final effectiveness metrics and explains the motivations behind developing three separate PCA models. The results of each PCA are described and the final algorithm for combining metrics to a single variable is presented.

3.2.1 Effectiveness Metrics Selection

The evaluation team used PCA to develop the dependent variable for the regression model (the program effectiveness metric). As described in Section 2, ten metrics were developed to measure program effectiveness. These metrics are classified into three general groups: savings achieved, technologies addressed, and cost effectiveness. There are two types of technologies addressed metrics: number of measures per site and number of end uses per site. There are two types of savings achieved metrics: ex post savings achieved and ex ante savings achieved. There are six types of cost effectiveness metrics: reported PAC, reported TRC, ex ante and ex post savings per gross incentive, and ex ante and ex post savings per total expenditure. While we recognize that these metrics may not necessarily align perfectly with each program's designed outcomes, this set of performance metrics best exemplify depth of retrofit and cost effectiveness.

Beyond the ten metrics discussed there were a few other metrics considered but ultimately not included in the program effectiveness scoring. These are the percent of HTR customers reached, the percent of DG customers reached, the percent of DR customers reached, and the number of programs a customer participated in after participation in the program of interest. While participation by HTR, DG, or DR customers may be desirable, these areas of program performance bear no impact in this study's focus on cost effectiveness and depth of retrofit, and were therefore not included in the final set of effectiveness metrics. With regard to the number of programs a customer participated in, this could be interpreted either positively or negatively. For instance, a site might have to participate in many programs because the first program did not address enough. Alternatively, a site might participate in more programs because the first program was educational as a feeder program. Since it is not clear cut whether number of programs is a positive or negative trait, it was not included in analysis.

3.2.2 Effectiveness Metrics Analysis

Table 3-3 below is a correlation matrix that shows how each of the ten metrics is correlated with each other. Correlation can range between -1 and 1. A value of zero means two variables are not correlated at all, an absolute value between 0.4 and 0.6 means two variables are moderately correlated, and those with an absolute value above 0.6 are highly correlated. In the table below, correlations above 0.5 are shown in bold text. Shading in each cell illustrates different patterns found in the correlation matrix. The white box, comprised of the first six metrics, is comprised entirely of correlations of 0.5 or higher, illustrating that these six metrics are all highly correlated. To the right of the white box, the medium-grey region highlights the correlation of those same six metrics against the technologies addressed and savings achieved metrics. The correlations between these sets of variables range from -0.3 to 0.1, indicating very weak, to absent, correlations. These two observations regarding the first six metrics, led to grouping the six cost effectiveness metrics together, apart from the others. With regards to the remaining four variables, we see that the two savings achieved metrics (Ex Ante Savings Achieved and Ex Post Savings Achieved) are highly correlated with each other (dark grey region) and are not correlated with the technologies addressed metrics (light grey region). And finally, the black shaded region shows that technologies addressed metrics are highly correlated with each other. These last findings led to grouping the technologies addressed and savings achieved metrics separately. Interestingly, the savings achieved and technologies addressed metrics were not negatively-correlated but were actually not correlated at all (light grey region).

Table 3-3: Effectiveness Metrics Correlation Matrix

Input Variables	TRC	PAC	Ex ante Savings per Cost	Ex post Savings per Cost	Ex ante Savings per Gross Inc.	Ex post Savings per Gross Inc.	Ex ante % Cons. Saved	Ex post % Cons. Saved	# Measure Classes	# End Uses
TRC	**1**	**0.8**	**0.7**	**0.7**	**0.5**	**0.5**	0.1	0.1	-0.1	-0.1
PAC	**0.8**	**1**	**0.9**	**0.9**	**0.6**	**0.6**	0.0	0.0	-0.1	0.0
Ex ante Savings per Cost	**0.7**	**0.9**	**1**	**1.0**	**0.7**	**0.6**	0.0	0.1	-0.1	0.0
Ex post Savings per Cost	**0.7**	**0.9**	**1.0**	**1**	**0.7**	**0.7**	-0.1	0.0	-0.2	-0.1
Ex ante Savings per Gross Inc.	**0.5**	**0.6**	**0.7**	**0.7**	**1**	**1.0**	-0.1	0.0	-0.3	-0.2
Ex post Savings per Gross Inc.	**0.5**	**0.6**	**0.6**	**0.7**	**1.0**	**1**	-0.2	0.0	-0.3	-0.2
Ex ante Savings Achieved	0.1	0.0	0.0	-0.1	-0.1	-0.2	**1**	**0.8**	0.1	0.0
Ex post Savings Achieved	0.1	0.0	0.1	0.0	0.0	0.0	**0.8**	**1**	0.0	0.0
# Measure Classes	-0.1	-0.1	-0.1	-0.2	-0.3	-0.3	0.1	0.0	**1**	**0.8**
# End Uses	-0.1	0.0	0.0	-0.1	-0.2	-0.2	0.0	0.0	**0.8**	**1**

PCA itself was also used as another method to confirm the three groupings of the effectiveness metrics. The ten effectiveness metrics were input into a single PCA. Table 3-1 above shows the eigenvalue PCA table. The first three PCs satisfied the Kaiser criterion (eigenvalue greater than one) with eigenvalues of 4.7, 2.0, and 1.7. Cumulatively, the first three PCs represent 84% of the data's variability, surpassing the minimum 70% threshold. Inspection of the scree plot (Figure 3-1 shows a large drop after PC1, and then a second drop after PC3. These results suggest keeping PCs 1, 2, and 3. However, when we review the Factor Pattern (Table 3-4), we find areas of concern for our analysis.

Table 3-4: Factor Pattern of PC1, PC2, and PC3

Input Variables	PC1	PC2	PC3
# Measure Classes	-0.4	**0.6**	**0.6**
# End Uses	-0.3	**0.5**	**0.8**
Ex ante Savings Achieved	-0.3	**0.8**	-0.5
Ex post Savings Achieved	-0.1	**0.8**	-0.6
TRC	**0.8**	0.2	-0.1
PAC	**0.9**	0.2	0.1
Ex ante Savings per Cost	**0.9**	0.2	0.1
Ex post Savings per Cost	**0.9**	0.1	0.1
Ex ante Savings per Gross Inc.	**0.9**	0.1	0.0
Ex post Savings per Gross Inc.	**0.9**	0.0	0.0

From the factor pattern we see that the six cost effectiveness metrics are positively, highly correlated with PC1 and the savings achieved and technologies addressed metrics are highly correlated with PC2 and PC3. Note that, technologies addressed metrics are positively correlated with PC2 and PC3, while savings achieved metrics are positively correlated with PC2 but negatively correlated with PC3. The negative correlations in the factor pattern cause concern with this PCA approach. Imagine we used PC1 as a measure of program success. The negative correlations associated with the depth of retrofit metrics would cause counter-intuitive results. Given two programs that perform equally well on the cost effectiveness metrics, the program that performed *worse* on the depth of retrofit metrics would score *higher* in PC1. This approach would bury the programs that do well on all accounts.

Further inspection of the factor pattern leads to the same three groupings as identified from the correlation matrix (cost effectiveness, technologies addressed, and savings achieved). The cost effectiveness metrics load strongly on PC1. Suggesting that the cost effectiveness metrics have a clear and distinct pattern from the depth of retrofit metrics. Both technologies addressed and savings achieved load onto PC2 and PC3. However both load positively on PC2, and only technologies addressed loads positively on PC3. The PC2 and PC3 eigenvalues are fairly similar in magnitude (2.0 and 1.7), meaning that PC2 and PC3 each capture a relatively equal amount of variability. This leads to the conclusion that about half the time technologies addressed trends with savings achieved and the other half of the time it is anti-correlated. Overall technologies addressed and savings achieved also have a clear and distinct pattern from each other as well as different from cost effectiveness. For these reasons, with support from the correlation matrix, we used three separate PCAs for creation of the final effectiveness metric.

3.2.3 PCA Models

The final variable reduction approach included three separate PCA models, once each for cost effectiveness, technologies addressed, and savings achieved.

Cost Effectiveness

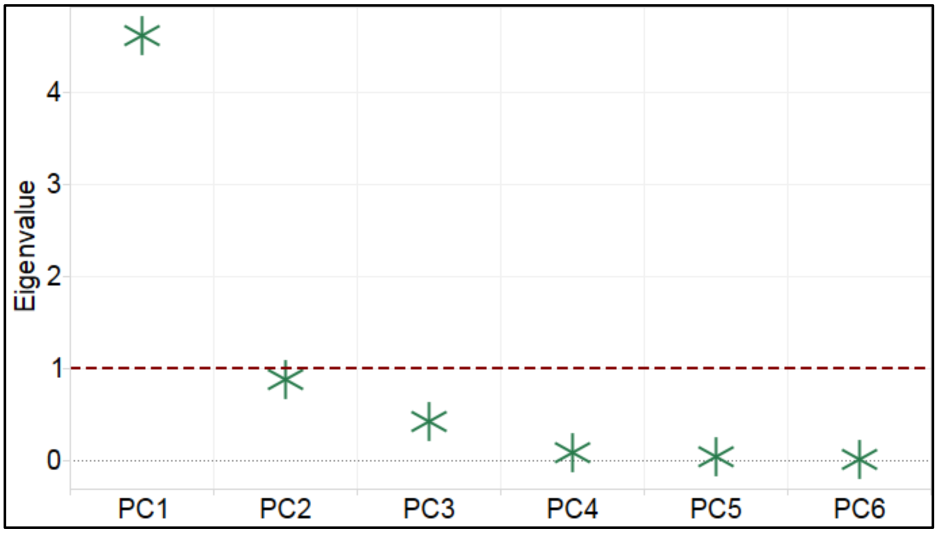
The cost effectiveness PCA consisted of six metrics: TRC, PAC, ex ante savings per gross incentive, ex post savings per gross incentive, ex ante savings per total program cost, and ex post savings per total program cost.

Below is the cost effectiveness eigenvalue PCA table (Table 3-5). PC1 was the only PC to satisfy the Kaiser criterion (eigenvalue greater than one) with a 4.6 eigenvalue. Representing almost 77% of the data's variability it surpassed the minimum 70% threshold. Along with the output from the scree plot (Figure 3-2) where we see a large drop after PC1, the evaluation team kept only PC1 as the measure of cost effectiveness.

Table 3-5: Cost Effectiveness PCA Eigenvalue Table

PC	Eigenvalue	Proportion	Cumulative
PC1	4.6	76.9%	77%
PC2	0.9	14.6%	91%
PC3	0.4	6.9%	98%
PC4	0.1	1.2%	99%
PC5	0.0	0.5%	100%
PC6	0.0	0.0%	100%

Figure 3-2: Cost Effectiveness PCA Scree Plot



The factor pattern (Table 3-6) illustrates the relationship between the input variables and PC1. All of the input variables are highly correlated with PC1. All six input variables measure a similar pattern in the program level data, called cost effectiveness.

Table 3-6: Cost Effectiveness PCA Factor Pattern

Input Variables	PC1	PC2	PC3	PC4	PC5	PC6
TRC	**0.8**	-0.3	0.5	0.1	0.0	0.0
PAC	**0.9**	-0.3	0.0	-0.2	0.0	0.0
Ex Ante Savings per Program Cost	**0.9**	-0.2	-0.2	0.1	-0.1	0.0
Ex Post Savings per Program Cost	**0.9**	-0.2	-0.3	0.1	0.1	0.0
Ex Ante Savings per Gross Incentive	**0.8**	**0.5**	0.0	0.0	-0.1	0.0
Ex Post Savings per Gross Incentive	**0.8**	**0.6**	0.0	0.0	0.1	0.0

Technologies Addressed

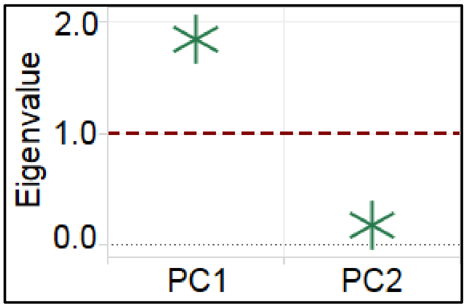
The technologies addressed PCA consisted of two metrics: number of measure classes addressed and number of end uses addressed.

Below is the technologies addressed eigenvalue PCA table (Table 3-7). PC1 was the only PC to satisfy the Kaiser criterion (eigenvalue greater than one) with a 1.8 eigenvalue. Representing 92% of the data's variability it surpassed the minimum 70% threshold. Along with the output from the scree plot (Figure 3-3) where we see a large drop after PC1, the evaluation team kept only PC1 as the measure of technologies addressed.

Table 3-7: Technologies Addressed PCA Eigenvalue Table

PC	Eigenvalue	Proportion	Cumulative
PC1	1.8	92%	92%
PC2	0.2	8%	100%

Figure 3-3: Technologies Addressed Scree Plot



The factor pattern (Table 3-8) illustrates the relationship between the input variables and PC1. Both input variables are highly correlated with PC1. Both input variables measure a similar pattern in the program level data, called technologies addressed.

Table 3-8: Technologies Addressed Factor Pattern

Input Variables	PC1	PC2
Measure Class per Site	1.0	0.3
End Use per Site	1.0	-0.3

Savings Achieved

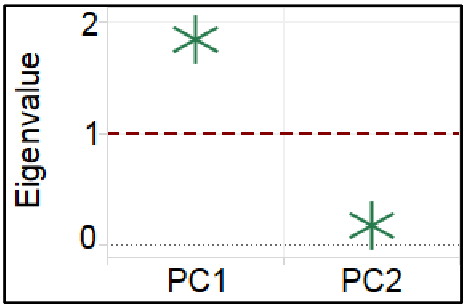
The savings achieved PCA consisted of two metrics: ex ante savings achieved and ex post savings achieved.

Below is the savings achieved eigenvalue PCA table (Table 3-9). PC1 was the only PC to satisfy the Kaiser criterion (eigenvalue greater than one) with a 1.8 eigenvalue. Representing 92% of the data's variability it surpassed the minimum 70% threshold. Along with the output from the scree plot (Figure 3-4) where we see a large drop after PC1, the evaluation team kept only PC1 as the measure of savings achieved.

Table 3-9: Savings Achieved PCA Eigenvalue Table

PC	Eigenvalue	Proportion	Cumulative
PC1	1.8	92%	92%
PC2	0.2	8%	100%

Figure 3-4: Savings Achieved Scree Plot



The factor pattern (Table 3-10) illustrates the relationship between the input variables and PC1. Both input variables are highly correlated with PC1. Both input variables measure a similar pattern in the program level data, called savings achieved.

Table 3-10: Savings Achieved Factor Pattern

Input Variables	PC1	PC2
Ex Ante Savings Achieved	1.0	0.3
Ex Post Savings Achieved	1.0	-0.3

3.2.4 Combined Score

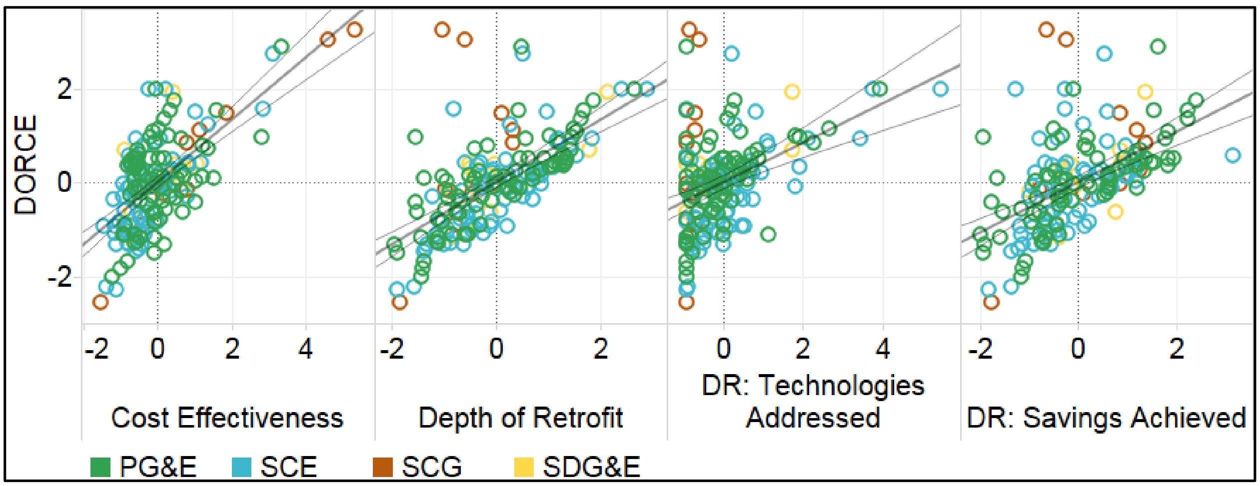
The evaluation team combined the three PCs from the cost effectiveness, technologies addressed, and savings achieved PCAs by the following steps.

1. Set Depth of Retrofit (DOR) = average(Technologies Addressed PC1, Savings Achieved PC1)
2. Standardize DOR to have a mean of zero and standard deviation of one
3. Set DORCE = average (DOR, cost effectiveness PC1)
4. Standardize DORCE to have a mean of zero and a standard deviation of one

This essentially gave weightings of 1/2 to cost effectiveness, 1/4 to technologies addressed, and 1/4 to savings achieved. Technologies addressed and savings achieved each got 1/4 weightings since each represent a different facet of depth of retrofit. Equal weightings were desired for depth of retrofit and cost effectiveness.

The four scatterplots in Figure 3-5 below show the relationships between the final program effectiveness metric (DORCE) and the components of that metric. Each circle represents a program and its color indicates the PA. Programs are plotted by their DORCE score (y-axis) against their cost effectiveness, depth of retrofit, technologies addressed, or savings achieved scores (x-axes). Linear trend lines, along with 95% confidence bands, are also included in each graphic. A few specific observations from the figure stand out. The figure illustrates how each individual component is positively correlated with the final program effectiveness metric, DORCE. It also shows how each of the depth of retrofit metrics (technologies addressed and savings achieved) are positively correlated with DORCE. This illustrates how DORCE rewards programs that achieved high cost effectiveness and high depth of retrofit. Whereas if a program did well in one area and not the other then a program would end up scoring somewhere in the middle on DORCE.

Figure 3-5: DORCE Relationship to Cost Effectiveness and Depth of Retrofit PCs



4

Modeling Program Effectiveness by Program Features

Having developed the comprehensive analysis dataset, and having developed the DORCE metric via principal components analysis, the structure was in place to view programs and the overall portfolio in terms of DORCE. As mentioned in the introduction of this report, the evaluation team engaged in three separate, complementary exercises that each provide actionable feedback on depth of retrofit and cost effectiveness: regression modeling, ranking, and residuals analysis. In this section we cover the regression modeling methods and findings.

4.1 Methods

While it is of interest to explore and compare the performance of each program on the effectiveness metrics developed (see section 5), a task of equal importance is to attempt an understanding of why the programs performed as they did. In this section, we discuss an approach to answer that question. Through regression analysis, we identify which program characteristics are associated with effective outcomes.

Regression analysis is a statistical tool used to estimate the relationships among variables. For instance, in the world of energy demand forecasting, regression techniques could be used to estimate the impact real-world elements, such as the weather or time of day, have on minute-by-minute demand. For our analysis, we modeled the impact various program characteristics have on program cost effectiveness, depth of retrofit, or DORCE score.

Program achievements, regardless of the metric used to gauge or measure them, are inevitably the result of complex, interacting phenomena. Outcomes are a function of various elements of program design and implementation, combined with the specific context of the customer population, economic and demographic dynamics outside the control of the program, weather patterns, and a multitude of other actions and considerations. While it is impossible to tease out all of these dynamics and their influence on a program, we identified measurable program characteristics that could potentially be associated with varying levels of success. These program characteristics are referred to as predictor or independent variables in the regression models. They include a program's target sector, associated building type(s), end use(s), and customer size(s), delivery mechanism, incentive structure, or the program budget areas of concentration.

