Guidehouse

2021 Energy Efficiency Top-Down Potential Prototype Analysis

Prepared for:

California Public Utilities Commission

Submitted by:

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Appendix X.A: Extrapolation Sample Comparison

Filename: "CPUC Top-Down Potential Appendix X.A 2021-08-31.*pdf*"
Description: This appendix shows for plots per page, comparing the relative frequency distribution of accounts in the core sample (CS) with those of the extrapolation sample (ES) by buckets of annual consumption. Each plot corresponds to a different scenario and demonstrates how, as the ES is expanded beyond the CS to include more accounts, the distributions deviate.

Appendix X.B: Incremental Cost Estimation

Filename: "CPUC Top-Down Potential Appendix X.B 2021-08-31.pdf"
Description: This appendix presents the complete set of plots showing the scatter plots of individual claim cost and present value of lifetime savings, as well as the fitted line that delivers estimated levelized cost of energy efficiency for the given end-use, for the specified fuel and segment.

Executive Summary

The California Public Utilities Commission (CPUC) conducts an energy efficiency potential and goals study (PG Study) every two years. The PG Study develops estimates of energy and demand savings potential in the service territories of California's major investor-owned utilities (IOUs). The PG study informs the CPUC as it proceeds to adopt goals and targets, providing guidance for the next IOU energy efficiency portfolios. The potential study is a framework based on existing policies and expectations of market uptake that assesses savings reasonably expected to be achievable by IOU-funded programs.

Potential studies are widely used to set energy efficiency portfolio goals, inform integrated resource planning, adjust load forecasts, and inform program design. While most of these studies use a bottom-up forecasting method, this study sets out to answer how a top-down, consumption-based approach might replace or improve the bottom-up, measure-based potential model.

There are inherent challenges in the bottom-up approach. It is an exercise of data management requiring assumptions where there are data gaps. To help address these issues, the CPUC set out to assess an aggregated, empirical, "top-down" approach to modeling potential. A top-down approach has its advantages. By looking at actual consumption the approach is firmly grounded in the real world. However, compiling large, representative datasets matching consumption to program participation are crucial, but difficult to create. Modeling based on past consumption also creates challenges when including new technologies and approaches, such as fuel-substitution or benefits-based goals and targets.

As a result of stakeholder requests and CPUC staff deliberation, Guidehouse was commissioned to conduct an exploratory study to develop and test a prototype[1] top-down modeling approach. This effort, being exploratory in nature, is **not** meant to inform the CPUC's goal setting process for the post 2021 cycle. The study is to provide context on if and how a top-down approach may work. As part of the exploration, the study also presents the trade-offs of the two approaches.

Background and Approach

The existing PG Study model is a "bottom-up" model. A bottom-up approach is generally defined as an approach that begins from very granular inputs (e.g., individual energy efficiency measures) and builds these up through assumptions about market dynamics and consumer behavior to deliver projections of potential future energy efficiency savings, and the cost of achieving those savings.

Some stakeholders have recommended the PG Study to consider alternative approaches to the existing bottom-up model. Specifically, these stakeholders have requested that consideration be given to a more aggregated, empirical, "top-down" approach to modeling potential that would use individual customer consumption data. Such an approach need not be mutually exclusive from a bottom-up approach. Part of this study is to examine potential elements of the two approaches that may be combined to produce more robust potential estimates. In that respect,

[1] For this study Guidehouse has deliberately chosen to identify its approach as a "prototype" – a preliminary model intended for testing and evaluation. A prototype is distinct from a "production" model in that the primary output of interest is not the output of the modeling approach itself, but the information and understanding gained about the capabilities and shortcomings of that modeling approach.

CPUC staff is seeking information to continually improve forecasting methods given changes in the policy, inputs and methods landscape.

To develop the prototype, Guidehouse identified the immediately available data sets to build a database. Out of this database, Guidehouse selected the appropriate sector, commercial, to study. From the sector-level data analysis, Guidehouse identified segments that had sufficient program and floorspace data for *efficient* and *less efficient* category development. The extrapolation analysis of a percent of the population from *less efficient* to *efficient* resulted in the top-down potential calculation.

Study Objectives

While the concept of a top-down potential study is not new, its application to a complex regulatory and goal setting process is untested in California. The long history of potential projection in California via bottom-up study has, to some degree, shaped the data landscape related to energy efficiency in this state to serve the needs of the bottom-up approach.

The differences in approach used by these two methods define the differences in the outputs they deliver. Since they are not perfect substitutes, this inevitably means that replacing one with the other would require trade-offs: there are simply some things that one method is better suited for than the other, and vice versa. While many of the types of trade-offs may be identified before any analysis is attempted, until both approaches have actually been modeled the materiality of those trade-offs may be unclear. It is only in undertaking to explore what data are available to support the development of a top-down approach (and what more data might be available for a wider-scale implementation) that the limits of what it can offer can be appreciated.

Accordingly, the purpose of this study is to achieve a better understanding of the practical benefits and limitations of a top-down empirical approach to potential estimation through the development of a prototype method for estimating potential with the use of readily available ("in-hand") data. For this study Guidehouse has deliberately chosen to identify its approach as a "prototype" – a preliminary model intended for testing and evaluation. A prototype is distinct from a "production" model in that the primary output of interest is not the output of the modeling approach, but the information and understanding gained about the capabilities and shortcomings of that modeling approach.

The purpose of this analysis is to identify paths forward for the adoption of a more consumption analytics approach to projecting energy efficiency potential. The goal is to explore the available data in enough detail to identify the most significant challenges to the expansion of a top-down approach and to be able to provide an analysis of how such an approach complements the conventional industry-standard bottom-up approach to projecting energy efficiency potential. In scoping out the analysis, Guidehouse, in consultation with CPUC staff, determined that the timely accomplishment of this goal[2] was best served by limiting the analysis to including only data already in CPUC's possession or else publicly available.

Prototype Development

The prototype analysis required to define the following steps with more detail in Section 2 of the report:

[2] All quantitative work was completed within four months of the provision of data to Guidehouse and within 3 months of the submission of the final workplan to the CPUC.

- **Assessment of Available Data.** Describes the data available to Guidehouse in the timelines required for the completion of this project. The data sets used were the CEC benchmarking and floorspace database, CEDARS program tracking data, utility account billing data, and the IEPR reference forecast.

- **Create the Building Database.** Describes how Guidehouse combined individual building floorspace data, IOU account consumption data, and historic program savings claims data to create the building database required for the subsequent steps in the analysis.

- **Segment Selection.** Details Guidehouse's considerations in selecting the segments from the building database to study as part of this analysis.

- **Split Sample with Proxy Variable.** Describes the development of the proxy variable used to identify *efficient* and *less efficient* buildings, and how these were compared to derive an estimate of energy efficiency potential.

- **Define Scenarios and Extrapolation Samples.** Outlines the issues related to extrapolating the potential estimated based on the sample of buildings included in our database out to a wider population and defines a set of four scenarios.

- **Project Potential and Distribute by End Use.** Describes how the elements above are combined to deliver the final projection of energy efficiency potential over the period of analysis.

Results

The development of the top-down prototype analysis results in key findings and recommendations for potential next steps for CPUC. Provided greater certainty can be obtained for representativeness of the sample and increased granularity in segmentation, the top-down methodology can meet many potential study output data requirements, though not all (see Table 1). All the top-down analysis outputs are available at the sector and end use level, not at a measure level.

Table 1: Requirements and Capabilities of Current Top-Down vs. Bottom-Up[3]

Model Requirement	Bottom-Up	Top-Down (Current Methodology)	Top-Down Study Notes
Separate forecasts for each IOU (setting goals)	+	+	Raw datasets can be mapped to an IOU
Supporting a TSB goal setting process	+	+	Calculated at the sector and end use level for the total savings in that year
Produce sufficient detail for IOUS and PA portfolio planning	+	+/-	Sometimes planning leverages measure level data which is not available

[3] Codes and standards and low-income potential does not appear in this table since they have their own methodologies.

Model Requirement	Bottom-Up	Top-Down (Current Methodology)	Top-Down Study Notes
Provides forecasting inputs to support procurement and planning efforts across multiple agencies	+	+/-	Forecasting inputs can be more aggregated at the end use level. Further disaggregation to available load shape level may be post- processed
Produce supply curves for IRP	+	+	Developed at the sector or end use level which aligns with the current measure bundle approach used
Quantify cost-effectiveness metrics	+	+	At the sector and end use level and not used for screening measures
Forecast 10-year time horizon	+	+	Based on historical consumption data
Produce cumulative EE savings for IEPR	+	+	Based on historical consumption data
Produce cumulative fuel substitution savings for IEPR	+	NA	Model was not tested with fuel substitution in the pilot analysis since there is minimal available date due to low historical penetration
Disaggregate DER types (energy efficiency, fuel substitution, energy efficiency/DR)	+	-	Analysis is based on historical penetration and savings data; as fuel substitution, EE-DR, and other DERs savings data grows, the information could be incorporated in an analysis
Separate Forecasts of Rebate Programs and BROs	+	-	Lack of measure level granularity does not allow disaggregating savings by program type source

Source: Guidehouse

Key findings from the prototype analysis include:

1. Given the currently available data, the top-down approach is at present an unsuitable as a complete replacement for the bottom-up approach for estimating commercial sector energy efficiency potential. Guidehouse recommends various solutions to supplement the data for future analysis.
2. Easy opportunities (“low hanging fruit”) are being depleted, and potential will become increasingly costly to obtain, particularly for natural gas.
3. The precision of top-down commercial sector potential estimation could be significantly improved with additional segmentation.
4. Despite some shortcomings, the cost data included in the CEDARS data can, when summarized appropriately, provide valuable insights for program planning.

5. With fewer consultant-generated inputs and assumptions (e.g. during the course of measure characterization) the top-down approach can offer increased transparency at reduced cost to CPUC and stakeholders.

6. To meet multiple stakeholder needs, further insights into the opportunity of post processing requirements need investigation to assess if the top-down is sufficient approach for forecasting potential.

Therefore, Guidehouse divides the recommendations in three levels:

- **Short-term recommendations** are those that could be implemented as part of the forthcoming potential estimation cycle (i.e., complete by spring 2023)
    - Enhancing the insight provided by the bottom-up analysis using the existing top-down analysis data set
    - Acquiring and vetting data that could be used to sufficiently enhance the top-down approach from a "prototype" to a "production" analysis.
- **Medium-term recommendations** are those that could be implemented as part of the next potential estimation cycle (i.e., complete by spring 2025)
    - Delivering production-quality potential analysis for the commercial sector
    - Producing prototype potential analysis for the industrial and agricultural sectors, sectors with facility demand patterns more idiosyncratic even than the commercial sector.
- **Long-term recommendations** are those that could be implemented by the time of the 2027 evaluation cycle and focus on the (conditional on the success of the short- and medium-term recommendations) transition of potential estimation to a top-down approach.
    - Evolving the industrial and agricultural top-down approaches from "prototype" to "production"
    - Migrating the residential potential estimation from a bottom-up to top-down approach
    - Executing opportunities to align the segmentation and granularity of the potential estimation with that of the IOU and CEC forecasting groups.

Contents of This Report

- **Introduction.** Chapter 1 of this report defines what is meant by a top-down estimate of energy efficiency potential, how this contrasts with the more traditional bottom-up approach, and what key questions Guidehouse has sought to resolve through the development of a prototype top-down approach.

- **Approach.** Chapter 2 of this report provides a detailed description of the data used in the top-down analysis, an explanation of how the analysis was conducted, and context for the reader regarding the areas of greatest uncertainty.

- **Results and Analysis.** Chapter 3 of this report provides the projected energy efficiency potential estimated using the top-down approach and discusses some of the implications of these results for future program planning.

- **Findings and Recommendations.** Chapter 4 of this report summarizes the key findings flowing from the prototype analysis (including the suitability of a top-down approach to replace the current bottom-up approach) and offers a series of recommendations for the CPUC and its stakeholders to consider over the short, medium, and long-term.

1. Introduction

The California Public Utilities Commission (CPUC) conducts an energy efficiency potential and goals study (PG Study) every two years. The PG Study develops estimates of energy and demand savings potential in the service territories of California's major investor-owned utilities (IOUs). The PG study informs the CPUC as it proceeds to adopt goals and targets, providing guidance for the next IOU energy efficiency portfolios. The potential study is a framework based on existing policies and expectations of market uptake that assesses savings reasonably expected to be achievable by IOU-funded programs.

Guidehouse has been conducting the last several cycles of the PG Study with the most recent being the 2021 PG Study. A key component of the PG Study is the Potential and Goals Model (PG Model). This model provides a platform to conduct quantitative scenario analysis that reflects the complex interactions among various inputs and policy drivers.

The existing PG Model is a "bottom-up" model. A bottom-up approach is generally defined as an approach that begins from very granular inputs (e.g., individual energy efficiency measures) and builds these up through assumptions about market dynamics and consumer behavior to deliver projections of potential future energy efficiency savings, and the cost of achieving those savings.

Some stakeholders have recommended the PG Study to consider alternative approaches to the existing bottom-up model. Specifically, these stakeholders have requested that consideration be given to a more aggregated, empirical, "top-down" approach to modeling potential that would use individual customer consumption data. Such an approach need not be mutually exclusive from a bottom-up approach. Part of this study is to examine potential elements of the two approaches that may be combined to produce more robust potential estimates. In that respect, CPUC staff is seeking information to continually improve forecasting methods given changes in the policy, inputs and methods landscape.

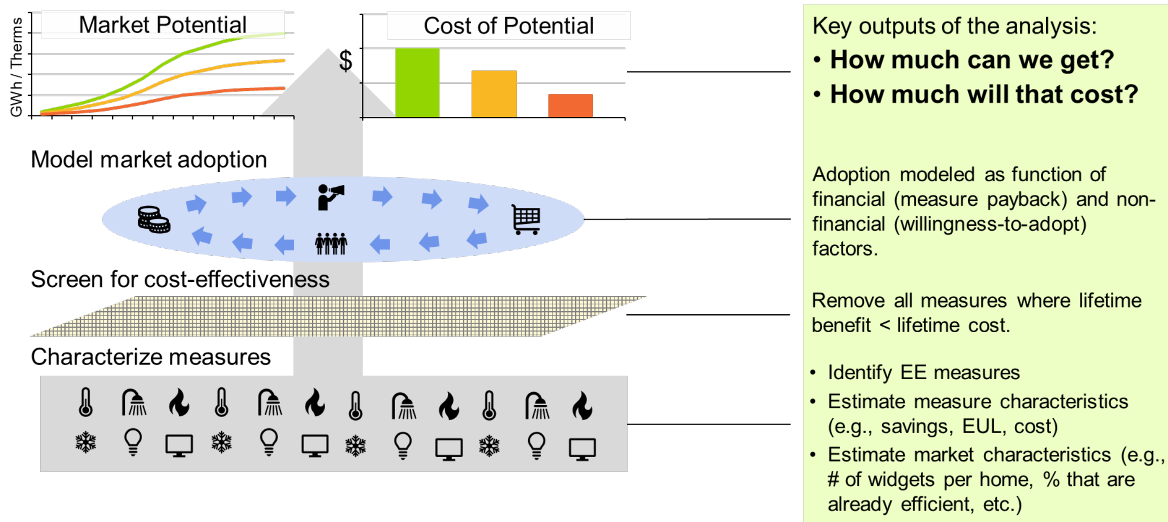
As a result of stakeholder requests and CPUC staff deliberation, Guidehouse was commissioned to conduct an exploratory study to develop and test a prototype[4] top-down modeling approach. This report describes the exploratory and testing efforts undertaking by Guidehouse. This effort, being exploratory in nature, is **not** meant to inform the CPUC's goal setting process for the post 2021 cycle.

1.1 What is Top-Down Potential?

The bottom-up approach to estimating energy efficiency potential builds up a projection of potential future energy efficiency measure adoption through the detailed characterization of individual energy efficiency measures and the application of these measures to modeled market dynamics and assumptions about consumer behavior. Figure 1-1 illustrates the bottom-up process at a high level.

[4] For this study Guidehouse has deliberately chosen to identify its approach as a "prototype" – a preliminary model intended for testing and evaluation. A prototype is distinct from a "production" model in that the primary output of interest is not the output of the modeling approach itself, but the information and understanding gained about the capabilities and shortcomings of that modeling approach.

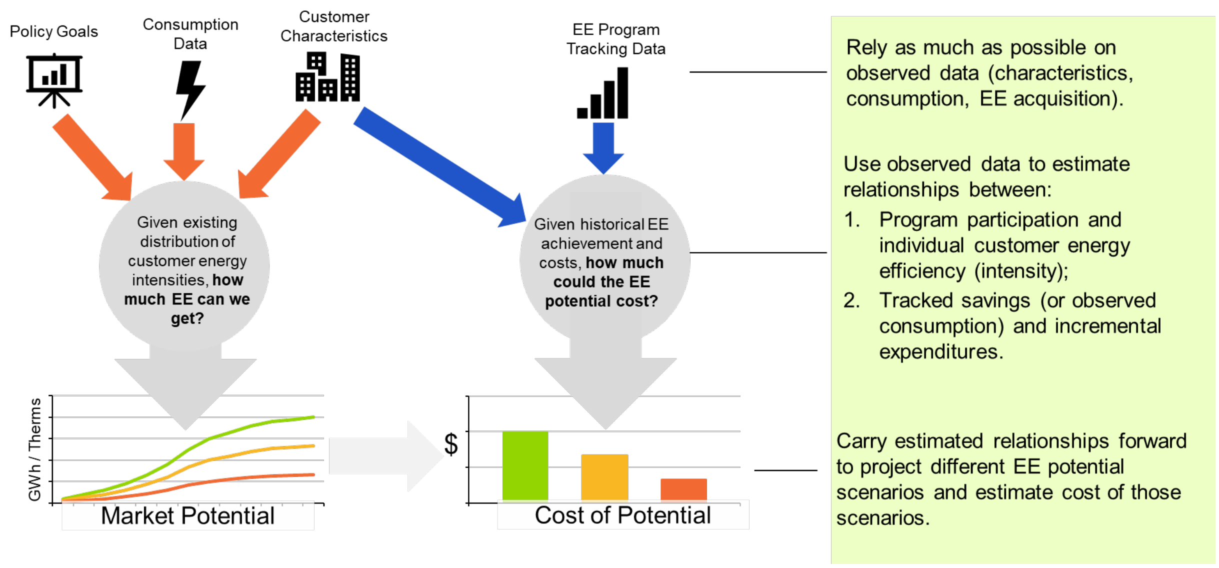
Figure 1-1: Bottom-Up Potential Estimation



Source: Guidehouse

A top-down approach by contrast is generally defined as an empirical approach that relies on observed historical customer consumption and other variables (e.g., historical program participation, floorspace, etc.). These observed data are used to estimate relationships that can be used, under certain assumptions, to develop a projection of energy efficiency potential and the cost of achieving that potential. Figure 1-2 illustrates a top-down approach.

Figure 1-2: Top-Down Potential Estimation



Source: Guidehouse

Guidehouse has previously undertaken a similar project in Ontario, Canada, as part of that province's triennial Conservation Potential Study.[5] As part of that engagement, Guidehouse

[5] This study was jointly commissioned by the Independent Electricity System Operator and the Ontario Energy Board (the provincial regulator). The engagement webpage may be found here: http://www.ieso.ca/2019-conservation-achievable-potential-study

developed, in parallel with the conventional bottom-up potential, a top-down econometric projection of energy efficiency potential in the hospital segment. This was supplemented with a comparative analysis of individual hospital energy intensities to provide additional context for the projected potential results.[6]

In undertaking this work, Guidehouse has leveraged the lessons from its Ontario work, the feedback of California stakeholders and the CPUC, and Guidehouse staff's experience with both load forecasting and energy efficiency potential estimation. This base of knowledge and feedback has been used to develop an approach for projecting the energy efficiency potential for a specific sub-set of California electricity and natural gas customers and to estimate the cost of achieving that potential.

1.2 Why Experiment with a Top-Down Approach to Potential Projection?

While the concept of a top-down potential study is not new, its application to a complex regulatory and goal setting process is untested in California. Furthermore, many of the existing data sets from workpapers/DEER, evaluation studies, program tracking databases and market studies lend themselves well to a bottom-up study. The long history of potential projection in California via bottom-up study has, to some degree, shaped the data landscape related to energy efficiency in this state to serve the needs of the bottom-up approach. It was unclear at the scoping of this study if the necessary data was available to conduct a top-down study.

A top-down study of energy efficiency potential is not a one-for-one substitute for a bottom-up study. The differences in approach used by these two methods define the differences in the outputs they deliver. Since they are not perfect substitutes, this inevitably means that replacing one with the other would require trade-offs: there are simply some things that one method is better suited for than the other, and vice versa. While many of the types of trade-offs may be identified before any analysis is attempted, until both approaches have actually been modeled the materiality of those trade-offs may be unclear. It is only in undertaking to explore what data are available to support the development of a top-down approach (and what more data might be available for a wider-scale implementation) that the limits of what it can offer can be appreciated.

Accordingly, the purpose of this study is to achieve a better understanding of the practical benefits and limitations of a top-down empirical approach to potential estimation through the development of a prototype method for estimating potential with the use of readily available ("in-hand") data. The sub-sections immediately below identify the theoretic benefits and limits of this empirical perspective and outline the data-centric philosophy adopted by Guidehouse and the CPUC to guide the development of the prototype analysis.

1.2.1 Benefits (and Limits) of an Empirical Perspective

Table 1-1 below provides a high-level summary of some of the key differences between the bottom-up and top-down approaches across three different study elements: the inputs, the

[6] The approach and results (referred to in the Ontario work as the "Whole Building Analysis") may be found described in detail in Chapter 8 of that report, available at the engagement web-page or by direct download here: http://www.ieso.ca/-/media/Files/IESO/Document-Library/conservation/APS/2019-Achievable-Potential-Study.pdf?la=en

modeling approach, and the outputs. The table summarizes trade-offs in how each type of study approaches each these elements.

Table 1-1: Summary of Theoretic Trade-Offs by Study Type

Study Element	Bottom-Up	Top-Down
Inputs Description	Market and measure characterization require thousands of inputs – dozens for each measure (e.g., savings, costs, saturation)	Requires historical claim-level savings data and consumption data across the same period and building floorspace data (necessary to estimate intensity).
Inputs Trade Off	Sheer number of input assumptions for measure characterization reduces transparency to stakeholders – detailed review and updates of all inputs impractical. Must identify all measures. Impossible to reasonably quantify uncertainty associated with output potential due to compounding (and unknown) uncertainty associated with inputs.	Relying on historical observations ties analysis to historical trends that may be of limited relevance if major structural changes in load drivers anticipated going forward (e.g., long-term effects of COVID, decarbonization legislation/regulation, etc.) Potential costs are tied to historical program trends.
Approach Description	Complex model of market dynamics and consumer choice, accounting for interactive effects between measures, across fuels, etc. Modeling tracks individual measure adoption explicitly controls for effects of codes and standards, and allows for "plug-and-play" scenario analysis.	Potential estimated based on a comparison of existing building intensities, with ultimate potential savings defined as an alignment of average intensities across two groups of buildings identified on the basis of a proxy variable as "efficient" or "less efficient". Costs derived on the basis of historically observed levelized costs of savings and average historic program costs.
Approach Trade Off	Deterministic nature of modeling requires many highly structured assumptions regarding consumer and firm behavior, the complexity of which reduces the transparency of modeling mechanics. Potential modeling implicitly applies elements of program design (e.g., incentive levels) which may not be reflective of design choices made in actual implementation. Though the deterministic nature of the bottom-up model suggests objectivity, its design, and the development of the inputs require analyst judgement and assumptions. The design of this approach requiring granular data may result that the nature and magnitude of these assumptions may not be transparent to stakeholders.	Overall modeling mechanics relatively simple, offering significant transparency, though a reliance on analysis of historical data (as opposed to established deterministic modeling mechanics) means that analyst judgement for market adoption plays a more obvious and explicit role in determining outcomes
Outputs	Highly granular outputs: available at the measure level if required. Measure-level cost-effectiveness testing ensures that scenarios can be defined that guarantee cost-effective portfolio potential.	Output potential and costs (including levelized costs) available at the segment and end-use level.

Outputs Trade Off	Outputs can include types of potential with little historical precedent (e.g., fuel substitution). Complex nature of modeled relationships and interactions, and embedded program design assumptions limit ability of stakeholders to qualitatively test sensitivity of results via post-processing. Measure-level granularity also makes possible estimation of purely technical and economic (as well as achievable) potential.	Lack of measure-level granularity can result in entire estimated potential for a given end use not being cost effective. Clarity/transparency of assumptions and effects make after-the-fact sensitivity testing by stakeholders possible.
Technical Potential	Delivered by bottom-up approach, but of questionable usefulness outside of model QC.	Not possible in top-down approach. Requires widget specific assumptions (saturation, technical suitability, density, etc.)
Economic Potential	Delivered by bottom-up approach	Not possible without widget-specific incremental measure costs or technical potential.
Achievable Potential	Delivered by bottom-up approach	Delivered by top-down approach.

At the highest level, the benefits and limitations of the top-down approach (relative to the bottom-up) flow from the fact that the top-down approach uses much fewer inputs but requires inputs of past observations.

The bottom-up approach requires the comprehensive characterization (savings, costs, penetration, saturation, etc.) and identification of all energy efficiency measures to be considered in the modeling. The top-down approach uses segment[7]-level intensities and costs, avoiding the complexities of tracking individual measure lifetimes or the need to identify reasonable and robust assumptions for the many measure characteristics required in the bottom-up approach. This renders the top-down approach much more transparent in many respects but means that projected energy efficiency potential cannot account for significant structural shifts that may render historical relationships unsuitable for projecting future energy efficiency. However, the bottom-up has similar limitations, for example: measure and program delivery costs. The top-down approach also requires the availability of representative, or ideally a comprehensive, sample of building or end use energy intensities.

The top-down approach indicates what potential is available if all of the *less efficient* buildings are upgraded to the average energy intensity of the *efficient* buildings[8] but makes no specific structural claim regarding *how* that state of affairs is attained (e.g., via incentives equivalent to 50% of incremental cost, etc.) .[9] The bottom-up approach, in contrast, applies deterministic market modeling (many parameters of which are derived from the market adoption study[10]) that projects achievable potential as a direct function of measure pay-back. The bottom-up approach

[7] A “segment” is a synonym for “building type” or “sub-sector” and is one step more granular than a sector. For example, the commercial sector includes the retail, health, grocery, etc. segments.

[8] In this report *less efficient* and *efficient* take on very specific definitions – see section 2.1.1 for more details.

[9] This is specific to the prototype analysis developed for this study. It is certainly possible to develop an estimated relationship between (for example) program spending and measure uptake. The most robust such behavioral modeling (e.g., a willingness-to-accept or willingness-to-pay study) requires extensive survey work to develop the data sources required for the discrete choice or conjoint analysis that drives such modeling, data collection activities outside the scope of this study.

[10] Attachment 1 to the PG Study report, California Energy Efficiency Market Adoption Characteristics Study.

implicitly makes a causal claim regarding the relationship between incentive levels and adoption that the top-down approach does not. Aside from the bottom-up approach's reliance on assumed incentive levels, both approaches are agnostic to program design elements. They attempt to project achievable potential using historical context in costs for the program administration and incentives. Additionally, they both anchor some aspect of the study based on the historical program achievements.

However, for the bottom-up study, achievable potential is often estimated under a variety of policy and program design scenarios typically selected to show a range of possible outcomes based off of the calculated technical potential (defined as the projected savings that would be achieved if all the highest efficiency measures that were technically feasible were installed as soon as practical) and economic potential (defined in the same way as the technical potential, with the constraint that only cost-effective measures can be considered). For achievable potential analysis, Guidehouse typically uses program-influenced levers to define the scenarios. The levers include assumed levels of program funding (e.g., incentive offerings) and assumptions of key parameters that determine market uptake (such as marketing effectiveness). Neither technical nor economic potential can be estimated under a top-down approach, as both require a highly granular set of assumptions about existing equipment. Additionally, program scenarios and levers approaches for developing a range of estimates sensitive to the most important model parameters are applicable for the prototype top-down approach. This is because the top-down approach developed in this study does not project potential based on modeled market behavior.

In summary, it is the granularity of these approaches that defines their differences. A bottom-up model is highly granular, allowing for much greater precision (in terms of the granularity of its disaggregation) in its outputs. The same granularity, however, makes it much less transparent than the top-down approach, and the sheer number of assumptions and inputs suggest that at least some of the precision it offers is spurious. The coarser nature of the top-down study allows it to be anchored more firmly to historical trends and assessed against past performance, but at the same time embeds an assumption that past performance is a reasonable guide to future achievement. These trade-offs are apparent even without the development of a prototype top-down analysis.

The principal purpose of this study, and the development of this prototype analysis is to better understand the materiality of these trade-offs by implementing a top-down analysis with the best available data and comparing the outputs with those of the bottom-up study. A secondary purpose of this study is to develop insights and techniques that could in the future be part of an integrated solution that incorporates elements of both the bottom-up and top-down approach in future years. The interaction may include elements such as acting as narrative context, calibration tools, and sanity checks.

1.2.2 Philosophy of Prototype Analysis Development

For this study Guidehouse has deliberately chosen to identify its approach as a "prototype" – a preliminary model intended for testing and evaluation. A prototype is distinct from a "production" model in that the primary output of interest is not the output of the modeling approach, but the information and understanding gained about the capabilities and shortcomings of that modeling approach.

The purpose of this analysis is to identify paths forward for the adoption of a more empirical approach to projecting energy efficiency potential. The goal is to explore the available data in enough detail to identify the most significant challenges to the expansion of such an approach and to be able to provide an analysis of how such an approach complements the conventional industry-standard bottom-up approach to projecting energy efficiency potential. In scoping out the analysis, Guidehouse, in consultation with CPUC staff, determined that the timely accomplishment of this goal[11] was best served by limiting the analysis to including only data already in CPUC's possession or else publicly available.

1.3 Goals, Ambitions, and Research Questions

This work is intended as a trial of a prototype alternative approach to the projection of energy efficiency potential to better inform the CPUC of the possibilities and limitations of such an approach. The goals of this analysis as set out in our workplan were to answer the following questions:

- What are the overall strengths and limitations of a top-down approach relative to the traditional bottom-up approach?
- What additional data would be required to allow this approach to be used on a wider scale?
- Are there specific sectors or segments for which a top-down approach to projecting potential is more appropriate than a bottom-up approach?
- Will a top-down approach provide sufficient data for all of the use cases of the PG study?
- How should the outputs of a top-down analysis fit in with the outputs of other energy efficiency activities used to inform planning?