An important task in regression analysis is model specification. We could theoretically include any and all program characteristics or other variables that come to mind as potentially related to program effectiveness. However, regression models can become over-specified with so many variables that essentially each program has its own predictor variable and no underlying patterns can be detected. To avoid this, we carefully selected program characteristics with known or theoretical relationships to effectiveness. We also leveraged statistical tools, such as adjusted R^2, which estimates the amount of data variability accounted for by the regression model. If the addition of one more predictor variable did not increase adjusted R^2, then we know that the new variable did not add anything substantive to the model, and we might choose to exclude it. Our task was to optimally specify the model by adding independent variable sets until the model approached the ceiling of what can be explained by the model, but without adding variable sets that add complexity without adding to the explanatory power of the model.

It's important to remember, that while we say the modeled variable (e.g., DORCE) is "explained by" the predictor variables, regression can only identify correlations among variables. Correlation does not equal causation. While the predictor variables in the regression models may coincide with high DORCE scores, there is no basis to say, through regression alone, whether those predictor variables caused high DORCE scores. However, a researcher familiar with California's non-residential programs can, in conjunction with independent research, come to educated conclusions regarding causality.

4.1.1 Regression

With the comprehensive analysis dataset and the DORCE metric in place, the regression modeling exercise for this project was a matter of exploring the explanatory power of different variable sets and moving toward an optimally specified model. Nested within that process was an iterative exercise using modeling outcomes to, in some cases, refine and re-characterize how input variables were defined to maximize the clarity of the model. The final model would show the relative magnitude of how differences in various program characteristics are correlated with differences in DORCE score.

As discussed in Section 2 on Data Development, several predictor variables were defined as categorical variables while others were defined as continuous variables. For example, Program Administrator is a categorical variable, with a set of discrete values (PG&E, SCE, SCG, and SDG&E). In contrast, the percentage of a program's participating sites that are considered Very Small (see section 2.4.2) is a continuous variable that can range from 0%-100%. Based on data available in the comprehensive analysis dataset, the categorical variables explored in the modeling process included Sector, GPG, PA, program cycle, and DI program status (DI program status is technically a binary variable with values of Yes and No, but can be considered a categorical variable). The continuous variables explored in the modeling process included percentage-based characterizations of: Customer Size, End Uses Addressed, Building Types Addressed, Incentive

Structure (Deemed or Custom), HTR Participation, DG participation, and Proportions of total program expenditures going to different sub-elements of program cost.

Stepwise Model Specification

The evaluation team used a stepwise, iterative process of building the model. The evaluation team reviewed model results, at each step, including the amount of data variability accounted for in the model (adjusted R^2), and the coefficients associated with each predictor variables. Aside from adjusted R^2, another model characteristic we monitored was the collinearity among predictor variables. A central assumption for linear regression is that the predictor variables are independent (i.e., no multicollinearity). When predictor variables are not independent, the theories behind linear regression no longer hold, and results may not be accurate. Therefore, with each additional predictor variable we added to the model, we checked for multicollinearity. We used a test statistic called tolerance, to check on the degree of collinearity in the model. Each predictor variable included in the model receives a tolerance value. Any value below 0.1 indicates potential multicollinearity among the predictor models. In cases where multicollinearity was suggested, we selected the predictor variable most relevant to our study.

In its first iteration, the model simply included target sector as the sole predictor variable. Then, we sequentially added GPG, Program Administrator, and Program cycle as additional steps in model specification. We noted the resulting influence on adjusted R^2, and chose a final model specification accordingly. While carefully monitoring to account for issues with collinearity, the evaluation team subsequently added variable sets for Customer size, End use, Building type, Percent deemed, DI program status, Percent HTR, Percent DG, and Percent of total program expenditure going to different sub-elements of program cost. As discussed in the Findings Section below, the final model was, based on the evaluation team's judgment, the optimal set of predictor variables with a significant and distinct effect on DORCE outcomes.

Sensitivity Testing

A key element in assessing the validity of a regression model is testing and noting how stable the model is relative to possible changes in the model's specification or in the configuration of the predictor variables. For example, if model outcomes are highly sensitive to different but mutually reasonable ways of defining the predictor variables and/or specifying the model, then it is not considered stable. In these cases, model outcomes are likely sensitive to and driven by specific outliers in the dataset and/or improperly addressed issues of collinearity among predictor variables, rather than robustly capturing and characterizing meaningful relationships among the variables.

The evaluation team employed a number of sensitivity testing elements for model stability. The stepwise model specification approach described above is itself a stability testing exercise, since it looks at the stability of the model relative to the addition of each additional predictor variable.

In that same vein, settling on a final model among a handful of slightly differently specified options in the final modeling stages is a sensitivity testing exercise. In that context one has effectively categorized the predictor variable sets into three groups: those with a significant impact on the modeled outcome metric, the potentially collinear predictor variables from which only one can be chosen for inclusion in the model, and the group of predictor variables whose inclusion or exclusion from the model makes very little difference to the model's overall explanatory power.

The evaluation team also explored the regression model's sensitivity to differences in the approach used to define certain continuous predictor variables. The continuous predictor variables in the model are expressed in terms of percentages, for example the percent of participating sites that are very small. However, the distribution of customer sizes within a program can be characterized either as the percentage of sites that are very small, or the percentage of savings from sites that are very small. As another part of our sensitivity analysis, we reviewed the impact on model results from using these two ways of defining the percentage related predictor variables.

The various sensitivity analyses gave no reasons for concern. As a result, the evaluation team is confident in the final model selection presented in the findings of this report section.

4.2 Findings

Ultimately, we developed five separate final regression models. The sole difference in the construction of these models was the chosen program effectiveness outcome, either DORCE, cost effectiveness, depth of retrofit, technologies addressed, or savings achieved. In this section, we review the regression output of these models, offering a view of the relationships between various program characteristics and program effectiveness scores.

It is also important to note here, at the outset, that some of the value from this modeling work is expected to come from focusing in on peer groups of programs that target similar customer segments, address similar end uses, and/or feature similar aspects of incentive design. That is, the value in looking at the entire portfolio through a commonly defined effectiveness lens is complemented by the value that comes from looking at subsets of programs that share common challenges and opportunities. For example, feedback about program effectiveness may be most relevant in some cases when focusing in on programs that address a specific building type or end use that is known to present challenges from a depth of retrofit and/or cost effectiveness standpoint. In this section of the report we provide an overall view at the portfolio level in terms of regression modeling outcomes. See the subsequent sections on Program Rankings and Residuals (Section 5), for detail that can be used to expressly compare peer programs.

4.2.1 Overall Program Effectiveness Score

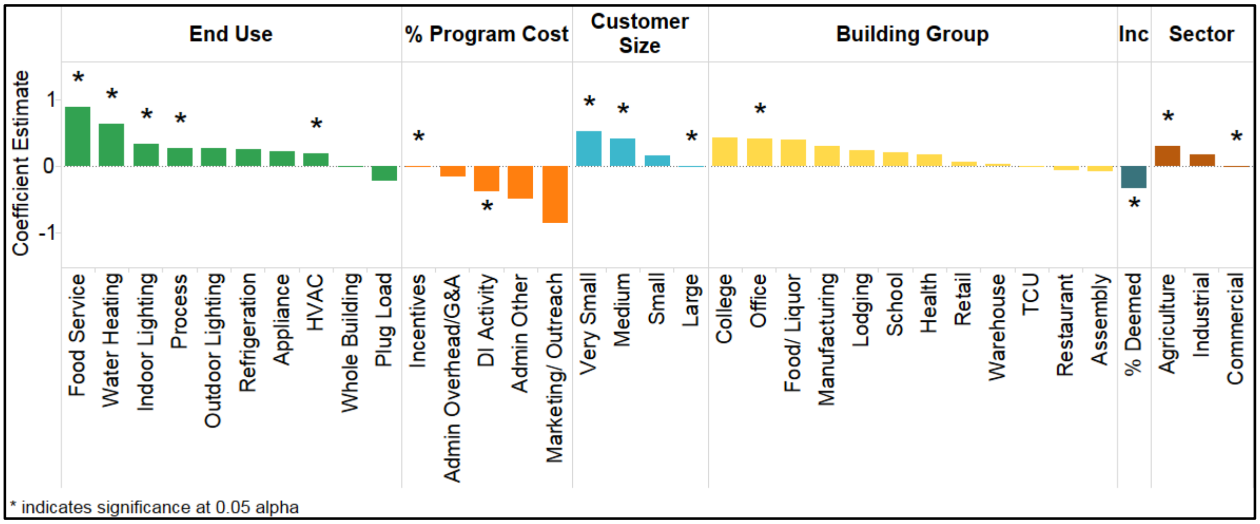
Figure 4-1 below shows the significant drivers of overall program effectiveness scores. The range in height of the bars shows how much the program effectiveness score varies as a function of different elements of program design and focus (i.e., the estimated coefficients). There are a variety of findings to be gleaned from this outcome. In this Section we look at the overall predictor variable sets that significantly influence program effectiveness outcomes. Then in Sections 4.2.2 and 4.2.3 we look deeper into the roles played specifically by the depth of retrofit scores and the cost effectiveness scores, respectively, in driving overall program outcomes.

A note on interpreting regression coefficients:

For color groupings such as Sector in Figure 4-1 below (as well as for all figures in Section 4.2), one of the values is arbitrarily assigned a coefficient estimate of zero, and the other values are defined in relation to that zero value. Hence, Commercial has been assigned a coefficient estimate of zero, and the coefficient estimates for other sectors are relative to that zero value. If, instead, Agriculture had been assigned a coefficient estimate of zero, then the whole group of coefficient values for sector would be shifted downward, but their relative relationships to each other would be preserved.

Because of this, coefficient estimates can be meaningfully compared across the values within a given color grouping. Coefficient estimates can also be meaningfully compared across color groupings in terms of the ***range*** *in coefficient magnitude (for example, End Use has a slightly greater range in coefficient estimates than % of Program Cost). However, it is not meaningful to draw conclusions across color groupings in terms of vertical shift based on which value in a given color grouping has arbitrarily been assigned a value of zero.*

Figure 4-1: Overall Program Effectiveness (DORCE) Significant Coefficients



The first observation of note from Figure 4-1 above is that variation in a program's focus on end use has significant impact on program effectiveness score. Specifically, while accounting for various other elements of program design, a focus on food service yields the highest effectiveness outcomes, while a focus on plug loads yields the lowest effectiveness outcomes. Water heating, indoor lighting, and process efficiency also stand out as positively correlated with program effectiveness.

Variation in a program's focus on customer size is also significantly correlated with effectiveness outcomes. While we don't see a statistical difference across customer size in terms of cost effectiveness, programs addressing large customers don't achieve proportional savings reductions on the same scale as those addressing smaller customers. As a result, programs focusing on smaller customers fare better than programs focusing on larger customers from an overall DORCE effectiveness standpoint. It is worth noting that, while a focus on very small customers (see section 2.4.2 for size definition) is most positively correlated with high DORCE scores, a focus on medium size customers comes in second place, followed by small and then large customers. See sections 4.2.2 and 4.2.3 for a discussion of the relative contributions to depth of retrofit and cost effectiveness scores, as well as other program characteristics that are relevant to this observed pattern.

Looking at building type, a focus on colleges/universities, offices, and food/liquor stores is associated with the highest effectiveness scores relative to other non-residential building types. This is particularly interesting given that one might think that generating high savings achieved is challenging in a large campus setting such as colleges and universities. Building types associated with low effectiveness include TCU, restaurant, and religious/public assembly.

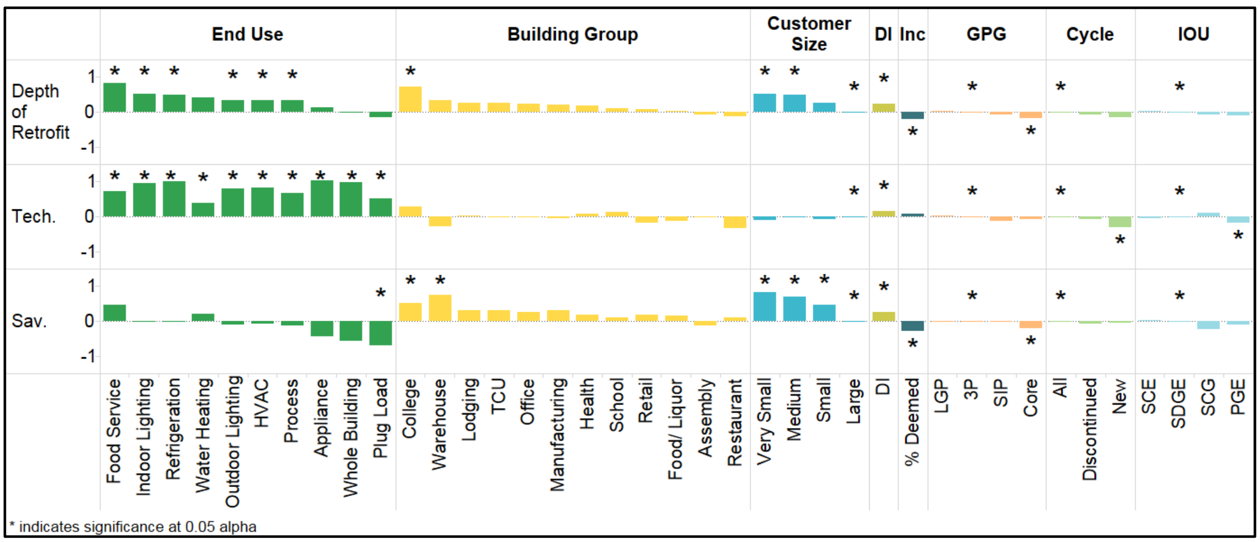
A program's target sector is also significantly correlated with its effectiveness score. While accounting for other elements of program design in the model, programs that target the agricultural sector have the most positive effectiveness outcomes, followed by the industrial sector. Programs that target commercial buildings are associated with lower effectiveness scores.

The degree to which a program includes deemed versus custom measures is significantly associated with DORCE score. Programs with a higher proportion of deemed measures generally fare worse than programs with a higher proportion of custom measures.

4.2.2 Depth of Retrofit Score

As mentioned previously, overall program effectiveness is evaluated in this study via the DORCE score that is equal parts depth of retrofit and cost effectiveness. In this section we look more narrowly at the depth of retrofit side of this equation. We look at how various aspects of program focus and design are associated with the depth of retrofit score, both in terms of the number of technologies addressed as well as in terms of savings achieved. Figure 4-2 below shows how different variable sets drive the depth of retrofit score in terms of its inputs.

Figure 4-2: Depth of Retrofit Significant Coefficients



Several observations are apparent from looking at Figure 4-2 above. The first is that depth of retrofit as measured by number of technologies addressed (middle row) shows a somewhat different pattern of association with various program characteristics than depth of retrofit as measured by savings achieved (bottom row).

As discussed in Section 3.2, depth of retrofit as measured by number of technologies addressed is effectively non-correlated with depth of retrofit as measured by savings achieved. This is an interesting and important finding from the analysis. Going after a larger number of end uses does not correlate with achieving a greater reduction in total energy consumed, on average. One likely interpretation of this is that more narrowly targeted programs, those that predominantly address a single end use, may also be typically targeting those end uses where a relatively high percentage reduction in total energy consumption is most achievable.

An illustrative example of differences between number of end uses and percentage reduction in energy consumption is customer size (column 3). A focus on smaller customers generally tracks positively with increasing savings achieved, while it generally tracks negatively with number of technologies addressed. This makes intuitive sense, since it’s likely easier on average to achieve high savings in, for example, a small hotel or motel, whereas a large industrial customer may provide an easier context for a high number of end uses and measure classes but a bigger challenge for savings achieved relative to total consumption. Since this customer size dynamic is more dramatic for savings achieved as shown by the larger bars, the overall depth of retrofit story (top row) closely mirrors the pattern for savings achieved.

Another illustrative example is the proportion of program measures that with incentive structures that are either deemed or custom (Column 4). On average, programs with a higher proportion of deemed measures are associated with a higher number of technologies addressed. By contrast, these same programs on average achieve lower savings achieved than programs that predominantly feature custom measures. The overall depth of retrofit score (top row) associated with this variable set shows a positive association with higher proportion of deemed measures. This serves as corroboration that custom measures, which by their nature are customized to the specific needs and circumstances of a participating site, generally achieve greater percentage reduction in overall energy usage than deemed measures do. Deemed measures tend to be applied somewhat more broadly than custom measures, but this broader application does not, on average, deliver greater percentage reductions in energy use.

There are also several variable sets where depth of retrofit as measured by number of technologies addressed follows a similar pattern to depth of retrofit as measured by savings achieved.

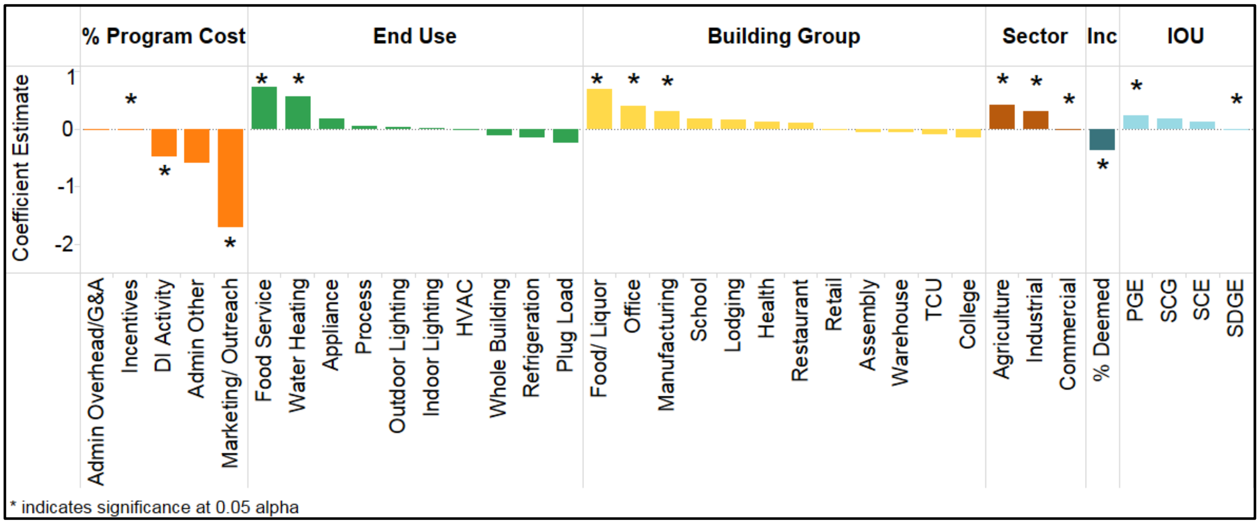
The modeling team also included Program Cycle as a variable in the regression model. It is worth noting that, on average, programs that were in existence in the 2010-2012 program cycle but that were discontinued at some point before 2014 fared somewhat better than programs that were new in 2013-2014 or that existed throughout the entire study period. Note that otherwise well-designed, programs, with good depth of retrofit and/or cost effectiveness, may have been phased out in some cases simply due to lack of adequate participation.

Gross Program Group is also a statistically significant driver of depth of retrofit. However, the degree to which GPG is associated with differences in effectiveness score is quite small relative to some other variable sets. Within that context, State Institutional Partnerships (SIP) score highest, followed by Third Party (3P) implemented programs, Local Government Partnerships (LGP), and lastly Core programs.

4.2.3 Cost Effectiveness Score

The regression model built specifically around program cost effectiveness serves as a useful standalone outcome from the regression effort. It also provides useful perspective on the cost effectiveness component of overall DORCE score. As shown in Figure 4-3 below, the proportion of program costs going toward various sub-elements of program expense has the largest magnitude impact on cost effectiveness. Specifically, programs putting a significant proportion of total dollars into marketing and outreach efforts are, on balance, less cost effective than those with a low investment in that area. The useful message from this finding is not necessarily that marketing and outreach expenses should be minimized. Rather, they should be cautiously and strategically applied, with the awareness that a large marketing outlay may do much more to increase program costs than it does to increase program savings. When trying to optimize marketing expense in the design of a given program it is a good idea to look at high ranking programs from this analysis that have a similar basic design and explore how they may have made optimal use of marketing dollars. It's possible that programs which are not getting enough participation end up pouring larger amounts of money into marketing. In either case, it's important for PA's to keep in mind that increasing marketing dollars might degrade cost effectiveness, and they should weigh competing priorities when making any increased marketing decisions. Similarly, it is a good idea to look at similar programs that have high residuals specifically with respect to cost effectiveness and/or to DORCE score overall. These are programs that have beaten the model's expectations based on their characteristics and may offer useful ideas.

Figure 4-3: Cost Effectiveness Coefficients

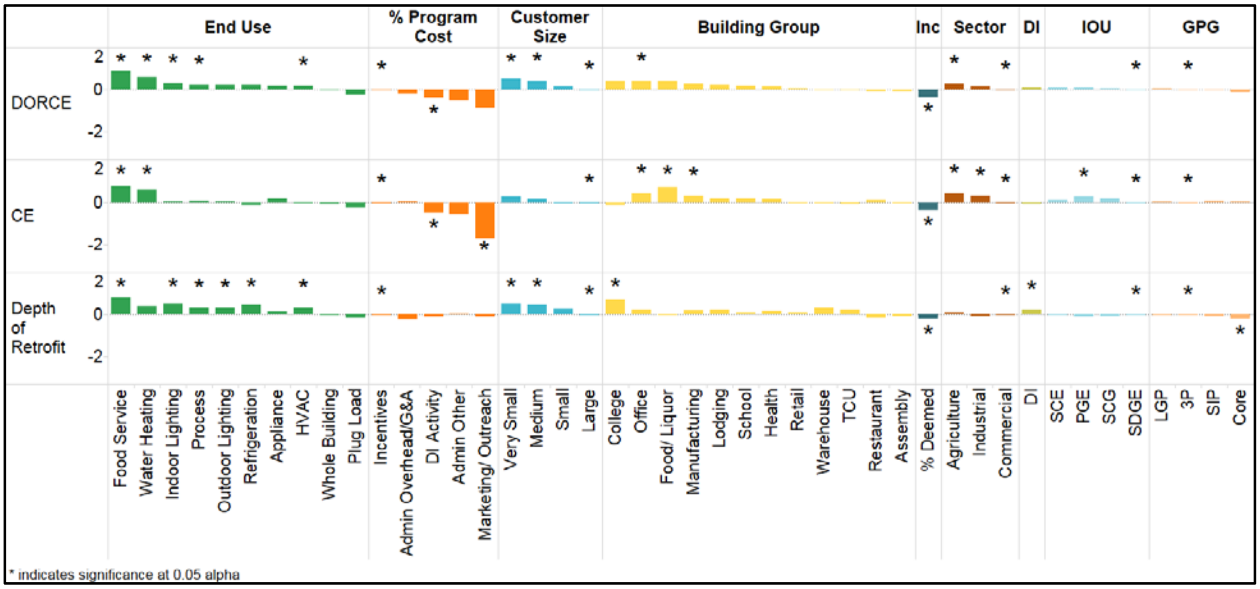


Second to sub-elements of program cost, the focus of programs by end use also has significant impact on cost effectiveness. Similar to overall DORCE score, programs that focus on food service and water heating tend to be particularly cost effective, while those focusing on plug loads stand out as ineffective from a cost standpoint. Building group is the next most significant predictor variable set, with programs focusing on food/liquor, offices, and manufacturing standing out in a positive cost effectiveness sense, and those focusing on TCU and colleges standing out somewhat negatively. Interestingly, colleges are near the top of the overall DORCE score, so their achievements in terms of depth of retrofit (DOR) effectively outweigh their relatively poor cost effectiveness. On balance, Programs focused on the agricultural and industrial sectors tend to be more cost effective than those focused on the commercial sector. Also, programs featuring custom measures are generally more cost effective than those featuring deemed measures. Among the program administrators, PG&E's programs are overall most cost effective, followed by those of SCG, SCE, and SDG&E after other characteristics driving cost effectiveness have been accounted for in the model.

4.2.4 Putting It All Together

Having walked through the regression model findings focused separately on depth of retrofit (DOR) and focused on cost effectiveness (CE), it is informative to look at the overall DORCE model again from the perspective of how the components contribute to the whole. Figure 4-4 below shows overall DORCE coefficient values as well as DOR and CE coefficient values for each variable set that was statistically significant in at least one of the three models.

Figure 4-4: DORCE, Cost Effectiveness, and Depth of Retrofit Significant Coefficients



There are a variety of interesting findings to be gleaned from this figure. The most prominent of these findings, and a central and important outcome of this research, is that in overall terms, depth of retrofit and cost effectiveness are meaningfully different. Though various sub components of the DOR and CE comparison within variable sets show similarities of different types and strengths, the overall message is that the paths taken to achieve greater depth of retrofit, on average, are not always accompanied with lower program cost effectiveness. This is surprising and counter-intuitive, and it yields a series of potentially useful insights about program and portfolio design.

End Use

In particular, the regression coefficients provide a map for where high levels of depth of retrofit may be achieved while nevertheless achieving average or even better than average cost effectiveness. Based on the 163 programs included in the analysis dataset, programs that target food service as an end use have performed better than their peers from both a depth of retrofit and cost effectiveness perspective.

Programs that target water heating have also performed better than their peers from both a depth of retrofit and cost effectiveness perspective, although they do not fare as well on depth of retrofit as those focusing on food service.

Program Cost Allocation

Another potential opportunity to achieve better than average depth of retrofit while also achieving high cost effectiveness lies in the proportional allocation of total program costs across various categories of expense such as incentives, DI activity, administrative costs, and marketing/outreach. All other things being equal, the regression models suggest that programs with a higher proportion of total program costs going toward incentives may fare better than their peers for both DOR and CE. Whereas cost effectiveness, as discussed previously, appears sensitive to marketing and outreach expenditures, DOR shows a more subdued response to all elements of program cost. The overall DORCE score therefore closely reflects the CE scores. It is important to note that, although a high proportion of expenditure on marketing and outreach correlates with low DORCE scores, this does not necessarily indicate causation. That is, it is possible that low program performance as captured in the low DORCE score for these programs may have motivated a high investment in marketing and outreach in response.

Customer Size

Importantly, a program's focus on customers of different size appears to have a significant impact on DORCE scores, and the finding likely runs counter to expectations for some people. Again, the patterns observed here may point the way to elements of the energy efficiency landscape where above-average depth of retrofit can be achieved while also achieving above-average cost effectiveness. Focusing on very small customers (<40 MWh or 8.5 Giga-therms annual consumption), on average, has yielded the best depth of retrofit outcomes while also yielding the best cost effectiveness outcomes. Similarly, focusing on medium size customers (300 to 1,740 MWh or 150 to 245 Giga-therms annual consumption) has yielded significantly above average depth of retrofit outcomes as well as above average cost effectiveness outcomes.

Building Type

A program's focus on one or more building types is also significantly correlated with DOR and CE outcomes, and therefore overall DORCE score. As with the other program descriptors discussed above, there may be opportunity to achieve both depth of retrofit objectives and cost effectiveness objectives by observing the ways in which the factors move in relation to each other. Programs focusing on colleges/universities generally experience excellent depth of retrofit outcomes, and these drive these programs to the highest DORCE scores among all building types, despite lower than average cost effectiveness. Programs focusing on offices and programs focusing on manufacturing generally score average on DOR, but they score above average on cost effectiveness, which drives above-average overall DORCE scores for these building types. Programs focusing on lodging generally experience the reverse; that is, they perform above average on DOR while coming in average (and therefore not penalized) on the cost effectiveness side. Programs focusing on food/liquor stores stand out for their cost effectiveness, which drives above average DORCE scores despite lower than average results for depth of retrofit.

Incentive Structure

Interestingly, programs with a greater focus on custom measures relative to deemed measures tend to score better for both cost effectiveness and depth of retrofit.

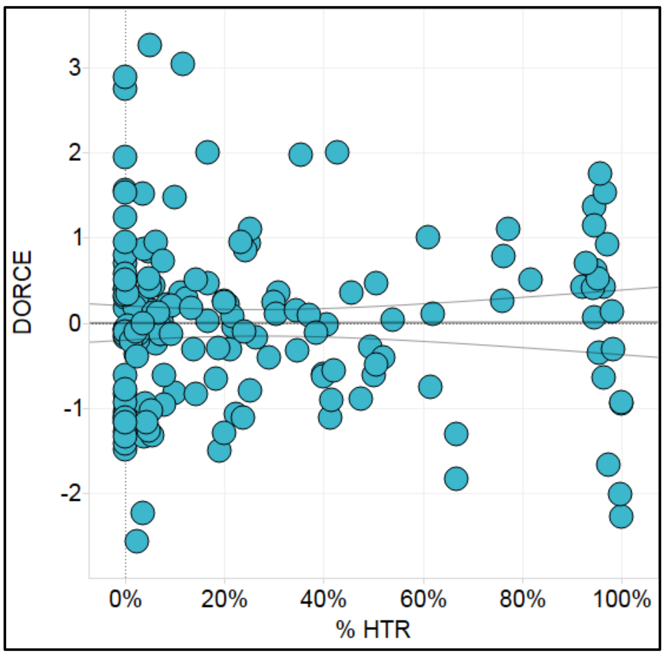
Sector

Programs focused on the agricultural sector perform better than average for cost effectiveness, while there is no statistically significant difference in depth of retrofit across sectors. Programs focused on the industrial sector show a similar pattern

Hard to Reach

It's of interest to note that the percent of participants within a program that are HTR was not a significant factor in any model. Figure 4-5 illustrates this concept, through a scatter plot of each program by their DORCE score and percentage of participants that are HTR. A simple linear regression trend line shows that there is no correlation between DORCE and HTR. In fact, there are quite a few programs that are entirely HTR which perform above average (DORCE = 0) on the DORCE metric.

Figure 4-5: Programs by DORCE Score and Percentage HTR



Additional Factors

While programs with a higher focus on direct install measures generally achieve greater depth of retrofit, this is paired with slightly lower than average cost effectiveness and does not yield a significant correlation with overall DORCE scores. Program administrator is similarly not significantly correlated with overall DORCE scores, though PG&E is associated with the highest overall cost effectiveness scores. Lastly, GPG is not significantly associated with overall DORCE scores, though Core programs stand out as the lowest among GPGs in terms of depth of retrofit.

5

Program Rankings and Residuals

In Section 4 we explored associations between general program design elements and DORCE score, as well as the relationship of those elements to the distinct components of DORCE score. In this section we shift focus and look at outcomes from the perspective of individual programs in terms of rank-ordered DORCE score and the distinct components of DORCE score. We also tie back to the regression models by revisiting the particular areas in the portfolio where cost effectiveness and depth of retrofit scores trend together, and we note specific programs that exemplify this trend.

We also review to what extent our regression models were able to predict the achieved DORCE scores. Using residuals (the difference between the observed and predicted DORCE value), we are able to identify programs that scored notably higher or lower than our models predicted. These programs perform in manners not explained by the modeled variables. Throughout our discussion of program rankings in this section, we will also examine the relationship between a program's overall ranking and residual. We will call out programs with large magnitude residuals from the high-, middle-, and low-scoring groups of programs in the overall ranking, as each of these groups tells a different story of program effectiveness and possible areas for improvement in portfolio design.

The scope of the ranking effort in the current reporting phase (Phase I) includes highlighting specific standout programs and making note of patterns in their DORCE rankings and residuals rankings. In Phase II of this research effort (scheduled for completion October 2016), Itron will provide additional detail on notably high- and low-scoring programs based on a careful review of the program implementation plans (PIPs), monthly reports, detailed tracking data, and other available data sources. This analysis will help fill in the picture of what may be driving high and low DORCE scores. We also recommend conducting process evaluation, including interviews with program managers, program implementers, and program participants, to further identify and characterize program features and actions that may be driving standout DORCE scores.

5.1 Methods

As described in Section 3, DORCE score is the combination of technologies addressed, savings achieved, and cost effectiveness metrics developed using PCA. Each program was assigned a DORCE ranking by sorting all 163 programs in descending DORCE order. The program was the highest DORCE score was given rank 1, and the program with the lowest score was assigned rank 163 (programs with equal DORCE scores were assigned the same rank). In a similar manner, programs were also assigned a ranking for technologies addressed, savings achieved, and cost effectiveness.

The residuals from each regression model (DORCE, technologies addressed, savings achieved, and cost effectiveness) were also ranked from 1 to 163. Residuals represent the difference in predicted score that cannot be explained by the model. We can interpret a program associated with a high residual as a program that performed above modeled expectations. There is some aspect contributing to the program's success that has not been accounted for in the model. Similarly, a program with a low residual can be said to have performed below modeled expectations. Note that when reviewing residuals we do not expect to see any patterns when comparing residuals to any of the program characteristics included in the model. They have already been controlled for in the regression model.

To understand the program rankings and residuals, the entire portfolio was ordered by DORCE ranking, while also showing each program's rank on the elements that contribute to DORCE. In this way, the ranking by DORCE is accompanied by a clear illustration of the degree to which technologies addressed, savings achieved, and cost effectiveness have served as the key drivers of overall DORCE score. The programs residual rankings in each regression model (DORCE, technologies addressed, savings achieved, and cost effectiveness) is also included in this view to incorporate an understanding of whether the characteristics included in our models predicted these rankings or if the program performed in unexpected ways.

As a reminder, Section 2 on data development notes data limitations and analytical decisions made in developing the comprehensive dataset. There are inherent challenges in site aggregation, matching program savings claims to customer billing accounts in some cases, and ex post savings availability. The evaluation team has taken steps to mitigate these inaccuracies or potential biases where we found it possible.

5.1.1 Interpretation

When reviewing the ranking results, it's important to keep in mind the methods behind the development of the DORCE scores and rankings. Inherent to the development of the DORCE scores through PCA is its comparative nature. PCA results in a new metric which is standardized to have a mean of zero and standard deviation of one. Therefore, the DORCE score is specific to the set of programs included in the analysis. The DORCE score is not a universal metric, but is subject to change depending on each new program year and program. This also means that all scores and interpretations of high or low performance are relative to the specific set of programs. A program is said to perform poorly because it performs worse than other programs in the portfolio. However, this poorly performing program, could be achieving objectively reasonable results.

Any easy illustration of this idea is to review program performance by TRC. The table below displays a list of 21 programs with cost effectiveness scores in the bottom third of scores, however their associated TRC is above 1.0. Typically, we would think of a program with TRC above one as performing adequately. However, in the framework we have setup, these programs are considered poor CE performers, regardless of their acceptable TRCs.

Table 5-1: Programs with Low CE Rank and TRC above One

Itron Program ID	Itron Program Name	CE Rank	TRC
PGE211007	ASSOCIATION OF MONTEREY BAY AREA GOVERNMENTS (AMBAG)	109	1.1
PGE211015	NAPA COUNTY	110	1.2
PGE211011	KERN	111	1.4
PGE210128	ENOVITY SMART	112	1.5
PGE211024	SAN FRANCISCO	113	1.3
PGE211021	SIERRA NEVADA	114	1.1
PGE211023	SILICON VALLEY	116	1.1
PGE211019	SAN MATEO COUNTY	117	1.1
PGE210118	FURNITURE STORE ENERGY EFFICIENCY	119	1.3
PGE210119	LED ACCELERATOR	120	1.5
PGE211016	REDWOOD COAST	122	1.0
PGE21006/PGE21015	COMMERCIAL HVAC	123	1.3
SCE-TP-037	Private Schools and Colleges Program	126	1.4
PGE211014	MENDOCINO COUNTY	127	1.0
PGE211018	SAN LUIS OBISPO COUNTY	128	1.1
SDGE3224	SW-COM-DEEMED INCENTIVES-HVAC COMMERCIAL	131	1.3
SCE-13-SW-002D	COMMERCIAL DIRECT INSTALL PROGRAM	132	1.4
PGE210125	CALIFORNIA PRESCHOOL ENERGY EFFICIENCY PROGRAM	134	1.1
SCE-13-SW-005B	LIGHTING INNOVATION PROGRAM	137	1.2
SCE-13-TP-017	ENERGY EFFICIENCY FOR ENTERTAINMENT CENTERS	144	1.1
SDGE3226	SW-COM DIRECT INSTALL	145	1.1

5.2 Findings

If the DORCE metric is successfully pointing in desired directions for program outcomes, then a rank-ordered listing of all programs by that metric can identify specific programs that stand out relative to their peers. The rank ordered listing of all 163 programs by DORCE score is shown in Table 8-4 in the appendix. Alongside the rankings for DORCE score in that table, the program rankings are also shown distinctly for cost effectiveness, depth of retrofit, technologies addressed, and savings achieved. In addition, program rankings are shown in that table for DORCE score residuals, as well as the residual rankings distinctly for cost effectiveness, depth of retrofit, technologies addressed, and savings achieved. Taken together, this full set of rankings offer a detailed yet concise summary of relative program achievements and key components of those achievements for all 163 programs included in the analysis. Note that any subsets of this rank ordering, such as focusing on third party-implemented programs that focus on small restaurants, can serve to identify specific programs that stand out relative to their peers, however the user chooses to define the comparison.

5.2.1 Pathways to DORCE

An observation that is immediately apparent from reviewing Table 8-4 is that there are a few main patterns with regard to high DORCE-scoring programs in terms of their component rankings for cost effectiveness and depth of retrofit. These can be regarded as "pathways" to high DORCE scores:

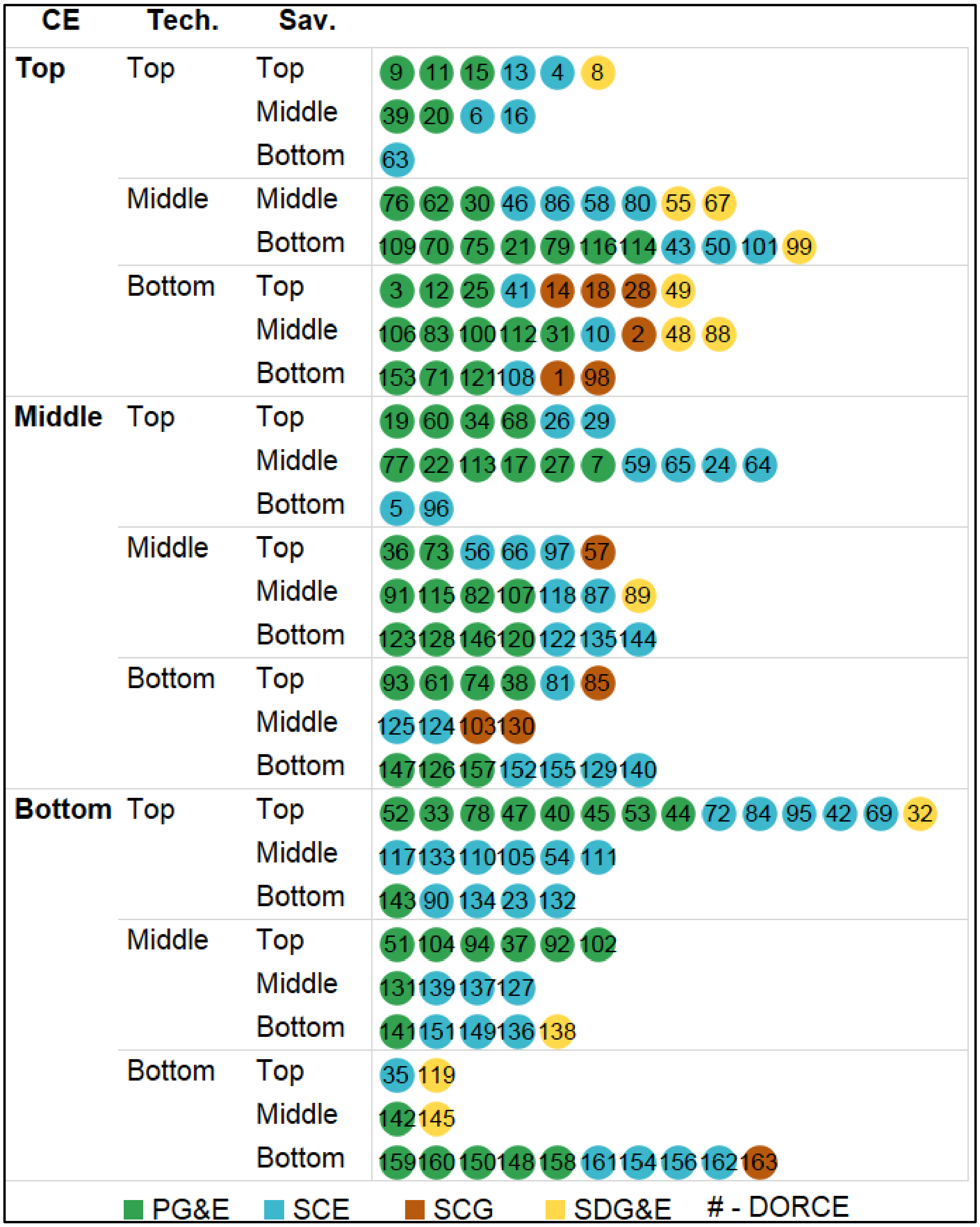
- Pathway #1 ("High CE"): Extremely high cost effectiveness
- Pathway #2 ("High DOR"): Extremely high depth of retrofit
- Pathway #3 ("High CE+DOR"): Notably high cost effectiveness and depth of retrofit

We make reference to each of these pathways in this section. Of the top 20% of programs by DORCE score, approximately equal numbers of programs follow each of these three pathways to a high DORCE score.