1.4 Current Downstream Use-Cases for Bottom-Up Projected Potential

The current bottom up model framework in the 2021 PG Study ultimately supports multiple related efforts (Section 4 provides a summary informing how the top-down projected potential supports the same efforts):

- Informs the CPUC as it proceeds to adopt goals and targets, providing guidance for the next IOU energy efficiency portfolios. Goals have historically been set by IOU and savings category (rebate programs separate from codes and standards). The 2021 PG study also output a new metric for consideration in goal setting: total system benefit (TSB). TSB is a monetary value of the benefits from energy efficiency programs (as opposed to reporting savings in kWh, kW, and therms)
- Guides the investor owned utilities (IOUs) and other program administrators in portfolio planning. Although a potential model cannot be the sole source of data for program administrator program planning activities, it can provide critical guidance for the program administrators as they develop their plans for the 2022 and beyond portfolio planning

[11] All quantitative work was completed within four months of the provision of data to Guidehouse and within 3 months of the submission of the final workplan to the CPUC.

period. IOU program planners tend to review savings potential at the sector, end use, measure, and building type level.

- Provides forecasting inputs to support the procurement and planning efforts of California's principal energy agencies including the CPUC, CEC, and California Independent System Operator (CAISO).
- The California Energy Commission (CEC) uses the CPUC-adopted goals to develop its forecast of additional achievable energy efficiency potential (AAEE) and additional achievable fuel substitution (AAFS). Furthermore, the data becomes an input to SB 350 scenario analysis which targets a doubling of the AAEE by 2030. CEC has historically needed potential broken down by IOU, sector, end use, climate zone, and savings category.
- Explores forecasting potential using Integrated Resource Planning (IRP) tools. The bottom up model delivered energy efficiency supply curves to the IRP model for further analysis. Energy efficiency supply curves provided 30 bundles of energy efficiency resource savings and their associated levelized cost and hourly load shape.

In reporting its findings and identifying recommendations for the consideration of the CPUC and its stakeholders, Guidehouse has explicitly considered these use-cases and the implications of moving away from the bottom-up approach.

1.5 Contents of this Report

The remainder of this report is divided into three chapters:

- **Approach.** Chapter 2 of this report provides a detailed description of the data used in the top-down analysis, an explanation of how the analysis was conducted, and context for the reader regarding the areas of greatest uncertainty.
- **Results and Analysis.** Chapter 3 of this report provides the projected energy efficiency potential estimated using the top-down approach and discusses some of the implications of these results for future program planning.
- **Findings and Recommendations.** Chapter 4 of this report summarizes the key findings flowing from the prototype analysis (including the suitability of a top-down approach to replace the current bottom-up approach) and offers a series of recommendations for the CPUC and its stakeholders to consider over the short, medium, and long-term.

2. Approach

This chapter describes the methods and data used to derive an estimate of energy efficiency potential using a top-down approach. As the introduction notes, the purpose of this analysis is to:

- Examine the data most readily available to the CPUC
- Identify and implement an approach to projecting different scenarios of electric and natural gas energy efficiency potential from 2022 to 2032 for a subset of commercial customers of the California IOUs (PG&E, SCE, SCG, and SDG&E)
- Use historical energy efficiency cost data to develop an estimate of the incremental equipment and program costs of the projected energy efficiency potential
- Understand the value of the alternative perspective offered by top-down energy efficiency potential
- Determine the most significant barriers to evolving this approach from a prototype to a production tool

Therefore, the outputs of the top-down approach tested in this report should not be considered as a replacement or alternative to the outputs provided by the bottom-up approach currently used by the CPUC to projecting energy efficiency potential.

This chapter details the data immediately available to support this analysis, the approach developed to use these data for projecting energy efficiency potential, and the cost of acquiring that potential.

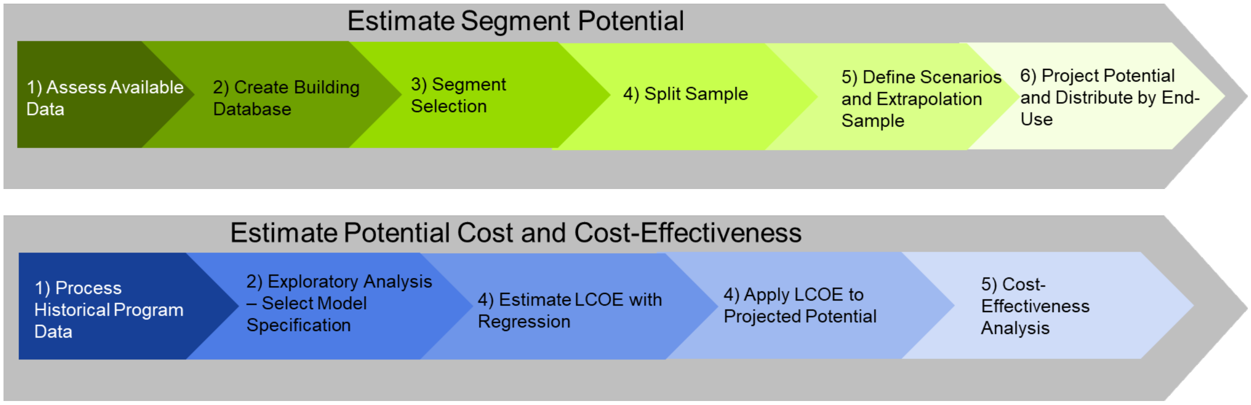
This chapter is divided into three sections:

1. Summary of Approach. This section summarizes the approach taken to project potential and estimate costs.
2. Estimate Segment Potential. This section describes how estimated energy efficiency potential is projected for the segments being studied.
3. Estimate Potential Cost and Cost-Effectiveness. This section describes the approach used to develop a cost for the projected potential.

2.1 Summary of Approach

The top-down potential approach consists of two parallel workstreams: energy efficiency potential projection and estimation of costs to achieve the potential. Figure 2-1 summarizes these workstreams at a high level, and additional detail also follows.

Figure 2-1: Cost and Potential, Parallel Workstreams



Source: Guidehouse

These two workstreams are functionally independent of one another until the end of the analysis when cost parameters are applied to the potential to calculate the estimated costs associated with the potential.

2.1.1 Estimate Segment Potential

The type, quality, and amount of data available at the time this study was conducted drove the approach to estimating segment potential. Following a review of the available data (discussed in section 2.2.1), Guidehouse developed a methodology to be tested for selected commercial segments (discussed in section 2.2.3) and relies on building consumption, floorspace, and past program participation data. Guidehouse consolidated the building data in a database for use in this analysis. Complete data is not available for every building in California, so our database is a “core sample” from which we extrapolate findings to the rest of the population.

The energy efficiency potential of each segment and fuel combination analyzed in the core sample is projected on the basis of a comparison of the energy intensity of a set of *efficient* and a set of *less efficient* buildings. Italics are used for these categories to reflect the fact that these labels are applied to individual buildings on the basis of historical participation in energy efficiency programs and are not necessarily reflective of individual building energy efficiency. That is, though *efficient* buildings have *on average* a lower energy intensity than the *less efficient* buildings, some individual buildings that are in the *less efficient* category may have a lower energy intensity than some individual buildings in the *efficient* category. Buildings are assigned to the *efficient* category if the average annual site savings tracked in the California Energy Data and Reporting Systems (CEDARS) database over three years (2017 through 2019) as a percentage of their 2019 consumption exceeds some segment and fuel-specific threshold (see section 2.2.4 for more details).

Energy efficiency potential is estimated by a comparison of these two groups. So, for example:

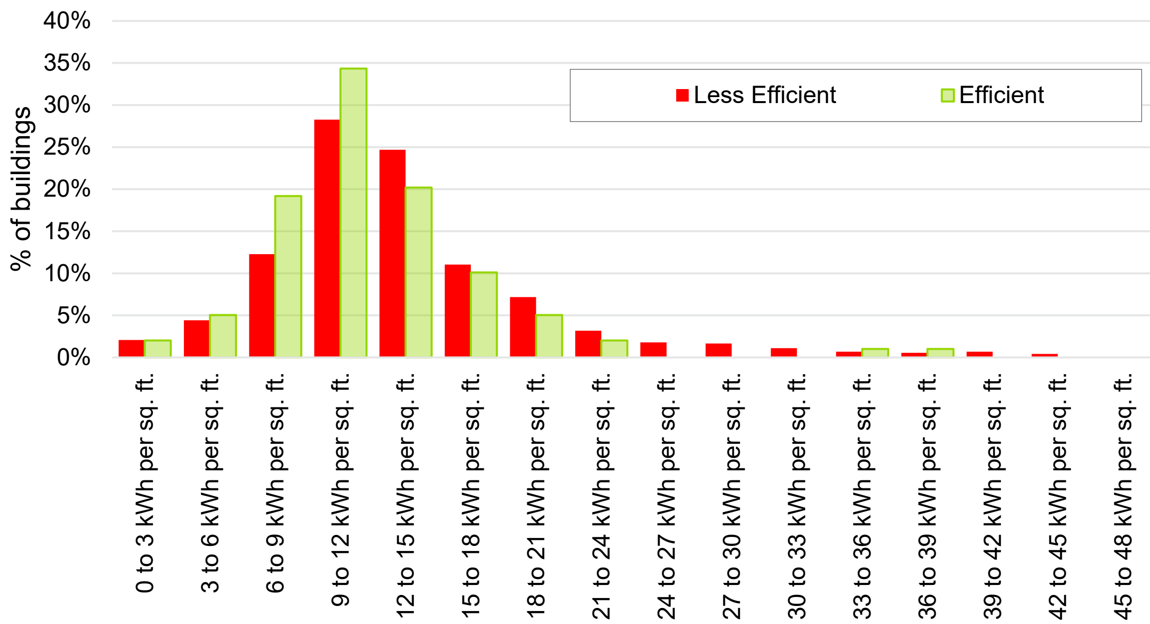
- The group of *efficient* office buildings has an average energy intensity that is 10% lower than that of the group of *less efficient* buildings

- Therefore, the energy efficiency potential achievable for the targeted *less efficient* buildings is a 10% reduction of their energy use. The energy efficiency potential is achieved by bringing the average energy intensity of the *less efficient* buildings in line with the average energy intensity of the *efficient* buildings.

Figure 2-2 illustrates this comparison of the Guidehouse-defined *efficient* and *less efficient* building energy intensities.[12] This figure is a frequency distribution showing the percentage of *efficient* (green) and *less efficient* (red) buildings in the available dataset for each bucket of energy intensity. For example, approximately 25% of *less efficient* buildings use an average of between 12 kWh and 15 kWh per square foot of floorspace per year in comparison with approximately 20% of *efficient* buildings.

The distribution of *efficient* buildings in aggregate skews toward less energy per square foot compared to the *less efficient* buildings; the green columns are taller on the left-hand side of the plot. This approach acknowledges the reality that there are many cases (on an individual basis) where a *less efficient* building uses less energy per square foot than an *efficient* building. For example, there are *less efficient* buildings that use between 3 kWh and 6 kWh per square foot per year and *efficient* buildings that use between 15 kWh and 18 kWh per square foot per year. The simple reality is that an office building in Los Angeles will have a larger thermal load than one in San Francisco and will consequently use more electricity for air conditioning, even if its equipment is extremely efficient.[13] The approach used by Guidehouse to split buildings into *efficient* and *less efficient* groupings acknowledges that reality while still allowing for a useful comparison across buildings.

Figure 2-2: Example Comparison of *efficient* and *less efficient* Building Intensities



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

[12] Detail regarding the data used for this plot is in section 2.2.

[13] As the available sample of floorspace data becomes larger, additional controls could be applied, such as sub-segmenting buildings geographically. This would improve the precision of the projected potential.

Whether a building may be labeled as *efficient* or *less efficient* is determined by a proxy variable that is correlated with, but is not directly driven by, building energy intensity. The proxy variable used in this case is average energy savings (tracked in CEDARS) achieved by a given site as a percentage of that site's 2019 energy consumption. In addition to being correlated with a lower energy intensity, the proxy (sometimes called an instrumental) variable selected is also correlated with demand side management (DSM) program participation.

The reasoning behind this construction is that if the proxy (or instrument) is correlated both with the desired outcome (lower energy intensity) and with a customer characteristic that can be influenced by program administrators (participation in utility programs), then it follows that increasing the prevalence of the characteristic, program participation, in customers may lead to an increase in the desired outcome: lower energy intensity.

Section 2.2.4 details how the team selected and applied the proxy variable, identifies how sensitive estimated potential is to different values of that proxy variable, and notes what the projected potential implicitly assumes about the conversion of *less efficient* buildings to the *efficient* category.

The comparison of building intensities provides the core theoretic basis for the projected potential presented in this analysis and is the most significant step in its estimation. This comparison delivers the estimated percentage decrease in energy consumption of the *less efficient* buildings required to align their intensity with that of the *efficient* buildings. Considerable additional analysis must build on this output (the estimated percent reduction in consumption) to deliver the final estimated potential.

Key additional steps to estimating potential include:

- Defining scenarios that explore the trade-offs of extrapolating the savings potential from the core sample of buildings in the building benchmarking database (which provides individual building intensities) to the overall population of buildings (for which individual building floorspace – and thus intensities – are unavailable).

- Identifying a reasonable assumption for how long it might take to convert all building owners and tenants of *less efficient* buildings to make them more like those of *efficient* buildings.

- Applying this assumption for the time required to achieve the estimated percentage reduction in consumption to extrapolation sample defined by each scenario to deliver an estimate of projected potential in each year across the the period of analysis.

Section 2.2 includes our approach for estimating energy efficiency potential and the assumptions driving that approach.

2.1.2 Estimate Potential Cost and Cost-Effectiveness

Estimating the potential cost in a top-down approach differs from a bottom-up study. The bottom-up analysis tracks the acquisition and retirement of individual pieces of equipment and the expenditures associated with that equipment in each year. The top-down approach tracks the cost of achieving the savings on the basis of an average levelized cost of energy (LCOE) estimated using historical data.

In a bottom-up potential study, cost estimation is conceptually straightforward: total resource costs are the sum of incremental measure and program administration costs. A bottom-up stock-and-flow model tracks the introduction and expiration of measures, allowing the analyst to identify precisely what the projected expenditures on energy efficiency measures are in each year, conditional on the accuracy of the modeled market dynamics.

A top-down approach lacks this widget-based detail. This study must take a more abstract approach, and instead of estimating the costs of different types of equipment, must estimate the costs of the savings directly. In this analysis, this is accomplished by using historical savings data to estimate the levelized cost[14] of savings. That is, program tracking data stored in the CEDARS database is used to estimate an LCOE for each combination of customer segment (e.g., offices, grocery, etc.) and end use (water heating, indoor lighting, etc.). This value can then be applied to savings by segment and end use achieved in each year to identify an estimate of the cost of those savings.

Put another way, the LCOE establishes the cost of energy savings achieved in each year as a function of the magnitude of the savings achieved in that year *but does not identify the schedule of when those costs are paid.* Conversely, the widget-based approach specifies the schedule for payment by assuming that incremental measure costs are paid for in the year the given measure is installed.

Figure 2-3 illustrates the difference between the bottom-up and top-down approaches through an investor-owned utility (IOU) in which there is only a single piece of equipment, no time value of money (i.e., a discount rate of zero), and no inflation.

In this example, the measure has an incremental cost of $5, and delivers benefits worth $1 per year for 10 years. The benefits stream is the same for both the bottom-up and top-down approaches. The allocation of the costs is different.

- In a bottom-up analysis, measure costs (or expenditures) would be identified as $5 in the first year and $0 in every year thereafter.
- In a top-down analysis no information exists about when equipment was installed or how long it will continue to deliver savings, only the annual savings values are available. The LCOE is applied to the savings in each year, providing an estimate of the costs attributable to savings delivered in each year. The figure illustrates the cost as equally distributed across the 10 years.

A helpful analogy may be that of buying a car: the bottom-up approach is like assuming that a new car is purchased outright, will last for some years (during which no more payments are made), and will eventually need to be replaced (at which point another large payment is required). The top-down approach is like assuming that you will lease a car for as many years

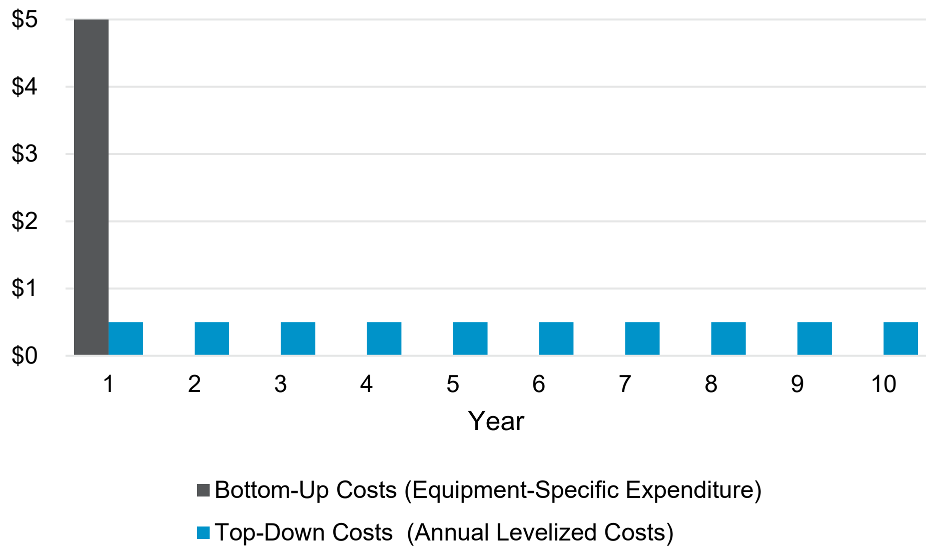
[14] The levelized cost of energy is "*cost that, if assigned to every unit of energy produced (or saved) by the system* [or energy efficiency measure] *over the analysis period, will equal the TLCC* [total life-cycle cost] *when discounted back to the base year.*"

Short, W.; Packey, Daniel J.; Holt, Thomas; National Renewable Energy Laboratory, *A Manual for the Economic Evaluation of Energy Efficiency and Renewable Energy Technologies*, March 1995, NREL/TP-562-5173 https://www.nrel.gov/docs/legosti/old/5173.pdf

This document is linked to in NREL's "Simple Levelized Cost of Energy (LCOE) Calculator Documentation" web-page, that can be found here: https://www.nrel.gov/analysis/tech-lcoe-documentation.html as you need to drive – it may periodically be replaced, but the annual payments are the same in each year.

The difference between how the two approaches to tracking costs is illustrated in Figure 2-3 below.

Figure 2-3: The Difference Between Tracking Costs Top-Down and Bottom-Up



Source: Guidehouse

Guidehouse applied LCOE data to the projected potential to estimate program costs and subsequently the program cost-effectiveness. Section 2.3 details the data and approach used to derive these.

2.2 Estimate Segment Potential

This section of Chapter 2 provides a detailed description of Guidehouse's approach to estimating segment potential. Figure 2-4 summarizes the mechanics that drive the potential estimation. The subsections that follow detail each of the steps in Figure 2-4. These are:

2.2.1 **Assessment of Available Data.** Describes the data available to Guidehouse in the timelines required for the completion of this project.

2.2.2 **Create the Building Database.** Describes how Guidehouse combined individual building floorspace data, IOU account consumption data, and historic program savings claims data to create the building database required for the subsequent steps in the analysis.

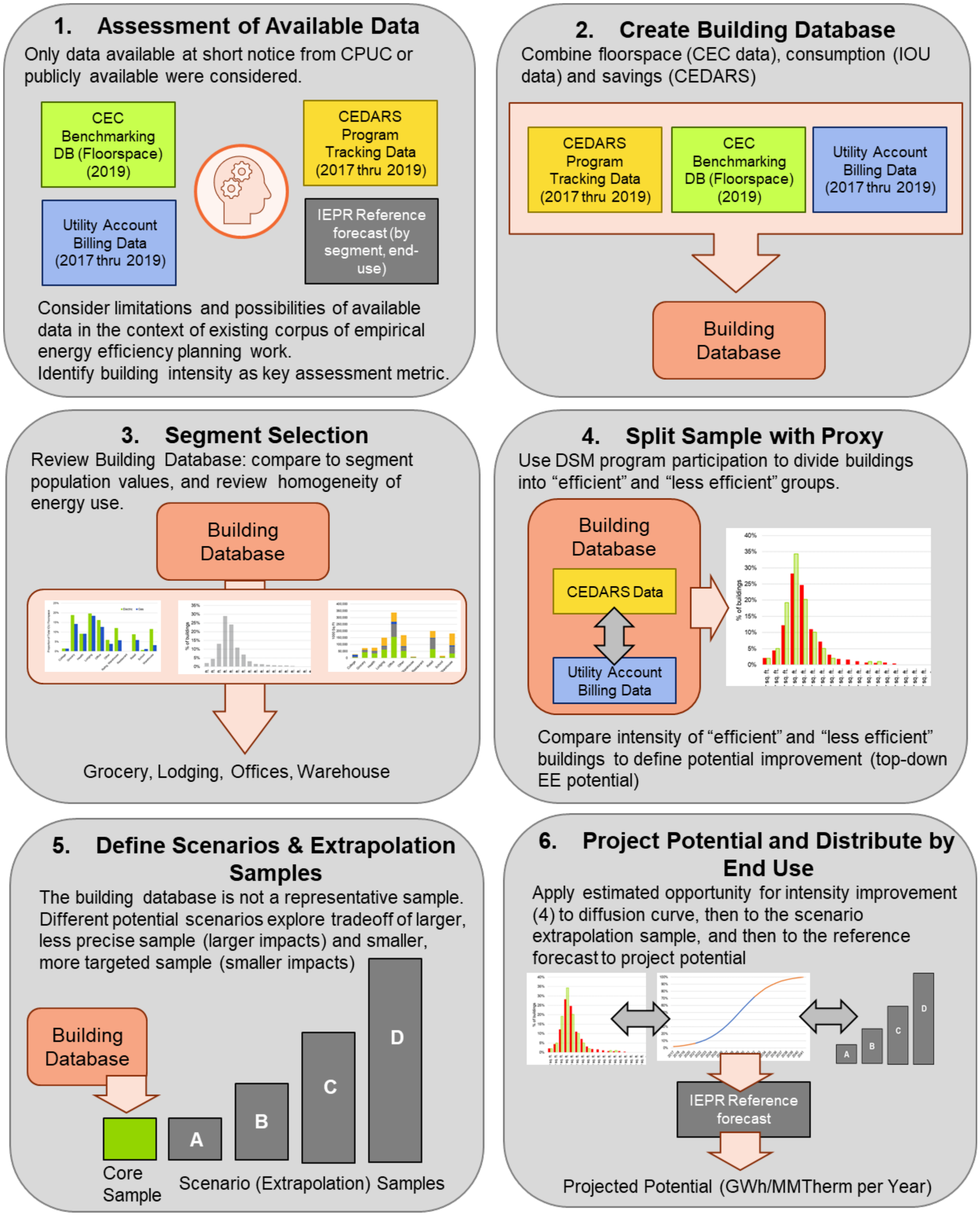
2.2.3 **Segment Selection.** Details Guidehouse's considerations in selecting the segments from the building database to study as part of this analysis.

2.2.4 **Split Sample with Proxy Variable.** Describes the development of the proxy variable used to identify *efficient* and *less efficient* buildings, and how these were compared to derive an estimate of energy efficiency potential.

2.2.5 **Define Scenarios and Extrapolation Samples.** Outlines the issues related to extrapolating the potential estimated based on the sample of buildings included in our database out to a wider population and defines a set of four scenarios.

2.2.6 **Project Potential and Distribute by End Use.** Describes how the elements above are combined to deliver the final projection of energy efficiency potential over the period of analysis.

Figure 2-4: Graphical Summary of Approach Mechanics



Source: Guidehouse

2.2.1 Assessment of Available Data

Guidehouse assessed the data available to support its development of an empirical, top-down approach. For this analysis, Guidehouse explicitly limited its data collection to sources that were publicly available, or else quickly and easily available for the CPUC staff to share with the team.

The intent of this analysis is to act as a proof of concept and an aid to understanding the benefits (and short-comings) of an empirical top-down approach. The CPUC and Guidehouse's focus in this exercise was to advance a *method* rather than to precisely quantify an output. Efforts at data collection, preparation, and vetting were therefore limited to those which could be accommodated under the project timeline and were sufficiently rigorous to support the development of this prototype approach. Put more simply, effectively accomplishing the goals of this proof-of-concept study does not require (and cannot justify the cost) of the intensely rigorous data gathering (from multiple data sets) and vetting undertaken by the bottom-up approach currently used to set IOU goals.

Guidehouse worked with CPUC staff to identify available sources, comparing these against the requirements of econometric forecasting approaches and cross-sectional intensity-based approaches.[15] The result of this development and exploratory analysis is laid out in Guidehouse's January 2021 workplan and described in greater detail in the remainder of this chapter. This sub-section provides a review of the datasets available to CPUC, or via public sources, that formed the core of that assessment and helped to determine the approaches used to estimate energy efficiency potential.

The most significant data sources used for this analysis are:

1. CEC Building Benchmarking Database.[16] This is a publicly available dataset of building floorspace and energy use for buildings in California with more than 50,000 square feet of floorspace.

2. CEDARS Data.[17] This is a data set that tracks all DSM program savings claims (and the associated energy efficiency measure characteristics and costs) made by California IOUs each year.

3. IOU CIS and Billing Data.[18] These data sets provide cross-sectional customer information (e.g., NAICS code) and annual consumption values.

[15] The Guidehouse staff engaged in this analysis had previously undertaken a top-down estimation of energy efficiency potential – referred to as the "whole building analysis" in Chapter 8 of Guidehouse Canada (f/k/a Navigant) prepared for the Independent Electricity System Operator (IESO) and the Ontario Energy Board (OEB), ***2019 Integrated Ontario Electricity and Natural Gas Achievable Potential Study***, December 2019 http://www.ieso.ca/2019-conservation-achievable-potential-study

[16] California Energy Commission, *Building Energy Benchmarking Program*, accessed December 18, 2020 https://www.energy.ca.gov/programs-and-topics/programs/building-energy-benchmarking-program

[17] Guidehouse used the version of the CEDARS claims data that includes personal identifiable information (provided by CPUC) in order to be able to match the claims data to utility customer data. Publicly available CEDARS claims data may be found here: https://cedars.sound-data.com/reports/record-level/

[18] California Public Utilities Commission, *Utility CIS and Billing Data*, provided by CPUC staff via secure file transfer

4. IEPR Forecast Consumption.[19] This data set includes a granular (by end-use and segment) breakdown of historical and forecast of statewide and IOU energy use, from 1990 through to 2030.

Other less consequential data sources include:

- The mapping of North American Industry Classification System (NAICS) to commercial segment names (to identify each individual customer's commercial segment);
- The CPUC's avoided costs (to calculate the total system benefit of estimated energy efficiency potential);
- The mapping of end use forecasts as part of the Integrated Energy Policy Report (IEPR) outputs to the energy efficiency equipment in the CEDARS database (to sort individual energy efficiency measures into the end use groups required for cost estimation), and;
- IOU-specific discount rates used as part of the bottom-up study (used to for time-value of money calculations, including the estimation of LCOEs).

Notable by its absence in the list above are any high-frequency AMI data. In setting the scope of this prototype analysis, Guidehouse deliberately rejected the possibility of using AMI data, either for projecting potential or for estimating its cost. The use of hourly customer data would certainly provide for greater nuance in this analysis; Guidehouse has highlighted some of the possible enhancements such data could offer in Chapter 4. In the context of this first-step prototype approach to gain lessons learned on the top-down potential value proposition, the benefits of using such data are substantially outweighed by the costs of doing so (in time and level of effort).

2.2.1.1 CEC Building Benchmarking Database

In December 2020, Guidehouse downloaded the publicly available CEC Building Benchmarking database.[20] These data were used to develop the core building dataset required to allow for the comparison of the energy intensity of *efficient* and *less efficient* buildings.

The Building Energy Benchmarking Program requires owners of large commercial and multifamily buildings to report energy use and building floorspace to the CEC on an annual basis.[21] The compliance requirements of this program means that the data tracked for these two subsectors are not representative of the population of California non-residential buildings.

[19] California Energy Commission, *California Energy Demand 2019*. Provided by CEC staff via e-mail.

[20] California Energy Commission, *Building Energy Benchmarking Program*, accessed December 18, 2020 https://www.energy.ca.gov/programs-and-topics/programs/building-energy-benchmarking-program

[21] Buildings are required to provide their data if total floorspace exceeds 50,000 square feet and they include either no residential units or 17 or more residential units. Additional information regarding data collection procedures may be found at:

California Energy Commission, *Building Energy Benchmarking Program Frequently Asked Questions,* accessed May, 2021.

https://www.energy.ca.gov/programs-and-topics/programs/building-energy-benchmarking-program/building-energy-benchmarking

Table 2-1 provides a high-level summary of the benchmarking database, the aggregate floorspace, 2019 energy consumption, and the number of buildings in each segment.

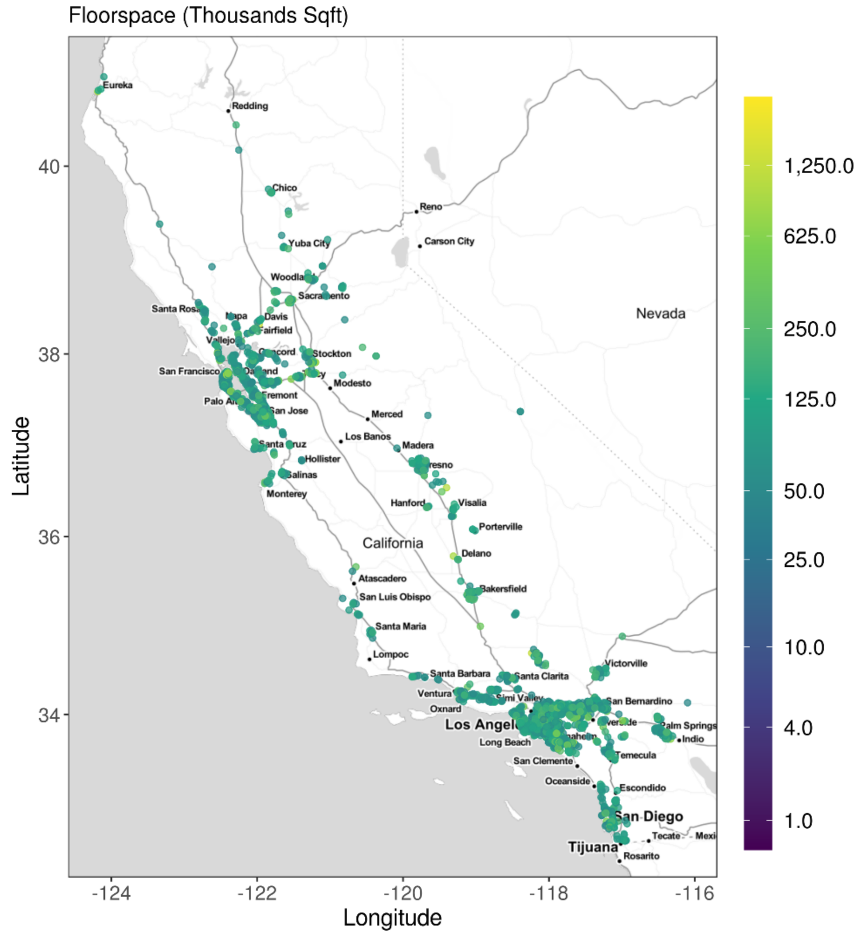
Table 2-1: Summary of Building Benchmarking Data

Segment	Floorspace (Million Sq Ft.)	GWh	MMTherm	# of Buildings
Multifamily	635	3,070	122	3,978
Office	382	5,289	52	2,218
Other	234	2,905	28	1,609
Retail	240	2,872	450	1,495
Warehouse	287	1,210	8	1,265
Grocery	80	2,223	460	772
Lodging	166	1,923	72	680
Health	82	1,915	53	540
College	28	396	16	162
School	18	101	2	140
Refrig. Warehouse	14	328	1	70
All Other Industrial	1	62	3	7
Restaurant	0.1	1	0.02	5

Source: CEC Benchmarking Database and Guidehouse analysis

Figure 2-5 provides the geographic distribution of building floorspace included in the benchmarking by ZIP code.