All 163 programs included in the analysis are shown in Figure 5-1 below, with respect to their performance on the cost effectiveness metric (CE), technologies addressed metric (Tech.), and savings achieved metric (Sav.). Each circle corresponds to a program, and is labeled with its DORCE ranking. To generate this graphic each program was identified as being in the top third, the middle third, or the bottom third in the rank order of scores for a given metric. As can be seen in the figure, six programs scored in the top third of programs for cost effectiveness, as well as for both the Technologies Addressed and the Savings Achieved parts of the depth of retrofit score. Another six programs were in the middle third of programs for cost effectiveness but in the top third of programs for both technologies addressed and savings achieved. The most populous group based on this type of categorization, with 14 programs, is those in the bottom third for cost effectiveness but in the top third for both technologies addressed and savings achieved. There were 10 programs that scored in the bottom third for all three components of the DORCE score.[20]

[20] See Appendix 8.4 for the full listing of program name and program ID by DORCE ranking

Figure 5-1: Programs by DORCE Ranking Components Third



5.2.2 Gas Targeting Programs

Notably, from an overall DORCE ranking perspective, the three top DORCE scoring programs included in the analysis are all gas-focused programs. SCG's Industrial Deemed Incentives program, SCG's Industrial Calculated Incentives program, and PG&E's Enhanced Automation Initiative are all gas-focused programs that perform exceptionally well on the DORCE metric. The two SCG programs follow the high DORCE score pathway of extremely high cost effectiveness

"High CE", while PG&E's Enhanced Automation Initiative follows the "High CE+DOR" pathway, since it scores in the top third of all programs for both cost effectiveness and depth of retrofit.

Alongside their high DORCE scores, each of these programs also has a high DORCE residual, scoring in the top third of program residuals overall. Notably, all three programs are in the top third for their CE residual, and PG&E's Enhanced Automation Initiative is also high ranking for its DOR residual. This means all three of these programs are outperforming what the regression model would predict, based on the overall features of the program, especially in terms of cost effective savings.

Table 5-2: Top Three DORCE Programs

Itron Program ID	Itron Program Name	Fuel Target	Rank			Residual Rank		
			DORCE	CE	DOR	DORCE	CE	DOR
SCG3716	SW-IND-DEEMED INCENTIVES	Gas	1	1	138	2	1	110
SCG3715	SW-IND-CALCULATED INCENTIVES	Gas	2	2	114	54	35	118
PGE21019	ENHANCED AUTOMATION INITIATIVE	Gas	3	3	51	1	2	3

Looking specifically at TRC and PAC scores, these three programs score at or near the top of the entire portfolio for one or both of these cost effectiveness metrics.

Table 5-3: Details on Top Three DORCE Programs

Itron Program ID	Itron Program Name	Sector	GPG	Incentive Structure	Reported TRC	Reported PAC
SCG3716	SW-IND-DEEMED INCENTIVES	Industrial	Core	Deemed	4.40	6.07
SCG3715	SW-IND-CALCULATED INCENTIVES	Industrial	Core	Custom	2.74	7.38
PGE21019	ENHANCED AUTOMATION INITIATIVE	Commercial	3P	Custom	4.15	4.83

Based on the exceptional performance of these programs, Itron recommends that program planners look expressly at particular avenues of unrealized opportunity for cost effective gas savings. In addition to the three top scoring programs noted here, there are an additional 12 programs in the top 20% of overall programs by DORCE score that are either gas-focused or both gas- and electric-focused. Using these 15 programs and the most recent gas savings potential study as reference points, Itron recommends that PAs consider review of these specific programs to the extent that effectiveness improvements potentially remain in each PA's service territory. Itron further recommends that PAs make use of additional detail on these programs that will be forthcoming in Phase II of this research effort to help unpack and understand what these programs are doing well from a DORCE standpoint.

5.2.3 Success in Both DOR and CE

In this section we revisit each of the noted areas from the multivariate regression modeling activity where program characteristics correspond similarly to cost effectiveness and depth of retrofit. We identify specific programs that exemplify each of these trends. We also provide observations related to the overall DORCE and DORCE components rankings, as well as the overall residual and residual component rankings for these programs.

For each of these areas where better than average cost effectiveness and depth of retrofit are being achieved simultaneously, Itron recommends careful review of the specific programs that embody the trend. We recommend that conspicuously successful programs be considered for review within the lens of possible additional cost-effective potential in light of the most recent potential study.

Food Service

As noted in Section 4.2, a focus on food service was associated with positive outcomes for both cost effectiveness and depth of retrofit. Here we revisit that finding and note specific programs that help drive that outcome. A few programs that focus partially on food service score notably well on DORCE and on one or both of the DOR and CE components. The SCG Commercial

Calculated Incentives program (SCG3710), which focuses on food service at 10% of its participating sites, is one of the highest-scoring programs in the portfolio (DORCE rank 14; CE rank 7). This is a Core program comprised of custom measures and focuses on gas savings for commercial customers. It's a medium sized program with 445 sites, and typical participants are restaurants, office buildings, lodging, and health. The preponderance of its participants are very small (63%), and the program achieves a relatively high reduction in energy consumption of approximately 11% for the typical participant. Notably, the program has high residuals across the board; it is in the top 10% of program residuals for DORCE and DOR and in the top 25% for CE, technologies addressed, and savings achieved.

The SCE Savings By Design program (SCE-13-SW-002G) focuses on food service at 8% of participating sites and is another very high scoring program in the portfolio (DORCE rank 13; CE rank 17; DOR rank 31; technologies addressed rank 20; savings achieved rank 52). The SCE Savings by Design program focuses on electric savings through custom measures focused on commercial customers. It is a large program, with 738 participating sites, and typical participants are retail stores, schools, food/liquor, office buildings, and restaurants.

Table 5-4: High-Performing Programs That Include Food Service

Itron Program ID	Itron Program Name	% Sites Food Service	% MMBTU reduction	Rank			Residual Rank		
				DORCE	CE	DOR	DORCE	CE	DOR
SCG3793	3P-IDEEA365-Instant Rebates! Point-Of-Sale Foodservice Rebate Program	100%	12%	85	65	77	111	92	108
SCG3711	SW-Com-Deemed Incentives	50%	9%	103	56	105	127	141	77
SCG3710	SW-Com-Calculated Incentives	10%	11%	14	7	71	16	34	14
SDGE3223	SW-Com-Deemed Incentives-Commercial Rebates	9%	7%	67	40	84	31	10	83
SCE-13-SW-002G	Savings By Design	8%	10%	13	17	31	32	37	28
PGE21012	Commercial Deemed Incentives	7%	4%	109	34	131	30	19	71
SCG3716	SW-Ind-Deemed Incentives	7%	6%	1	1	138	2	1	110

Water Heating

A few programs that address water heating in whole or in part illustrate the pathway to success in in both depth of retrofit and cost effectiveness. While SCG's 3P-SAVEGAS program (SCG3766) is inherently narrow from an end use perspective (100% focused on water heating savings), it is a very high scoring program on both cost effectiveness and proportional reduction in energy consumption. These combine to yield a high DORCE score (DORCE rank 28). Somewhat similarly, SDG&E's 3P-NRes02 - SaveGas - Hot Water Control program (SDGE3162) is exclusively focused on water heating savings, but its achievements in high cost effectiveness and high reductions in energy consumption yield a DORCE score within the top third (DORCE rank 49). SDG&E's Savings by Design program (SDGE3118E/SDGE3222) has a broader end use focus, being one-third focused on water heating savings. It is one of the top scoring programs in the portfolio from a depth of retrofit standpoint, led both by the array of technologies addressed and the reductions in energy consumption. It is also in the top third of cost effectiveness scores.

Table 5-5: High-Performing Water Heating Programs

Itron Program ID	Itron Program Name	% Sites Water Heating	Rank			Residual Rank		
			DORCE	CE	DOR	DORCE	CE	DOR
SCG3766	3P-SAVEGAS	100%	28	25	59	64	43	81
SDGE3162	3P-NRes02 - SaveGas - Hot Water Control	100%	49	32	76	46	40	75
SDGE3118E/SDGE3222	SW-COM-SAVINGS BY DESIGN	33%	8	39	4	43	110	7

<u>High Percentage of Total Program Cost Going to Incentives</u>

Across the portfolio, a typical program devotes approximately 40% of total program costs to incentives. Table 5-5 and Table 5-6 below illustrate several programs that devote a conspicuously high proportion of total program expenditures to incentives while achieving above average outcomes for both cost effectiveness and depth of retrofit. SCE's Automatic Energy Review for Schools Program (SCE-TP-033) which devotes 66% of total expenditures to incentives, is a highly cost effective program that also scores in the top third of depth of retrofit scores. It's favorable depth of retrofit score is driven both by a relatively large number of technologies addressed and relatively high proportional reduction in energy consumption. SDG&E's Savings By Design program (SDGE3118E/SDGE3222), described in other sections of this report as high scoring across all components of the DORCE score, devotes 65% of total program expenditures to incentives. PG&E's Department Of Corrections And Rehabilitation program (PGE2110014) devotes 69% of program expenditures to incentives, and achieves scores in the top third of both cost effectiveness and depth of retrofit, especially driven by the high number of technologies addressed. PG&Es Staples Low Pressure Irrigation DI program (PGE210133), which devotes 93% of program expenditures to incentives, achieves scores in the top third for both cost effectiveness and depth of retrofit, in this case especially driven by high proportional reduction in energy use. PG&E's California Community Colleges program achieves a high depth of retrofit score, driven especially by the high number of technologies addressed, while turning in an average performance on cost effectiveness.

Table 5-6: High-Performing Programs with a High Percentage of Total Program Expenditure Going to Incentives

Itron Program ID	Itron Program Name	% Spending on Incentives	Rank			Residual Rank		
			DORCE	CE	DOR	DORCE	CE	DOR
SCE-TP-033	Automatic Energy Review For Schools Program	66%	4	4	50	5	4	62
SDGE3118E/SDGE3222	SW-Com-Savings By Design	65%	8	39	4	43	110	7
PGE2110014	Department Of Corrections And Rehabilitation	69%	20	46	29	36	42	51
PGE210133	Staples Low Pressure Irrigation DI	93%	25	30	47	18	36	8
PGE2110011	California Community Colleges	69%	27	76	22	145	88	142

Table 5-7: More Details on High-Performing Programs with a High Percentage of Total Program Expenditure Going to Incentives

Itron Program ID	Itron Program Name	Target Sector	GPG	Incentive Structure	DI/non	Fuel	Sites	Claims	% Sties Interior Lighting
SCE-TP-033	Automatic Energy Review For Schools Program	Com	3P	C	non-DI	Elec	3	6	33%
SDGE3118E/SDGE3222	SW-Com-Savings By Design	Com	Core	C	non-DI	Both	979	2969	67%
PGE2110014	Department Of Corrections And Rehabilitation	Com	SIP	C	DI	Both	34	213	61%
PGE210133	Staples Low Pressure Irrigation DI	Ag	3P	D	DI	Elec	106	110	0%
PGE2110011	California Community Colleges	Com	SIP	C	DI	Both	93	413	37%

A Focus on Very Small Customers

A number of programs that focus on very small customers score above average or within the top third of both cost effectiveness and depth of retrofit. SCG's Agricultural Calculated Incentives program (SCG3719) is 86% focused on very small customers and achieves a top 15% overall DORCE score. The program is especially strong in cost effectiveness but is also in the top 40% of programs on depth of retrofit, driven especially by proportional reduction in energy use. SCG's 3P-IDEEA365-Instant Rebates! Point-Of-Sale Foodservice Rebate Program (SCG3793) is 67% focused on very small customers Programs with approximately 40% or higher focus on very small customers that also achieve scores in the top third for both cost effectiveness and depth of retrofit include PG&Es Energy Fitness program (PGE210113), Madera program (PGE211012) and Fresno program (PGE211010). All three of these are at the absolute top of the scale in terms of proportional reduction in energy consumption.

Table 5-8: High-Performing Programs That Focus on Very Small Customers

Itron Program ID	Itron Program Name	%Very Small	% Small	Rank			Residual Rank		
				DORCE	CE	DOR	DORCE	CE	DOR
SCG3719	SW-Ag-Calculated Incentives	86%	0%	18	15	58	132	150	41
SCG3793	3P-IDEEA365-Instant Rebates! Point-Of-Sale Foodservice Rebate Program	67%	20%	85	65	77	111	92	108
SCG3766	3P-Savegas	67%	5%	28	25	59	64	43	81
SCG3710	SW-Com-Calculated Incentives	63%	6%	14	7	71	16	34	14
PGE210113	Energy Fitness Program	46%	48%	9	35	5	9	7	27
PGE211012	Madera	40%	50%	15	53	9	13	12	25
PGE211010	Fresno	39%	52%	11	44	8	11	9	32

Manufacturing

A focus on manufacturing yields cost effectiveness outcomes that are above average on balance while returning average results from a depth of retrofit perspective. One notable program that illustrates this trend is SCG's Agricultural Calculated Incentives program (SCG 3719). This program is 77% focused on manufacturing and achieves a top 15% DORCE score, top 10% cost effectiveness score, and top 40% depth of retrofit score, driven especially by proportional reduction in energy use. Table 5-8 below shows the group of programs that illustrate the trend of above average scores on cost effectiveness and average or above average scores on depth of retrofit.

Table 5-9: High-Performing Manufacturing Programs

Itron Program ID	Itron Program Name	% Sites Manufacturing	Rank			Residual Rank		
			DORCE	CE	DOR	DORCE	CE	DOR

SCG3719	SW-Ag-Calculated Incentives	77%	18	15	58	132	150	41
PGE21038	Wine Industry Efficiency Solutions	76%	77	81	64	67	97	48
SCE-13-SW-003C	Industrial Deemed Energy Efficiency Program	67%	66	62	66	97	138	21
SCE-13-TP-012	Refinery Energy Efficiency Program	36%	16	11	61	25	21	19
SCE-13-TP-008	Nonmetallic Minerals And Products	26%	63	42	81	89	114	24
PGE210113	Energy Fitness Program	8%	9	35	5	9	7	27
SDGE3233	SW-Ind-Deemed Incentives	52%	89	59	88	39	16	90
SCE-13-TP-006	Food & Kindred Products	18%	50	22	96	37	44	33
SCE-13-TP-009	Comprehensive Chemical Products	16%	87	55	87	105	108	72

5.2.4 Poor DORCE Performance

In addition to highlighting conspicuously effective programs, the DORCE score and its associated components also highlights programs that are performing below average on both cost effectiveness and depth of retrofit. Table 5-9 below shows the 20% of programs with the lowest DORCE scores in the portfolio, including their DORCE component scores and residuals. In the large majority of these cases, programs with the lowest DORCE scores are performing in the bottom third or bottom half of programs for both cost effectiveness and depth of retrofit.

There are any number of reasons why a program may get a low DORCE score. Some of these reasons may reflect the fact that the program is targeting an area of the overall portfolio where cost effective, deep energy savings are particularly hard to achieve. A program may also get a low DORCE score due to ineffective elements of its design or implementation that could be improved through re-visiting and potentially re-vamping the program. Itron recommends that PAs review programs with conspicuously low DORCE scores to try to evaluate and understand the drivers of low scores and whether program modifications are warranted. An important tool to assist in the assessment of low DORCE-scoring programs is the residual, which is discussed in the next section.

Table 5-10: Programs with Poor DORCE Performance

Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	CE	DOR
SCE-13-L-003E	County Of San Bernardino Energy Efficiency Partnership	132	135	106	122	106	95
SCE-13-L-002H	Eastern Sierra Energy Leader Partnership	133	162	65	34	111	20

Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	CE	DOR
SCE-13-L-002K	Kern County Energy Leader Partnership	134	157	82	78	79	65
SCE-13-TP-004	Data Center Energy Efficiency	135	89	134	142	53	156
SCE-13-TP-017	Energy Efficiency For Entertainment Centers	136	144	101	75	70	100
SCE-13-L-002O	South Bay Energy Leader Partnership	137	149	103	137	72	147
SDGE3239	SW-Ag-Deemed Incentives	138	140	113	136	130	133
SCE-13-L-002F	Gateway Cities Energy Leader Partnership	139	158	89	118	125	105
SCE-TP-018	Chemical Products Efficiency Program	140	104	133	130	131	87
PGE210123	Healthcare Energy Efficiency Program	141	152	112	152	160	130
PGE21006/PGE21015	Commercial HVAC	142	123	127	133	154	68
PGE2227	Cement Production And Distribution Energy Efficiency	143	146	116	140	134	102
SCE-13-TP-021	Enhanced Retrocommissioning	144	92	145	110	89	117
SDGE3224	SW-Com-Deemed Incentives-HVAC Commercial	145	131	126	121	101	109
PGE2198	Data Centers Cooling Controls Program	146	75	155	29	58	38
PGE2204	Smartvent For Energy-Efficient Kitchens	147	98	142	33	55	52
PGE210128	Enovity Smart	148	112	146	144	153	120
SCE-13-L-003D	County Of Riverside Energy Efficiency Partnership	149	141	128	149	156	125
PGE210119	LED Accelerator	150	120	144	162	161	160
SCE-13-L-002A	City Of Beaumont Energy Leader Partnership	151	156	117	123	69	139
SCE-13-SW-002F	Nonresidential HVAC Program	152	96	148	126	66	143
PGE2220	Assessment, Implementation, And Monitoring (AIM) Program	153	52	163	135	87	155
SCE-13-SW-005B	Lighting Innovation Program	154	137	137	114	85	106
SCE-13-TP-010	Comprehensive Petroleum Refining	155	108	149	151	151	137
SCE-13-TP-013	Cool Schools	156	118	152	58	18	114
PGE210210	Industrial Recommissioning Program	157	74	162	158	136	161
PGE210130	RSG AERCX	158	143	151	157	128	159
PGE2242	Cool Cash	159	153	153	153	163	104
PGE21037	Light Exchange Program	160	160	154	161	152	163

Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	CE	DOR
SCE-13-SW-001E	Residential HVAC Program	161	161	159	160	155	158
SCE-L-004D	Energy Leader Partnership Program	162	155	161	147	126	140
SCG3712	SW-Com-Nonres HVAC	163	163	160	163	162	157

5.2.5 Residuals

In this section we focus on high residuals for programs whose overall DORCE scores fall in the bottom third, middle third, and top third of the overall portfolio.