Figure 2-5: Geographic Distribution of All CEC Benchmarking Floorspace



Source: California Energy Commission, and Guidehouse analysis

2.2.1.2 CEDARS Data

CPUC staff and vendors provided Guidehouse with CEDARS claims data for 2017 through 2019 and a mapping to identify nonresidential downstream claims.[22]

These datasets include as many as 260 different fields or variables, but for the purposes of this work the most relevant used by Guidehouse included the following:

- Life cycle savings (kWh, kW, and therms)
- Effective useful life

[22] Downstream claims were identified on the basis of a field in the data flagging the name of the evaluation report associated with that claim. In some cases, a precise mapping could not be provided. For example in some cases a group of claims identified by a given evaluation report name included both downstream and non-downstream claims or included both residential and non-residential claims. In such cases, Guidehouse included all claims and filtered out those the team assessed to be inappropriate or irrelevant claims at a later step of the analysis.

- Incremental measure cost[23]
- A series of fields identifying the end use of the measure associated with the given claim (technology group, technology type, use category)
- A unique ID for identifying the site[24] of the savings.

Table 2-2 summarizes the number of claims and volume of total net life cycle savings associated with those claims in the dataset provided by CPUC prior to applying any filtering aside from that noted above.

Table 2-2: Summary of CEDARS Program Non-Residential Tracking Data

IOU	Year	# of Unique Claims	Total Lifecycle Net Savings (GWh)	Total Lifecycle Net Savings (MMTherm)
PG&E	2017	214,755	2,656	97
SCE	2017	173,407	1,926	1
SCG	2017	61,712	54	55
SDG&E	2017	43,412	368	10
PG&E	2018	181,814	2,131	73
SCE	2018	109,870	809	1
SCG	2018	29,507	4	59
SDG&E	2018	28,560	365	5
PG&E	2019	35,257	1,830	70
SCE	2019	13,728	448	1
SCG	2019	27,874	1	57
SDG&E	2019	25,803	193	4

Source: CEDARS

Numerous additional filters were applied to these data as part of the analysis (e.g., filtering by segment, etc.) and are briefly described in Sections 2.2 and 2.3.

2.2.1.3 IOU CIS and Billing Data

CPUC staff and consultants provided Guidehouse with customer information system (CIS) data for all four IOUs. For PG&E, SCE, and SDG&E, this included both cross-sectional data (e.g., NAICS code, fuel type, site ID for matching to CEDARS data) and annual consumption data for the 3 years of interest (2017, 2018, and 2019). In the case of SCG, the CIS data provided did not include any consumption values requiring annual consumption values to be drawn from monthly billing data provided by CPUC staff and consultants.

[23] Incremental costs for claims with a non-zero remaining useful life were drawn from the measure's second baseline incremental measure cost.

[24] Guidehouse understands that the site ID within the CEDARS data is the most reliable unique key for linking claim data to account consumption data. Since a given site may correspond to many accounts (but each account may have only one site ID), this creates some additional "noise" in the data when attempting to attribute savings values to a given building or account.

These were combined to create an annual consumption panel data set of all non-residential customers to which additional filters (described in greater detail below) were applied to develop the data used in the analysis. Table 2-3 summarizes the aggregate annual consumption values and number of unique account numbers (with annual consumption values greater than zero) included in these data.

Table 2-3: CIS and Billing Data – Annual Nonresidential Consumption by IOU

Fuel	IOU	Total Non-Residential Consumption			Unit	Mean # of Accounts[25]
		2017	2018	2019		
Electricity	PG&E	52,995	52,659	45,912	GWh	730,553
Electricity	SCE	54,401	55,547	53,856	GWh	718,200
Electricity	SDG&E	12,186	12,886	15,536	GWh	171,556
Natural Gas	PG&E	5,595	6,246	6,283	MMTherm	232,725
Natural Gas	SCG	3,228	2,956	2,905	MMTherm	214,567
Natural Gas	SDG&E	499	430	301	MMTherm	27,969

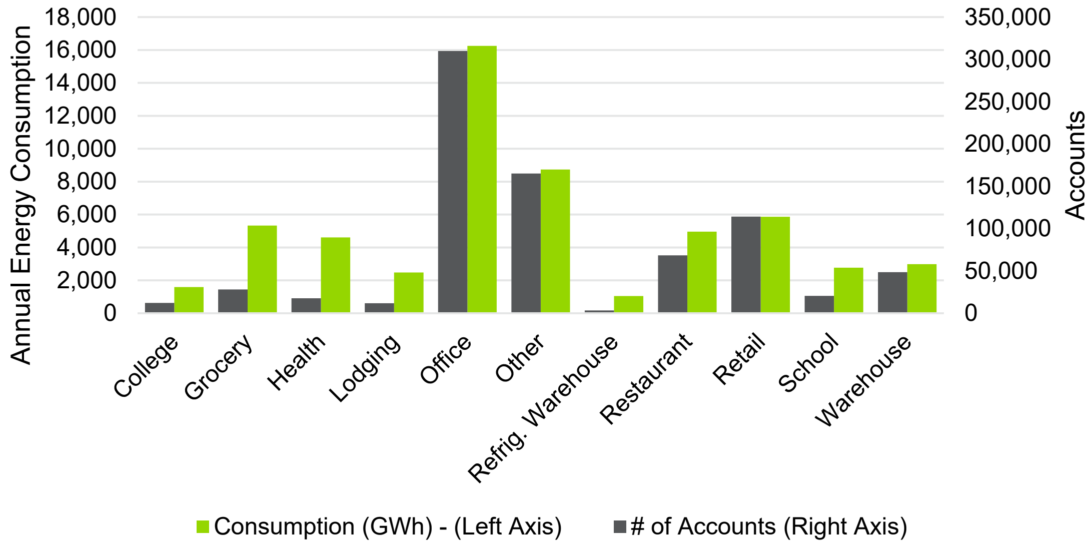
Source: IOU consumption data, and Guidehouse analysis

Customer NAICS codes in the CIS data were used to map each account to a different commercial segment. Commercial segment names were selected to align with those used as part of the bottom-up study and are consistent with those used in the CEC's IEPR forecast. For the purposes of this analysis, Guidehouse combined IEPR building types 1 (Sml-Office) and 12 (Lrg. Office) into a single "Office" segment.[26] Figure 2-6 shows the aggregate electricity consumption (left-hand axis) and count of customer accounts (right-hand axis) across the three electric IOUs in 2019.

[25] This is the average number of accounts present in the data across the three years of data available.

[26] The NAICS code mapping available to Guidehouse only identified the type of business and not its size. Without reliable floorspace data for the individual customers, Guidehouse was unable to split offices by size.

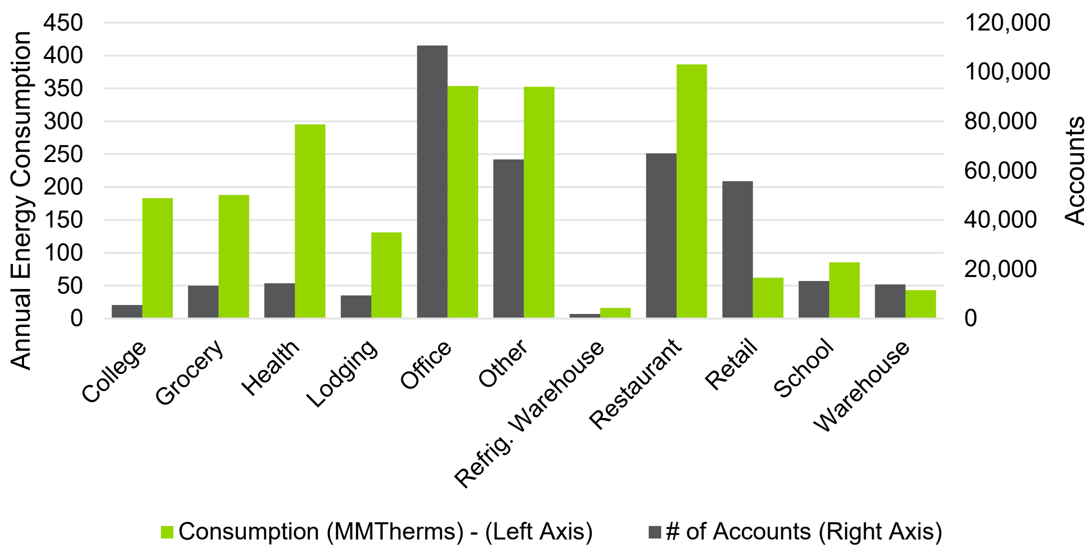
Figure 2-6: 2019 CIS Electricity Consumption and Accounts by Segment



Source: Guidehouse

Figure 2-7 shows the aggregate natural gas consumption (left-hand axis) and count of customer accounts (right-hand axis) across the three natural gas IOUs in 2019.

Figure 2-7: 2019 CIS Natural Gas Consumption and Accounts by Segment



Source: Guidehouse

2.2.1.4 IEPR Forecast Consumption

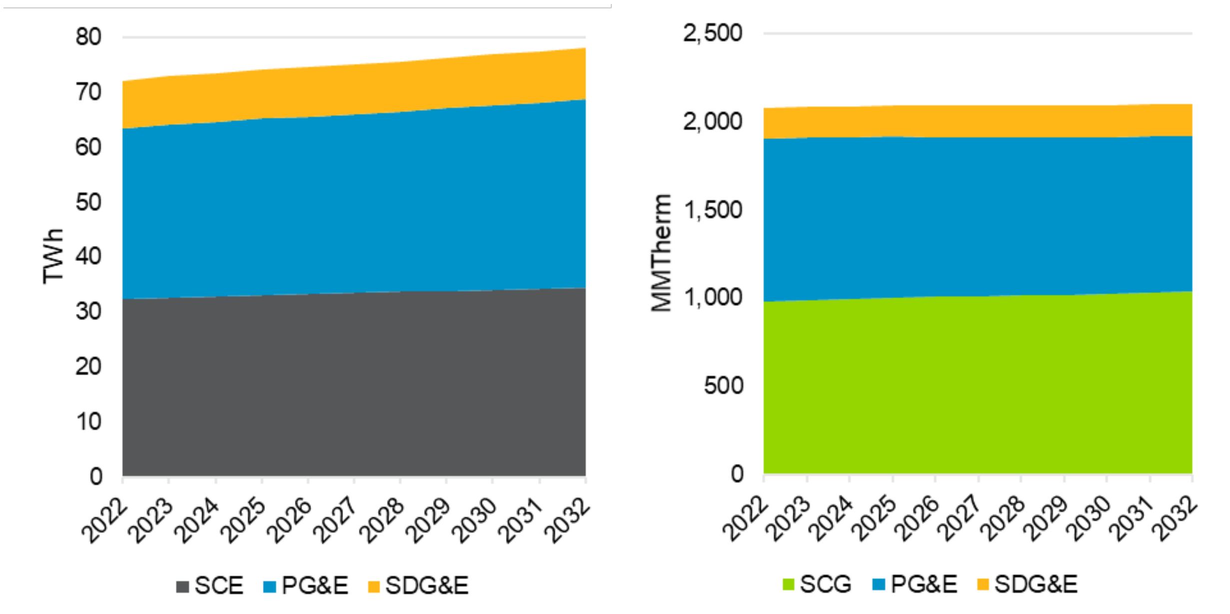
The final core dataset Guidehouse used for this analysis was the IEPR forecast of IOU energy consumption by segment (building type) and end use.[27] For this analysis, Guidehouse applied

[27] California Energy Commission, *California Energy Demand 2019.* Provided by CEC staff via email.

the annual distribution of consumption across IOUs, segments, and end uses to the sector-level reference forecast originally developed from this input for the bottom-up forecast.

Figure 2-8 shows the “Mid” scenario reference forecast for electricity (left) and natural gas (right) for the commercial sector, by IOU.

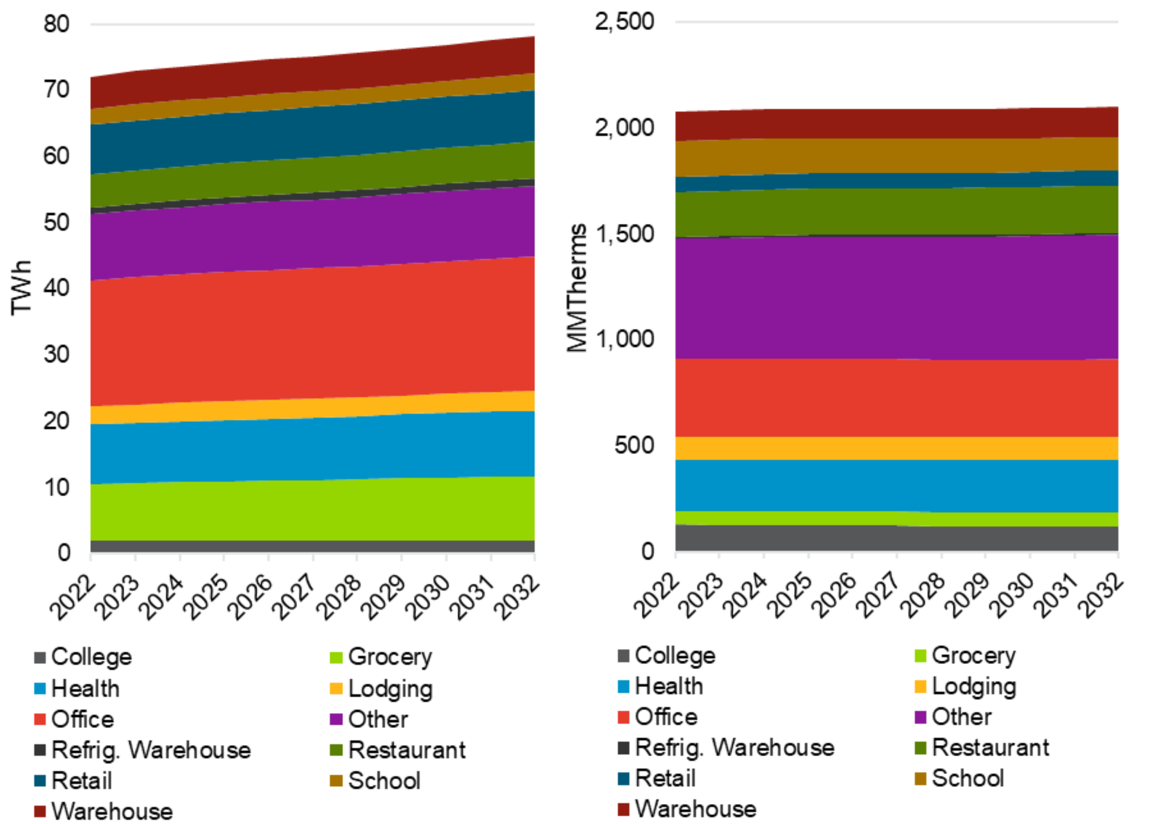
Figure 2-8: IPER Commercial Sector Mid-Scenario Reference Forecast Consumption by IOU



Source: California Energy Commission and Guidehouse analysis

Figure 2-9 summarizes the forecast electricity and natural gas consumption for the four IOUs, but split instead by commercial segment (building type).

Figure 2-9: IEPR Commercial Sector Reference Forecast Consumption by Segment (Building Type)



Source: California Energy Commission and Guidehouse analysis

2.2.2 Create the Building Database

A dataset of individual buildings that includes floorspace, energy consumption, and past program participation data is necessary for the top-down analysis. After ingesting the utility account data (cross-sectional and consumption), the CEDARS data (downstream savings claims), and the CEC benchmarking data (building floorspace and total building consumption), Guidehouse proceeded with some additional data preparation and the combining of all three sets.

2.2.2.1 CEC Benchmarking Data

The only unique key available for joining building data (floorspace) with IOU account data and CEDARS savings data was the building address included in the CEC benchmarking dataset. To maximize the likelihood of achieving a reliable match between the addresses in the CEC Benchmarking database and the utility account data, Guidehouse standardized the addresses through the use of the geocodio API.[28]

[28] https://www.geocod.io/

Guidehouse then flagged all addresses insufficiently specific for robust matching (e.g., missing street number) and all cases within the dataset where multiple observations appeared to include the same address. Where multiple observations included the same address and the address included a street number these were combined into a single observation. Buildings with insufficiently specific addresses were discarded.

2.2.2.2 IOU Consumption Data

As with the CEC Benchmarking data, IOU utility customer addresses were geocoded to prepare for matching to the CEC Benchmarking set. The team discarded accounts with insufficiently specific geocoded addresses, as was done with the CEC Benchmarking data, described in 2.2.2.1, above.

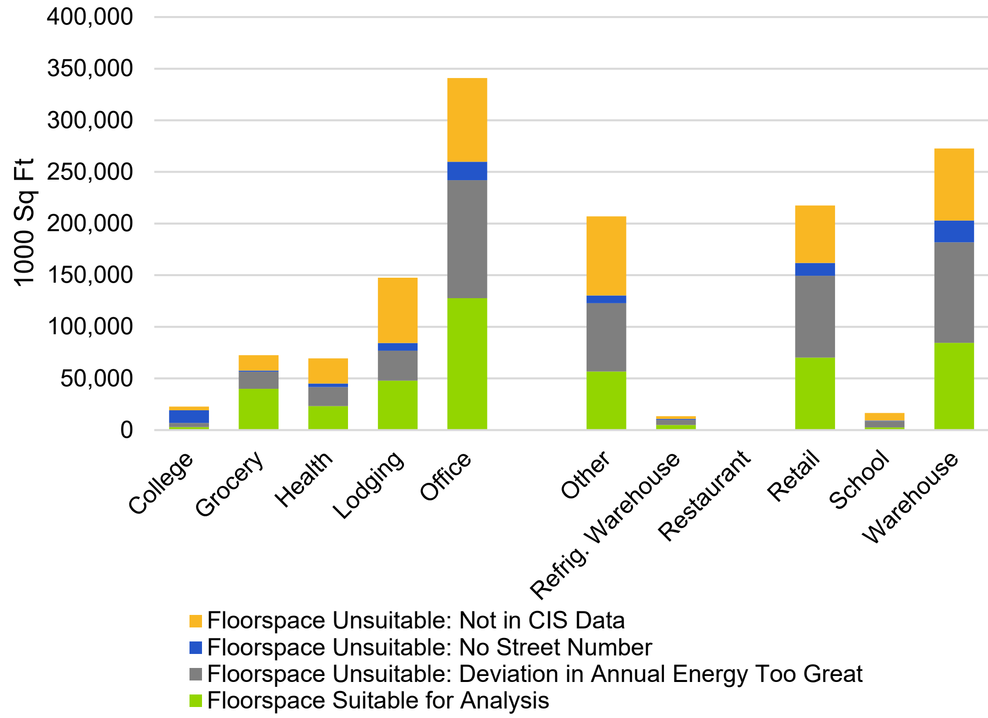
Consumption and account data were then filtered to include only those accounts with non-zero levels of consumption in 2019 (the data year for the CEC benchmarking data) and then joined to the CEC benchmarking data on the basis of the geocoded addresses.

Guidehouse excluded buildings in the CEC Benchmarking data with no matches in the utility account data as they are likely customers of publicly owned utilities and not in scope. Likewise, when the sum of account consumption for 2019 for a given building (there are typically multiple accounts for a single building) deviated by more than 50% in absolute terms from the consumption reported by that building in the CEC Benchmarking dataset, the team excluded the building from the analysis. This exclusion was applied to correct for the possibility that either too few accounts or too many accounts were mapped to the given building (potentially due to imprecisions in geocoding).

After applying its quality and relevance filters (i.e., the categories shown in Figure 2-10 and referred to above), Guidehouse found that over all segments, 37% and 33% of building floorspace was retained for the analysis (for electricity and gas, respectively). These proportions rise to 40% and 36% (for electricity and gas, respectively) when only the four segments of interest (Grocery, Lodging, Office, Warehouse) were included.

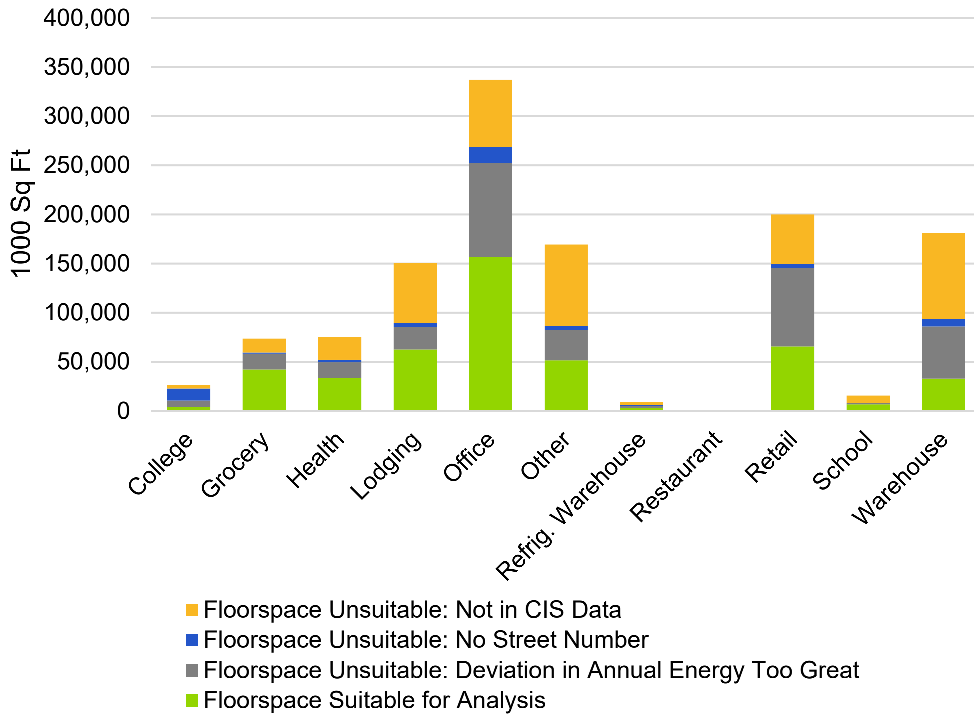
Figure 2-10 and Figure 2-11 show the distribution of floorspace included (in green) or excluded from the analysis on the basis of the three principal filters referenced in the text above. Only the building floorspace in green was determined to be suitable for inclusion in the analysis, and the remaining building data were excluded from the dataset.

Figure 2-10: Distribution of Floorspace Included or Excluded – Electricity



Source: IOU consumption data, CEC Benchmarking Database and Guidehouse analysis

Figure 2-11: Distribution of Floorspace Included or Excluded – Natural Gas



Source: IOU consumption data, CEC Benchmarking Database and Guidehouse analysis

Two final filters were applied to CEC Benchmarking data:

- Buildings were excluded if 2019 reported (in the CEC Benchmarking dataset) natural gas consumption was less than 50 therms or 2019 reported electricity consumption was less than 10 MWh.[29] This outlier exclusion was applied to remove likely vacant buildings or buildings with potentially suspect data – commercial premises of 50,000 square feet or more (the key criterion for inclusion in the data set) in regular use are unlikely to have such low consumption.

- Buildings with an energy intensity (either therms per square foot or kWh per square foot) that was more than three standard deviations of the mean (by segment) were excluded. This is a relatively conventional outlier removal rule designed to ensure against the presence of data-entry errors or highly exceptional observations that could skew sample averages inappropriately.

These final filters resulted in the exclusion of approximately 1% of the remaining buildings across all segments, a limited impact.

[29] Note this criterion is applied to building consumption, not account consumption. Since multiple accounts may be found in a single building it is thus possible to exclude buildings with consumption reported in the CEC Benchmarking data that is below these values without excluding accounts with annual consumption below these values.

2.2.2.3 Program Participation Data

In assessing the most suitable proxy variable that could be used to segment both the buildings in the CEC benchmarking database and the overall population of utility account data into *efficient* and *less efficient* buildings or accounts, Guidehouse determined that the best source for such a variable would be historic program participation data from CEDARS. The team based this decision on two factors: 1) high quality program participation data are available for the entire relevant population and 2) an assumption that commercial decision makers choosing to participate in IOU downstream programs are more likely than their peers that do not participate in such programs to also undertake other energy efficiency activities to reduce the energy intensity of their buildings.

This required joining the CEDARS data to the other building data collected (IOU consumption and building benchmarking). This was accomplished using the program tracking site ID. This site ID is allocated to all accounts submitting claims tracked by CEDARS. Guidehouse assigned each claim's savings to the building that shared an address with the customer account that was part of the site for those savings.

Table 2-4 summarizes some of the key summary statistics of the final building database Guidehouse developed.

Table 2-4: Final Building Database Summary Statistics

Segment	Number of Buildings	Mean Accts/Building	# of Buildings with ANY CEDARS Claims	Avg # Claims (2017 - 2019) per Building with >0 Claims
Electricity				
College	15	1.5	4	2.3
Grocery	352	1.8	204	1.5
Health	193	3.6	39	0.9
Lodging	293	2.0	158	1.4
Office	824	4.3	231	1.4
Other	491	2.1	92	4.4
Refrig. Warehouse	23	1.6	4	0.7
Retail	403	6.5	211	1.6
School	26	1.6	6	1.4
Warehouse	395	2.7	52	1.4
Natural Gas				
College	24	1.1	3	0.4
Grocery	387	1.2	198	1.1
Health	245	1.4	42	0.9
Lodging	348	1.3	132	1.2
Office	930	1.3	164	1.4
Other	430	1.2	45	3.4

Segment	Number of Buildings	Mean Accts/Building	# of Buildings with ANY CEDARS Claims	Avg # Claims (2017 - 2019) per Building with >0 Claims
Refrig. Warehouse	14	1.0	1	0.3
Retail	403	1.9	94	1.9
School	65	1.3	13	0.6
Warehouse	164	1.2	11	1.1

Source: CEDARS, IOU consumption data, CEC Benchmarking Database and Guidehouse analysis

2.2.3 Segment Selection

The motivation for limiting the prototype analysis to the commercial sector is described in earlier in Chapter 1:

- The homogeneity and intuitive nature of the residential sector (among other factors) mean that the bottom-up approach is likely more robust in the residential sector than in others (i.e., the incremental benefit of a top-down approach is lower in the residential sector).
- The site-specific nature of industrial and agricultural loads, and their generally poor correlation with other observable and available features (e.g., floorspace, acres of crop), requires a more finely targeted approach than was deemed suitable for a trial or prototype analysis.

In defining its approach, Guidehouse limited its analysis to two to five segments (building types) in the commercial sector. This section identifies those segments and explains what motivated their selection.

The team identified two key criteria for determining which segments should be included in the analysis: (1) the availability of data for the given segment, and (2) the relative homogeneity of the end uses across buildings, within the segment.

The first of these criteria is important in that an analysis can only be as robust as the data that inform it. Once it became apparent to Guidehouse staff that individual building floorspace data would be required for the analysis, and that the CEC Building Benchmarking data represented the only publicly available data cataloguing individual building floorspace, it was clear that the constraints of this dataset would define the segments selected.

The second of the selection criteria—the need for relative homogeneity in end uses[30]—is a more flexible and subjective criterion. Homogeneity in end uses is important because it reduces statistical noise in the data that may confound the correlation between the selected proxy variable used to split buildings into *efficient* and *less efficient* and average building energy

[30] An example may be helpful here: residential customers are generally quite homogenous in the distribution of end-uses: the percentage of annual electricity use devoted to (e.g.,) cooking is reasonably similar across most homes, and the temporal distribution is also relatively similar (e.g., most cooking energy takes place in the evening). The commercial sector as a whole is not nearly as homogenous as the residential sector (patterns of use vary widely), and even within individual segments (e.g., health care, colleges), the distribution of energy by end-use, as well as its temporal distribution can vary widely from building to building.

intensity. As section 2.1.1 mentions, a core component of defining the energy efficiency potential of a segment is the ability to use a proxy variable[31] (previous program participation) to identify *efficient* and *less efficient* buildings.

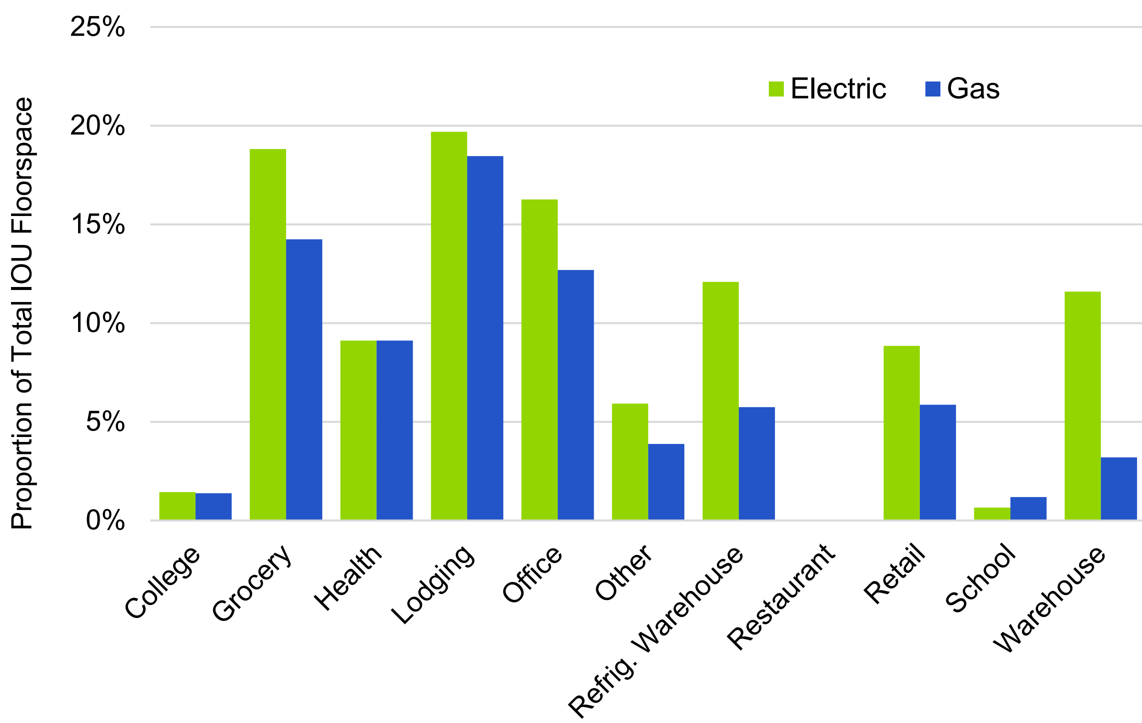
Sub-section 2.2.3.1 addresses this more subjective criterion (the assumed homogeneity of segment end-uses) in detail. Sub-section 2.2.3.2 addresses the criterion of data availability by comparing the data available in the CEC Benchmarking data by segment in relation to population statistics. Sub-section 2.2.3.3 identifies the selected segments and provides the specific reasoning for their inclusion.

2.2.3.1 Data Availability

Guidehouse selected segments for the analysis based on the data available in the CEC Benchmarking dataset. Specifically, after applying a number of quality-control criteria (as Section 2.2.2.2 details in Figure 2-10 and Figure 2-11), Guidehouse compared the floorspace of the remaining buildings in the database to the floorspace of each of the IOUs to assess which segments might offer the greatest coverage.

Figure 2-12 compares the aggregate floorspace by segment of the buildings included in the benchmarking database that Guidehouse determined could be included in the analysis to the total segment floorspace across the four IOUs in 2019, drawn from the bottom-up analysis.[32]

Figure 2-12: CEC Benchmarking Floorspace Compared to Total Floorspace



[31] In statistics and econometrics this variable would be referred to as an instrument or instrumental variable.

[32] Aggregate floorspace data used in the bottom-up analysis is drawn from IEPR and is adjusted to reflect the four IOUs included in the analysis.
California Energy Commission, *California Energy Demand 2019.* Provided by CEC staff via e-mail.

Source: IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

As this plot indicates, the Grocery, Lodging, and Office segments are the three segments in the CEC Benchmarking database that provide the most coverage of segment floorspace across the four IOUs. A secondary tier of segments of at least 5% of the total floor space have material (if less substantial) coverage includes Warehouse, Refrigerated Warehouse, Retail, and Health.

2.2.3.2 Intra-Segment Heterogeneity

The proxy variable's effectiveness in defining *efficient* and *less efficient* buildings is a function of how closely correlated this variable is with building energy intensity. The greater the variation in end uses within a segment, the more noise exists,[33] and the weaker the correlation between the proxy and the building intensity becomes. This section illustrates and explains the issue. The two approaches used by Guidehouse to mitigate the effects of this issue are described in sections 2.2.3.3 (excluding the segments likely to have the most material heterogeneity) and 2.2.4.2 (the selection of the threshold value of prior participation in energy efficiency programs used to split customers into *efficient* and *less efficient* groups.

The proxy variable can successfully be used to split buildings into *efficient* and *less efficient* groups because, aside from the savings delivered by the program measures, selection into the program reveals an active interest by the customer in energy efficiency. When comparing two similar office buildings (similar vintage, similar types of tenants, etc.), the building whose owners consistently invest in energy efficiency measures will use less energy per square foot than the building whose owners do not.

The precision of this approach suffers, however, the more different the buildings compared are from one another. The more different those two buildings are the less precisely the proxy variable can be used to identify which building is likely to have a lower energy intensity because of the number of other features to which differences in energy intensity could be attributable.

For example, in the health segment the consumption per square foot of an urban center teaching hospital, a regional health-care unit, and a physiotherapy facility are all going to be quite different. In this case, a proxy variable (such as historic program participation) may not provide sufficiently strong signal to reliably segment buildings such that *efficient* buildings have a lower energy intensity (on average) than *less efficient* buildings. Without additional facility-specific information (to control for these factors) this segment is likely inappropriate to include.[34]

2.2.3.3 Selected Segments

Based on its data assessment, Guidehouse determined that Grocery, Lodging, and Office segments should all be included in the analysis from the first tier segments (i.e., those segments for which buildings in the CEC benchmarking database accounted for more than 5% of the

[33] It is possible, likely even, that much of this noise could be controlled for in a more targeted, segment-specific analysis. For example, by splitting up the "health" sector into more specifically defined sub-segments, e.g., labs and research facilities, acute care hospitals, etc.

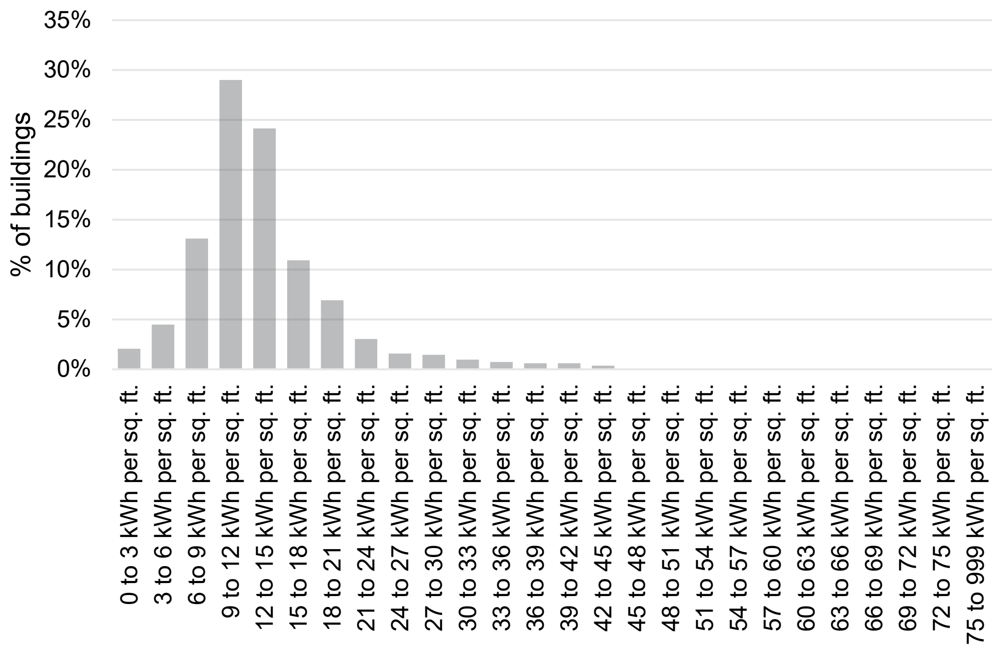
[34] Guidehouse has previously conducted such an analysis of hospitals by using bed occupancy rates to control for differences between facilities. Such segment specificity is beyond the scope of this analysis, however. See Chapter 8 ("Whole Building Analysis") of:

Guidehouse (formerly Navigant) prepared for the Independent Electricity System Operator and Ontario Energy Board, *2019 Integrated Ontario Electricity and Natural Gas Achievable Potential Study*, September 2019.
https://www.ieso.ca/2019-conservation-achievable-potential-study

floorspace in those segments – see Section 2.2.3.1). Guidehouse did however have some concern about the heterogeneity within the Grocery segment.

This concern is illustrated by comparing the frequency distribution histogram of electric energy intensity for the Office segment (one which would generally be accepted as relatively homogenous in the distribution of end uses) with that of the Grocery segment. Figure 2-13 shows the distribution of office building energy intensities in the CEC Benchmarking database. This is a reasonably symmetrical distribution, relatively tight around the mean.

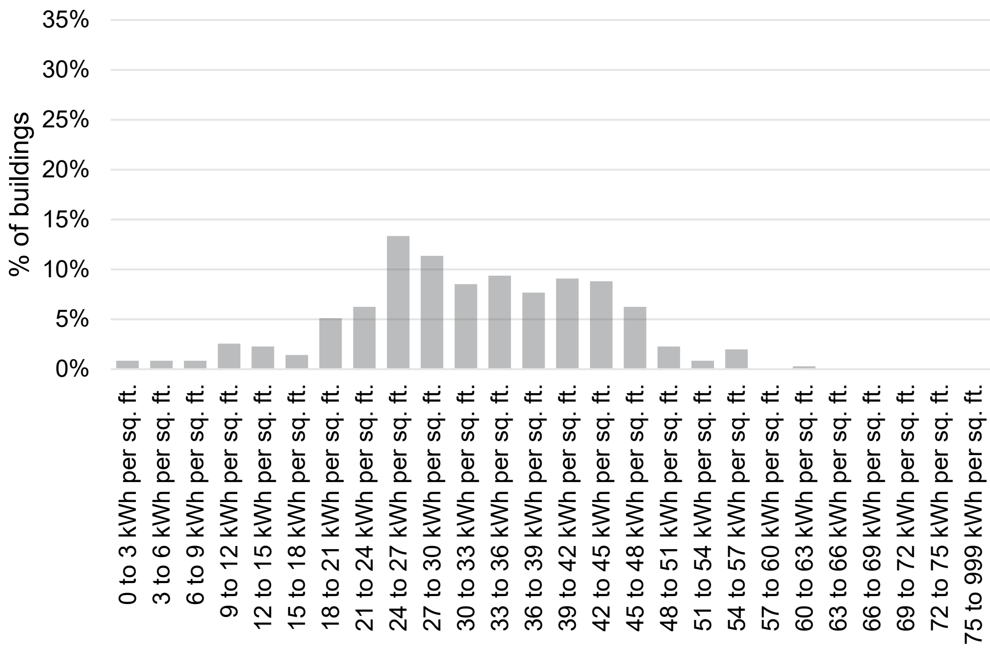
Figure 2-13: Office Segment – Distribution of Building Electricity Intensity



Source: CEC Benchmarking Database, and Guidehouse analysis

Consider the same plot, but showing the distribution of Grocery building energy intensities (Figure 2-14. This distribution is much wider, revealing considerable heterogeneity in the segment. Despite this, it is included as one of the segments in the analysis because of the proportion of overall IOU Grocery floorspace it accounts for.

Figure 2-14: Grocery Segment – Distribution of Building Electricity Intensity



Source: CEC Benchmarking Database, and Guidehouse analysis

Among the second tier segments (for which floorspace available in the data set account for less than 5% of total IOU floorspace in that segment), which are Health, Refrigerated Warehouses, Warehouses, and Retail:

- The Refrigerated Warehouses segment is excluded due to the small number of such buildings for which data are available (70 in the database in total, see Table 2-1, and only 27 after excluding buildings not in one of the IOUs' service territories or as part of Guidehouse's QC process).

- The Health and Retail segments are excluded due to the heterogeneity of the segments (assessed *a priori* and confirmed through an examination of a frequency distribution similar to those shown for Grocery).

- The Warehouse segment is included as these buildings are expected to be relatively homogenous and though the data-set includes less than 5% of the warehouse floorspace in buildings that use natural gas, it does include more than 5% of of all warehouse floorspace in the IOUs' service territory.

The four segments selected by Guidehouse for this analysis are: Grocery, Offices, Lodging, and Warehouses.

2.2.4 Split Sample with Proxy Variable

Once the team created the building database, Guidehouse conducted some exploratory analysis to identify a reasonably robust proxy variable in the CEDARS data that could be used to segment buildings into *efficient* and *less efficient*.

The two proxy variables that were explored in the most depth were the average number of program savings claims made and the average annual net savings across the 3 years data were available as a percentage of 2019 consumption. In the end, Guidehouse staff assessed that total savings achieved relative to building consumption would likely be a better predictor of a customer's energy intensity than simply the number of claims submitted. The basis of this assessment was in part the observation that incremental measure costs tend to vary more widely by claim than by estimated energy units saved. This means that the magnitude of savings achieved by a customer tends to be a more consistent predictor of the dollars spent on energy efficiency than the number of claims made by the customer. This should in turn mean that the magnitude of savings is a better predictor of other energy efficiency attitudes and behaviors that contribute to some buildings having lower energy intensities than other, similar, buildings.

Guidehouse staff then segmented buildings in the database on the basis of average building savings over the period 2017 through 2019 as a percentage of 2019 building account consumption. This is the proxy variable that creates the *efficient* and *less efficient* groups of buildings.

2.2.4.1 Efficient and Less Efficient Building Split

Each building segment had its own analysis to determine the *efficient* and *less efficient* building split. This section:

- Identifies the threshold of documented CEDARS savings (as a percentage of consumption) used to split each segment
- Provides a frequency distribution of building intensities comparing *efficient* and *less efficient* buildings
- Provides the estimated percentage savings achievable if the *less efficient* customers can be transformed into *efficient* customers such that they reduce their average energy intensity to the level of the *efficient* customers.

Section 2.2.4.2 describes Guidehouse's approach to selecting the threshold percentage value used to split buildings into *efficient* and *less efficient* groupings and provides some insight into the sensitivity of the percentage savings to that threshold.

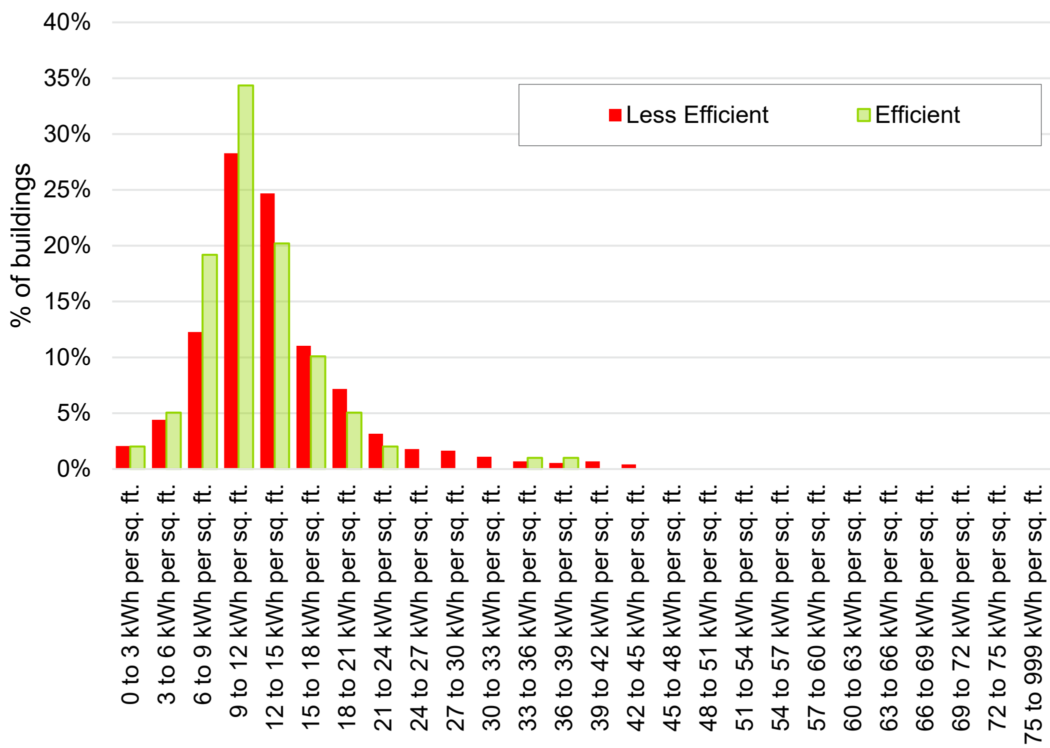
For the **electricity customers in the Office segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 0.25%[35] of 2019 account consumption.[36] This resulted in 12% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 11.8% lower than that of *less efficient* buildings. This suggests that if, by program interventions, educational programs or other outreach to *less efficient* building owners can be made to adopt the same proclivity for energy

[35] The approach used to select the threshold applied to each segment is discussed in 2.2.4.2, below.

[36] For each building there are two distinct measures of consumption: account consumption (the sum of the annual consumption of all accounts that Guidehouse could map to the building address), and building consumption, which is the energy value included in the CEC Benchmarking data. The former value is used to identify efficient and less efficient buildings, but the latter value (since it derives from the same source as the floorspace estimate) is what is used to assess the building energy intensity. Though these two values are often different, recall from Section 2.2.3.3 that Guidehouse excluded from the analysis those instances where the absolute difference between the account and building consumption exceed 50% of the building consumption for the given fuel.

efficiency as the *efficient* buildings, energy consumption of those *less efficient* buildings could be reduced by 11.8%. Figure 2-15 compares the frequency distribution of *efficient* and *less efficient* Office buildings, bucketed by energy intensity. This is a relative frequency distribution, meaning that it shows the percentage of each category of building (*efficient* or *less efficient*) that falls into each bucket of energy intensity. So, for example, nearly 35% of *efficient* Office buildings in the data-set have an energy intensity of between 9 and 12 kWh per square foot. A relative distribution is used to provide a normalized comparison between the two groups. If a y-axis of building counts (rather than percentage of buildings) was used, comparing the two would be more difficult because, by the nature of the analysis, there tend to be many more *less efficient* than *efficient* buildings in each segment.

Figure 2-15: Office – Electric



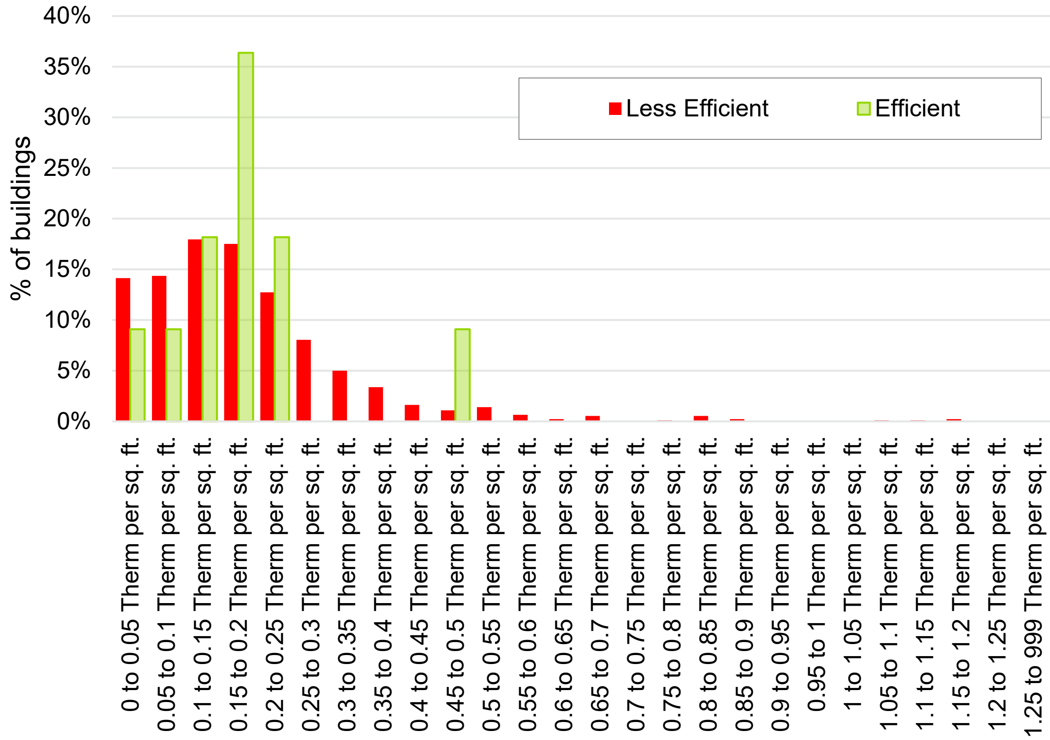
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For the **natural gas customers in the Office segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 2.5% of 2019 account consumption.[37] This resulted in 1.2% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 9% lower than that of *less efficient* buildings. This suggests that if the *less efficient* building owners can be made to adopt at the same proclivity for energy efficiency as the *efficient* buildings, energy consumption of those *less efficient* buildings could be reduced by 9%.

[37] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.

Figure 2-16 compares the frequency distribution of *efficient* and *less efficient* Office buildings, bucketed by natural gas energy intensity.

Figure 2-16: Office – Natural Gas



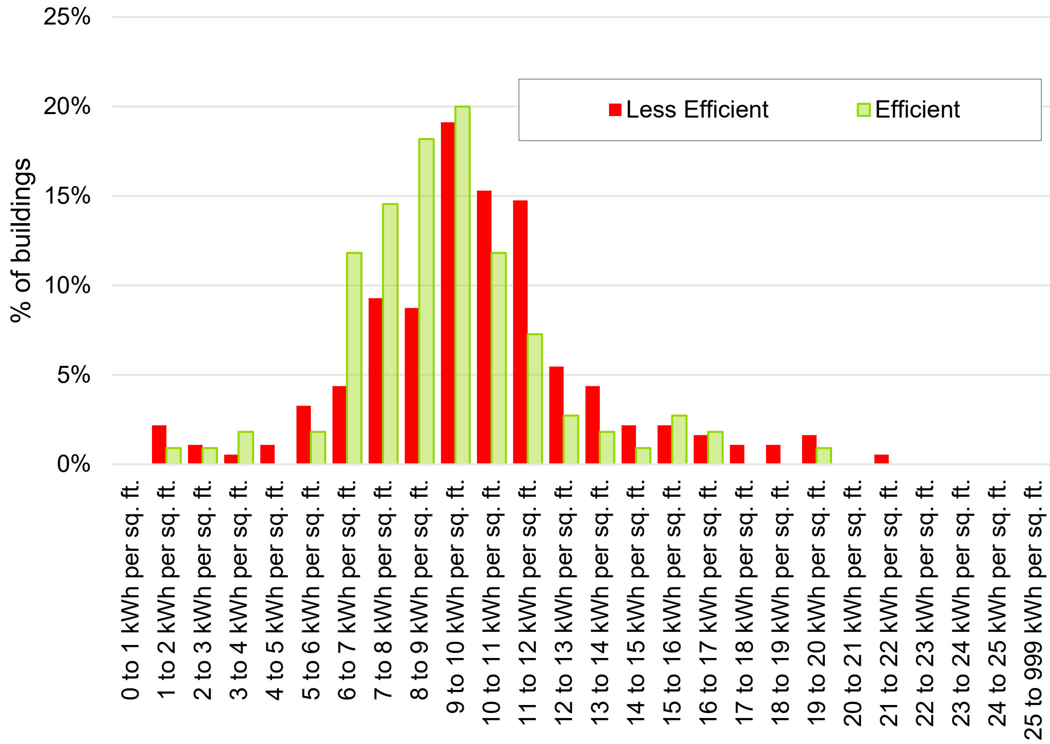
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For the **electricity customers in the Lodging segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 0.25% of 2019 account consumption. [38] This resulted in approximately 38% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 10% lower than that of *less efficient* buildings.

Figure 2-17 compares the frequency distribution of *efficient* and *less efficient* Lodging buildings, bucketed by energy intensity.

[38] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.

Figure 2-17: Lodging – Electricity



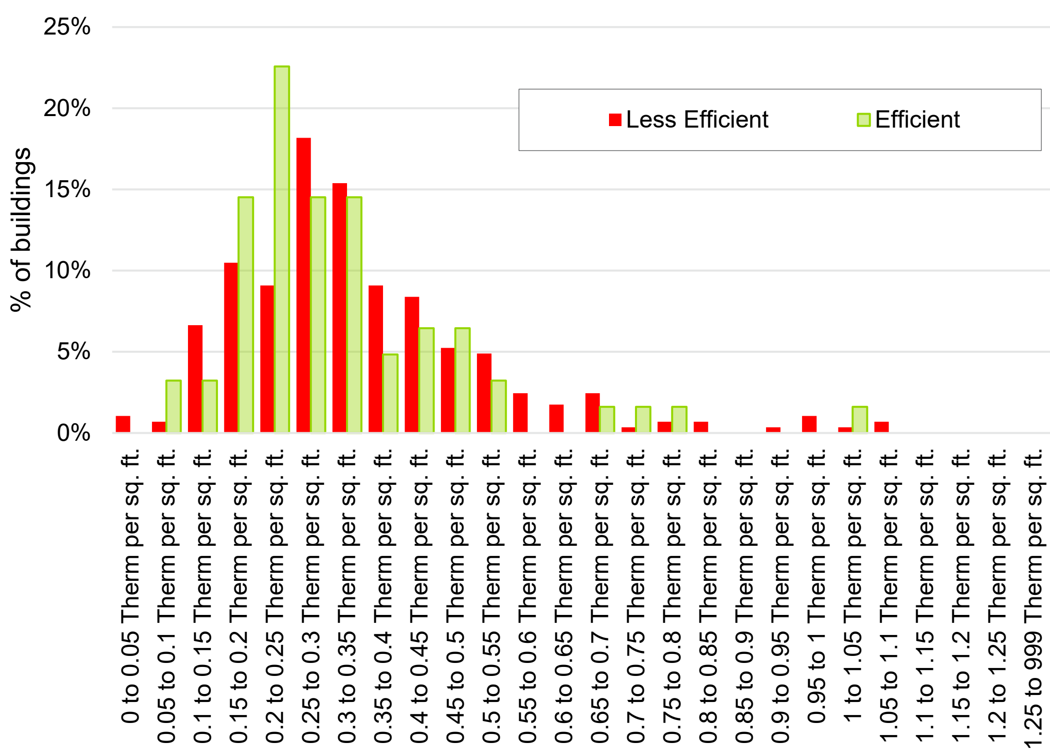
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For the **natural gas customers in the Lodging segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 0.25% of 2019 account consumption. [39] This resulted in approximately 18% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 10% lower than that of *less efficient* buildings.

Figure 2-18 compares the frequency distribution of *efficient* and *less efficient* Lodging buildings, bucketed by energy intensity.

[39] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.

Figure 2-18: Lodging – Natural Gas



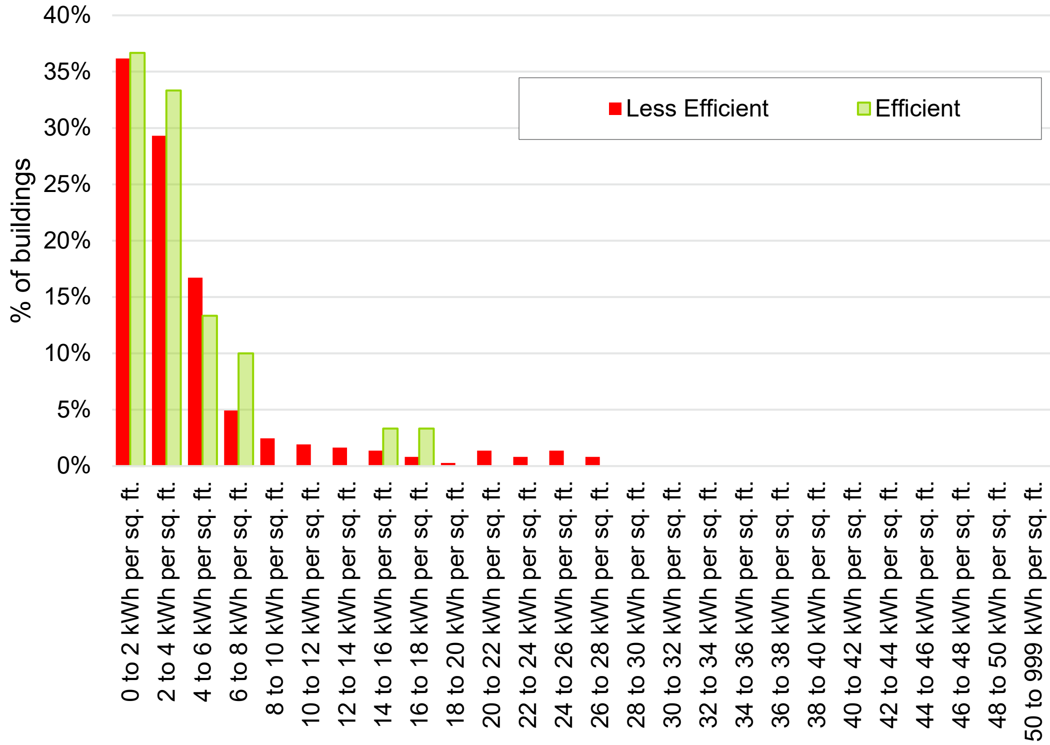
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For the **electricity customers in the Warehouse** segment, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 0.25% of 2019 account consumption. [40] This resulted in approximately 8% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 14% lower than that of *less efficient* buildings.

Figure 2-19 compares the frequency distribution of *efficient* and *less efficient* Warehouse buildings, bucketed by energy intensity.

Figure 2-19: Warehouse – Electricity

[40] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.



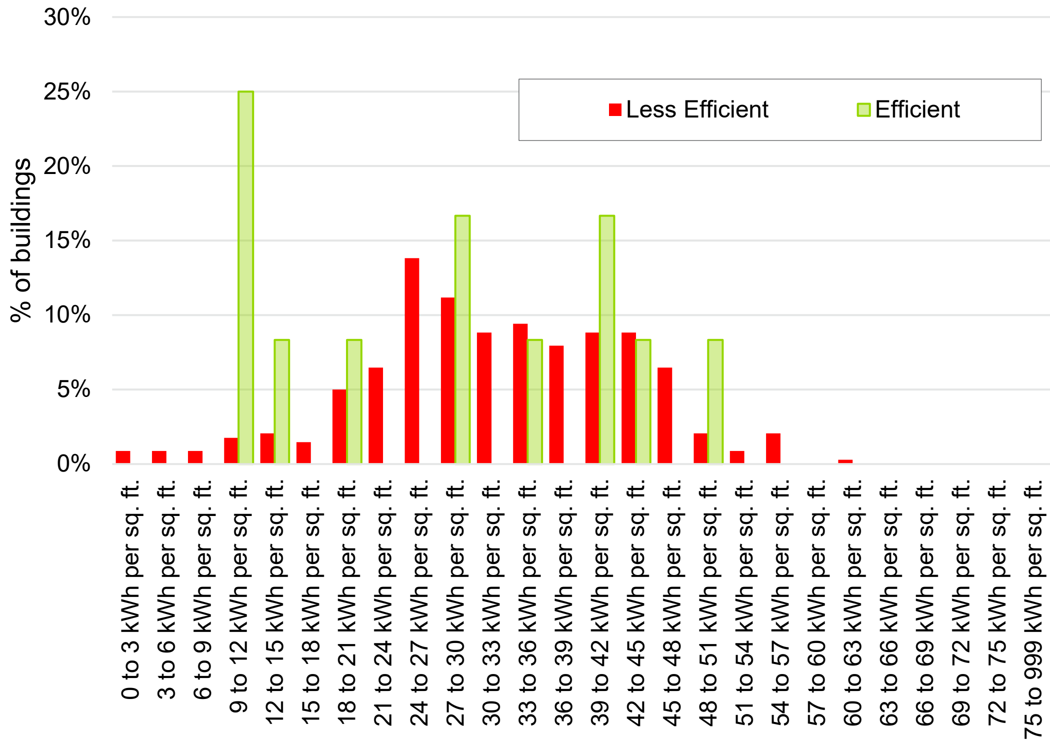
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For natural gas, Guidehouse excluded the Warehouse segment due to there being too few buildings with any savings claims to reasonably support the analysis. Per Table 2-4, only 11 Warehouse buildings included in the database made any claims over the 3-year period from 2017 through 2019.