Residuals for low DORCE Programs

Table 5-10 below shows the set of nine programs whose DORCE scores fall in the bottom third of all programs but whose residuals fall in the top third of all programs. In terms of the CE and DOR components of DORCE score, most of these programs fall in the middle third of all programs for one of these components and the bottom third for the other component.

What is significant from a residuals perspective is that these programs are outperforming modeled expectations. In other words, even though these are relatively low DORCE scoring programs overall, they are outperforming programs of similar design. Generally speaking, these programs and their peers are likely targeting areas of the portfolio where deep, cost effective savings are harder to achieve. As shown in the rightmost columns of the table, the strong residuals for these programs (rank 54 or better) are driven by a better-than-expected performance on cost effectiveness, depth of retrofit, or both. PG&Es Lighting Innovation program and PGE&s Comprehensive Retail Energy Management program are 2 particular programs that exceeded modeled expectations especially for cost effectiveness. PG&E's Air Care Plus program and SCE's South Santa Barbara County Energy Leader Partnership are 2 particular programs that exceeded modeled expectations especially for depth of retrofit.

Table 5-11: Bottom DORCE Scores with High Residuals

Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	CE	DOR
PGE21016	Air Care Plus	115	85	97	19	67	9

SCE-13-L-002P	South Santa Barbara County Energy Leader Partnership	110	159	43	24	99	15
PGE21042	Lighting Innovation	126	61	143	28	17	70
PGE2198	Data Centers Cooling Controls Program	146	75	155	29	58	38
PGE2204	SmartVent For Energy-Efficient Kitchens	147	98	142	33	55	52
SCE-13-L-002H	Eastern Sierra Energy Leader Partnership	133	162	65	34	111	20
PGE2183	Comprehensive Retail Energy Management	123	80	121	38	6	124
PGE2214	Energy Efficiency Program For Entertainment Centers	131	148	93	44	102	16
PGE2191	Medical Building Tune-Up	128	73	139	52	29	93

Residuals for medium DORCE programs

Similar to the low DORCE-scoring programs with high residuals, Table 5-11 below shows the programs in the middle third of overall DORCE scores but with residuals in the top third of programs. As with the low DORCE-scoring programs, these program are outperforming peer programs of similar design that may also be focused on areas of the portfolio where cost-effective, deep savings are difficult to achieve. A few programs with notably high residuals specifically on cost effectiveness include SCE's Retail Energy Action Program, SDG&E's SW-Com-Deemed Incentives-Commercial Rebates, and SDG&E's SW-Ind-Deemed Incentives program. A few programs with notably high residuals specifically on the depth of retrofit side include SCG's 3P-Preps program, SCE's City Of Long Beach Energy Leader Partnership program, and PG&E's California Wastewater Process Optimization program.

Table 5-12: Middle Third DORCE Scores with High Residuals

Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	DORCE	CE
SCG3758	3P-Preps	57	102	36	3	41	1
SCE-13-L-002B	City Of Long Beach Energy Leader Partnership	59	99	37	7	33	5
SCE-TP-025	Retail Energy Action Program	81	86	60	12	14	45
SCE-13-L-002G	Community Energy Leader Partnership	65	106	40	14	24	17
SCE-13-TP-003	Healthcare EE Program	96	58	94	15	13	61
SCE-TP-015	Industrial Gasses	80	49	86	17	32	37
SDGE3221	SW-Com-Calculated Incentives-RCx	88	45	102	21	23	42
PGE21022	Industrial Deemed Incentives	83	36	104	26	38	13
SCE-13-L-002R	Western Riverside Energy Leader Partnership	105	150	49	27	81	18

PGE21012	Commercial Deemed Incentives	109	34	131	30	19	71
SDGE3223	SW-Com-Deemed Incentives-Commercial Rebates	67	40	84	31	10	83
SDGE3233	SW-Ind-Deemed Incentives	89	59	88	39	16	90
PGE21025	California Wastewater Process Optimization	61	72	55	42	133	6
SCE-TP-037	Private Schools And Colleges Program	69	126	34	45	90	34
SCE-13-SW-002C	Commercial Deemed Incentives Program	86	48	91	48	30	88
PGE21018	Energysmart Grocer	70	26	108	50	47	76
PGE21032	Agricultural Deemed Incentives	79	19	132	51	28	113

Residuals for high DORCE programs

Among low-, mid-, and high DORCE-scoring programs, it is least surprising to see that a number of the highest DORCE scoring programs in the portfolio also have conspicuously high residuals. Since these are the highest DORCE scoring programs, it stands to reason that part of their high scores comes from exceeding modeled expectations for programs of similar design. Table 5-12 shows the programs that are in the top third of the portfolio for both DORCE residual and overall DORCE score. Itron recommends that these programs be reviewed in more detail to help identify drivers of their success and that they be considered for potential expansion and extension in light of remaining cost effective potential in each PA's service territory. The additional detail on a selection of these programs that will be forthcoming in Phase II of this research effort may serve as a useful resource to help unpack and understand what these programs are doing well from a DORCE standpoint.

Table 5-13: Top Third DORCE Scores with High Residuals

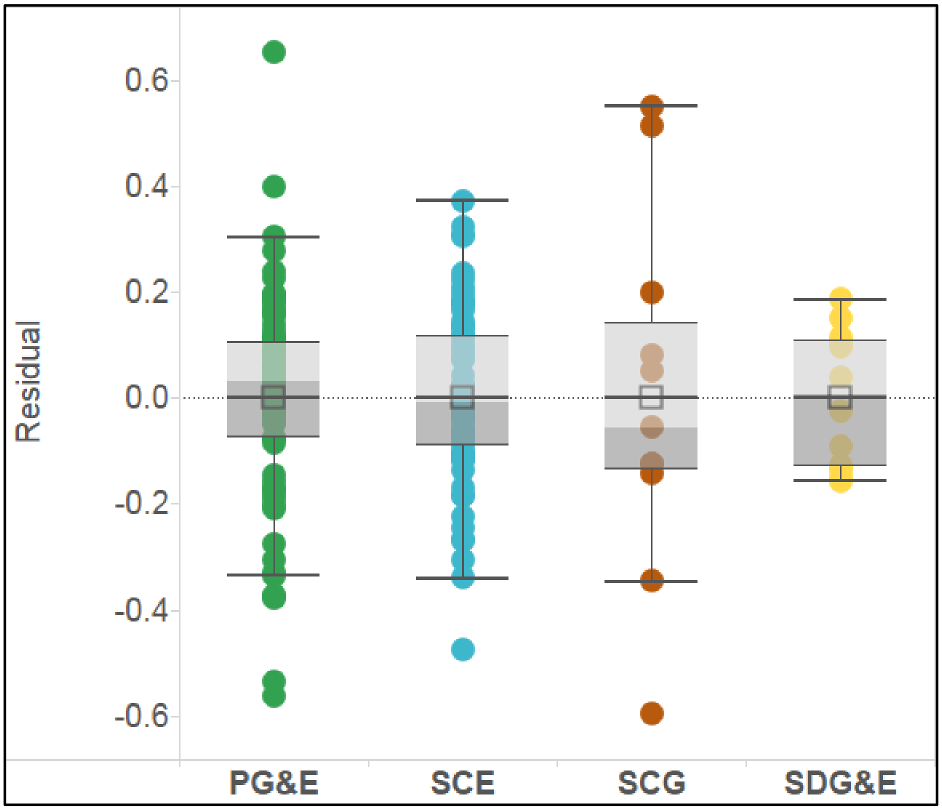
Itron Program ID	Itron Program Name	Rank			Residual Rank		
		DORCE	CE	DOR	DORCE	CE	DOR
PGE21019	Enhanced Automation Initiative	3	3	51	1	2	3
SCG3716	Sw-Ind-Deemed Incentives	1	1	138	2	1	110
PGE210120	Monitoring-Based Commissioning	12	8	54	4	8	4
SCE-TP-033	Automatic Energy Review For Schools Program	4	4	50	5	4	62
SCE-TP-027	Monitoring-Based Commissioning	10	5	125	6	3	153
SCE-13-TP-020	Ideea365 Program	35	138	11	8	112	2
PGE210113	Energy Fitness Program	9	35	5	9	7	27
PGE21029	Refinery Energy Efficiency Program	21	6	157	10	5	141
PGE211010	Fresno	11	44	8	11	9	32

PGE211012	Madera	15	53	9	13	12	25
SCG3710	Sw-Com-Calculated Incentives	14	7	71	16	34	14
PGE210133	Staples Low Pressure Irrigation Di	25	30	47	18	36	8
PGE21035	Dairy Energy Efficiency Program	39	51	52	20	20	44
SCE-13-TP-005	Lodging EE Program	26	69	25	22	39	35
PGE210311	Process Wastewater Treatment Em Pgm For Ag Food Processing	31	10	100	23	26	40
SCE-13-TP-012	Refinery Energy Efficiency Program	16	11	61	25	21	19
SCE-13-SW-002G	Savings By Design	13	17	31	32	37	28
SCE-13-L-002S	City Of Adelanto Energy Leader Partnership	6	50	3	35	11	80
PGE2110014	Department Of Corrections And Rehabilitation	20	46	29	36	42	51
SCE-13-TP-006	Food & Kindred Products	50	22	96	37	44	33
SCE-13-L-003B	California Dept. Of Corrections And Rehabilitation Ee Partnership	24	60	24	40	62	49
PGE210118	Furniture Store Energy Efficiency	51	119	28	41	51	56
SDGE3118E/SDGE3222	Sw-Com-Savings By Design	8	39	4	43	110	7
SDGE3162	3P-Nres02 - Savegas - Hot Water Control	49	32	76	46	40	75
PGE211014	Mendocino County	37	127	16	47	82	58
SCE-13-L-003A	California Community Colleges Energy Efficiency Partnership	23	115	6	49	57	64
PGE211023	Silicon Valley	53	116	30	53	96	29
SCG3715	Sw-Ind-Calculated Incentives	2	2	114	54	35	118

Distribution of Residuals by Program Administrator

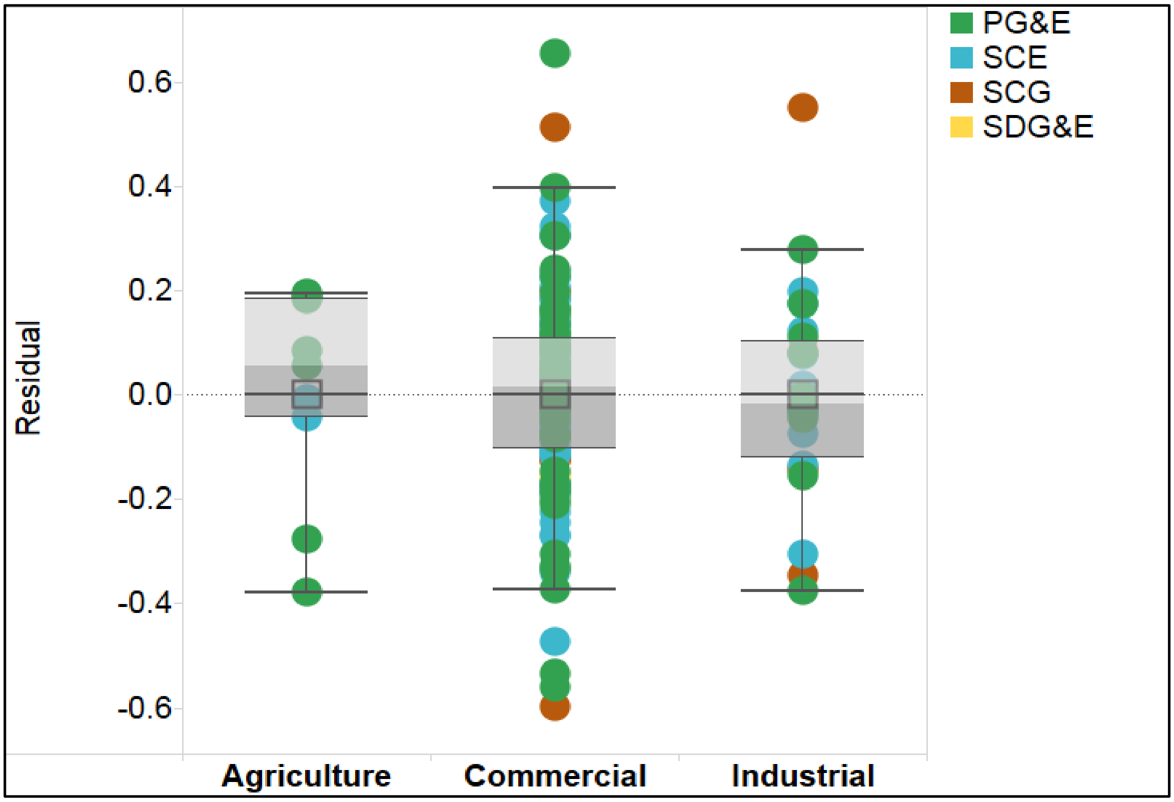
Looking at DORCE residuals across Program Administrators, PG&E programs have the highest median residuals (shown as the boundary between the darker and lighter portions of the box in Figure 5-2 below), followed by SCE and SDG&E, with SCG performing the poorest from a residuals standpoint with a negative median value.

Figure 5-2: Program Effectiveness Model Residuals by Program Administrator



Looking at residuals by sector, programs that target the agricultural sector have the highest median residuals, followed by programs that target the commercial sector. Those that target the industrial sector have the lowest median residuals, and the median is a negative value.

Figure 5-3: Program Effectiveness Model Residuals by Sector



6

Conclusions

The overarching purpose of this research effort is to be both backward-looking and forward-looking. Reflecting on the 2010-2014 period (and including 2015 in Phase II), which specific programs and general patterns in program design have correlated most with high program effectiveness in terms of achieving cost-effective, deep energy savings? Looking forward, how can the DORCE score best be used to inform program- and portfolio design toward achieving the stated objectives of the CA Strategic Plan? What are the next steps that will further refine and increase the usefulness of this approach?

6.1 Key Findings

Key findings from the Phase I analysis include:

- Generally, an increase in technologies addressed does not necessarily mean either an increase, or a decrease, in savings achieved.
- Tradeoffs are not always necessary between depth of retrofit and cost effectiveness, as it's only minimally observable that success in depth of retrofit sometimes corresponds with decreases in cost effectiveness.
- On balance, focus on very small customers yields higher DORCE returns than focusing on large customers.
- A focus on food service and a focus on water heating are both associated with both depth of retrofit and cost effective energy savings, while plug loads are the least effective focus.
- A relatively high proportion of total program cost toward incentives and, conversely, a low proportion of total program costs toward marketing and outreach correspond with better effectiveness outcomes.
- Colleges (and campus-style buildings generally), offices, and food/liquor stores stand out as building types with high returns on cost-effective, deep savings, while restaurants and public assembly building types give the lowest returns.
- The top-scoring programs in the entire portfolio are highly cost-effective gas programs
- Approximately equal numbers of programs achieve high effectiveness scores (top 20%) via three pathways:

  - Notably high (though not the highest) scores on both depth of retrofit and cost effectiveness
  - Exceptionally strong cost effectiveness with reasonable depth of retrofit
  - Exceptionally strong depth of retrofit with reasonable cost effectiveness
- Some particular programs significantly outperform peer programs of similar design.

All of the findings noted above, in addition to being informative at the portfolio level, may be most useful when viewed in narrower contexts, such as for subsets of programs that share one or more similar features. When viewed among subsets of programs, program rankings and residuals can put a program's achievements in context and may be particularly relevant from a program planning perspective. In effect, this type of sub-setting provides the opportunity to control for additional ways in which programs differ from one another.

6.2 Program and Portfolio Planning Tools

The tools developed in this research effort may serve planners in working to meet program- and portfolio level objectives. Importantly, the fact that a particular type of program has been highly effective in the past does not necessarily indicate that the same type of program would be highly effective looking forward. It's possible that most of the achievable potential in a given niche has been realized and that continuing to go after very similar savings would become less cost-effective and/or achieve less deep savings with continued effort.

Findings from this research effort could be used in conjunction with additional data sources to fill out a more complete picture of where cost-effective, deep energy savings opportunities remain. Potential studies provide a useful and detailed characterization of the technical and economic potential for additional savings across geographic, firmographic, and demographic strata. Details about effective program design from this research effort may help target that potential in carefully tailored ways. Census data, when used alongside program data, CIS/billing data, and possibly additional data sources, may serve a similar purpose.

6.3 Scope of Comprehensiveness Analysis Phase II

The best outcomes from this research effort, and the most useful tools, will likely emerge from an iterative process with stakeholders to refine the tools and target them toward make it as useful as possible. Following review of the Phase I outcomes described in this report, the evaluation team hopes to engage with stakeholders around the parts of the analysis that are most and least useful and potential changes to the tools that refine their applicability and usefulness. For example, there may be considerations from a program- and portfolio planning perspective that would suggest additional or different inputs or weights to the program effectiveness metric to align its outcomes more precisely with objectives from the CA Strategic Plan.

In addition to refinements to the tools based on stakeholder feedback, the evaluation team will add the 2015 ex ante program data and the 2014 ex post program data to the overall models and analysis in Phase II. Consistencies and differences in model structure and findings as a result of adding more data will be noted in the Phase II reporting.

Phase II reporting will also include profiling of specific programs that have come to light for their high effectiveness in the Phase I research effort. The evaluation team expects to use several data sources to help fill in the picture for stand-out programs. We will review the Program Implementation Plans (PIPs) for details on program design and implementation. We will review program tracking data and monthly cost reporting data for details in terms of the distribution of program expenditures across marketing and other expense areas to shed light on possible key drivers of TRC and other program outcomes. An examination of program delivery mechanisms via these data sources may yield useful information in terms of how the program is reaching participants, the degree to which the program customizes its efforts around individual participants, and the potential roles of the utility representatives and other key actors in driving the success of the program. In addition, the 2013-2014 Third Party Commercial Program Value and Effectiveness Study conducted by Opinion Dynamics Corporation (ODC) is expected to serve as a potentially useful data source for details on 3P-implemented programs that stand out from a comprehensiveness analysis perspective.

This program profiling research is expected to provide standalone value in profiling conspicuously effective programs. While it will stop short of conducting interviews with program implementers and other individuals with insight into program design and implementation, it may be seen as teeing up potential process evaluation work that would extend and build more insight into key drivers of cost-effective, deep savings for these programs.

7

Recommendations

The evaluation team has distilled a series of recommendations, primarily aimed at program administrators that flow from the research conducted in this report. These recommendations range from the general to the specific. They generally center on using the DORCE metric and other findings from this work to refine program and portfolio planning in service of meeting the state's ambitious energy savings goals per the Strategic Plan.

- **Recommendation #1**: Program administrators should incorporate DORCE score and its observed relationships with certain program characteristics laid out in this research when reflecting on past program performance and to inform potential future performance. DORCE scores and accompanying component scores may provide useful insight for deciding how to allocate funds, trying to enhance current programs, and developing new program concepts. The research described in this report represents a foray into developing a new, empirically based metric of program effectiveness. It is the first significant effort to fold cost effectiveness and depth of retrofit into a single score. This allows for careful examination of the relationship between cost effectiveness and deep energy savings, as well as the charting out of pathways to high achievement by this metric. In doing so, the score provides a window and a yardstick on the relative success of individual programs and general program approaches to achieving deep energy savings cost effectively.
- Importantly, the DORCE metric is accompanied in this report by detailed and transparent information on all component scores for depth of retrofit and cost effectiveness, as well as a detailed map of correlations between DORCE and its component scores across all programs and significant program elements in the portfolio. A central finding of this research is that program cost effectiveness, number of technologies addressed, and proportional reduction in energy usage are uncorrelated when looking across the whole portfolio. Another central finding is that statistically significant positive correlations exist between cost effectiveness and depth of retrofit in various subsections of the portfolio that may offer insight on where and how to pursue cost effectiveness and depth of retrofit simultaneously.
- Multiple policy objectives in California are dependent on achieving high levels of energy efficiency penetration across all sectors of the state economy while ensuring cost-effective use of ratepayer funds. We encourage program administrators in California to engage with this set of tools as a targeted viewpoint on program performance in light of these aims.