For the **electricity customers in the Grocery segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 3% of 2019 account consumption. [41] This resulted in approximately 3.4% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 15% lower than that of *less efficient* buildings. Figure 2-20 compares the frequency distribution of *efficient* and *less efficient* Grocery buildings, bucketed by energy intensity. The clustering apparent in this plot may be related to the heterogeneity of the Grocery segment as a whole. This feature, and its implications, are discussed in greater length at the end of this section.

[41] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.

Figure 2-20: Grocery – Electricity



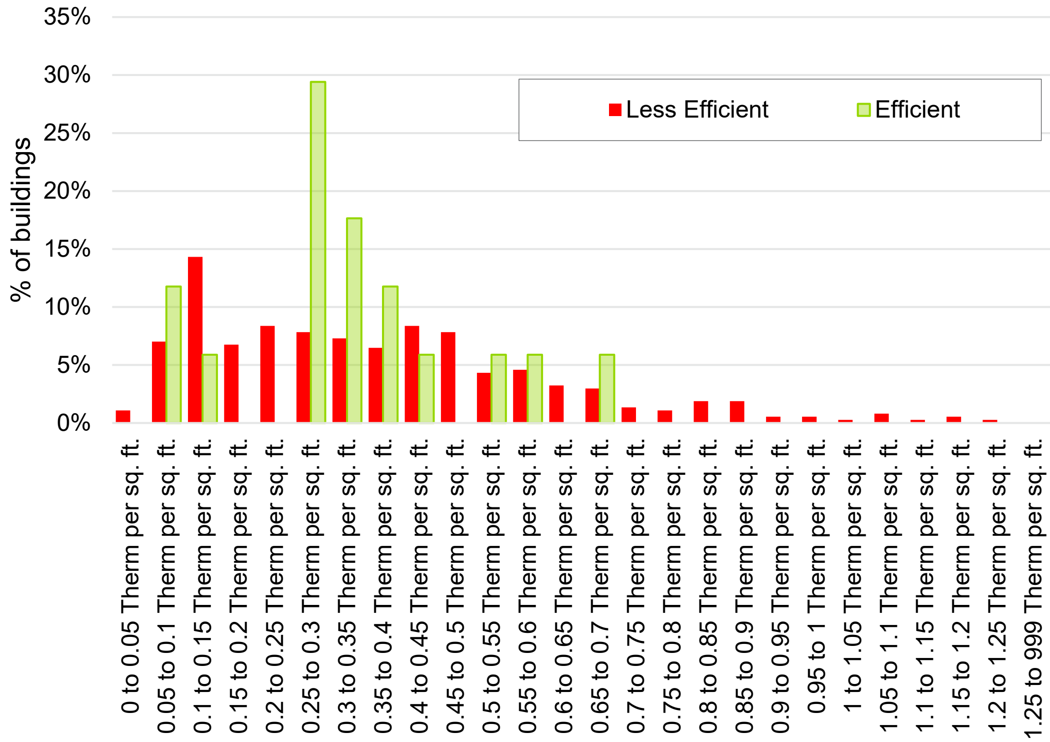
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

For the **natural gas customers in the Grocery segment**, Guidehouse allocated customers to the *efficient* category if average annual savings from 2017 through 2019 were more than 3% of 2019 account consumption. [42] This resulted in approximately 4.4% of buildings being identified as *efficient*, with the average energy intensity of these buildings being 12% lower than that of *less efficient* buildings.

Figure 2-21 compares the frequency distribution of *efficient* and *less efficient* Grocery buildings, bucketed by energy intensity.

[42] A discussion of how the thresholds were selected and the sensitivity of potential to those thresholds is presented in sub-section 2.2.4.2.

Figure 2-21: Grocery – Gas



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Table 2-5 summarizes key building analysis. There is considerable variation in the percentage of buildings that are (under the proxy metric selected) considered *efficient* – as many as 38% of electric Lodging buildings are *efficient*, but as few as 1.2% of gas Office buildings are *efficient*.

Table 2-5: Building Analysis Summary Statistics

Segment	Fuel	Total Number of Buildings	Total Floorspace (Thousands Sq Ft)	*efficient* Threshold: Avg. Savings (2017-2019) as % of 2019 Consumption	% of Buildings that are *efficient*	% Improvement in Intensity (Savings)
Office (Large)	E	824	126,098	0.25%	12%	12%
Office (Large)	G	930	155,519	2.50%	1.2%	9%
Lodging	E	293	46,265	0.25%	38%	10%
Lodging	G	348	61,963	0.25%	18%	10%
Warehouse	E	395	83,667	0.25%	8%	14%
Grocery	E	352	40,026	3.00%	3%	15%
Grocery	G	387	41,266	3.00%	4%	12%

Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Table 2-5 also indicates an almost bi-modal distribution (the values all cluster around two points, not just one) in the threshold value used to identify *efficient* and *less efficient* buildings (0.25% versus above 2.5%). This value is related to the strength of the instrument (the proxy variable) in predicting the group of more efficient buildings. Where this instrument is strongest, i.e., where the segment is relatively homogenous and where the savings variable can be most accurately tied to the building (see Section 2.2.4.2), then a lower threshold (for example 0.25% instead of 2.5%) is sufficient to identify the split, and the higher the proportion of buildings will be allocated to the *efficient* group.

Where the instrument (the proxy) is weaker, a more aggressive threshold is required to split the groups. Consider the following analogy: when searching for an object on the ground at night, the darker the object (the weaker the instrument) the brighter the flashlight (the more aggressive the threshold) must be to find it. Sub-section 2.2.4.2 discusses this in greater detail.

The plots above show that the effectiveness of the proxy variable in defining *efficient* and *less efficient* buildings varies by segment or building type. Intuitively, one should expect the distribution of *efficient* buildings to look similar to *less efficient* buildings, but simply shifted to the left. This is the case for Lodging (both fuels), Offices (electric), and Warehouses (electric).

For Grocery and Offices (gas), the distributions of *efficient* and *less efficient* building efficiencies are different, undermining confidence in the robustness of the proxy variable in defining the two groups. In these cases, the proxy (or instrument) is weaker. An instrumental variable is a strong predictor of the variable of interest (in this case, energy intensity) when it is strongly correlated with that variable, but only weakly correlated (or, in an ideal situation, orthogonal – not correlated at all) to other variables.

For example, compare office electricity end uses to grocery store electricity end uses. Regardless of the size of the office, the distribution of end use electricity consumption is likely to be reasonably consistent. The majority is split evenly between lighting and HVAC, with most of the remainder servicing small to moderate plug loads (e.g., computers, other office equipment, etc.).

In grocery stores, refrigeration is the dominant electric end use, and the ratio of refrigerated space to unrefrigerated space can vary significantly across buildings. Consider the difference between a grocery chain with a focus on produce and dry goods in comparison with one that offers bulk purchases of meat and prepared foods, or, for the case of gas, one that bakes bread and prepares hot food on the premises and one that does not.

If this additional set of correlations cannot be effectively controlled for (for example, by splitting the two types of store into separate sub-samples, or through the use of additional independent variables in a regression analysis), it reduces the strength of the instrument. The proxy variable is less effective at identifying *efficient* and *less efficient* buildings. Chapter 4 discusses this effect and the data that could be used to mitigate it.

2.2.4.2 Selection of Thresholds and Savings Sensitivity

Sub-section 2.2.4.1 outlined, the savings potential (expressed as the percentage improvement in building energy intensity) estimated for each segment is determined on the basis of the threshold value selected as the instrument to split buildings into *efficient* and *less efficient* categories. Given the overriding importance of this variable to the outcome of the analysis, any discussion of how the Guidehouse team selected these values must be accompanied by an illustration of how sensitive the final result is to fluctuations in these values.

Figure 2-22 plots the outcome potential (y-axis, a percentage reduction) as a function of the savings threshold selected as the proxy variable value used to create the *efficient* and *less efficient* building groupings (the x-axis, average savings 2017–2019 as a percentage of 2019 consumption).

In examining this plot, a few key characteristics are evident:

1. **Magnitude of Threshold Is Correlated with Potential.** All of the series plotted below are trending up. If a linear trend was plotted for each one, all seven would have a positive slope. That is, on average, the more aggressive the threshold (savings as a percentage of consumption), the higher the potential (or the lower the energy intensity of the *efficient* buildings). A more aggressive threshold raises the bar for the target of what is means for a *less efficient* building to be converted to an *efficient* building.

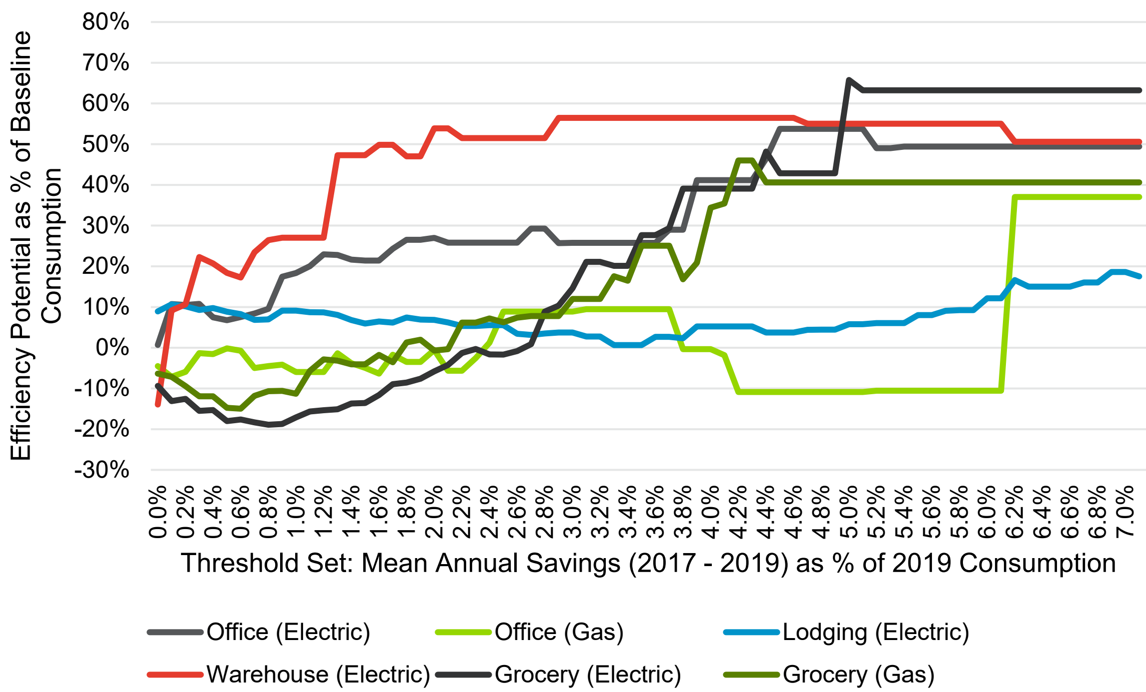
2. **In Some Cases, Potential Is Negative When the Threshold Is Low.** The left-hand side of the figure shows that when the threshold is very low, the potential may be negative. This is particularly true of the Grocery (Electric) and Grocery (Gas) series. At these lower thresholds the signal from the proxy or instrument is weak relative to the noise (expected random variation in building energy intensity) so marginal increments in the threshold do not yield increases in potential. As the threshold (value on the x-axis) increases, the signal strengthens and the expected relationship asserts itself: the potential trends up (the average slope of the line becomes positive), in sync with the magnitude of the threshold.

3. **At Higher Thresholds, Trends for Some Segments Flatten**. This is a result of the relatively limited sample available in the CEC Benchmarking data. Where a series flattens completely across a range of threshold values, this is an indication that the split of *efficient* and *less efficient* buildings is not changing over that range of values. That is an indication of the relatively small number of buildings in one or the other groupings. For example, the red line (Warehouses, Electric) flattens out between the threshold value of 2.9% and 4.6%. In this range of values, the split of *efficient* and *less efficient* buildings remains constant, with *efficient* buildings accounting for 1.5% of all buildings in the sample.

   The green line, (Offices, Electric) flattens as well at higher threshold values, but flattens to a lower level. As is the case with other series that flatten out, this is because at these higher thresholds the vast majority of buildings are assigned to the *less efficient* category already, making the average intensity of *efficient* buildings highly sensitive to changes in the set of buildings that deliver that average.[43]

[43] One potential confounding issue for this segment and fuel combination is that the buildings included in the CEC database and that passed through the Guidehouse QC filters generally consume very little gas: approximately two-thirds of all office buildings in the Guidehouse dataset consume less than 0.2 therms per square foot per year. In contrast, less than 20% of buildings in the Lodging segment and less than 30% of the buildings in the Grocery segment use that little natural gas.

Figure 2-22: Sensitivity of Potential to Savings Threshold



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Guidehouse's core assumption *that the more the businesses housed in a building participate in DSM programs, the lower their energy intensity* is supported by these data. There can be no doubt as to the directionality of this relationship.

Equally clear, however, is that the specific parameters of this relationship are highly uncertain – the data are noisy. This implicitly indicates that the estimated potential that can be projected on the basis of these values will also be highly uncertain. To understand how this precision could be improved, two factors must be considered: those factors that weaken the "signal" provided by the proxy (or instrumental) variable (savings as a percentage of consumption), and those factors that increase the statistical noise that make that signal more difficult to detect.

These factors are discussed in greater detail in sub-section that follows.

2.2.4.3 Sources of Imprecision

As the analysis above demonstrates, the trends in potential identified using the proxy variable are directionally consistent with expectations (i.e., that a certain level of participation in energy efficiency programs can be an effective predictor of average building intensity) but are highly uncertain. Chapter 4 provides some recommendations (principally related to data collection) that, if adopted, could substantially improve the statistical precision of the analysis. Immediately below the key issues that those recommendations address – the problems that they will help solve – are described in greater detail with some illustrative examples.

Strength of Signal

The proxy variable's signal is weakened when there are other variables that are also reasonably strongly correlated with segment-specific energy intensity, i.e., covariates. Such covariates are more likely to be present as the homogeneity of the segment decreases. Conversely, such covariates are less likely to be an issue when the segment is relatively homogenous.

For example, regardless of the kinds of operations that inhabit them, offices tend to have relatively similar electricity use patterns. For these types of customers, the signal of the proxy variable will tend to be stronger.

Grocery stores, however, are more varied, and would probably benefit from being further sub-segmented, depending on the market they serve. Some offer prepared food (hot or frozen) and may even house restaurants, others may offer principally produce. The fact that there are distinct types of grocery stores within the larger segment means that there exists another (at present) unobserved variable that is correlated with demand. This results in a signal delivered by the proxy variable—when all types of grocery stores are combined into a single category—that is much weaker than for offices. Acquiring more data may correct this issue. If grocery stores can be categorized more finely (for example using data gathered as part of a commercial end use survey) this would reduce the *systematic* differences between different groups of stores in those new categories, make the signal of the proxy variable stronger and the results of the analysis more certain.

Volume of Statistical Noise

The other element driving uncertainty is the statistical noise in the data, arising from errors or imprecision in the data that underlie the analysis. One significant source of imprecision in this analysis is the imprecision associated with the matching of utility consumption data to building floorspace data on the basis of the address Even after applying geo-coding to CEC Benchmarking data entries and to utility account data, matching on the basis of character strings is notoriously imprecise.[44]

Guidehouse mitigated some of this imprecision by excluding buildings where the deviation between reported energy use in the CEC Benchmarking data deviated too significantly from the aggregate consumption of the matched accounts (see sub-section 2.2.2.2, Figure 2-10 and Figure 2-11). Despite this mitigation, however, material deviations remain, and likely compound when CEDARS claims data were mapped to the utility account sites. There are undoubtedly some instances of savings being attributed to buildings that did not achieve them and savings not attributed to buildings that did. Such errors could be reduced in future, though doing so would require careful detective work applied on a site-by-site basis; a level of detail beyond what was required (or in scope) for this proof-of-concept analysis.

Guidehouse has explicitly noted these sources of imprecision to make this analysis as transparent as possible. This transparency is essential given the degree to which professional judgement must play a role in determining what Guidehouse determines to be the most accurate estimate of potential. Guidehouse's selection of the proxy metric's threshold level used to split the buildings into *efficient* and *less efficient* groups was made based on where the signal

[44] Matching two addresses from different data sources is challenging because of the nearly infinite possible variation in how an address may be entered into a database. Techniques exist for "fuzzy matching" but validation can be time-consuming to execute. Guidehouse attempted to ensure an accurate mapping of addresses by geo-coding all addresses into a common format first, but the success of this approach is limited by the specificity of the input address.

from that proxy variable was strong enough to be visible through the noise. This is why the threshold is much higher for the Grocery segment than the Lodging segment.

The data included in the CEC Benchmarking database represents only a fraction of the buildings in the commercial segments of interest—another imprecision. The question is: To what degree can the information above be used to project potential for the entire segment? This question is pertinent because the sample for each segment in the CEC Benchmarking database is not representative of the overall segment, since that effort explicitly targets only the largest buildings in the state. This question, and how it helps to define the different scenarios examined in this study, is addressed in Section 2.2.5.

2.2.5 Define Scenarios and Extrapolation Samples

Bottom-up potential studies typically model three kinds of energy efficiency potential scenario: technical, economic, and achievable (or market) potential. Of these, achievable potential is often estimated under a variety of policy and program design scenarios typically selected to show a range of possible outcomes. Technical potential is usually defined as the projected savings that would be achieved if all the highest efficiency measures that were technically feasible were installed as soon as practical. Economic potential is usually defined in the same way as the technical potential, with the constraint that only cost-effective measures can be considered.

Neither technical nor economic potential can be estimated under a top-down approach, as both require a highly granular set of assumptions about existing equipment. Developing a prototype top-down potential approach is encouraged if the desire is to avoid restrictive and unverifiable assumptions.

For achievable potential analysis, Guidehouse typically uses program-influenced levers to define the scenarios. The levers include assumed levels of program funding (e.g., incentive offerings) and assumptions of key parameters that determine market uptake (such as marketing effectiveness). Neither of these approaches for developing a range of estimates sensitive to t the most important model parameters are applicable for the prototype top-down approach developed as part of this study. This is because the top-down approach developed in this study does not project potential based on modeled market behavior.

Guidehouse developed scenarios for the top-down potential estimate to transparently identify the sensitivity of the estimated potential to which that potential is extrapolated, and to illustrate some of the trade-offs that must be considered in projecting an overall segment outcome from a relatively specific sample.

As Section 2.2.4.2 notes, the CEC benchmarking database is not designed to provide a representative sample of the IOUs' customers in each segment. It is highly restrictive to assume that the potential estimated in the analysis for the core sample (CS) of *less efficient* buildings included in the CEC Benchmarking data can be applied to all commercial customers in the same segment. It also is highly restrictive to assume that the CEC Benchmarking customers are so different from the remaining pool of customers that it is inappropriate to extrapolate the projected potential to any customers at all beyond those in the CS.

Guidehouse has therefore defined four top-down potential scenarios, each reflective of a progressively larger extrapolation sample (ES) (i.e., samples that grow beyond the CS of *less efficient* buildings). The scenarios are:

1. Scenario A – Core Sample Only
2. Scenario B – Extrapolation 1
3. Scenario C – Extrapolation 2
4. Scenario D – Population

Scenario A potential is a projection of the energy efficiency potential only for those customers[45] identified in the building analysis, in this case the ES is the same as CS. Scenario D, at the other end of the spectrum, assumes that the potential identified (i.e., the projected potential improvement in energy intensity) can be applied to the entire segment population. Scenarios B and C fall in the middle.

The extrapolation samples for Scenario B and C represent compromises between the most conservative approach (effectively no extrapolation) to the least (extrapolate to entire segment population). To define these scenarios, Guidehouse examined the effect on the distribution of account annual energy use as additional accounts were progressively added to the core sample, and selected two extrapolation samples (one for Scenario B, and one for Scenario C) that appeared to represent a reasonable compromise between Scenario A (in which the extrapolation sample is likely to be too narrowly defined) and Scenario D (in which the extrapolation sample is likely to be too broadly defined).

Guidehouse used the following approach:

1. For each account in the CS, Guidehouse identified the *less efficient* accounts[46] in the population from the same segment with the most similar, the second-most similar, the third-most similar (and so on) consumption to the given account.
2. Guidehouse eliminated duplicate matches. If account X (not included in the CS) is the best match for account Z and account Y (both included in the CS), it must be included in the ES only once.
3. This creates a series of extrapolation samples, each growing in size as more possible matches are included.

This allowed Guidehouse to iteratively compare the distribution of account consumption by segment between the core and the extrapolation samples to better understand the potential consequences for the accuracy of the projection as the extrapolation sample is expanded.

As the number of matches allowed in the extrapolation grows, the proportion of the population to which potential is extrapolated grows. However, so does the deviation between the core and extrapolation samples' distribution of energy consumption per account resulting in increased uncertainty in the potential estimates.

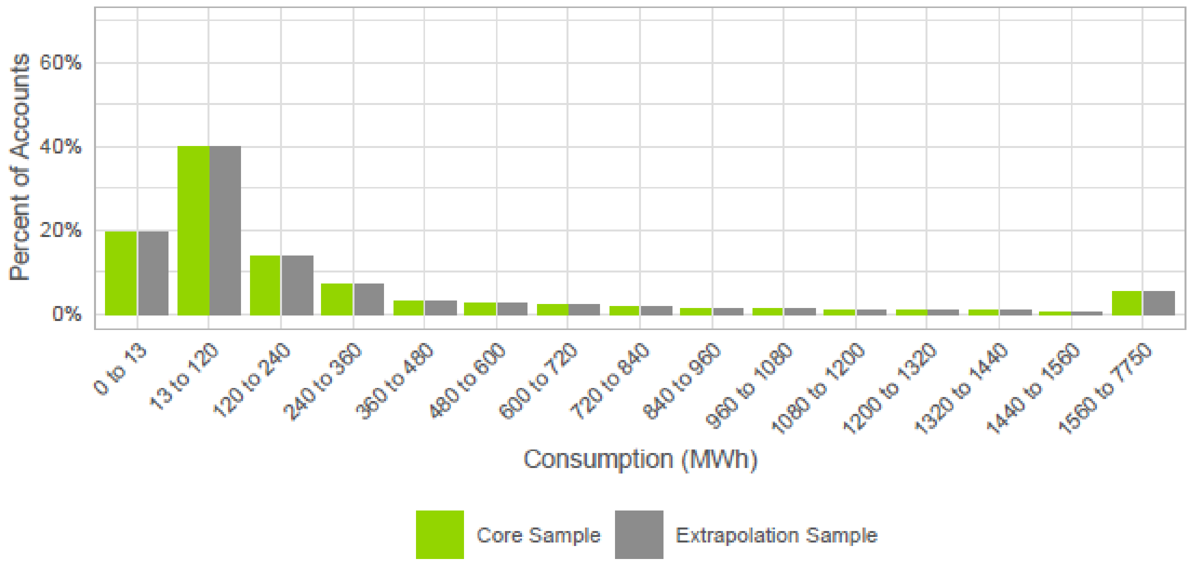
Consider the example of electricity consumption in warehouses shown in Figure 2-23, below. In this figure the extrapolation sample is limited to the core sample.

[45] The mechanics of this process are outlined in the next section.

[46] *Less efficient* accounts are identified in the same manner as *less efficient* buildings – by a comparison of 2019 site consumption and average annual site savings tracked over a 3-year period.

In Scenario A, only the potential associated with the accounts included in the building analysis (above) is considered. By construction, the distribution of annual consumption is identical across the two samples (e.g., nearly 40% of accounts consume between 13 MWh and 120 MWh per year). Warehouses in the CS of electric accounts represent approximately 2% of total electric warehouse accounts with an aggregate 2019 consumption that is approximately 9% of total segment consumption.

Figure 2-23: Warehouses, Electric – CS and ES Comparison (Scenario A)



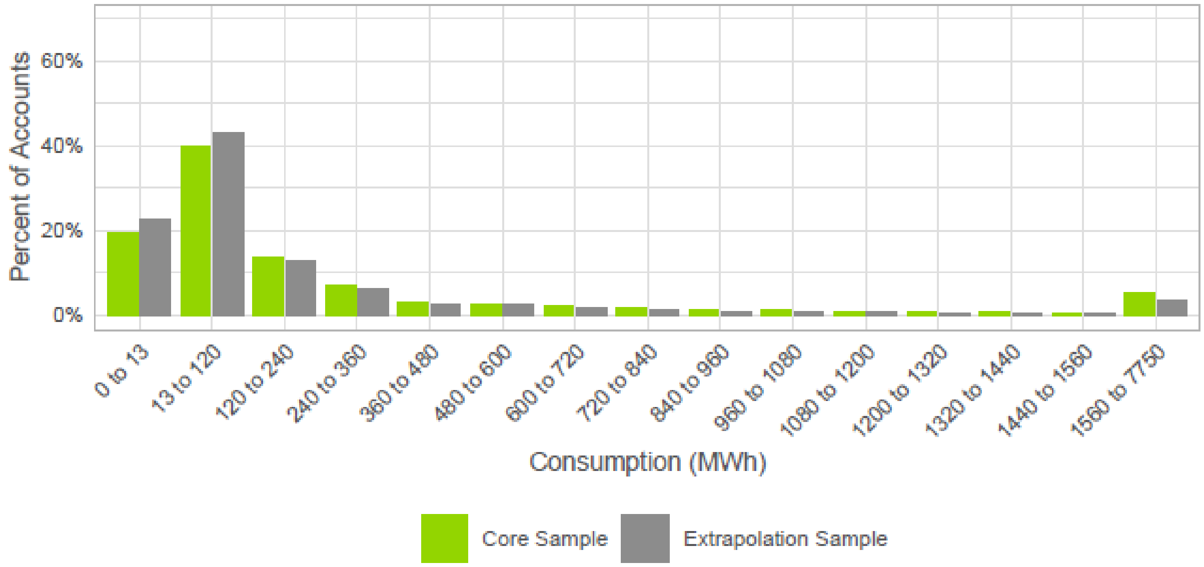
Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Consider the impact on that distribution of increasing the size of the extrapolation sample to include some accounts not in the core sample. In Figure 2-24, the extrapolation sample includes all the accounts in the CS and as many as three additional accounts for each CS account. That is, a data set is constructed that includes every account in the CS, and then for that account, an additional three accounts from *less efficient* accounts that have the most similar annual consumption to the given account in the CS. Duplicates are then removed from this data set (since a single account could conceivably be the best match for one CS account and the second-best match for a different CS account). This delivers the ES.

Where the Scenario A extrapolation sample (which is really just the CS) included approximately 2% of warehouse accounts and 10% of warehouse consumption, this expanded ES for Scenario B includes about 6% of warehouse accounts and nearly one-quarter of all warehouse consumption. In other words, the base consumption of the extrapolation sample has grown by 2.5 times, meaning that the potential has also grown by that amount.

Is it still reasonable to apply the analysis developed on the basis of the CS out to the ES? Although this cannot be affirmed categorically, the fact that the overall changes in the distribution of 2019 account consumption (see Figure 2-24) appear relatively small suggests that the extrapolation is reasonable.

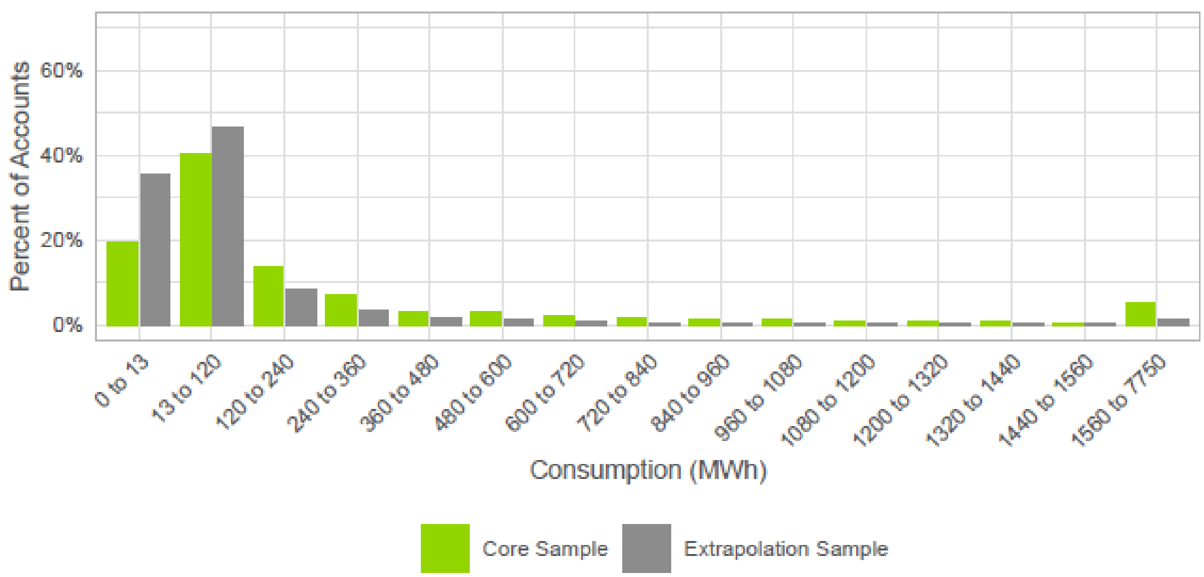
Figure 2-24: Warehouse, Electric – CS and ES Comparison (Scenario B)



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

The ES is expanded further in Scenario C, such that it includes approximately 35% of total segment consumption, or approximately 3.5 times as much segment consumption as the Scenario A ES, the deviation between the distribution of CS and ES consumption grows (see Figure 2-25). The effect of the incremental extrapolation is striking—where in Scenario B the ES showed only a slightly greater proportion of accounts in the lowest consumption bucket, the ES in Scenario C the proportion of accounts in that lowest consumption bucket is nearly twice that of the CS.

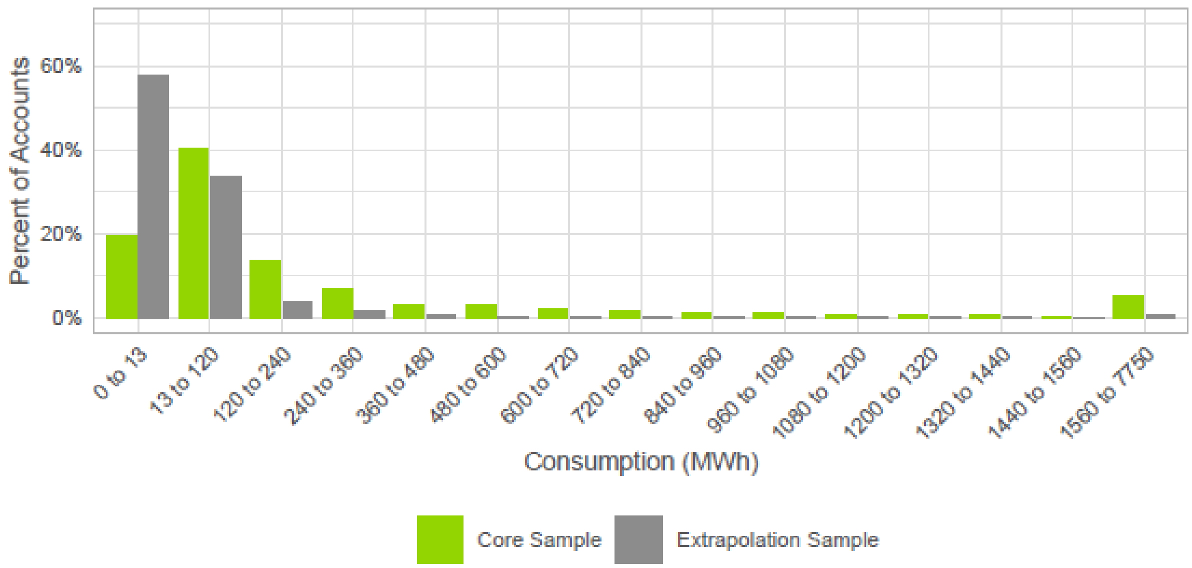
Figure 2-25: Warehouse, Electric – CS and ES Comparison (Scenario C)



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Finally, to show the bounds of the variation, Figure 2-26 compares the Scenario D ES (which includes all warehouse accounts not in the *efficient* buildings identified in Section 2.2.4) to the CS. These distributions are very different from one another, indicating that there must be considerably greater uncertainty associated with projecting potential on the basis of this ES than, for example, Scenario A ES. Notably, 60% of the population of accounts fall into the lowest consumption bucket, in contrast to only 20% of those accounts in the CS. Given the nature of the CEC Benchmarking data (which targets buildings with more than 50,000 square feet of floorspace) this result is unsurprising, though it does suggest that caution should be exercised in extrapolating the potential estimated using the CS to the overall population.

Figure 2-26: Warehouse, Electric – CS and ES Comparison (Scenario D)



Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

Plots of the CS and ES distributions for all segments and fuels may be found in Appendix X.A, under a separate cover. To differentiate between the ES distribution relative to the CS distribution, the buckets for these distributions are deliberately set such that 20% of CS accounts are the lowest bucket and 5% are the highest bucket. The remaining bucket range definitions are selected to segment the range between the highest and lowest consumption buckets in 13 equal parts.

Table 2-6 shows the proportion of total segment consumption captured by the extrapolation sample in each scenario. For example, CS electric Warehouse account consumption represents approximately 9% of segment consumption. This climbs as high as 95% for Scenario D, which extrapolates potential from the CS to the entire population. The reason Scenario D values never equal 100% is that neither the core sample nor the extrapolation samples include those buildings or sites found in the analysis to be *efficient*.

Table 2-6: Proportion of Segment Consumption in Extrapolation Sample – By Scenario

Fuel	Scenario	Grocery	Lodging	Office	Warehouse
E	A - Core Sample Only	16%	10%	7%	9%
E	B - Extrapolation 1	25%	21%	24%	23%
E	C - Extrapolation 2	35%	29%	33%	33%
E	D - Population	99%	82%	94%	95%
G	A - Core Sample Only	6%	14%	7%	N/A
G	B - Extrapolation 1	15%	24%	25%	N/A
G	C - Extrapolation 2	25%	31%	34%	N/A
G	D - Population	98%	90%	99%	N/A

Source: CEDARS, IOU consumption data, CEC Benchmarking Database, and Guidehouse analysis

2.2.6 Project Potential and Distribute by End Use

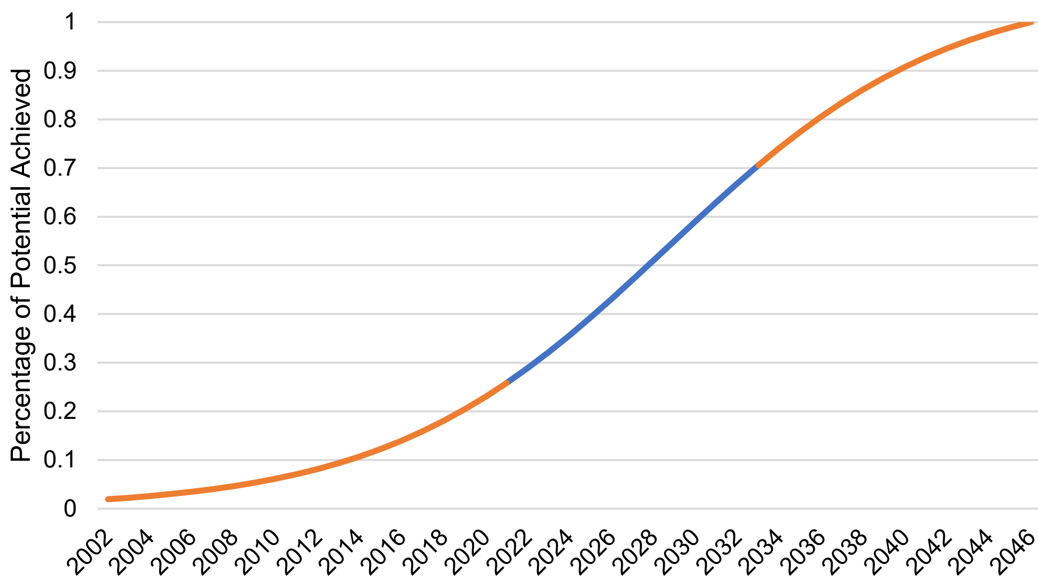
Scenario potential is estimated by combining the values identified in Table 2-5 (potential as the percentage improvement in energy intensity) and Table 2-6 (percentage of segment potential to which potential is applicable) with an S-shaped curve to reflect IOU program achievement growth over time, and reference forecast.

As Table 2-5 indicates, Guidehouse identified the potential energy reduction that could be achieved if the *less efficient* building owners and tenants become more like the *efficient* building owners and tenants, and the average energy intensity of the *less efficient* buildings could be brought down to match the average energy intensity of the *efficient* buildings. This is a reasonable estimate of the ultimate total potential that could be achieved, but some assumption must be made regarding the timeline required to achieve it.

Guidehouse assumed the process of converting *less efficient* buildings to *efficient* buildings takes a total of 25 years. Further, Guidehouse assumed this process would build on the success of existing DSM programs and messaging in the field since 2002. Finally, Guidehouse assumed that the pattern of program achievement would conform with the standard assumption of adoption as an S-shaped curve. Figure 2-27 shows the S-shaped curve used to distribute projected achievement.[47] The blue portions of the curve represent this study's period of analysis, whereas the orange portions represent years either following, or preceding, the period of analysis.

[47] For the purposes of this exercise, Guidehouse simply used a standard logistic sigmoid function, with annual output values normalized to deliver a maximum value of 100% in the assumed terminal year. Should, in future, this approach be adopted for potential projection a more sophisticated version based on geographically specific factors (e.g., outputs of a commercial end-use survey across different points in time) could be used to better parametrize this curve.

Figure 2-27: S-Shaped Curve Used to Shape Potential Achievement



Source: Guidehouse

Overall segment energy efficiency potential is forecast in each year by multiplying:

- The estimated ultimate potential improvement in segment energy intensity (Table 2-5)
- The proportion of that percentage improvement that is achieved in each year (Figure 2-27)
- The proportion of total segment consumption to which the potential is applicable (Table 2-6)
- The reference forecast consumption for the given segment in the year specified (Figure 2-9)

The simplicity of approach (the manner in which these values are combined to deliver the potential) is deliberate and aligned with the overall philosophy driving this study: to be as transparent as possible, especially regarding analytic choices strongly informed by the professional judgement of the analyst. Guidehouse anticipates that some reviewers might disagree with (for example) its assumption about the length of time required to achieve the transition of all buildings from *less efficient* to *efficient*—the S-shaped curve in Figure 2-27. With the transparency provided, it is simple to recalculate a new series of projected potential estimates reflecting (for example) a more aggressive assumption regarding how quickly IOU programs could capture the potential Table 2-5 identified.

The above procedure summarized in bullets identifies overall segment potential, but this is an insufficient output. Projections of energy efficiency potential must provide an estimate of potential by end use so the appropriate avoided costs can be applied and total system resource benefits estimated. Guidehouse considered three different distributions to apply to segment potential to estimate end use potential:

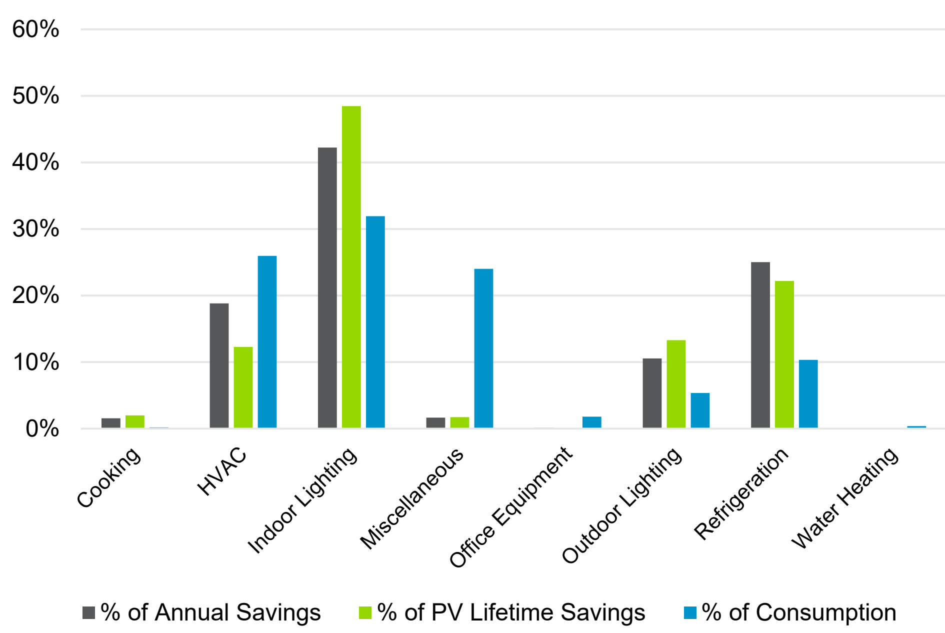
- **Annual energy savings.** Potential will be proportional to the end use distribution of average annual downstream savings tracked in CEDARS from 2017 through 2019.
- **Present value of lifetime energy savings.** Potential will be proportional to the end use distribution of the present value of lifetime energy savings from 2017 through 2019.
- **Annual average consumption.** Potential will be proportional to the end use distribution of consumption as forecast by the CEC for the IEPR.

Figure 2-28 shows the distribution of each of these metrics for the segments included in the electricity analysis.

- The grey column shows the average annual savings in each end-use as a percentage of total savings;
- The green column shows the present value of lifetime savings for each end-use as a percentage of total present value lifetime savings; and,
- The blue column shows end-use consumption as a percentage of total consumption.

It is immediately evident that although (as would be expected) the distribution of the two types of savings values are very similar, the savings distribution differs materially for the consumption distribution in a few end-uses.

Figure 2-28: End-Use Savings and Consumption as a Percentage of Total – Electricity, All Segments



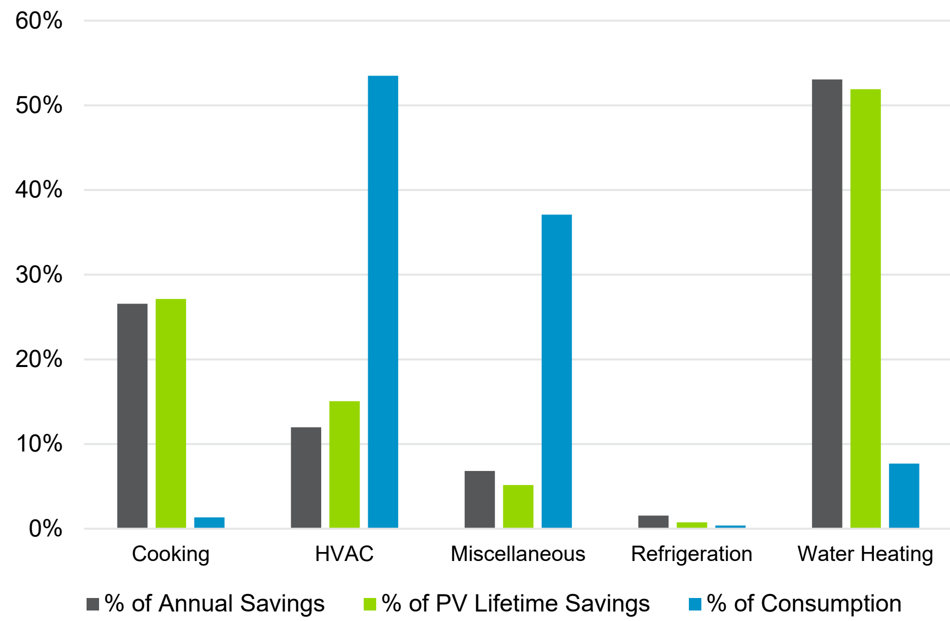
Source: CEDARS, CEC IEPR, CEC Benchmarking Database, and Guidehouse analysis

Indoor lighting, for example accounts for approximately 50% of present value lifetime savings but only 30% of consumption; refrigeration accounts for approximately 20% of savings but only

10% of consumption. These disparities become even more apparent as the results are disaggregated to specific segments: in offices, outdoor lighting accounts for approximately 30% of savings, but only 5% of consumption; in lodging, HVAC accounts for 70% of average annual savings, but only 40% of consumption.

Such disparities are even more marked when considering natural gas. Figure 2-29 shows the same distribution as above, but for natural gas. Cooking accounts for more than a quarter of savings, but barely 1% of consumption, and water heating accounts for more than half of all savings, but less than 10% of consumption.

Figure 2-29: End-Use Savings and Consumption as a Percentage of Total – Natural Gas, All Segments



Source: CEDARS, CEC IEPR, CEC Benchmarking Database, and Guidehouse analysis

The reason for this disparity is intuitive: as may be seen below (in Table 2-7), natural gas water heating and cooking savings have been much less expensive to procure than (for example) HVAC savings. The understandable result is that DSM programs have historically targeted the “low-hanging fruit” that were most cost-effective.

It is clear from these comparisons, however, that the current distribution of savings cannot be sustainable very far into the future. If potential energy efficiency were to be achieved at the levels projected by this analysis and distributed across end-uses in the same way as in the past, potential savings would eventually (for those high-savings end-uses) have to exceed consumption.

For this reason, Guidehouse determined that it would be most prudent to assume that the end-use distribution of energy efficiency in the period of analysis would match that of historical consumption, rather than historical savings. Should this prototype approach be expanded upon, additional analysis should be deployed to assess the most cost-effective mix of end-uses feasible from which overall potential should be achieved.

2.3 Estimate Potential Cost and Cost-Effectiveness

This section describes how Guidehouse developed and applied the estimated cost of energy efficiency to the analysis. It is divided into three sub-sections:

1. **Incremental Measure Costs.** Describes how Guidehouse estimated the incremental measure LCOE applied to projected potential.
2. **Program Costs.** Describes how Guidehouse adapted the approach used by the bottom-up analysis to derive an estimate of program delivery costs on a per lifetime kWh (or therm) basis.
3. **Cost-Effectiveness.** Describes how Guidehouse assess the portfolio cost-effectiveness of the projected potential by IOU and segment.

Annualization

Since the top-down study does not track a schedule of installations of individual measures, it likewise cannot track the savings and lifetimes of individual measures or their costs. Savings and costs are instead tracked as annualized values: energy units saved in a given year, the total system benefits associated with those savings in the same given year, and the total annualized costs of those savings (derived as a product of the savings themselves and the estimated annualized unit cost – e.g., $/kWh – of those savings).

The main difference in the two approaches is assessing the benefits.

In contrast, the approach for cost-effectiveness and (now the TSB) goals assessment traditionally was based on individual measure installations using the present value of the benefits over the lifetime of the savings based on the year of installation. The top-down looks at the value in the year the savings occur whereas the bottom-up considers the lifetime benefits of a measure in the year in which it was installed.

2.3.1 Incremental Measure Costs

Guidehouse estimated the LCOE by segment, end use, and fuel using a simple univariate regression analysis. The incremental measure costs (in constant 2020 dollars) of claims in the CEDARS database were regressed on the PV of lifetime energy savings net of free ridership and spillover (calculated on the basis of the life cycle savings and EUL provided in the database). The team did not include an intercept in the regression (since zero savings should cost $0). A separate regression was estimated for each unique combination of segment, end use, and fuel, and the single estimated parameter delivered by each regression represents the average estimated LCOE.[48]

Where a claimed measure delivered savings in both fuels, the incremental cost was divided by fuel proportionate to the positive savings delivered for each fuel, expressed in common units. This addresses issues related to (for example) a costly measure for which most, but not all, savings are for natural gas. In this example, this hypothetical measure could skew the estimated LCOE for electricity up if the full cost is regressed against just the (relatively small) electricity savings.

Where a claimed measure delivers negative savings (interactive effects) for a given fuel it was excluded from that fuel's regression and the full measure cost was regressed on the savings only for the fuel that delivers positive savings. Measures with a zero incremental cost were also excluded on the basis of Guidehouse's assumption that in most cases the claimed measure did

[48] This value is analytically equivalent to a cost-weighted average of individual claim LCOEs, though the use of a regression analysis makes an assessment of the uncertainty of the estimate very convenient.

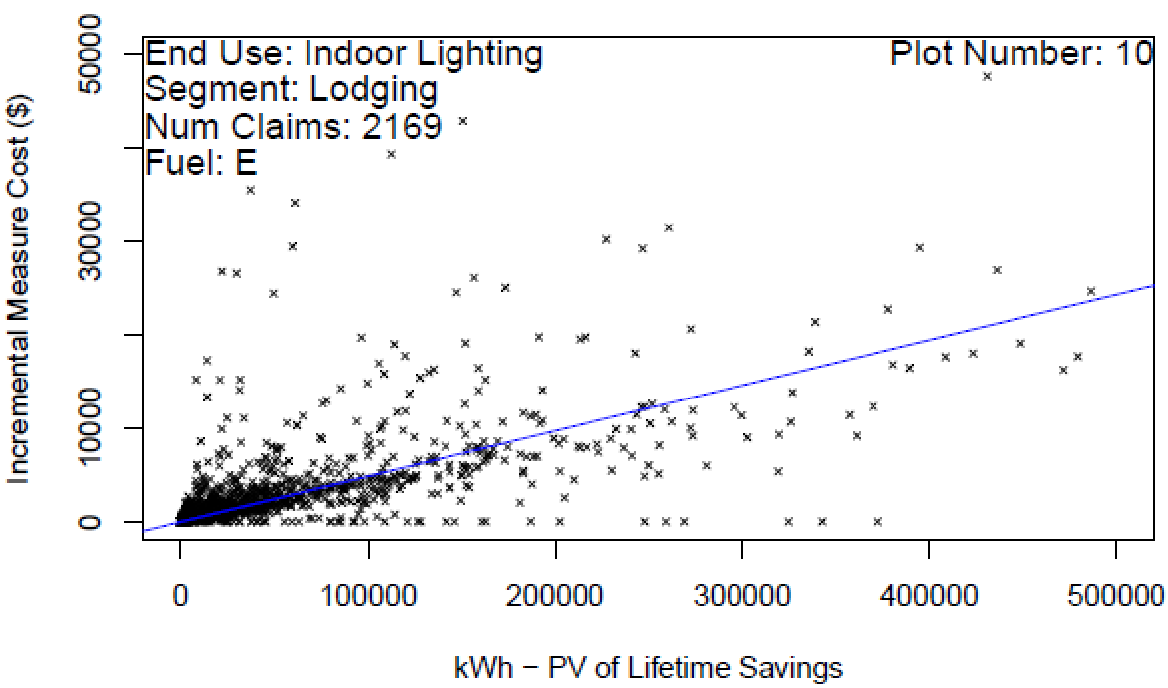
indeed have an incremental cost, but for whatever reason it was not captured in the CEDARS data.

The estimated cost relationship (and the input values that drive that relationship) can, because of the simplicity of the model, be visualized with a scatter plot and line, such an example is shown in Figure 2-30, below.

In this plot, HVAC claims by IOU customers taking electric service whose NAICs code defines them as part of the Lodging segment are plotted as a small "x." These points (each of which represents a distinct claim within the CEDARS data) show various combinations of present value energy savings[49] (x-axis) and incremental measure cost (y-axis).

The blue line represents the average relationship estimated using the data in the scatterplot. The slope of this line represents the average LCOE (in constant 2020 dollars) to be applied to the energy efficiency potential projected in each year of the period of analysis.

Figure 2-30: Example Cost Estimation



Source: CEDARS, Guidehouse analysis

Guidehouse estimated a set of non-linear models to estimate a convex cost function more aligned with economic theory (i.e., that as savings opportunities are progressively achieved, incremental opportunities become more costly). Because the underlying cost and savings data used estimate the function are (for the most part) based on deemed savings (which scale

[49] It is unusual to apply a present value to a quantity (in this case energy) rather than a value (e.g., dollars), and may, in some circumstances be regarded as inappropriate, since the time value of money is intended to represent the trade-off between present spending, and the foregone investment opportunity the money thus spent represents. The characterization of the LCOE as the total life-cycle cost of a resource divided by the present value of the energy it delivers (or in this case saves) is a generally accepted industry metric developed to compare the life cycle costs of resources with differing lifetimes. See the Short, Packey, and Holt NREL citation above for more detail.

linearly), Guidehouse realized that, with the CEDARS data as a base, a linear estimation of cost was appropriate.

A complete set of plots (one for each combination of segment and end use for which claims are available after Guidehouse's data prep) may be found in Appendix X.B (under a separate cover).

Table 2-7 provides the estimated LCOE in constant 2020 dollars. All estimated regression parameters were statistically significant at the 95% confidence level, and all but two were statistically significant at the 99% confidence level. The team applied these costs to the projected potential to develop the aggregate costs used for cost-effectiveness testing.

Table 2-7: Estimated LCOEs ($2020)

Fuel	Unit	End Use	Grocery	Lodging	Office	Warehouse
E	$/kWh	Cooking	$0.09	$0.06	$0.05	$0.02
E	$/kWh	HVAC	$0.07	$0.08	$0.08	$0.08
E	$/kWh	Indoor Lighting	$0.09	$0.05	$0.10	$0.06
E	$/kWh	Miscellaneous	$0.05	$0.06	$0.10	$0.06
E	$/kWh	Outdoor Lighting	$0.05	$0.12	$0.10	$0.06
E	$/kWh	Refrigeration	$0.04	$0.05	$0.05	$0.02
E	$/kWh	Water Heating	$0.02	$0.07	$0.01	N/A
E	$/kWh	Office Equipment	N/A	N/A	$0.21	N/A
G	$/therm	Cooking	$0.45	$0.66	$0.47	N/A
G	$/therm	HVAC	$1.38	$0.66	$1.59	N/A
G	$/therm	Miscellaneous	$2.00	$1.38	$0.28	N/A
G	$/therm	Refrigeration	$1.82	N/A	$2.27	N/A
G	$/therm	Water Heating	$0.28	$0.44	$0.50	N/A

Source: CEDARS, Guidehouse analysis

2.3.2 Program Costs

Guidehouse developed an estimate of program costs per net life cycle savings for the top-down analysis using the same inputs and similar approach to that used for the bottom-up analysis. As with the bottom-up analysis, program costs were developed using the 2021 CEDARS filing.[50] The team estimated the average program costs per unit of energy saved by dividing the sum of weighted program costs by the sum of aggregate net energy savings.

This delivers an estimated program cost that is fuel- and IOU-specific. These were assumed to be constant in real terms going forward, and were, along with the incremental costs (estimated above) applied to total savings in each year of the period of analysis. Table 2-7 shows the estimated program costs.

[50] California Energy Data and Reporting System, *Record-Level Data – 2021 Filing*

Table 2-8: Estimated Program Costs

Utility	Program Costs	
	Electricity ($/kWh)	Gas ($/therm)
PG&E	$0.020	$0.583
SCE	$0.019	N/A
SCG	N/A	$0.371
SDG&E	$0.009	$0.270

Source:

2.3.3 Cost-Effectiveness

Guidehouse used the estimated potential, the program and incremental costs, and previously estimated avoided costs to calculate a TRC ratio by utility and fuel type. The benefits in this ratio (the avoided costs) were estimated as part of the bottom-up study, the approach for which is described in detail in Appendix J of that document.[51]

The avoided costs used for the bottom-up analysis consist of a series of annual values, $/kWh, $/kW, and $/therm, identifying the avoided cost benefit of an annual reduction in energy or peak demand. The avoided costs are utility-specific and, in the case of electric energy and peak demand, end use-specific as well. Guidehouse mapped the top-down end uses to those of the bottom-up study with the assistance of the analysts for that project and applied the avoided costs to projected potential in each year. The avoided costs used for this analysis are the 2021 avoided costs, provided in July of 2021. These are considerably lower than the previous iteration of avoided costs used in the initial analysis.

For estimating potential peak demand reductions (and so the benefits associated with these reductions), Guidehouse used the CEDARS claims data previously used to estimate the LCOEs. The team calculated the ratio of aggregate energy savings to aggregate reported demand savings on a segment and end use-specific basis. Guidehouse then applied this factor to projected electric energy potential in each year.

[51] Guidehouse prepared for California Public Utilities Commission, *2021 Energy Efficiency Potential and Goals Study – Draft*, April 2021

3. Results and Analysis

This chapter presents the outputs of the top-down analysis: the projection of estimated energy efficiency potential including Total System Benefits (TSB) from 2022 through 2032, costs, and cost-effectiveness including the TRC ratio. This chapter concludes with a discussion of these outputs, some of the insights they offer for the IOU program planning process and how the outputs compare to those presented by the bottom-up analysis.

This chapter is divided into two sections:

1. Energy Efficiency Potential
2. Cost-Effectiveness

3.1 Energy Efficiency Potential

This section provides projections of estimated energy efficiency potential for electricity and natural gas over the 11-year period of analysis from 2022 through 2032 for the Grocery, Lodging, Office and Warehouse (electricity only) segments. In addition to aggregate potential across all segments and end uses, charts and descriptions are provided of potential (across the four scenarios) from more granular perspectives (e.g., by end use or by segment). In a few instances, the equivalent bottom-up potential for the same segments is presented alongside the top-down potential for comparison.

The bottom-up potential presented here is a sub-set of the overall bottom-up potential and includes only energy efficiency savings (no fuel substitution) for the four segments examined in the top-down study.

Figure 3-1 presents the net incremental first-year electricity energy efficiency by projection year and scenario. It includes the net incremental first-year energy efficiency potential of the same segments for one of the bottom-up study's scenarios.

Incremental and Cumulative Potential

Bottom-up potential studies typically report potential savings as either incremental or cumulative.

The naming refers not to achieved energy savings but rather measure adoption:

- **Incremental efficiency potential** is an estimate of the savings delivered in the given year by the measures adopted in that year.
- **Cumulative efficiency potential** is an estimate of the savings delivered in the given year by all the measures adopted (accumulated) in prior years that have not reached the end of their expected useful life. It is *not* the cumulative savings achieved across multiple years.

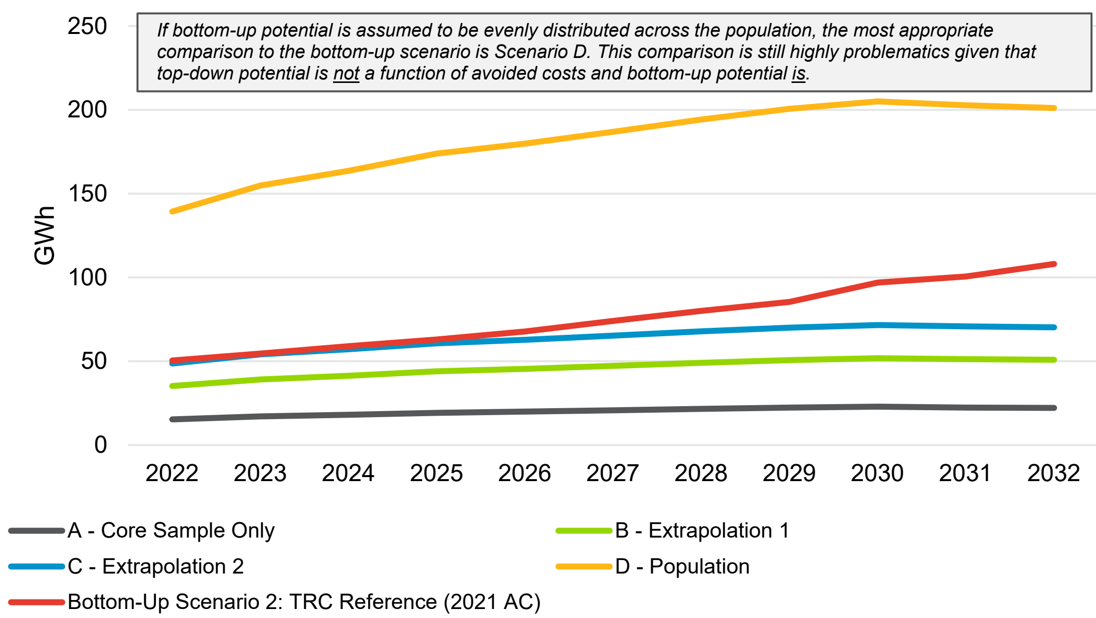
In moving beyond a widget-based paradigm, these naming conventions (which are based on the timing of measure adoption, irrelevant in top-down) are no longer appropriate, and may even result in some avoidable confusion.
Despite these issues, Guidehouse has retained the bottom-up nomenclature in this top-down study in an effort to help readers better understand the appropriate comparison with results in the bottom-up study.

In comparing the top-down scenario potential series with the example from the bottom-up study, two important differences between the approaches must be considered:

- **Applicable Population.** In the bottom-up study the only limits placed on the population to which the measures apply were driven by questions of measure saturation and technical feasibility. In contrast, the top-down approach limits the applicable population in all but Scenario D. Scenarios A, B, and C allow potential to be applied only to a subset of the population. This approach to defining scenarios is intended to balance the need for universality (i.e., applying results to the entire segment population) with the understanding that the core sample of buildings that drive the estimated potential are unrepresentative of the overall segment population.

- **Avoided Costs.** Top-down potential (as estimated for this prototype analysis) is agnostic to cost-effectiveness; regardless of the avoided costs, the potential is the same since it is defined by a comparison of two groups of buildings. Bottom-up potential, in contrast is a function of cost-effectiveness. Since only cost-effective measures (i.e., where avoided costs exceed measures and program costs) are included in the bottom-up potential, changes in avoided costs can substantially affect bottom-up potential.