Recommendation #2: Consider using DORCE score to help identify standout programs across various segments of the nonresidential portfolio. One particular area of value may come from identifying programs that are performing better than their peers specifically in areas of the portfolio where deep, cost effective savings are historically challenging.

- Based on the outcomes of this work, we recommend that program administrators look closely at their high performing programs and consider investing additional resources in them to continue what they are doing well. Of course, as financial investment advisors are always quick to say, past performance is no guarantee of future performance. Indeed, it may be that a program's success means it has already accomplished most of what can be cost effectively accomplished in a given area. With this caveat acknowledged, programs that are achieving at a high level should be built upon and encouraged.

Recommendation #3: Explore what makes certain programs successful by conducting detailed process evaluation on likely drivers of notably successful and unsuccessful programs.

- In service of the previous recommendation, we recommend investing in process evaluation focused on highly effective as well as highly ineffective programs. Through interviews with program managers, program implementers, participants, and possibly other parties, the central objective of this work should be to identify the particular practices and dynamics that appear most responsible for influencing the program's effectiveness score. It is possible that this research will highlight practices that make a particular program design and/or implementation approach especially well-suited to its participant population. Also, effective approaches that influence the program's cost effectiveness and/or depth of retrofit achievements may have broad application across programs of different kinds.
- Looking into conspicuously ineffective programs from a process evaluation perspective may yield separate and complementary insights. This work may yield patterns in terms of incorrect assumptions regarding costs and/or savings made during the planning and/or implementation phases of ineffective programs. As with the focus on high-scoring programs, some findings may apply to very particular circumstances while others may be broader in their application.
- **Recommendation #4**: Consider using DORCE score to help take a closer look at programs that score low on both cost effectiveness and depth of retrofit. Use the combination of rankings and/or residuals to help characterize and frame a process of looking into low performing programs, understanding why, and taking steps to modify, reorient, or halt ineffective programs. In addition to looking at low-scoring programs overall in this regard, it may be instructive to look at low-scoring programs specifically compared against peers that target similar elements of the portfolio. A comparison of outcomes to expectations may help structure program improvements.

- Conspicuously low-scoring programs may represent an inefficient use of program administrator resources or a particularly challenging set of circumstances for generating cost-effective savings, or both. These programs may be lowering a utility's overall performance at the portfolio level. The DORCE score, including its separate cost effectiveness and depth of retrofit components and the regression models, provides a means of identifying and beginning to characterize these programs from both a cost effectiveness standpoint and a depth of retrofit standpoint. We recommend program administrators use these tools to identify low performing programs, begin to diagnose what's going on, and consider whether modifications to the program's structure are warranted.

Recommendation #5: Go after unrealized energy efficiency potential throughout the state using a targeted approach that includes DORCE score as a strategic component paired with the most recent potential study.

- Look into unrealized potential while overlaying DORCE lens for prioritizing
- Same as with any financial investment, past performance is not necessarily an indicator of future performance. It may be that a given program's strong performance means it has already successfully pursued most of the cost effective potential in its area of focus. Hence the importance of overlaying DORCE with potential studies.
- Consider adding and/or modifying programs based on this lens
- The DORCE score and its supporting components provide a view of program achievements over the 2010-2014 period. The analysis provides feedback on specific programs and general program approaches that may also prove effective looking forward. However, this depends sensitively on the remaining technical and economic potential for energy savings in the areas addressed by conspicuously effective programs. We recommend reviewing potential studies such as the Energy Efficiency Potential and Goals Study for 2015 and Beyond[21] using program DORCE scores as a lens for characterizing that potential.

Recommendation #6: Consider setting and working toward portfolio level objectives for DORCE.

- Use the regression models to balance portfolio objectives
- A variety of oft-cited quotes address the notion that measuring something is a critical part of the pathway to improving it. As mentioned previously, the DORCE score is a foray into measuring the combination of cost effectiveness and depth of retrofit. The study team believes that reaching for high scores on this metric also supports programs in moving toward statewide energy efficiency objectives.
- Naturally, it takes a diverse set of programs in a given PA's portfolio to target and pursue energy savings across the full array of sectors, building types, customer sizes, and end uses.

[21] The Energy Efficiency Potential and Goals Study for 2015 and Beyond: http://www.cpuc.ca.gov/General.aspx?id=2013

It is inevitable that some of these savings will be more cost effective than others. We recommend that planners use the DORCE score to think about setting and meeting portfolio objectives as well as individual program objectives. For example, when targeting savings in a particular building type, programs that address that building type can be isolated and directly compared from the perspective of DORCE and the DOR and CE components. Also, planners can use DORCE score to consciously balance areas where energy savings are known to be minimally cost effective at best with areas where cost effective savings are easier to achieve.

Recommendation #7: Use the DORCE metric to reduce stranded energy efficiency potential.

- As mentioned elsewhere in this report, TRC is a ubiquitous and centrally used metric to evaluate programs and to serve as a threshold criterion for allowing planned programs to proceed. However, TRC is ineffective at identifying cases where (and the extent to which) a program design achieves less than the total potential cost effective savings among its participants. In particular, TRC measures the cost effectiveness of savings achieved but is blind to whether or not additional potential energy savings were left behind and stranded in the process. There may be cases where a broad set of measures is cost effective when these measures are pursued collectively through a confined set of program touch points, but the less cost effective portion of these measures may become non-cost-effective after "cream skimming" by narrowly focused programs. The DORCE score provides a system of recognizing and potentially rewarding and/or prioritizing programs that reach for deeper savings. If minimizing stranded potential energy savings is an objective, DORCE score provides a clearer and more powerful lens than TRC in reaching toward it.

Recommendation #8: Make a point of exploring and potentially targeting gas savings potential. Several gas-focused programs performed among the highest of all programs in this study, driven primarily by exceptionally high scores on both the TRC and PAC cost effectiveness tests. For any comparisons across fuels in this analysis, findings are based on defining electric and gas savings in terms of source energy.

- Gas programs are very cost effective (4 of the top 5 TRC programs target either gas or both fuel type savings). Also, 9 out of 20 gas targeting programs are in the top third of DORCE scores (i.e., a disproportionate amount of gas targeting programs ~50% are in the top 33% of programs overall).

Recommendation #9: Use the tools from this research effort in multifaceted, flexible, and creative ways. If cost effectiveness is the highest order priority, consider using the tool to maximize depth of retrofit given cost effectiveness constraints. Consider using the tools to come up with and frame new goals and priorities.

- If cost effectiveness as the highest order priority, consider using the tool to maximize DOR given CE constraints

- Customize the use of the tool to answer your own questions and to look from multiple angles.
- Maybe use it to come up with and frame some new goals and priorities.

8

Appendix

8.1 Program List

Table 8-1: Program List

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
PGE	PGE21006/ PGE21015	COMMERCIAL HVAC	PGE21061/ PGE21063/ PGE21065	PGE21015
PGE	PGE21011	COMMERCIAL CALCULATED INCENTIVES	PGE21011	PGE21011
PGE	PGE210110	MONITORING-BASED PERSISTENCE COMMISSIONING	PGE2187	PGE210110
PGE	PGE210111	LODGINGSAVERS	PGE2190	PGE210111
PGE	PGE210112	SCHOOL ENERGY EFFICIENCY	PGE2193	PGE210112
PGE	PGE210113	ENERGY FITNESS PROGRAM	PGE2194	PGE210113
PGE	PGE210114	ENERGY SAVERS	PGE2195	PGE210114
PGE	PGE210115	RIGHTLIGHTS	PGE2196	PGE210115
PGE	PGE210116	SMALL BUSINESS COMMERCIAL COMPREHENSIVE	PGE2197	PGE210116
PGE	PGE210117	ENERGY-EFFICIENT PARKING GARAGE	PGE2199	PGE210117
PGE	PGE210118	FURNITURE STORE ENERGY EFFICIENCY	PGE2200	PGE210118
PGE	PGE210119	LED ACCELERATOR	PGE2202	PGE210119
PGE	PGE21012	COMMERCIAL DEEMED INCENTIVES	PGE21012	PGE21012
PGE	PGE210120	MONITORING-BASED COMMISSIONING		PGE210120
PGE	PGE210122	CASINO GREEN	PGE2205	PGE210122
PGE	PGE210123	HEALTHCARE ENERGY EFFICIENCY PROGRAM	PGE2206	PGE210123
PGE	PGE210124	OZONE LAUNDRY ENERGY EFFICIENCY	PGE2209	PGE210124
PGE	PGE210125	CALIFORNIA PRESCHOOL ENERGY EFFICIENCY PROGRAM	PGE2212	PGE210125
PGE	PGE210126	K-12 PRIVATE SCHOOLS AND COLLEGES AUDIT RETRO	PGE2213	PGE210126
PGE	PGE210128	ENOVITY SMART		PGE210128

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
PGE	PGE210130	RSG AERCX		PGE210130
PGE	PGE210133	STAPLES LOW PRESSURE IRRIGATION DI		PGE210133
PGE	PGE21016	AIR CARE PLUS	PGE2181	PGE21016
PGE	PGE21017	BOILER ENERGY EFFICIENCY PROGRAM	PGE2182	PGE21017
PGE	PGE21018	ENERGYSMART GROCER	PGE2185	PGE21018
PGE	PGE21019	ENHANCED AUTOMATION INITIATIVE	PGE2186	PGE21019
PGE	PGE21021	INDUSTRIAL CALCULATED INCENTIVES	PGE21021	PGE21021
PGE	PGE210210	INDUSTRIAL RECOMMISSIONING PROGRAM	PGE2228	PGE210210
PGE	PGE21022	INDUSTRIAL DEEMED INCENTIVES	PGE21022	PGE21022
PGE	PGE21025	CALIFORNIA WASTEWATER PROCESS OPTIMIZATION	PGE2221	PGE21025
PGE	PGE21026	ENERGY EFFICIENCY SERVICES FOR OIL PRODUCTION	PGE2222	PGE21026
PGE	PGE21027	HEAVY INDUSTRY ENERGY EFFICIENCY PROGRAM	PGE2223	PGE21027
PGE	PGE21028	INDUSTRIAL COMPRESSED AIR PROGRAM	PGE2224	PGE21028
PGE	PGE21029	REFINERY ENERGY EFFICIENCY PROGRAM	PGE2225	PGE21029
PGE	PGE21031	AGRICULTURAL CALCULATED INCENTIVES	PGE21031	PGE21031
PGE	PGE210310	DAIRY INDUSTRY RESOURCE ADVANTAGE PGM	PGE2235	PGE210310
PGE	PGE210311	PROCESS WASTEWATER TREATMENT EM PGM FOR AG FOOD PROCESSING	PGE2236	PGE210311
PGE	PGE21032	AGRICULTURAL DEEMED INCENTIVES	PGE21032	PGE21032
PGE	PGE21035	DAIRY ENERGY EFFICIENCY PROGRAM	PGE2230	PGE21035
PGE	PGE21036	INDUSTRIAL REFRIGERATION PERFORMANCE PLUS	PGE2231	PGE21036
PGE	PGE21037	LIGHT EXCHANGE PROGRAM	PGE2232	PGE21037
PGE	PGE21038	WINE INDUSTRY EFFICIENCY SOLUTIONS	PGE2233	PGE21038
PGE	PGE21039	COMPREHENSIVE FOOD PROCESS AUDIT & RESOURCE EFFICIENCY PGM	PGE2234	PGE21039
PGE	PGE21042	LIGHTING INNOVATION		PGE21042
PGE	PGE2110011	CALIFORNIA COMMUNITY COLLEGES	PGE21261	PGE2110011
PGE	PGE2110012	UNIVERSITY OF CALIFORNIA/CALIFORNIA STATE UNIVERSITY	PGE21262	PGE2110012

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
PGE	PGE2110013	STATE OF CALIFORNIA	PGE21263	PGE2110013
PGE	PGE2110014	DEPARTMENT OF CORRECTIONS AND REHABILITATION	PGE21264	PGE2110014
PGE	PGE2110051	LOCAL GOVERNMENT ENERGY ACTION RESOURCES (LGEAR)	PGE2125/ PGE2140	PGE2110051
PGE	PGE211007	ASSOCIATION OF MONTEREY BAY AREA GOVERNMENTS (AMBAG)	PGE2130	PGE211007
PGE	PGE211009	EAST BAY	PGE2132	PGE211009
PGE	PGE211010	FRESNO	PGE2131/ PGE2133	PGE211010
PGE	PGE211011	KERN	PGE2134	PGE211011
PGE	PGE211012	MADERA	PGE2135	PGE211012
PGE	PGE211013	MARIN COUNTY	PGE2136	PGE211013
PGE	PGE211014	MENDOCINO COUNTY	PGE2137	PGE211014
PGE	PGE211015	NAPA COUNTY	PGE2138	PGE211015
PGE	PGE211016	REDWOOD COAST	PGE2139	PGE211016
PGE	PGE211018	SAN LUIS OBISPO COUNTY	PGE2141	PGE211018
PGE	PGE211019	SAN MATEO COUNTY	PGE2142	PGE211019
PGE	PGE211020	SANTA BARBARA	PGE2143	PGE211020
PGE	PGE211021	SIERRA NEVADA	PGE2144	PGE211021
PGE	PGE211022	SONOMA COUNTY	PGE2145	PGE211022
PGE	PGE211023	SILICON VALLEY	PGE2146	PGE211023
PGE	PGE211024	SAN FRANCISCO	PGE2147	PGE211024
PGE	PGE211025	SAVINGS BY DESIGN (SBD)	PGE21042	PGE211025
PGE	PGE2183	Comprehensive Retail Energy Management	PGE2183	
PGE	PGE2189	Cool Controls Plus	PGE2189	
PGE	PGE2191	Medical Building Tune-Up	PGE2191	
PGE	PGE2198	Data Centers Cooling Controls Program	PGE2198	
PGE	PGE2201	California High Performance Lighting Program	PGE2201	
PGE	PGE2204	SmartVent for Energy-Efficient Kitchens	PGE2204	
PGE	PGE2214	Energy Efficiency Program for Entertainment Centers	PGE2214	
PGE	PGE2220	Assessment, Implementation, and Monitoring (AIM) Program	PGE2220	
PGE	PGE2227	Cement Production and Distribution Energy Efficiency	PGE2227	
PGE	PGE2242	Cool Cash	PGE2242	
SCE	SCE-13-L-002A	CITY OF BEAUMONT ENERGY LEADER PARTNERSHIP	SCE-L-004A	SCE-13-L-002A
SCE	SCE-13-L-002B	CITY OF LONG BEACH ENERGY LEADER PARTNERSHIP	SCE-L-004B	SCE-13-L-002B

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
SCE	SCE-13-L-002C	CITY OF REDLANDS ENERGY LEADER PARTNERSHIP	SCE-L-004C	SCE-13-L-002C
SCE	SCE-13-L-002D	CITY OF SANTA ANA ENERGY LEADER PARTNERSHIP	SCE-L-004E	SCE-13-L-002D
SCE	SCE-13-L-002E	CITY OF SIMI VALLEY ENERGY LEADER PARTNERSHIP	SCE-L-004F	SCE-13-L-002E
SCE	SCE-13-L-002F	GATEWAY CITIES ENERGY LEADER PARTNERSHIP	SCE-L-004G	SCE-13-L-002F
SCE	SCE-13-L-002G	COMMUNITY ENERGY LEADER PARTNERSHIP	SCE-L-004H	SCE-13-L-002G
SCE	SCE-13-L-002H	EASTERN SIERRA ENERGY LEADER PARTNERSHIP	SCE-L-004J	SCE-13-L-002H
SCE	SCE-13-L-002J	DESERT CITIES ENERGY LEADER PARTNERSHIP	SCE-L-004I/ SCE-L-004N	SCE-13-L-002J
SCE	SCE-13-L-002K	KERN COUNTY ENERGY LEADER PARTNERSHIP	SCE-L-004L	SCE-13-L-002K
SCE	SCE-13-L-002L	ORANGE COUNTY CITIES ENERGY LEADER PARTNERSHIP	SCE-L-004M	SCE-13-L-002L
SCE	SCE-13-L-002M	SAN GABRIEL VALLEY ENERGY LEADER PARTNERSHIP	SCE-L-004O	SCE-13-L-002M
SCE	SCE-13-L-002N	SAN JOAQUIN VALLEY ENERGY LEADER PARTNERSHIP	SCE-L-004P	SCE-13-L-002N
SCE	SCE-13-L-002O	SOUTH BAY ENERGY LEADER PARTNERSHIP	SCE-L-004Q	SCE-13-L-002O
SCE	SCE-13-L-002P	SOUTH SANTA BARBARA COUNTY ENERGY LEADER PARTNERSHIP	SCE-L-004R	SCE-13-L-002P
SCE	SCE-13-L-002Q	VENTURA COUNTY ENERGY LEADER PARTNERSHIP	SCE-L-004S	SCE-13-L-002Q
SCE	SCE-13-L-002R	WESTERN RIVERSIDE ENERGY LEADER PARTNERSHIP	SCE-L-004U	SCE-13-L-002R
SCE	SCE-13-L-002S	CITY OF ADELANTO ENERGY LEADER PARTNERSHIP	SCE-L-004V	SCE-13-L-002S
SCE	SCE-13-L-002T	WEST SIDE ENERGY LEADER PARTNERSHIP	SCE-L-004W	SCE-13-L-002T
SCE	SCE-13-L-003A	CALIFORNIA COMMUNITY COLLEGES ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005A	SCE-13-L-003A
SCE	SCE-13-L-003B	CALIFORNIA DEPT. OF CORRECTIONS AND REHABILITATION EE PARTNERSHIP	SCE-L-005B	SCE-13-L-003B
SCE	SCE-13-L-003C	COUNTY OF LOS ANGELES ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005C	SCE-13-L-003C
SCE	SCE-13-L-003D	COUNTY OF RIVERSIDE ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005D	SCE-13-L-003D
SCE	SCE-13-L-003E	COUNTY OF SAN BERNARDINO ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005E	SCE-13-L-003E
SCE	SCE-13-L-003F	STATE OF CALIFORNIA ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005F	SCE-13-L-003F
SCE	SCE-13-L-003G	UC/CSU ENERGY EFFICIENCY PARTNERSHIP	SCE-L-005G	SCE-13-L-003G