Figure 3-1: Statewide Net First-Year Incremental Electric Savings (GWh) by Scenario



Source: Guidehouse

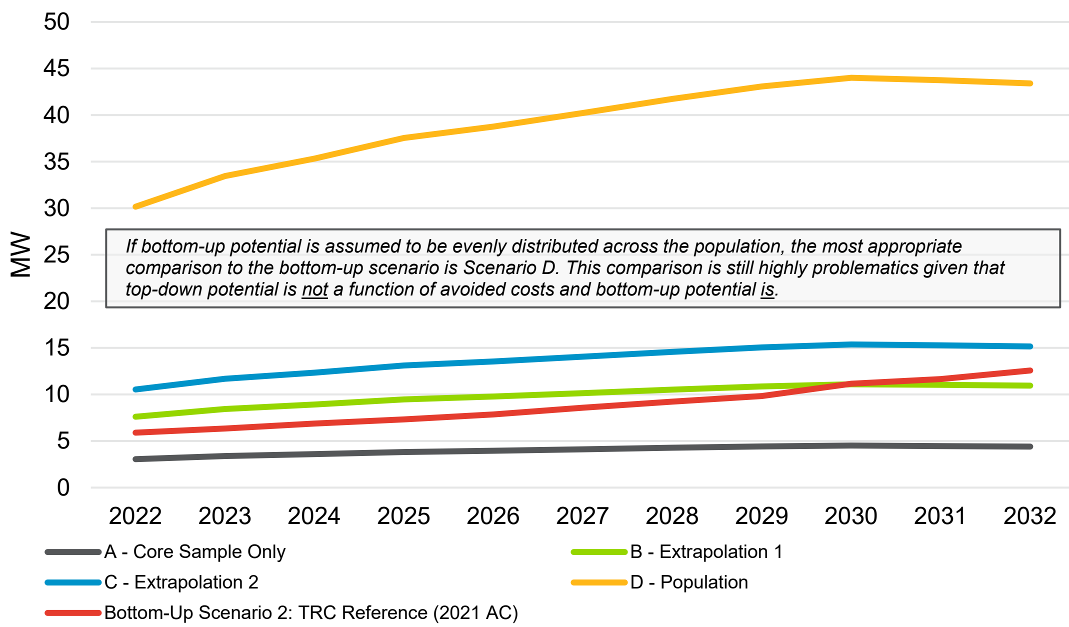
The chart above highlights the challenge of comparing top-down and bottom-up potential. Scenario D (which includes the entire population) should be the most comparable to the bottom-up potential, since that is also derived from a population-wide value. The difference, however, is that bottom-up potential is modeled on the basis of measure-level TRC ratios: measures that aren't cost-effective (under the current metric for cost effectiveness) are not included, whereas top-down potential is estimated through a comparison of average building energy intensities, without consideration of cost-effectiveness.

This highlights a fundamental difference between the two approaches that makes comparing their outputs a challenge. The top-down approach estimates the potential that might reasonably be expected to be attained based on the observed performance of a set of comparable buildings. The cost-effectiveness of this potential is then estimated *given historical program activities and achievement*. The bottom-up approach estimates what individual measures are projected to be cost-effective during the period of analysis and models the savings only of the deployment of these measures.

While the top-down approach may provide a more accurate estimate of opportunity (by considering individual building data), the bottom-up offers a more precise prescription for future program design (by specifying the cost-effective measure and segment combinations).

Figure 3-2 shows the estimated peak demand electricity energy efficiency potential associated with each scenario. In the top-down analysis, the team derived this by taking the ratio of aggregate historical demand savings to energy savings (from CEDARS claims data) and applying it to the projected energy savings potential. This ratio is calculated separately for each combination of end use and segment. The change in difference between the bottom-up example scenario and the top-down Scenario D potential (between energy and demand) is likely driven by differences between the projected future measure mix (for the bottom-up potential) and the observed historical measure mix (for the top-down). One potential confounding factor may be the redefinition of peak hours. The historical data used to develop the kW to kWh ratio includes the period from 2017 through 2019.

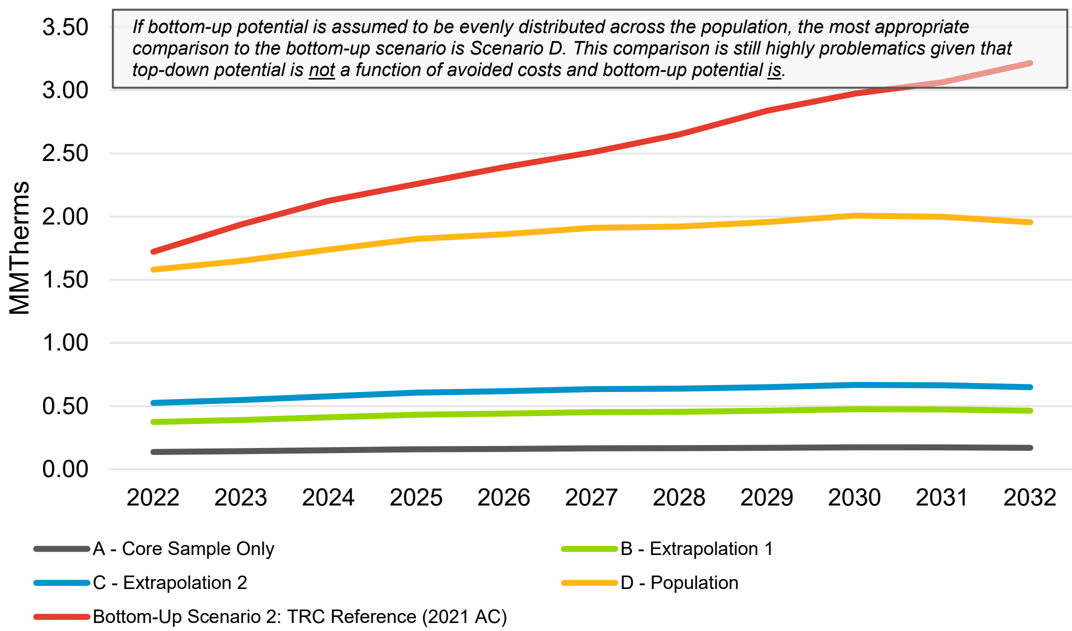
Figure 3-2: Statewide Net First-Year Incremental Peak Demand Savings by Scenario



Source: Guidehouse

Figure 3-3 presents the net incremental first-year natural energy efficiency by projection year and scenario. It includes the net incremental first-year energy efficiency potential of the same segments for one of the bottom-up study's scenarios. It is noteworthy that while the bottom-up Scenario 2 potential is much lower than the top-down Scenario D potential for electric energy, for natural gas the bottom-up Scenario 2 potential is *higher* than the top-down Scenario D potential for natural gas energy. Given that bottom-up potential is a function of measure cost-effectiveness, this indicates that a much higher proportion natural gas energy efficiency measures are cost-effective, compared to electric energy efficiency measures.

Figure 3-3: Statewide Net First-Year Incremental Gas Savings by Scenario



Source: Guidehouse

Figure 3-4 presents potential as a percentage of energy consumption (the reference forecast).

A comparison of potential with reference forecast consumption is an intuitive diagnostic in assessing projected energy efficiency potential. Expressing potential as a percentage of the reference forecast adds contextual information and can be used for benchmarking results against those reported for other jurisdictions[52] (or previous studies in the same jurisdiction). Figure 3-4 shows the aggregate energy efficiency potential of the segments included in the analysis as a percentage of the reference forecast consumption for those segments for each scenario, over an indicative 3 years within the period of analysis.

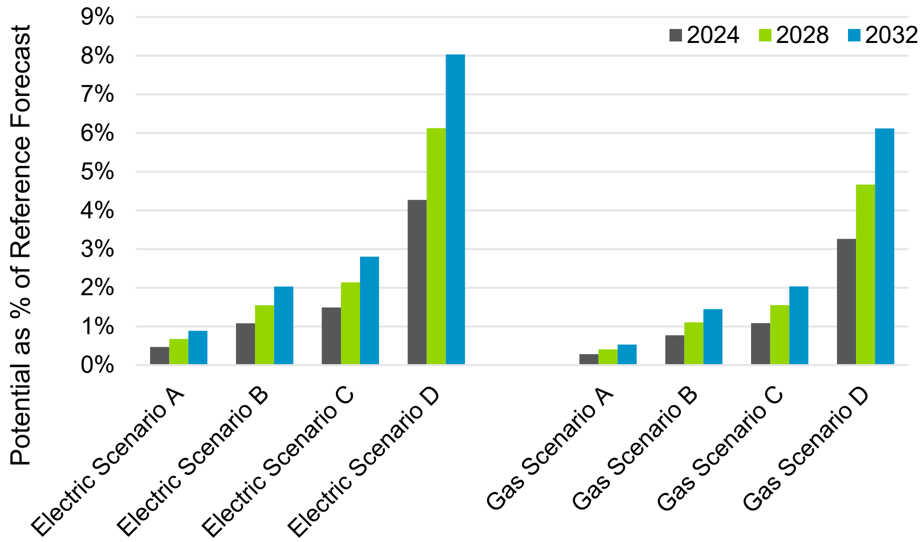
The numerator of the percentage is the “cumulative” energy efficiency potential. For example, for Scenario D, in 2032, the cumulative potential is 8% of the reference forecast consumption. This means the total energy efficiency savings expected to be realized in that year (regardless of whether the measures that provide those savings were adopted in that year or an earlier one) are such that total consumption for that sector in that year would be 8% less than predicted in the reference forecast.

[52] See, for example, Appendix H of:

Guidehouse Canada (f/k/a Navigant) prepared for the Independent Electricity System Operator (IESO) and the Ontario Energy Board (OEB), *2019 Integrated Ontario Electricity and Natural Gas Achievable Potential Study*, December 2019

http://www.ieso.ca/2019-conservation-achievable-potential-study

Figure 3-4: Overall "Cumulative" Potential as a Percentage of Reference Forecast



Source: Guidehouse

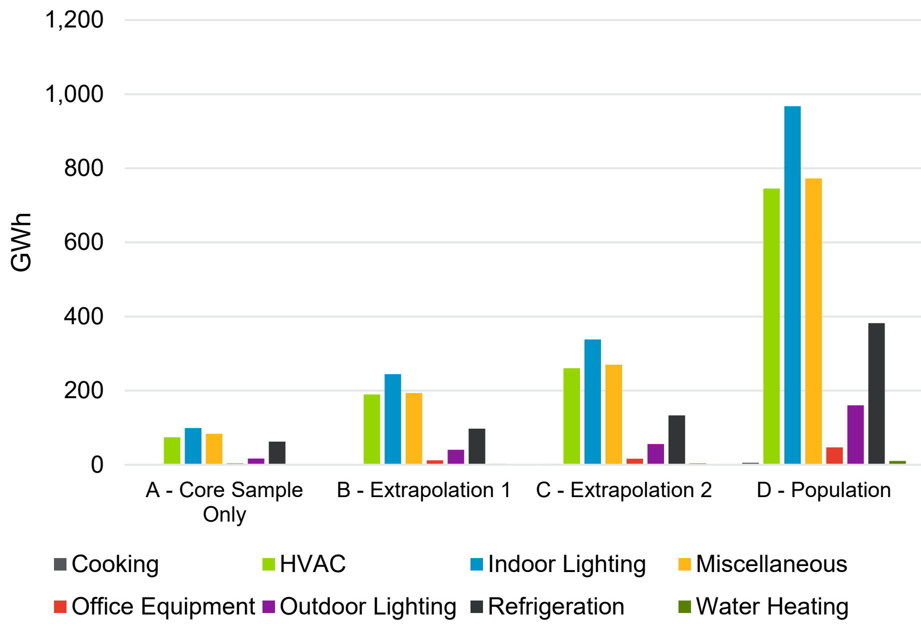
Per Section 2.2.6, savings are assumed to be distributed proportional to end use consumption by segment, so there is little difference between end use potential as a percentage of forecast consumption (e.g., water heating potential as a percentage of the reference forecast is approximately the same as HVAC potential as a percentage of the reference forecast, despite HVAC potential being much larger in absolute terms).

This distribution is consistent across end uses by year and scenario. An examination of this distribution in the terminal year of the period of analysis across all scenarios can provide insight as to the projected potential across all years. Future iterations of the top-down approach may apply some quasi-optimization to project potential by a different proportion of implementation across end uses.

Figure 3-5 provides this distribution for projected electric energy potential. The most significant deviations from the distribution of historical electricity savings by end use (see Figure 2-28, above) are in the HVAC, Refrigeration, Miscellaneous, and (to a lesser extent) Indoor Lighting end uses. The most material deviation is for the Miscellaneous end use, for which there is little historical DSM achievement (presumably because of the variety of equipment types),[53] despite this end use accounting for approximately one-quarter of all electricity consumption in the sector.

[53] Miscellaneous electricity measures include, but not limited to, process pumping VFD, connect power strip, servers, and PC power management.

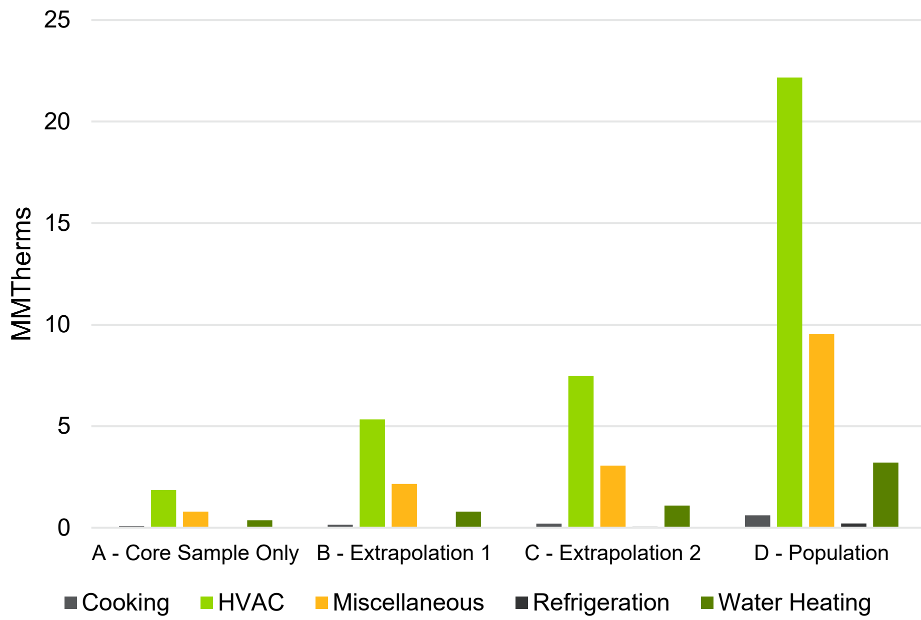
Figure 3-5: Cumulative Electric Energy Potential by End Use (2032)



Source: Guidehouse

Figure 3-6 provides the distribution of projected natural gas efficiency potential. As with electric energy, a significant deviation between the projected potential distributed according to consumption and distribution of historic savings (see Figure 2-29) is in the difficult-to-reach Miscellaneous end use. However, an even larger deviation is observable for Water Heating and HVAC. Over half of the historic downstream DSM achievement in the segments of interest is in the Water Heating end use, despite it accounting for less than 10% of overall natural gas consumption. In contrast, the proportion of potential projected (~60%) to need to come from the HVAC end use is approximately 4 times higher than that end use's share of historic savings (~12%–15%, see Figure 2-29).

Figure 3-6: Natural Gas Potential by End Use (2032)

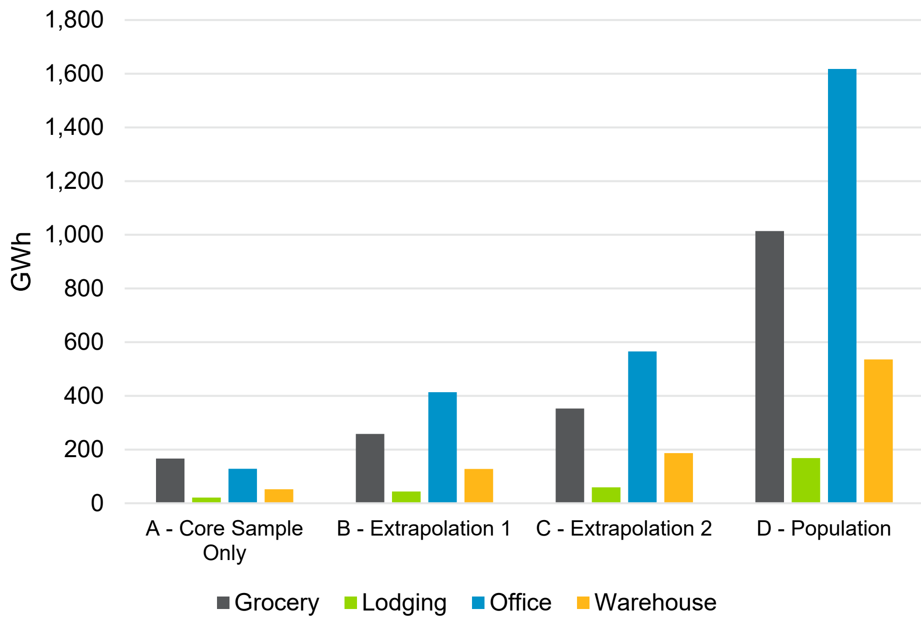


Source: Guidehouse

The key take-away from these comparisons (i.e., projected potential distributed across end uses based on the share of historic end use consumption vs. historic savings by end use) is this: in the past energy savings have been obtained disproportionately from certain end uses. Specifically, savings have been disproportionately obtained from end uses where measure costs tend to be lowest (see the LCOEs in Table 2-7). This strategy – collecting the "low-hanging fruit" – cannot continue indefinitely. In the future, if energy efficiency savings are to continue to grow, they will need to be obtained from end uses in which savings are (historically) more costly, in particular in the HVAC end-use.

Figure 3-7provides the projected potential for all four segments included in the top-down analysis of electric energy efficiency potential. The calculated potential is a function of the segment-level consumption and the estimate in percent improvement in intensity (see Table 2-5 for percentage values).

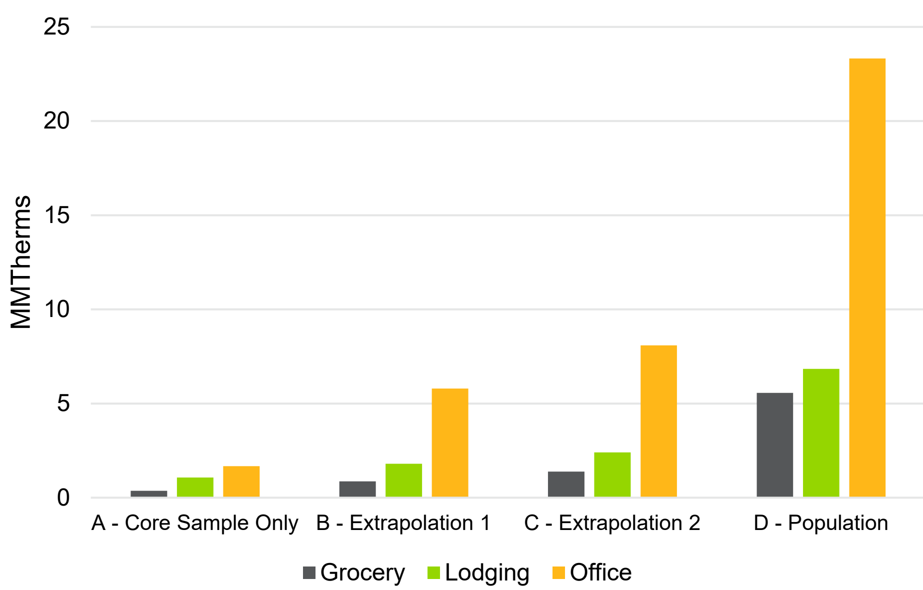
Figure 3-7: Electric Energy Potential by Segment (2032)



Source: Guidehouse

Figure 3-8 provides the distribution of projected natural gas potential by segment. The same factors drive this distribution as they do electric energy potential: ultimate potential intensity improvement and share of consumption.

Figure 3-8: Natural Gas Potential by Segment (2032)



Source: Guidehouse

3.2 Cost-Effectiveness

This section provides study outputs related to questions of cost-effectiveness: the TSB, incremental and program costs, and the ratio of these two, the TRC ratio.

Comparing TSB from the bottom-up and top-down studies is challenging. In the bottom-up study, the TSB in each year represents the sum of the discounted lifetime savings for all the measures adopted in the given year. In essence, it is a metric that quantifies future benefits. The total system benefits reported for the year 2022 are not only the benefits achieved in 2022, (though some of them are), they are the benefits achieved in 2022, 2023, 2024, and so on that are *being delivered by the measures adopted in 2022*.

By contrast, the top-down approach can report only the TSB achieved in the given year, since there are no specific measures and so no measure lives to track. This is calculated by applying the avoided cost unit benefits to the total (cumulative[54]) savings achieved each year. The TSB identified in the year is the sum of the total system benefits attributable to the total savings also achieved in that year. In other words, instead of calculating a measure level TSB in a given year, the top-down analysis approach calculates the TSB for the total savings in that year. Post-processing analysis may occur to determine the segment and end use related TSB, as appropriate.

An illustrative example may be helpful: consider a very simple bottom-up study in which in year 1 a single measure that saves 10 kWh per year and lasts 20 years is adopted. Compare this with a top-down study that projects an incremental 10 kWh of potential is achieved in each year. In year 1 of the study, the bottom-up study would report the TSB associated with 200 kWh (10 kWh for 20 years of assumed future achievement), while the top-down would report the TSB associated with 10 kWh. In year 2, the bottom-up would report no TSB (no new measure adopted that year) whereas top-down would continue to report 10 kWh.

Figure 3-9 provides the estimated TSB by year and scenario across both fuels. These values are constant (inflation-adjusted or real) 2020 dollars. The upward curvature of the lines reflects the increase in time of the avoided costs (TSB) in real terms. This curvature becomes more pronounced (reflecting inflation) if nominal values are used. Note that unlike the potential itself, no direct comparison is possible between the TSB output by the top-down and the TSB output by the bottom-up potential estimation. Bottom-up TSB (as it is calculated by the DSMSim model and output for reporting) represents, in any given year, the total life-time avoided cost benefit (discounted appropriately) of all measures installed in that year. The top-down TSB represents the avoided cost benefit achieved in a given year – i.e., it is simply the reduction in energy consumption in the given year, multiplied by the avoided cost benefit of that reduced energy consumption.[55](See text box on annualization in section 2.3.)

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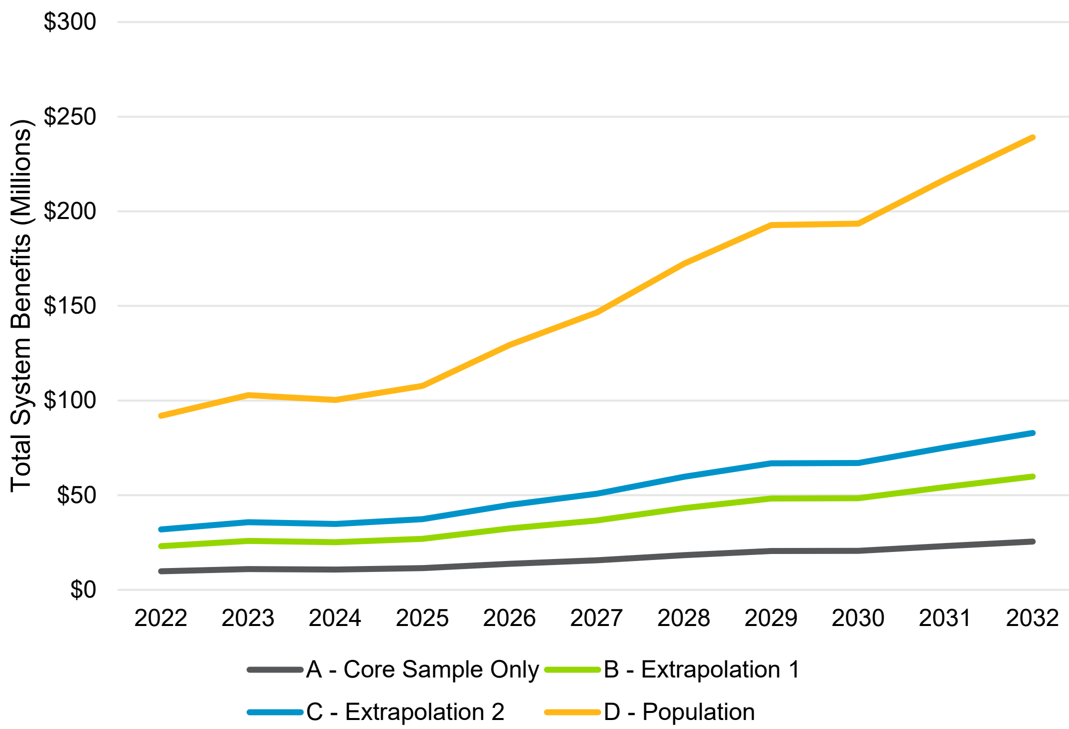
[54] See text-box in section 3.1; in a widget-based, bottom-up approach the annual savings associated with the cumulative adoption of measures that have not reached the end of their EUL are referred to as cumulative savings. These savings should not be misunderstood to be the accumulation of savings from year-to-year, but rather the annual savings related to the accumulation of measures.

[55] An example may illustrate the issue: consider a scenario in which only a single measure is introduced in Year 1, which will save 10 kWh per year and will last 10 years. In the bottom-up potential reporting, the TSB in Year 1 would be the benefits associated with the 100 kWh of lifetime savings for that measure – its total present value lifetime benefit, and the TSB in Year 2 would be zero. In contrast in the top-down potential reporting, the TSB in Year 1 would be the benefits associated with the 10 kWh of savings achieved in Year 1, and the TSB in Year 2 would be the benefits associated with the 10 kWh of savings achieved in Year 2, etc.

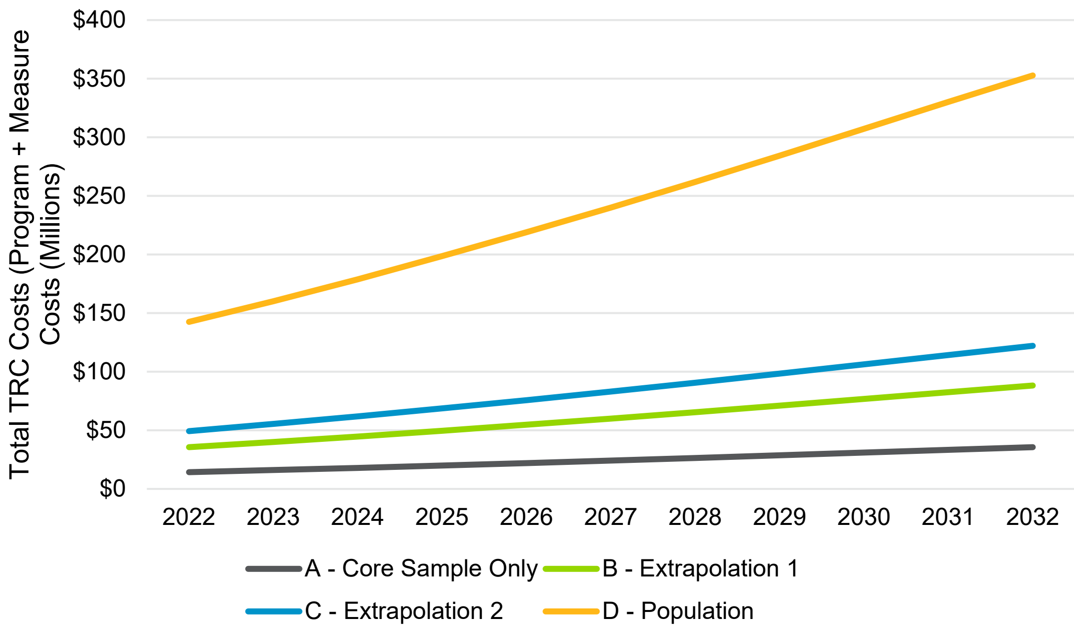
Figure 3-9: Statewide Total System Benefit ($ Millions) by Scenario



Source: Guidehouse

Figure 3-10 shows the sum of estimated incremental costs (see Table 2-7) and program costs (Table 2-8) when applied to the projected potential in each scenario. These values are shown in constant (real) 2020 dollars. Since Guidehouse assumed that all such costs remain constant in real terms over time, the curvature of the lines reflects the slope of cumulative energy efficiency potential.

Figure 3-10: Statewide Total Potential Costs ($ Millions) by Scenario



Source: Guidehouse

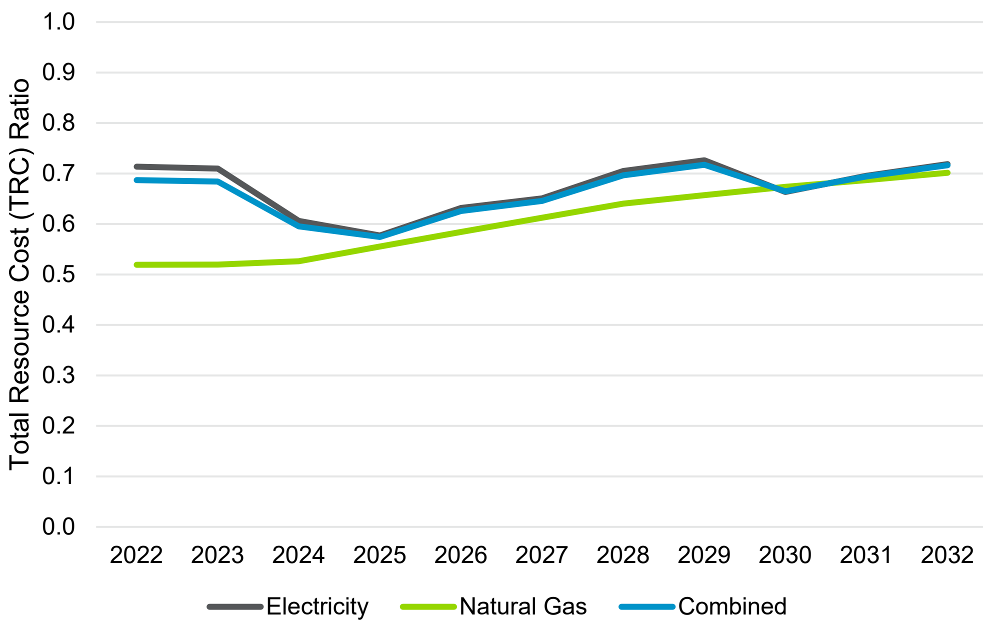
One significant difference in output between the top-down and bottom-up analysis is that the bottom-up analysis typically reports (as in Figure 4-11 of the April 23 bottom-up draft report) incentive and non-incentive resource program costs. This is possible in the bottom-up analysis, as incentives play a key role in that estimation, driving market dynamics, adoption, potential, and cost-effectiveness. In the top-down approach, the abstraction away from a widget-based approach makes the estimation of incentive costs superfluous. Though the top-down approach implicitly assumes the presence of incentives it does not make the same deterministic assumptions about consumer preferences and market dynamics as the bottom-up approach so no explicit assumptions for incentives are required.

The costs presented in Figure 3-10 include program administrative costs and the estimated incremental costs of achieving savings (as delivered by the LCOEs, the estimation of which section 2.3.2 describes).

Combined, these values provide an annual value for the TRC ratio. This is shown by year for each fuel for Scenario A, in Figure 3-11.[56] The figure also shows the combined TRC in each year (for both gas and electric measures). This plot reveals that aggregate energy efficiency potential projected by this analysis is not cost-effective in any year of the period of the analysis. This result is driven by the assumed end use distribution of potential (proportionate to consumption by end use), the estimated LCOEs for each end use and the projected avoided costs used.