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
SCE	SCE-13-SW-001E	HVAC PROGRAM	SCE-SW-007E	SCE-13-SW-001E
SCE	SCE-13-SW-002B	COMMERCIAL CALCULATED PROGRAM	SCE-SW-002B	SCE-13-SW-002B
SCE	SCE-13-SW-002C	COMMERCIAL DEEMED INCENTIVES PROGRAM	SCE-SW-002C	SCE-13-SW-002C
SCE	SCE-13-SW-002D	COMMERCIAL DIRECT INSTALL PROGRAM	SCE-SW-002D	SCE-13-SW-002D
SCE	SCE-13-SW-002F	NON-RESIDENTIAL HVAC PROGRAM	SCE-SW-007A	SCE-13-SW-002F
SCE	SCE-13-SW-002G	SAVINGS BY DESIGN	SCE-SW-005a	SCE-13-SW-002G
SCE	SCE-13-SW-003B	INDUSTRIAL CALCULATED ENERGY EFFICIENCY PROGRAM	SCE-SW-003B	SCE-13-SW-003B
SCE	SCE-13-SW-003C	INDUSTRIAL DEEMED ENERGY EFFICIENCY PROGRAM	SCE-SW-003C	SCE-13-SW-003C
SCE	SCE-13-SW-004B	AGRICULTURE CALCULATED ENERGY EFFICIENCY PROGRAM	SCE-SW-004B	SCE-13-SW-004B
SCE	SCE-13-SW-004C	AGRICULTURE DEEMED ENERGY EFFICIENCY PROGRAM	SCE-SW-004C	SCE-13-SW-004C
SCE	SCE-13-SW-005B	LIGHTING INNOVATION PROGRAM		SCE-13-SW-005B
SCE	SCE-13-TP-003	HEALTHCARE EE PROGRAM	SCE-TP-006	SCE-13-TP-003
SCE	SCE-13-TP-004	DATA CENTER ENERGY EFFICIENCY	SCE-TP-010	SCE-13-TP-004
SCE	SCE-13-TP-005	LODGING EE PROGRAM	SCE-TP-012	SCE-13-TP-005
SCE	SCE-13-TP-006	FOOD & KINDRED PRODUCTS	SCE-TP-013	SCE-13-TP-006
SCE	SCE-13-TP-007	PRIMARY AND FABRICATED METALS	SCE-TP-014	SCE-13-TP-007
SCE	SCE-13-TP-008	NONMETALLIC MINERALS AND PRODUCTS	SCE-TP-016	SCE-13-TP-008
SCE	SCE-13-TP-009	COMPREHENSIVE CHEMICAL PRODUCTS	SCE-TP-017	SCE-13-TP-009
SCE	SCE-13-TP-010	COMPREHENSIVE PETROLEUM REFINING	SCE-TP-019	SCE-13-TP-010
SCE	SCE-13-TP-011	OIL PRODUCTION	SCE-TP-020	SCE-13-TP-011
SCE	SCE-13-TP-012	REFINERY ENERGY EFFICIENCY PROGRAM	SCE-TP-021	SCE-13-TP-012
SCE	SCE-13-TP-013	COOL SCHOOLS	SCE-TP-023	SCE-13-TP-013
SCE	SCE-13-TP-014	COMMERCIAL UTILITY BUILDING EFFICIENCY	SCE-TP-026	SCE-13-TP-014
SCE	SCE-13-TP-017	ENERGY EFFICIENCY FOR ENTERTAINMENT CENTERS	SCE-TP-036	SCE-13-TP-017
SCE	SCE-13-TP-018	SCHOOL ENERGY EFFICIENCY PROGRAM	SCE-TP-024/ SCE-TP-038	SCE-13-TP-018

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
SCE	SCE-13-TP-020	IDEEA365 PROGRAM		SCE-13-TP-020
SCE	SCE-13-TP-021	ENHANCED RETROCOMMISSIONING		SCE-13-TP-021
SCE	SCE-L-004D	Energy Leader Partnership Program	SCE-L-004D	
SCE	SCE-TP-008	Comprehensive Beverage Manufacturing & Resource Efficiency	SCE-TP-008	
SCE	SCE-TP-015	Industrial Gasses	SCE-TP-015	
SCE	SCE-TP-018	Chemical Products Efficiency Program	SCE-TP-018	
SCE	SCE-TP-025	Retail Energy Action Program	SCE-TP-025	
SCE	SCE-TP-027	MONITORING-BASED COMMISSIONING		SCE-TP-027
SCE	SCE-TP-028	MONITORING-BASED PERSISTENCE COMMISSIONING PROGRAM		SCE-TP-028
SCE	SCE-TP-031	Management Affiliates Program	SCE-TP-031	
SCE	SCE-TP-033	Automatic Energy Review for Schools Program	SCE-TP-033	
SCE	SCE-TP-037	Private Schools and Colleges Program	SCE-TP-037	
SCE	SCE-TP-0608	Coin Operated Laundry Program	SCE-TP-0608	
SCG	SCG3710	SW-COM-CALCULATED INCENTIVES	SCG3607/ SCG3625	SCG3710
SCG	SCG3711	SW-COM-DEEMED INCENTIVES	SCG3608	SCG3711
SCG	SCG3712	SW-COM-NONRES HVAC		SCG3712
SCG	SCG3715	SW-IND-CALCULATED INCENTIVES	SCG3611	SCG3715
SCG	SCG3716	SW-IND-DEEMED INCENTIVES	SCG3612	SCG3716
SCG	SCG3719	SW-AG-CALCULATED INCENTIVES	SCG3602	SCG3719
SCG	SCG3720	SW-AG-DEEMED INCENTIVES	SCG3603	SCG3720
SCG	SCG3757	3P-SMALL INDUSTRIAL FACILITY UPGRADES	SCG3662	SCG3757
SCG	SCG3758	3P-PREPS	SCG3663	SCG3758
SCG	SCG3766	3P-SAVEGAS	SCG3673	SCG3766
SCG	SCG3793	3P-IDEEA365-INSTANT REBATES! POINT-OF-SALE FOODSERVICE REBATE PROGRAM		SCG3793
SDGE	SDGE3117E	ENERGY SAVINGS BID (ENCUMBERED)	SDGE3117	
SDGE	SDGE3118E/ SDGE3222	SW-COM-SAVINGS BY DESIGN	SDGE3118	SDGE3222
SDGE	SDGE3162	3P-NRes02 - SaveGas - Hot Water Control	SDGE3162	
SDGE	SDGE3220	SW-COM-CALCULATED INCENTIVES-CALCULATED	SDGE3105	SDGE3220
SDGE	SDGE3221	SW-COM-CALCULATED INCENTIVES-RCX	SDGE3170	SDGE3221
SDGE	SDGE3223	SW-COM-DEEMED INCENTIVES-COMMERCIAL REBATES	SDGE3106	SDGE3223

IOU	ITRON PROGRAM ID	ITRON PROGRAM NAME	Program ID - 1012	Program ID - 1314
SDGE	SDGE3224	SW-COM-DEEMED INCENTIVES-HVAC COMMERCIAL	SDGE3161	SDGE3224
SDGE	SDGE3226	SW-COM DIRECT INSTALL	SDGE3167/ SDGE3174	SDGE3226
SDGE	SDGE3231	SW-IND-CALCULATED INCENTIVES-CALCULATED	SDGE3109	SDGE3231
SDGE	SDGE3233	SW-IND-DEEMED INCENTIVES	SDGE3110	SDGE3233
SDGE	SDGE3237	SW-AG-CALCULATED INCENTIVES-CALCULATED	SDGE3100	SDGE3237
SDGE	SDGE3239	SW-AG-DEEMED INCENTIVES	SDGE3101	SDGE3239

8.2 Measure Group to Measure Class

Table 8-2: Measure Group to Measure Class

Measure Class	Measure Group
Ag Irrigation	AG IRRIGATION
Ag Pumping	Ag Pump Controls
	AG PUMP OTHER
	AG PUMP OVERHAUL
	AG PUMP TESTING
	AG PUMP VFD
Appliance	APPLIANCE CLOTHES WASHER
	APPLIANCE DISHWASHER
	APPLIANCE FREEZER
	APPLIANCE RECYCLE FREEZER
	APPLIANCE RECYCLE REFRIGERATOR
	APPLIANCE RECYCLE ROOM AC
	APPLIANCE REFRIGERATOR
	VENDING MACHINE
Food Service	FOOD SERVICE
HVAC Chillers	HVAC CENTRAL PLANT
	HVAC CHILLER AIR COOLED
	HVAC CHILLER OTHER
	HVAC CHILLER WATER COOLED
HVAC Controls	HVAC CONTROLS BOILER
	HVAC CONTROLS COMPRESSOR
	HVAC CONTROLS EMS
	HVAC CONTROLS FAN
	HVAC CONTROLS FUME HOOD
	HVAC CONTROLS OTHER

Measure Class	Measure Group
	HVAC CONTROLS PTAC
	HVAC CONTROLS RESET
	HVAC CONTROLS STEAM SYSTEM
	HVAC CONTROLS THERMOSTAT
	HVAC CONTROLS TIMER
	HVAC DCV
HVAC Distribution System Components	HVAC COMPRESSOR VFD
	HVAC COOLING OTHER
	HVAC COOLING TOWER
	HVAC DUCT INSULATION
	HVAC DUCT SEALING
	HVAC ECONOMIZER ADDITION
	HVAC ECONOMIZER WATER SIDE
	HVAC FAN VFD
	HVAC MOTOR REPLACEMENT
	HVAC OTHER VFD
	HVAC PUMP OTHER
	HVAC PUMP REPLACEMENT
	HVAC PUMP SYSTEM OPTIMIZATION
	HVAC PUMP VFD
	HVAC VAV CONVERSION
	HVAC VENTILATION FAN
	HVAC VENTILATION OTHER
	HVAC VRF/MINI SPLIT
HVAC DX Equipment	HVAC COMPRESSOR REPLACEMENT
	HVAC EVAP COOLER
	HVAC PTAC-PTHP
	HVAC ROOFTOP OR SPLIT SYSTEM
	HVAC ROOM AC
HVAC Envelope	BUILDING ENVELOPE CEILING-ROOF INSULATION
	BUILDING ENVELOPE COOL ROOF
	BUILDING ENVELOPE INSULATION OTHER
	BUILDING ENVELOPE NEW WINDOWS
	BUILDING ENVELOPE OTHER
	BUILDING ENVELOPE WALL INSULATION
	BUILDING ENVELOPE WINDOW FILM
	BUILDING ENVELOPE WINDOW OTHER
HVAC Heating Equipment	HVAC BOILER
	HVAC BOILER STACK ECONOMIZER
	HVAC FURNACE
HVAC Maintenance	HVAC AIR FILTER REPLACEMENT

Measure Class	Measure Group
	HVAC COIL CLEANING
	HVAC ECONOMIZER REPAIR
	HVAC FAN REPAIR
	HVAC MAINTENANCE
	HVAC RCA
HVAC Other	HVAC HEATING OTHER
	HVAC OTHER
Indoor Lighting - CFL	LIGHTING INDOOR CFL > 30 WATTS
	LIGHTING INDOOR CFL 3 WAY
	LIGHTING INDOOR CFL A LAMP
	LIGHTING INDOOR CFL BASIC
	LIGHTING INDOOR CFL FIXTURE
	LIGHTING INDOOR CFL GLOBE
	LIGHTING INDOOR CFL OTHER
	LIGHTING INDOOR CFL REFLECTOR
Indoor Lighting - Controls	LIGHTING INDOOR CONTROLS DAYLIGHTING
	LIGHTING INDOOR CONTROLS HI-LO
	LIGHTING INDOOR CONTROLS OTHER
	LIGHTING INDOOR CONTROLS WALL OR CEILING MOUNTED OCCUPANCY SENSOR
	LIGHTING INDOOR FIXTURE INTEGRATED OCCUPANCY SENSOR
Indoor Lighting - HID	LIGHTING INDOOR HID
Indoor Lighting - LED	LIGHTING INDOOR LED FIXTURE
	LIGHTING INDOOR LED LAMP
	LIGHTING INDOOR LED OTHER
	LIGHTING INDOOR LED REFLECTOR LAMP
Indoor Lighting - Linear	LIGHTING INDOOR HIGH BAY FLUORESCENT
	LIGHTING INDOOR LINEAR FLUORESCENT
	LIGHTING INDOOR LINEAR FLUORESCENT DELAMPING
Indoor Lighting - Other	LIGHTING INDOOR COLD CATHODE
	LIGHTING INDOOR INDUCTION
	LIGHTING INDOOR LED EXIT SIGN
	LIGHTING INDOOR LED SIGNAGE
	LIGHTING INDOOR OTHER
LED Streetlight	LIGHTING OUTDOOR LED STREET LIGHT
	LIGHTING OUTDOOR LED STREETLIGHT
Other	OTHER
Outdoor Lighting	LIGHTING OUTDOOR CFL > 30 WATTS
	LIGHTING OUTDOOR CFL BASIC
	LIGHTING OUTDOOR CFL FIXTURE
	LIGHTING OUTDOOR COLD CATHODE
	LIGHTING OUTDOOR CONTROLS OTHER

Measure Class	Measure Group
	LIGHTING OUTDOOR CONTROLS PHOTOCELL
	LIGHTING OUTDOOR CONTROLS TIME CLOCK
	LIGHTING OUTDOOR HID
	LIGHTING OUTDOOR INDUCTION
	LIGHTING OUTDOOR LED FIXTURE
	LIGHTING OUTDOOR LED HOLIDAY
	LIGHTING OUTDOOR LED OTHER
	LIGHTING OUTDOOR LED SIGNAGE
	LIGHTING OUTDOOR LINEAR FLUORESCENT
	LIGHTING OUTDOOR OTHER
Plug Loads	PLUG LOAD DESKTOP COMPUTER
	PLUG LOAD MONITOR
	PLUG LOAD OTHER
	PLUG LOAD PC POWER MANAGEMENT
	PLUG LOAD PRINTER COPIER MULTIFUNCTION
	PLUG LOAD SENSOR
	PLUG LOAD TELEVISION
Pool	POOL COVER
	POOL HEATER
	POOL PUMP
Process compressed air	PROCESS COMPRESSED AIR COMPRESSOR
	PROCESS COMPRESSED AIR CONTROLS
	PROCESS COMPRESSED AIR OTHER
	PROCESS COMPRESSED AIR SYSTEM CONFIGURATION
	PROCESS COMPRESSED AIR VFD
Process cooling	PIPE INSULATION COLD APPLICATION
	PROCESS COMPUTING OPERATIONS DATA CENTER AIR FLOW MANAGEMENT
	PROCESS COOLING
	PROCESS COOLING CONTROLS
	TANK INSULATION COLD APPLICATION
Process heating	PIPE INSULATION HOT APPLICATION
	PROCESS BOILER
	PROCESS BOILER BURNER UPGRADE
	PROCESS BOILER CONDENSATE HEAT RECOVERY
	PROCESS BOILER CONTROLS OTHER
	PROCESS BOILER STACK HEAT RECOVERY
	PROCESS BOILER TUNEUP
	PROCESS HEAT RECOVERY
	PROCESS HEATING
	STEAM TRAP HP
	STEAM TRAP LP

Measure Class	Measure Group
	TANK INSULATION HOT APPLICATION
Process other	PROCESS COMPUTING OPERATIONS DATA CENTER HVAC OTHER
	PROCESS COMPUTING OPERATIONS DATA CENTER UPS
	PROCESS COMPUTING OPERATIONS SERVER VIRTUALIZATION
	PROCESS DEHYDRATOR
	PROCESS FAN
	PROCESS GREENHOUSE HEAT CURTAIN
	PROCESS GREENHOUSE IR FILM
	PROCESS INJECTION MOLDING
	PROCESS OTHER
	PROCESS OTHER CONTROLS
	PROCESS OZONE LAUNDRY
	PROCESS WASTEWATER AERATOR
	PROCESS WASTEWATER CONTROL
	PROCESS WASTEWATER OTHER
	PROCESS WATER SUPPLY CONTROL
	PROCESS WATER SUPPLY OTHER
Process Pumping & Motors	OTHER MOTOR REPLACEMENT
	PROCESS FAN VFD
	PROCESS MOTOR CONTROLS
	PROCESS MOTOR REPLACEMENT
	PROCESS OIL WELL PUMP OFF CONTROLLERS
	PROCESS OIL WELL PUMPING OTHER
	PROCESS OTHER VFD
	PROCESS PUMPING
	PROCESS PUMPING CONTROLS
	PROCESS PUMPING VFD
	PROCESS VACUUM PUMP
	PROCESS VACUUM PUMP VFD
	PROCESS WASTEWATER PUMP
	PROCESS WASTEWATER VFD
	PROCESS WATER SUPPLY PUMP
	PROCESS WATER SUPPLY VFD
RCX	RETROCOMMISSIONING HVAC
	RETROCOMMISSIONING LIGHTING
	RETROCOMMISSIONING PROCESS
	RETROCOMMISSIONING REFRIGERATION
Refrigeration Controls	REFRIGERATION CONTROLS ASH
	REFRIGERATION CONTROLS EVAPORATOR FAN
	REFRIGERATION CONTROLS FLOATING HEAD PRESSURE
	REFRIGERATION CONTROLS FLOATING SUCTION PRESSURE

Measure Class	Measure Group
	REFRIGERATION CONTROLS OTHER
	REFRIGERATION EMS
Refrigeration End-Use Measures	REFRIGERATION CASE DOOR
	REFRIGERATION CASE LED LIGHTING
	REFRIGERATION CASE LIGHTING OTHER
	REFRIGERATION CASE REPLACEMENT
	REFRIGERATION DOOR CLOSER
	REFRIGERATION DOOR GASKET
	REFRIGERATION ICE MACHINE
	REFRIGERATION NIGHT COVER
	REFRIGERATION STRIP CURTAIN
Refrigeration Other	REFRIGERATION COIL CLEANING
	REFRIGERATION OTHER
Refrigeration Plant Equipment	REFRIGERATION COMPRESSOR
	REFRIGERATION COMPRESSOR VFD
	REFRIGERATION CONDENSER
	REFRIGERATION CONDENSER VFD
	REFRIGERATION EVAPORATOR EC MOTORS
	REFRIGERATION EVAPORATOR VFD
Water Heating	WATER HEATING BOILER
	WATER HEATING CONTROLS
	WATER HEATING FAUCET AERATOR
	WATER HEATING OTHER
	WATER HEATING PUMPING
	WATER HEATING SHOWERHEAD
	WATER HEATING STORAGE WATER HEATER
	WATER HEATING TANKLESS WATER HEATER
Whole Building	WHOLE BUILDING NRNC
	WHOLE BUILDING RETROFIT
	WHOLE BUILDING RNC

8.3 Building Type to Building Group Map

Table 8-3: Building Type to Building Group

Building Group	Building Type
Agricultural	Ag & Water Pump
	Agricultural
	Agricultural Produce Farms
	Farm/Agriculture
	Greenhouse
Assembly	Assembly
Both Residential and Commercial	Both Residential and Commercial
Commercial	Commercial
Education - College	Education - College
	Education - Community College
	Education - University
Education - School	Education - Primary School
	Education - Relocatable Classroom
	Education - School
	Education - Secondary School
Food/Liquor	Food Store
	Food/Liquor
	Grocery
Health/Medical	Health/Medical - Care
	Health/Medical - Clinics
	Health/Medical - Hospital
	Health/Medical - Med Office
	Health/Medical - Nursing Home
Industrial	Industrial
Lodging	Hotel/Motel
	Lodging - Guest Room
	Lodging - Hotel
	Lodging - Motel
Manufacturing	Manufacturing Biotech
	Manufacturing Light Industrial
Mining	Mining
Miscellaneous Commercial	Miscellaneous Commercial
Office	Office
	Office - Large
	Office - Small
	Property Managers
Restaurant	Restaurant

Building Group	Building Type
	Restaurant - Fast-Food
	Restaurant - Sit-Down
Retail	Retail
	Retail - Multistory Large
	Retail - Single-Story Large
	Retail - Small
Transportation - Communication - Utilities	Transportation - Communication - Utilities
Unknown	Street Lights
	Unknown
Upstream	Upstream
Warehouse	Storage - Conditioned
	Storage - Unconditioned
	WAREHOUSE
	Warehouse - Refrigerated

8.4 Program Ranking

Table 8-4: Program Score and Residual Rankings

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
SCG3716	SW-IND-DEEMED INCENTIVES	1	1	138	137	117	2	1	110	148	82
SCG3715	SW-IND-CALCULATED INCENTIVES	2	2	114	114	83	54	35	118	95	111
PGE21019	ENHANCED AUTOMATION INITIATIVE	3	3	51	153	10	1	2	3	157	1
SCE-TP-033	Automatic Energy Review for Schools Program	4	4	50	48	54	5	4	62	74	84
SCE-13-L-003G	UC/CSU ENERGY EFFICIENCY PARTNERSHIP	5	84	1	1	151	124	100	128	147	140
SCE-13-L-002S	CITY OF ADELANTO ENERGY LEADER PARTNERSHIP	6	50	3	3	87	35	11	80	160	63

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
PGE2110012	UNIVERSITY OF CALIFORNIA/CALIFORNIA STATE UNIVERSITY	7	70	2	2	75	66	65	60	33	77
SDGE3118E /SDGE3222	SW-COM-SAVINGS BY DESIGN	8	39	4	12	15	43	110	7	113	3
PGE210113	ENERGY FITNESS PROGRAM	9	35	5	43	2	9	7	27	54	22
SCE-TP-027	MONITORING-BASED COMMISSIONING	10	5	125	153	84	6	3	153	137	147
PGE211010	FRESNO	11	44	8	47	4	11	9	32	75	29
PGE210120	MONITORING-BASED COMMISSIONING	12	8	54	153	11	4	8	4	76	6
SCE-13-SW-002G	SAVINGS BY DESIGN	13	17	31	20	52	32	37	28	39	23
SCG3710	SW-COM-CALCULATED INCENTIVES	14	7	71	120	37	16	34	14	17	25
PGE211012	MADERA	15	53	9	52	3	13	12	25	58	27
SCE-13-TP-012	REFINERY ENERGY EFFICIENCY PROGRAM	16	11	61	41	69	25	21	19	11	26
PGE210122	CASINO GREEN	17	64	12	5	107	73	27	126	141	117
SCG3719	SW-AG-CALCULATED INCENTIVES	18	15	58	122	23	132	150	41	125	44
PGE210115	RIGHTLIGHTS	19	77	10	35	8	99	127	55	41	59
PGE2110014	DEPARTMENT OF CORRECTIONS AND REHABILITATION	20	46	29	10	92	36	42	51	25	88
PGE21029	REFINERY ENERGY EFFICIENCY PROGRAM	21	6	157	93	161	10	5	141	5	161
PGE210111	LODGINGSAVERS	22	82	13	9	62	154	158	151	94	149
SCE-13-L-003A	CALIFORNIA COMMUNITY COLLEGES ENERGY EFFICIENCY PARTNERSHIP	23	115	6	4	130	49	57	64	105	32
SCE-13-L-003B	CALIFORNIA DEPT. OF CORRECTIONS AND	24	60	24	7	103	40	62	49	152	14

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
	REHABILITATION EE PARTNERSHIP										
PGE210133	STAPLES LOW PRESSURE IRRIGATION DI	25	30	47	153	9	18	36	8	83	13
SCE-13-TP-005	LODGING EE PROGRAM	26	69	25	16	50	22	39	35	15	39
PGE2110011	CALIFORNIA COMMUNITY COLLEGES	27	76	22	6	109	145	88	142	90	135
SCG3766	3P-SAVEGAS	28	25	59	153	14	64	43	81	127	97
SCE-TP-028	MONITORING-BASED PERSISTENCE COMMISSIONING PROGRAM	29	94	15	14.5	32	103	157	22	8	18
PGE21031	AGRICULTURAL CALCULATED INCENTIVES	30	13	85	99	67	62	91	30	21	28
PGE210311	PROCESS WASTEWATER TREATMENT EM PGM FOR AG FOOD PROCESSING	31	10	100	125	63	23	26	40	47	43
SDGE3226	SW-COM DIRECT INSTALL	32	145	7	13	35	129	142	123	62	116
PGE211011	KERN	33	111	14	19	21	71	74	92	50	102
PGE211020	SANTA BARBARA	34	107	19	24	24	60	59	82	43	103
SCE-13-TP-020	IDEEA365 PROGRAM	35	138	11	153	1	8	112	2	24	4
PGE210114	ENERGY SAVERS	36	83	32	72	16	85	80	96	49	107
PGE211014	MENDOCINO COUNTY	37	127	16	61	5	47	82	58	98	56
PGE210124	OZONE LAUNDRY ENERGY EFFICIENCY	38	63	45	153	6	61	117	12	138	8
PGE21035	DAIRY ENERGY EFFICIENCY PROGRAM	39	51	52	42	58	20	20	44	19	51
PGE211019	SAN MATEO COUNTY	40	117	21	18	33	70	95	53	91	35
SCE-13-SW-004B	AGRICULTURE CALCULATED ENERGY	41	38	67	133	28	106	135	47	115	37

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
	EFFICIENCY PROGRAM										
SCE-13-SW-002D	COMMERCIAL DIRECT INSTALL PROGRAM	42	132	17	26	18	90	132	54	23	73
SCE-13-SW-003B	INDUSTRIAL CALCULATED ENERGY EFFICIENCY PROGRAM	43	14	115	79	124	115	104	99	38	112
PGE2110051	LOCAL GOVERNMENT ENERGY ACTION RESOURCES (LGEAR)	44	136	18	38	12	72	107	59	48	58
PGE211021	SIERRA NEVADA	45	114	26	51	13	83	75	91	116	68
SCE-13-SW-002B	COMMERCIAL CALCULATED PROGRAM	46	21	92	77	82	86	46	121	56	121
PGE211018	SAN LUIS OBISPO COUNTY	47	128	23	31	20	84	83	97	53	105
SDGE3220	SW-COM-CALCULATED INCENTIVES-CALCULATED	48	16	109	112	78	96	52	115	4	141
SDGE3162	3P-NRes02 - SaveGas - Hot Water Control	49	32	76	153	34	46	40	75	86	92
SCE-13-TP-006	FOOD & KINDRED PRODUCTS	50	22	96	60	110	37	44	33	40	47
PGE210118	FURNITURE STORE ENERGY EFFICIENCY	51	119	28	91	7	41	51	56	68	60
PGE210126	K-12 PRIVATE SCHOOLS AND COLLEGES AUDIT RETRO	52	142	20	23	27	101	129	86	97	57
PGE211023	SILICON VALLEY	53	116	30	30	30	53	96	29	84	24
SCE-13-L-002T	WEST SIDE ENERGY LEADER PARTNERSHIP	54	129	27	8	89	68	115	23	6	53
SDGE3117E	ENERGY SAVINGS BID (ENCUMBERED)	55	20	107	100	93	134	61	154	100	157
SCE-13-L-002L	ORANGE COUNTY CITIES ENERGY	56	95	38	69	25	95	94	98	63	89

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
	LEADER PARTNERSHIP										
SCG3758	3P-PREPS	57	102	36	70	19	3	41	1	1	2
SCE-13-TP-014	COMMERCIAL UTILITY BUILDING EFFICIENCY	58	37	78	83	68	77	84	67	31	95
SCE-13-L-002B	CITY OF LONG BEACH ENERGY LEADER PARTNERSHIP	59	99	37	25	55	7	33	5	34	5
PGE211007	ASSOCIATION OF MONTEREY BAY AREA GOVERNMENTS (AMBAG)	60	109	35	34	38	57	56	57	88	45
PGE21025	CALIFORNIA WASTEWATER PROCESS OPTIMIZATION	61	72	55	129	17	42	133	6	92	7
PGE21027	HEAVY INDUSTRY ENERGY EFFICIENCY PROGRAM	62	31	95	63	106	108	118	36	12	52
SCE-13-TP-008	NONMETALLIC MINERALS AND PRODUCTS	63	42	81	21	134	89	114	24	7	74
SCE-13-L-003F	STATE OF CALIFORNIA ENERGY EFFICIENCY PARTNERSHIP	64	88	48	36	57	92	145	31	27	33
SCE-13-L-002G	COMMUNITY ENERGY LEADER PARTNERSHIP	65	106	40	17	65	14	24	17	28	17
SCE-13-SW-003C	INDUSTRIAL DEEMED ENERGY EFFICIENCY PROGRAM	66	62	66	105	39	97	138	21	124	20
SDGE3223	SW-COM-DEEMED INCENTIVES-COMMERCIAL REBATES	67	40	84	62	85	31	10	83	70	83
PGE211022	SONOMA COUNTY	68	105	41	37	46	117	86	112	77	119
SCE-TP-037	Private Schools and Colleges Program	69	126	34	44	31	45	90	34	16	40

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
PGE21018	ENERGYSMART GROCER	70	26	108	73	116	50	47	76	78	98
PGE21026	ENERGY EFFICIENCY SERVICES FOR OIL PRODUCTION	71	12	140	153	113	55	45	73	146	34
SCE-13-L-002D	CITY OF SANTA ANA ENERGY LEADER PARTNERSHIP	72	121	39	53	29	74	54	101	71	90
PGE211009	EAST BAY	73	67	69	98	47	81	31	107	145	100
PGE210116	SMALL BUSINESS COMMERCIAL COMPREHENSIVE	74	57	73	113	48	93	119	50	106	55
PGE21021	INDUSTRIAL CALCULATED INCENTIVES	75	9	150	97	156	102	68	138	10	156
PGE21011	COMMERCIAL CALCULATED INCENTIVES	76	33	99	84	97	65	63	69	14	93
PGE21038	WINE INDUSTRY EFFICIENCY SOLUTIONS	77	81	64	28	81	67	97	48	13	64
PGE211016	REDWOOD COAST	78	122	42	39	42	143	120	132	57	130
PGE21032	AGRICULTURAL DEEMED INCENTIVES	79	19	132	107	135	51	28	113	67	125
SCE-TP-015	Industrial Gasses	80	49	86	66	86	17	32	37	65	36
SCE-TP-025	Retail Energy Action Program	81	86	60	123	26	12	14	45	104	49
PGE210110	MONITORING-BASED PERSISTENCE COMMISSIONING	82	66	74	82	64	59	137	11	26	10
PGE21022	INDUSTRIAL DEEMED INCENTIVES	83	36	104	110	76	26	38	13	69	12
SCE-13-L-002J	DESERT CITIES ENERGY LEADER PARTNERSHIP	84	151	33	27	43	125	148	79	42	96
SCG3793	3P-IDEEA365-INSTANT REBATES! POINT-OF-SALE FOODSERVICE REBATE PROGRAM	85	65	77	153	36	111	92	108	101	109

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
SCE-13-SW-002C	COMMERCIAL DEEMED INCENTIVES PROGRAM	86	48	91	95	74	48	30	88	107	80
SCE-13-TP-009	COMPREHENSIVE CHEMICAL PRODUCTS	87	55	87	57	95	105	108	72	87	86
SDGE3221	SW-COM-CALCULATED INCENTIVES-RCX	88	45	102	111	73	21	23	42	159	11
SDGE3233	SW-IND-DEEMED INCENTIVES	89	59	88	78	79	39	16	90	134	54
SCE-13-L-002E	CITY OF SIMI VALLEY ENERGY LEADER PARTNERSHIP	90	133	46	11	138	104	73	127	81	136
PGE2189	Cool Controls Plus	91	78	75	89	60	109	116	74	32	75
PGE211015	NAPA COUNTY	92	110	56	71	51	116	77	111	112	114
PGE2201	California High Performance Lighting Program	93	90	68	153	22	98	98	66	155	50
PGE211013	MARIN COUNTY	94	124	53	59	45	119	103	103	109	101
SCE-13-L-002Q	VENTURA COUNTY ENERGY LEADER PARTNERSHIP	95	139	44	46	41	113	124	85	82	78
SCE-13-TP-003	HEALTHCARE EE PROGRAM	96	58	94	45	122	15	13	61	66	81
SCE-13-TP-018	SCHOOL ENERGY EFFICIENCY PROGRAM	97	97	63	90	44	155	144	152	158	145
SCG3757	3P-SMALL INDUSTRIAL FACILITY UPGRADES	98	24	136	116	132	156	147	150	142	138
SDGE3231	SW-IND-CALCULATED INCENTIVES-CALCULATED	99	28	129	92	141	131	139	84	18	123
PGE21028	INDUSTRIAL COMPRESSED AIR PROGRAM	100	29	130	153	96	87	105	43	143	15
SCE-13-TP-007	PRIMARY AND FABRICATED METALS	101	41	118	81	128	56	78	26	64	31
PGE211024	SAN FRANCISCO	102	113	62	85	49	139	122	122	139	113

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
SCG3711	SW-COM-DEEMED INCENTIVES	103	56	105	126	70	127	141	77	73	79
PGE210125	CALIFORNIA PRESCHOOL ENERGY EFFICIENCY PROGRAM	104	134	57	68	53	94	123	46	120	30
SCE-13-L-002R	WESTERN RIVERSIDE ENERGY LEADER PARTNERSHIP	105	150	49	40	56	27	81	18	37	16
PGE21017	BOILER ENERGY EFFICIENCY PROGRAM	106	43	122	124	94	63	48	78	140	42
PGE210310	DAIRY INDUSTRY RESOURCE ADVANTAGE PGM	107	79	90	58	102	80	22	136	118	128
SCE-13-TP-011	OIL PRODUCTION	108	23	147	128	142	100	50	131	123	115
PGE21012	COMMERCIAL DEEMED INCENTIVES	109	34	131	104	133	30	19	71	61	85
SCE-13-L-002P	SOUTH SANTA BARBARA COUNTY ENERGY LEADER PARTNERSHIP	110	159	43	22	59	24	99	15	22	19
SCE-TP-031	Management Affiliates Program	111	125	70	32	88	146	146	134	36	143
PGE210117	ENERGY-EFFICIENT PARKING GARAGE	112	54	119	135	77	138	121	116	150	76
PGE210112	SCHOOL ENERGY EFFICIENCY	113	100	80	49	90	76	109	39	55	48
PGE211025	SAVINGS BY DESIGN (SBD)	114	18	158	103	157	88	49	144	108	154
PGE21016	AIR CARE PLUS	115	85	97	75	99	19	67	9	2	46
PGE21036	INDUSTRIAL REFRIGERATION PERFORMANCE PLUS	116	47	135	86	147	150	140	145	133	139
SCE-13-L-002C	CITY OF REDLANDS ENERGY LEADER PARTNERSHIP	117	147	72	54	71	82	113	63	60	66
SCE-13-L-002M	SAN GABRIEL VALLEY ENERGY LEADER PARTNERSHIP	118	87	111	88	108	112	15	149	103	148

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
SDGE3237	SW-AG-CALCULATED INCENTIVES-CALCULATED	119	130	83	153	40	69	143	10	96	9
PGE2110013	STATE OF CALIFORNIA	120	71	123	96	131	107	60	129	80	129
PGE21039	COMPREHENSIVE FOOD PROCESS AUDIT & RESOURCE EFFICIENCY PGM	121	27	156	117	154	159	149	162	93	163
SCE-13-L-002N	SAN JOAQUIN VALLEY ENERGY LEADER PARTNERSHIP	122	103	98	55	114	120	25	148	79	153
PGE2183	Comprehensive Retail Energy Management	123	80	121	74	137	38	6	124	44	122
SCE-13-SW-004C	AGRICULTURE DEEMED ENERGY EFFICIENCY PROGRAM	124	101	110	121	72	91	76	94	153	69
SCE-13-L-003C	COUNTY OF LOS ANGELES ENERGY EFFICIENCY PARTNERSHIP	125	91	120	118	91	141	71	146	162	126
PGE21042	LIGHTING INNOVATION	126	61	143	142	121	28	17	70	45	62
SCE-TP-0608	Coin Operated Laundry Program	127	154	79	94	61	148	159	119	151	87
PGE2191	Medical Building Tune-Up	128	73	139	109	140	52	29	93	52	94
SCE-TP-008	Comprehensive Beverage Manufacturing & Resource Efficiency	129	68	141	153	119	79	64	89	130	65
SCG3720	SW-AG-DEEMED INCENTIVES	130	93	124	119	105	128	93	135	89	134
PGE2214	Energy Efficiency Program for Entertainment Centers	131	148	93	65	104	44	102	16	3	41
SCE-13-L-003E	COUNTY OF SAN BERNARDINO ENERGY EFFICIENCY PARTNERSHIP	132	135	106	33	149	122	106	95	121	91

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
SCE-13-L-002H	EASTERN SIERRA ENERGY LEADER PARTNERSHIP	133	162	65	50	66	34	111	20	30	21
SCE-13-L-002K	KERN COUNTY ENERGY LEADER PARTNERSHIP	134	157	82	29	123	78	79	65	20	99
SCE-13-TP-004	DATA CENTER ENERGY EFFICIENCY	135	89	134	101	139	142	53	156	122	151
SCE-13-TP-017	ENERGY EFFICIENCY FOR ENTERTAINMENT CENTERS	136	144	101	56	118	75	70	100	51	110
SCE-13-L-002O	SOUTH BAY ENERGY LEADER PARTNERSHIP	137	149	103	87	101	137	72	147	102	150
SDGE3239	SW-AG-DEEMED INCENTIVES	138	140	113	80	115	136	130	133	29	142
SCE-13-L-002F	GATEWAY CITIES ENERGY LEADER PARTNERSHIP	139	158	89	76	80	118	125	105	85	108
SCE-TP-018	Chemical Products Efficiency Program	140	104	133	134	112	130	131	87	99	70
PGE210123	HEALTHCARE ENERGY EFFICIENCY PROGRAM	141	152	112	67	129	152	160	130	72	127
PGE21006/PGE21015	COMMERCIAL HVAC	142	123	127	136	98	133	154	68	126	61
PGE2227	Cement Production and Distribution Energy Efficiency	143	146	116	14.5	163	140	134	102	46	146
SCE-13-TP-021	ENHANCED RETROCOMMISSIONING	144	92	145	102	148	110	89	117	9	133
SDGE3224	SW-COM-DEEMED INCENTIVES-HVAC COMMERCIAL	145	131	126	130	100	121	101	109	129	120
PGE2198	Data Centers Cooling Controls Program	146	75	155	106	155	29	58	38	35	71
PGE2204	SmartVent for Energy-Efficient Kitchens	147	98	142	153	120	33	55	52	114	38
PGE210128	ENOVITY SMART	148	112	146	153	127	144	153	120	117	118
SCE-13-L-003D	COUNTY OF RIVERSIDE ENERGY	149	141	128	108	126	149	156	125	135	106

Itron Program ID	Itron Program Name	Score Rank					Residuals Rank				
		DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved	DORCE	Cost Effectiveness	Depth of Retrofit	Technologies Addressed	Savings Achieved
	EFFICIENCY PARTNERSHIP										
PGE210119	LED ACCELERATOR	150	120	144	140	125	162	161	160	154	158
SCE-13-L-002A	CITY OF BEAUMONT ENERGY LEADER PARTNERSHIP	151	156	117	64	136	123	69	139	59	152
SCE-13-SW-002F	NON-RESIDENTIAL HVAC PROGRAM	152	96	148	131	145	126	66	143	156	137
PGE2220	Assessment, Implementation, and Monitoring (AIM) Program	153	52	163	153	160	135	87	155	128	132
SCE-13-SW-005B	LIGHTING INNOVATION PROGRAM	154	137	137	139	111	114	85	106	136	72
SCE-13-TP-010	COMPREHENSIVE PETROLEUM REFINING	155	108	149	127	150	151	151	137	132	124
SCE-13-TP-013	COOL SCHOOLS	156	118	152	115	152	58	18	114	110	104
PGE210210	INDUSTRIAL RECOMMISSIONING PROGRAM	157	74	162	132	162	158	136	161	119	162
PGE210130	RSG AERCX	158	143	151	153	143	157	128	159	111	160
PGE2242	Cool Cash	159	153	153	153	144	153	163	104	131	67
PGE21037	LIGHT EXCHANGE PROGRAM	160	160	154	141	146	161	152	163	163	159
SCE-13-SW-001E	RESIDENTIAL HVAC PROGRAM	161	161	159	138	153	160	155	158	161	155
SCE-L-004D	Energy Leader Partnership Program	162	155	161	153	159	147	126	140	144	131
SCG3712	SW-COM-NONRES HVAC	163	163	160	153	158	163	162	157	149	144