[56] Since the distribution of end-use potential (in proportion) is essentially the same across each scenario, costs and benefits are linear in potential (by end-use), and since the TRC is a ratio of aggregate benefits and costs, TRCs should be nearly identical across scenarios.

Figure 3-11: TRC Ratio Over Time – Scenario A (Electric and Natural Gas Energy)



Source: Guidehouse

The failure of the top-down potential portfolio to pass the TRC cost-effectiveness test is best evaluated by comparing the average avoided cost benefit per kWh and per therm with the average incremental and program costs per therm. Table 3-1 and Table 3-2 show these mean unit benefits and costs for electricity and natural gas, respectively. In both cases, the benefit is less than the costs. The mean incremental cost in most cases is either greater or nearly equal the mean avoided cost benefit across the segments and end uses.

Table 3-1: Mean Unit Electricity Benefits and Costs (Constant $2020)

Year	Mean Avoided Cost Benefit ($/kWh)	Mean Incremental Cost ($/kWh)	Mean Program Admin Cost ($/kWh)	TRC
2022	$0.07	$0.07	$0.02	**0.7**
2023	$0.06	$0.07	$0.02	**0.7**
2024	$0.06	$0.07	$0.02	**0.6**
2025	$0.05	$0.07	$0.02	**0.6**
2026	$0.06	$0.07	$0.02	**0.6**
2027	$0.06	$0.07	$0.02	**0.7**
2028	$0.06	$0.07	$0.02	**0.7**
2029	$0.07	$0.07	$0.02	**0.7**
2030	$0.06	$0.07	$0.02	**0.7**
2031	$0.06	$0.07	$0.02	**0.7**
2032	$0.07	$0.07	$0.02	**0.7**

Source: Guidehouse

Table 3-2: Mean Unit Natural Gas Benefits and Costs (Constant $2020)

Year	Mean Avoided Cost Benefit ($/therm)	Mean Incremental Cost ($/therm)	Mean Program Admin Cost ($/therm)	TRC
2022	$1.02	$1.10	$0.46	**0.7**
2023	$0.81	$1.10	$0.46	**0.5**
2024	$0.81	$1.10	$0.46	**0.5**
2025	$0.82	$1.10	$0.46	**0.5**
2026	$0.87	$1.10	$0.46	**0.6**
2027	$0.91	$1.10	$0.46	**0.6**
2028	$0.96	$1.11	$0.46	**0.6**
2029	$1.00	$1.11	$0.46	**0.6**
2030	$1.03	$1.11	$0.46	**0.7**
2031	$1.05	$1.11	$0.45	**0.7**
2032	$1.07	$1.11	$0.45	**0.7**

Source: Guidehouse

The high (relative to the benefits) average incremental cost for each fuel's savings potential is simply a function of the segment and end-use specific LCOEs (Table 2-7) and the mix of potential by end use (Figure 3-6, Figure 3-8). For example, as Figure 3-6 shows, HVAC potential accounts for nearly two-thirds of natural gas total potential. This natural gas end use is costly, with an LCOE (the Office and Grocery segments account for approximately 80% of potential) that exceeds the mean avoided benefits Table 3-2 shows. For electricity, as may be seen in Figure 3-7 potential is driven most significantly by the Office segment and (Figure 3-5) by indoor lighting. In Table 2-7 it can be seen that the LCOE for Indoor Lighting in the Office Segment is approximately 10 cents per kWh – considerably higher than the average system benefits, even before accounting for program costs. In summary, the above shows that, given the average historical cost of procuring energy efficiency by end-use, and the assumption that in the future energy efficiency will be acquired from end-uses in proportion to the consumption in those end-uses, neither natural gas energy nor electricity efficiency potential is not cost-effective.

Historically, an extremely high proportion of natural gas energy efficiency has been acquired from two end-uses (water heating and cooking) where the costs of doing so are relatively low. Continuing to acquire energy efficiency from these end-uses at the same rate as in the past, at the levels required to achieve the potential estimated here is, infeasible given the proportion of total consumption these end-uses represent. Therefore, acquiring the potential estimated here cost-effectively would require substantially reducing both the incremental costs associated with (for example) HVAC equipment and materially reducing program costs unless the avoided cost benefits of natural gas increase considerably.

The issue for electricity is a bit different: though there are differences between the distribution of historical savings and consumption by end use they are much less extreme than for natural gas. Additionally, the major end uses (HVAC, Indoor Lighting, and Miscellaneous) do not have LCOEs that are substantially higher than the average LCOE across end uses, quite different from natural gas where (for example) Office HVAC savings cost approximately $1.59 per therm and water heating savings cost only 50 cents per therm. The (relatively) greater consistency in electricity avoided costs across end uses suggests that identifying the significantly lower-cost measures necessary to achieve cost-effectiveness under the current avoided costs may be more challenging for electricity than natural gas.

4. Findings and Recommendations

This chapter provides Guidehouse's key findings from the development of the top-down prototype analysis and provides recommendations for potential next steps for CPUC. Guidehouse's recommendations should help CPUC consider how to continue evolving its approach to estimating the DSM and fuel substitution potential used to set IOU goals.

Provided greater certainty can be obtained for representativeness of the sample and increased granularity in segmentation, the top-down methodology can meet many potential study output data requirements, though not all (see). All the top-down analysis outputs are available at the sector and end use level, not at a measure level.

Table 4-1: Requirements and Capabilities of Current Top-Down vs. Bottom-Up[57]

Model Requirement	Bottom-Up	Top-Down (Current Methodology)	Top-Down Study Notes
Separate forecasts for each IOU (setting goals)	+	+	Raw datasets can be mapped to an IOU
Supporting a TSB goal setting process	+	+	Calculated at the sector and end use level for the total savings in that year
Produce sufficient detail for IOUS and PA portfolio planning	+	+/-	Sometimes planning leverages measure level data which is not available
Provides forecasting inputs to support procurement and planning efforts across multiple agencies	+	+/-	Forecasting inputs can be more aggregated at the end use level. Further disaggregation to available load shape level may be post- processed
Produce supply curves for IRP	+	+	Developed at the sector or end use level which aligns with the current measure bundle approach used
Quantify cost-effectiveness metrics	+	+	At the sector and end use level and not used for screening measures
Forecast 10-year time horizon	+	+	Based on historical consumption data
Produce cumulative EE savings for IEPR	+	+	Based on historical consumption data
Produce cumulative fuel substitution savings for IEPR	+	NA	Model was not tested with fuel substitution in the pilot analysis since there is minimal available date due to low historical penetration

[57] Codes and standards and low-income potential does not appear in this table since they have their own methodologies.

Model Requirement	Bottom-Up	Top-Down (Current Methodology)	Top-Down Study Notes
Disaggregate DER types (energy efficiency, fuel substitution, energy efficiency/DR)	+	-	Analysis is based on historical penetration and savings data; as fuel substitution, EE-DR, and other DERs savings data grows, the information could be incorporated in an analysis
Separate Forecasts of Rebate Programs and BROs	+	-	Lack of measure level granularity does not allow disaggregating savings by program type source

Source: Guidehouse

4.1 Findings

4.1.1 Finding 1: Given the currently available data, the top-down approach is at present an unsuitable as a complete replacement for the bottom-up approach for estimating commercial sector energy efficiency potential.

- Improve availability of building level data. This is a short-term issue until a better building database becomes available (see section 4.2.1). More specifically, a key weakness of the top-down approach, as it is presently specified, is the need to extrapolate an estimated potential from a relatively small group of buildings unrepresentative of the overall population (i.e., the large buildings included in the CEC's benchmarking database) to the entire population.

- Limited and unrepresentative publicly available floorspace data. There are potential solutions for remedying the floorspace data in the medium term with non-public data sources (see section 4.2.2). The acquisition of proprietary building floorspace data for the overall population of buildings (or even a reasonably large representative sample) combined with additional building characteristics (e.g., from a commercial end-use survey) could deliver the ability to estimate potential from a core sample that is more representative of the overall population. This would increase the robustness of the projection. At present, the core sample represents between approximately 7% and 16% of total segment consumption (see Table 2-6), but since the CEC database includes only the largest buildings, the number of utility accounts in the core sample accounts for a little less than 2% of all utility accounts in the population considered by the analysis. If CEC database or a similar data set could be expanded even to 25% of accounts this would substantially improve the likelihood that a truly representative core sample could be created for this type of analysis.

  Increasing the size of the core sample would also improve the signal-to-noise ratio in comparing *less efficient* and *efficient* buildings and provide a higher-confidence estimate of that potential. Likewise, additional segmentation (e.g., splitting the grocery segment into a produce grocery, dry goods grocery, bulk grocery, etc.) would also improve the signal-to-noise ratio and likely result in a more consistent relationship between the potential percentage efficiency improvement of converting *less efficient* to *efficient* buildings, further building confidence in the ultimate potential estimated on the basis of that percentage improvement.

4.1.2 Finding 2: Easy opportunities ("low hanging fruit") are being depleted, and potential will become increasingly costly to obtain, particularly for natural gas.

- High natural gas savings in certain end uses. Historically, as demonstrated in section 2.2.6, energy efficiency program achievement by end-use has not matched the distribution of consumption by end-use. This is particularly true for natural gas. Historically the cooking end-use has accounted for approximately a quarter of all savings achieved in the segments examined in this study, and the water-heating end-use has accounted for approximately half of all savings achieved in the segments of interest. The cooking end-use and water heating end-use – taken together – account for less than 10% of overall natural gas consumption in the segments included in this study.

  The reason for this disparity (between the end-use distribution of consumption and historic savings) is almost certainly driven by considerations of cost-effectiveness. In procuring energy efficiency it is only rational to acquire savings from the lowest-cost sources first. Section 2.3 clearly demonstrates that those end-uses from which savings have been disproportionately obtained in the past are also those end-uses where the levelized cost of energy is lowest.

- Historic distribution of energy savings by end-use cannot be used as a guide for future program design assumptions. In particular, the natural gas savings have historically been obtained disproportionately from water heating and cooking end-uses. The average annual natural gas consumption for water heating across the three historic years included in this study (aggregated across segments and IOUs) is only approximately 50 million therms. In contrast, based on the building comparison analysis and the Scenario D (population) extrapolation sample, the natural gas cumulative energy efficiency potential in 2032 is nearly 700 million therms per year. Clearly half of this potential cannot come from water heating savings. While this issue is also (to a much lesser degree) present in the electricity analysis, the larger number of end-uses, and the (generally) more consistent magnitude of historic LCOEs of savings make the problem much less acute than for natural gas.

4.1.3 Finding 3: The precision of top-down commercial sector potential estimation could be significantly improved with additional segmentation.

- Homogeneity in segmentation. Section 2.2.4 defines the *less efficient* and *efficient* distributions of each segment's building energy intensities. Segments with a less homogenous distribution of end-uses (e.g., Grocery), the "signal" provided by the proxy variable is weaker. These segments therefore require the use of a higher threshold value of the proxy variable to split the sample, resulting in a relatively small *efficient* group of buildings (e.g., 12% of Office/Electric buildings are *efficient* whereas only 3.4% of Grocery/Electric buildings are *efficient*). As the group of *efficient* buildings diminish, the uncertainty (imprecision) of the estimated available potential increases. As Section 2.2.4.3 notes, greater segmentation (e.g., splitting Grocery into sub-segments on the basis of total floorspace devoted to refrigeration vs. produce and dry goods) could substantially improve the strength of the signal. This would require improved cross-sectional data (for example from a commercial end use survey).

- Larger data sets for increased precision. Increased segmentation inevitably results in a smaller sample of buildings in each segment, which will tend to erode precision. Achieving greater statistical precision cannot be accomplished through additional segmentation only – it must be supported by the collection of more commercial building floorspace data to expand the pool of buildings for segmentation.

- Improvements in normalization steps. In the same way that the characterization of the market and the measures is key to bottom-up potential, the key to estimating top-down potential is the comparison across customers. This comparison can be robust only when it is possible to control for or normalize away potentially confounding effects (e.g., dry goods grocery vs. produce grocery, etc.). Additional segmentation and more building floorspace data would improve normalization and deliver a more reliable estimate.

4.1.4 Finding 4: Despite some shortcomings, the cost data included in the CEDARS data can, when summarized appropriately, provide valuable insights for program planning.

- Understanding program cost-effectiveness, historically and in the future. LCOEs provide a very effective way to understand and evaluate the continuing cost-effectiveness of existing programs, and their appropriateness for the future. For example, as shown in Table 2-7, the LCOE for natural gas in the HVAC end-use for the Grocery and Office segment is well over one dollar per therm. In contrast, the 2020 avoided cost benefit of natural gas savings is materially *less* than one dollar per therm. This means that existing programs to deliver HVAC energy efficiency natural gas savings are highly unlikely to be cost-effective in the future. The insight here is clear: either the HVAC-related natural gas programs need to be comprehensively re-designed to target more cost-effective measures, or they should cease to be offered.

  The same type of analysis can be applied to all end-uses, segment and fuel combinations to assist with portfolio and program planning. Another example is the HVAC end-use for electricity. As shown in Figure 2-28, although HVAC consumption accounts for approximately a quarter of overall consumption (of the segments under consideration), it accounts for only about 10% of lifetime savings and 18% of annual savings. This is in contrast to indoor lighting (nearly 50% of lifetime savings, approximately 30% of consumption). The LCOE, however, for HVAC is in the Grocery and Office segments markedly less than the LCOE for indoor lighting. This suggests that refocusing existing programs on HVAC measures could be more cost-effective than continuing with existing programs focused on lighting measures.

- LCOE accuracy is dependent on the accuracy of the measure cost estimates and the historical program measure mix composition. Though a potentially powerful tool for planning, care must be taken in relying on LCOEs to support analyses and policy changes to remain cognizant of the limitations of LCOEs derived from CEDARs data. LCOEs estimated using historical data are inherently backward looking, reflecting past program achievement. For example, as noted above, the LCOEs for the natural gas HVAC are very high, suggesting that the programs offering such measures either need to be re-designed or else suspended. An examination of the CEDARs data would indicate what the measure mix that is driving this LCOE and could suggest how programs could be re-designed.

Analysts must also remember that individual measure costs are estimated averages, which may not account for the increasing marginal costs that might be anticipated as certain measures become saturated in the market. For example, the very high proportion of savings that are provided by the water-heating end-use could indicate saturation of the market with lower-cost measures, meaning that the water heating LCOE is inappropriately low to be used for program planning.

4.1.5 Finding 5: With fewer consultant-generated inputs and assumptions (e.g. during the course of measure characterization) the top-down approach can offer increased transparency at reduced cost to CPUC and stakeholders.

- Simplistic data modeling with fewer data points. The integrated model-driven bottom-up analysis requires a massive data development and maintenance effort. Each iteration (e.g., by segment) of each energy efficiency or fuel substitution measure requires dozens of inputs, and the estimated adoption path of each measure depends on a complex model of market dynamics and inter-measure interactions. This complexity makes effective external review challenging, costly, and time-consuming, reducing transparency. This can provoke significant frustration from stakeholders, particularly IOUs whose activities may be circumscribed by the outcomes of the modeling. A top-down approach, though it relies on hundreds of thousands (if not millions) of individual data-points, uses many fewer individual *streams* of data than the bottom-up approach. This, and the abstraction away from individual widget-level modeling, means that the overall structure of data interactions is clearer and therefore considerably more transparent.

- Use of professional judgement. The abstraction and (relative) simplicity of the top-down approach offers increased transparency but does come at a cost: projected achievable potential is more *directly* and obviously impacted by the professional judgment of the team undertaking the analysis.

    - The bottom-up deterministic modeling of market dynamics is a more automated process and therefore provides the appearance of a more objective, mechanistically-driven estimate of potential. Naturally, analyst judgement plays a pivotal role in bottom-up model development and maintenance (e.g., the choices of which interactions should be modeled, the functional forms of the model relationships, etc.). The bottom-up does use multiple levers that calibrate the model providing a complex set of decisions that also result in professional judgement but aligned with the historical context of the program delivered savings. These choices by model developers define the range of outcomes for the bottom-up analysis, but do so in a less direct fashion than in the top-down approach. This will generally make the outputs of a bottom-up analysis less subjective than the top-down approach overall, though those areas in which subjective analyst judgement is applied will be less obvious or transparent than in the top-down approach.

    - The more direct reliance and transparency on analyst judgement by the top-down approach requires that this judgement be supported by persuasive arguments using the evidence of historical and forecast trends. This renders the process more transparent both explicitly (by the development of the reasoning required to justify analytic choices) and implicitly (by acknowledging the central role of expert judgement in projection rather than delegating decisions to the mechanics of a complex proprietary model). Furthermore, the increased relative transparency of the top-down analysis could improve stakeholder understanding and engagement.

4.1.6 Finding 6: To meet multiple stakeholder needs, further insights into the opportunity of post processing requirements need investigation to assess if the top-down is sufficient approach for forecasting potential.

- IRP and Load Forecasting (IEPR and AAEE): Post-processing analysis of the top-down study outputs can provide the necessary granularity at the sector, end-use level of data for the different study needs. Any further analysis beyond the IRP and IEPR at a technology level will not be available from the top-down (for example, the FSSAT uses the PG study technology level measure characterization for technology level analysis). The CEC teams must assess if the altered deliverables still meets their analysis requirements.

- Program design and planning: CPUC will need to dive into program administrator use cases of the PG study to determine the technology granularity needs.
- Fuel Substitution: Disaggregation efficiency and fuel substitution in consumption-based analysis needs to be explored. Additionally, historical program context is minimal to provide grounding of “efficient” and “inefficient” analysis across the population. Further insights and pilot analysis will be necessary to solidify that top-down approaches can work for fuel substitution potential forecasting.
- DER disaggregation: Similar to fuel substitution, when looking at the interaction of increasing or decreasing consumption on annual or even hourly basis may be challenging as the source of the increase or decrease may vary. Pinpointing the opportunity – either efficiency, (building or vehicle) electrification, storage, or generation – will be important and must be considered if a viable analysis in a top-down approach.

4.2 Recommendations

This Recommendations section of Chapter 4 is itself divided into three levels: short, medium and long term.

- **Short-term recommendations** are those that could be implemented as part of the forthcoming potential estimation cycle (i.e., complete by spring 2023)
    - Enhancing the insight provided by the bottom-up analysis using the existing top-down analysis data set
    - Acquiring and vetting data that could be used to sufficiently enhance the top-down approach from a “prototype” to a “production” analysis.
- **Medium-term recommendations** are those that could be implemented as part of the next potential estimation cycle (i.e., complete by spring 2025)

  - Delivering production-quality potential analysis for the commercial sector
  - Producing industrial and agricultural sector prototype potential analysis which have more individualistic facility demand patterns than the commercial sector.

- **Long-term recommendations** are those that could be implemented by the time of the 2027 evaluation cycle and focus on the (conditional on the success of the short- and medium-term recommendations) transition of potential estimation to a top-down approach.
  - Finalize the models for the non-residential sectors
  - Incorporate modeling for the residential sector

In developing its recommendations to the CPUC, Guidehouse has done so with an acute awareness of:

1. The intellectual capital that has been invested in the bottom-up approaches available to the CPUC for potential estimation, and
2. The development of a downstream analytic infrastructure that relies on outputs from that analysis.

On the first issue, any recommendation for change in the modeling approach must reflect an awareness of the fact that – for all their imperfections – bottom-up potential estimation techniques are now relatively mature. Since their emergence decades ago immense strides have been made in adjusting the theoretical and practical elements of these models to minimize the effects of any structural shortcomings. Examples include: an increasing emphasis on scenario and sensitivity analysis, improved calibration to historical and forecast consumption and program achievement, and greater integration of customer choice data in informing model market dynamics.

Guidehouse seeks to ensure that its recommendations – while not a prisoner to the sunk cost fallacy – recognize that any potential alternative approach will too have its growing pains and require investment over time, some part of the costs of which would fall upon California rate-payers. Guidehouse has therefore, in developing its recommendations, considered each of them through the lens of their long-term effectiveness and the value-for-money they offer to California rate-payers.

On the second issue, Guidehouse understands that there exists an established set of downstream processes that rely a specific set of outputs provided by the Potential and Goals study. Though an alternative approach to projecting potential may – in some cases – reproduce such outputs, any structural shift in the potential estimation approach will impact the granularity of the outputs and the manner in which such outputs may be interpreted, and thus have potentially significant ramifications for any dependent downstream processes. Finding 6 in section 4.1.6 provides the implications both positive and negative for the simplification of outputs from the top-down to the downstream uses cases of the PG Study.

Given both considerations, Guidehouse believes that an incremental approach to the ongoing evolution of California's established structure for estimating IOU potential and goals is prudent and appropriate. It is within this context that Guidehouse has developed its recommendations.

Guidehouse has structured its recommendations into three categories. Though these are referred to in terms of level of effort, it is really a question of data availability that has driven the categorization. The use of the terms level of touch is more a reflection of Guidehouse's assessment of the data required for each recommendation might be available to (and validated by) analysts.

The three categories of recommendation are provided below, along with the headline recommendation. The detail of the recommendations is provided in the sub-sections that follow.

- **Short-Term Recommendations.** Guidehouse's recommendations based on the data currently available and the top-down approach as implemented for this prototype analysis. Guidehouse recommends that the CPUC consider:

    1. Leveraging existing CEDARS data (and the cost estimation analysis tested above) to benchmark projected potential costs output by any bottom-up analyses conducted in the future.
    2. Exploring and identifying sources of data that could allow for the intensity-normalization of energy consumption in the agricultural and industrial sectors in the same way floorspace has been used for the commercial sector in this report. This exploration should begin with direct engagement with the relevant industrial associations (e.g., the Aerospace Industries Association, the Dairy Institute of California, etc.) to develop a better understanding of how to identify the most energy efficient facilities and where to find reliable data sources that can enable a comparative assessment of different facilities' efficiency.
    3. Obtaining and reviewing a sample of proprietary commercial floorspace data from one or more vendors (e.g. CoStar or Dun and Bradstreet) to identify whether it would be suitable for supporting an expansion of the top-down analysis across more commercial segments.
    4. Examining the data included in the forthcoming California Commercial End-Use Survey (CEUS) to determine whether these data could supplant or supplement the CEC Benchmarking data used in this top-down study in order to deliver a more robust and representative top-down projection of potential.
    5. Undertaking to identify to what degree a top-down approach might be suitable for the projection fuel substitution potential, and the associated cost of such substitution.

- **Medium-Term Recommendations.** In the medium term, if the data identified in the short-term recommendations above are found to be sufficient to expand the scope of the top-down analysis to all other commercial segments and/or to other non-residential sectors (industrial and agricultural) and to allow for a more confident extrapolation of estimated potential from the core sample to the population, Guidehouse recommends that the CPUC consider

    1. Replacing the commercial sector bottom-up approach with a top-down approach that reflects the enhancements identified in the short-term recommendations above.

2. Developing a prototype top-down approach suitable for the agricultural and industrial sectors and develop a top-down projection of potential in these sectors in parallel with the bottom-up.

- **Long-Term Recommendations.** In the longer term, conditional on the successful implementation of the short- and medium-term recommendations, Guidehouse recommends that the CPUC consider completing the transition from a bottom-up approach to a top-down approach by evolving the industrial and agricultural top-down approaches from “prototype” to “production” and migrating the residential potential estimation from a bottom-up to top-down approach. Furthermore, throughout this process, Guidehouse would recommend that the CPUC look for (and execute) any opportunities to align the segmentation and granularity of the potential estimation with that of the IOU and CEC forecasting groups.

4.2.1 Short-Term Recommendations

In the short term, assuming no significant expansion of the data available to undertake a top-down projection of energy efficiency potential, and therefore the need to use (and improve upon) the same set of procedures adopted in this prototype analysis for developing a wider-scale top-down analysis, Guidehouse would make the following recommendations.

Guidehouse recommends that the CPUC consider:

1. **Leveraging existing CEDARS data (and the cost estimation analysis tested above) to benchmark projected potential costs output by any bottom-up analyses conducted in the future.**

   The CEDARS data is a very rich and detailed set of DSM program participation data. Guidehouse would recommend that CPUC consider, for the next iteration of the Potential and Goals study, leveraging CEDARS data to develop a set of estimated levelized cost of energy (LCOE) values for each combination of fuel, segment, end-use, and (if the data can support it) IOU. LCOEs should be developed both for the end-uses applied in the PG study as well as to the (overlapping) IEPR end-uses.

   In developing these LCOEs, an effort should be made (when defining the IEPR end-use LCOEs) to provide estimates for the heating, ventilation, and cooling end-uses separately (Guidehouse combined these for expediency in the prototype analysis). Such LCOEs should also be developed for fuel substitution measures, if sufficient historical data are available to support such an analysis.

   These LCOEs can then be applied to projected future potential values estimated by the existing bottom-up approach and provide a valuable benchmark to compare the costs projected by the bottom-up approach with the average costs of historical achieved savings. Forward-looking projections of cost will of course incorporate various assumptions that are likely to deliver estimated incremental levelized costs that are lower than those predicted by extrapolating the historically estimated LCOEs (e.g., reductions in technology costs). Identifying the disparities (and their causes) between the bottom-up projection of costs provided by the model and the projected costs derived by applying the historical average LCOEs to bottom-up projected potential can however, provide a valuable quality control step, help improve study transparency, and build stakeholder confidence in the results.

2. **Exploring and identifying sources of data that could allow for intensity-normalization of energy consumption in the agricultural and industrial sectors in the same way floorspace has been used for the commercial sector in this report.**

   Potential estimation is, at its simplest, the process of identifying the current state of consumer energy efficiency and, based on this, determining what the potential improvement could be. In a widget-based approach, the estimated improvement is derived from equipment-based assumptions.

   In an empirical (top-down) approach, the estimated improvement is derived based on a comparison of peers: opportunity for improvement is defined as bringing the least efficient up to the standard of the most efficient. Crucial to this process is the ability to normalize individual building energy consumption to ensure that the comparison that drives the estimate is reasonable and legitimate: to ensure that apples are being compared to apples.

   Normalization can be performed across a number of variables (e.g., year-over-year comparisons of gas consumption are typically applied to weather-normalized data), but some of the most effective units of normalization can be

   - *Residential Sector:* Structural dwelling type (e.g., kWh/detached house)
   - *Commercial Sector:* Floorspace by building type (square feet) – this is what was used in this prototype analysis.
   - *Agricultural Sector:* Volume of water pumped (for irrigated agriculture) by crop type, animal headcount by type of livestock.
   - *Industrial Sector:*
     1. *Small/Medium Industrial:* Floorspace, *if* segmentation can be relatively fine-grained (e.g., tool and die, automotive repair, etc.)
     2. *Large Industrial:* Number of employees[58], *if* segmentation can be relatively fine-grained.

   For the residential and commercial sector, structural dwelling type and floorspace of individual buildings may be available (for a sample of the population) in residential and commercial end use surveys, and are almost certainly available from commercial data providers. For the industrial and agricultural sectors, Guidehouse is unaware of what data sources are available to support additional normalization. Guidehouse would recommend actively engaging with the relevant industry associations as a starting point for identifying such information. The commercial providers of commercial floorspace and residential structural dwelling type data may also be able to provide market intelligence (via proprietary databases) derived from data-scraping activities that could support this effort.

3. **Obtaining and reviewing a sample of proprietary commercial floorspace data from one or more vendors to identify whether it would be suitable for supporting an expansion of the top-down analysis across more commercial segments.**

[58] Economic output by segment would of course be preferable, but this is likely to be even more difficult to acquire than employee volume.

The current prototype top-down analysis was, by design, limited to consider only data immediately available to the CPUC (i.e., already in its possession) or else in publicly available databases. Given the findings of the analysis above, Guidehouse would recommend undertaking an assessment of the quality, representativeness, and granularity of building floorspace data available from commercial vendors. If a reasonably robust set of data for individual commercial buildings in California can be reasonably accurately mapped to site ID (in the CEDARS data) and customer account ID (in the IOU billing data) this could allow for a valuable evolution of the top-down approach.

If accurate floorspace data are available from commercial vendors, the top-down approach could be expanded to include all of the commercial segments. If such data can be shown to be comprehensive or representative of the overall population of buildings, this could significantly reduce the uncertainty associated with the extrapolation of potential beyond the core sample. Recall that because the building sample (the CEC Benchmarking data) is not representative of the overall population in the four selected building segments, extrapolating impacts out from the core sample to the wider population may be problematic – this is the driver behind the selection of the different scenarios. If sufficient floorspace data are available to ensure a wholly representative data set, then results can be extrapolated with much greater certainty. This would make it unnecessary to use scenario analysis to explore the uncertainty that comes from extrapolating the results from the core sample to the population. In this case, scenario analysis could be used to explore the sensitivity of potential to other key variables of interest.

4. **Examining the data included in the forthcoming California Commercial End-Use Survey (CEUS) to determine whether these data could supplant or supplement the CEC Benchmarking data used in this top-down study in order to deliver a more robust and representative top-down projection of potential.**

   The 2022 CEUS[59] will include data collected from approximately 27,000 commercial sites in order to characterize for these sample sites the NAICS code, end use fuel saturations, estimated floor space, energy use, electricity load profiles, and other data. These data could be matched to program participation data and utility account consumption data and be used to develop a data set that could replace (or be added to) the existing CEC Benchmarking data.

   As with the proprietary commercial floorspace data referenced above, the adoption of these data could significantly improve the precision and accuracy of the projected potential. In the top-down analysis undertaken for this study, the core sample of buildings used to estimate the opportunity for improvements in energy intensity is not representative of the broader population. If the CEUS can allow for the replication of the analysis above, but with a core sample of buildings that is truly representative of the population, then a scenario analysis to explore the uncertainty associated with extrapolation is unnecessary. In this case, scenario analysis could be used to explore the sensitivity of potential to other key variables of interest.

[59] California Energy Commission, *California Commercial End-Use Survey*, accessed June 2021 https://www.energy.ca.gov/data-reports/surveys/california-commercial-end-use-survey#accordion-1075

5. **Undertaking to identify to what degree a top-down approach might be suitable for the projection fuel substitution potential, and the associated cost of such substitution.**

   The prototype top-down approach used in this study is explicitly focused on energy efficiency, and not fuel substitution, potential. The existing bottom-up approach delivers both. Fuel substitution (i.e., electrification of natural gas end-uses) potential projection is in some way conceptually simpler than energy efficiency potential projection: the upper limit of available potential (all existing gas consumption) is known *a priori*. The real challenge of fuel substitution projection, however, is less to do with the estimated level of what volume of substitution is possible, but more to do with the cost (and cost-effectiveness) of such substitution.

   Given the relatively sparse historical record of IOU programs targeting fuel substitution, it seems unlikely that the approach used for estimating LCOEs for energy efficiency (in this top-down study) would be appropriate or applicable to estimating the costs associated with fuel substitution. The core challenge therefore, for the development of a top-down approach to projecting the potential for fuel substitution would be developing a robust estimate of the cost of such potential, absent the availability of any material amount of historical data. One data source that may provide insight on costs is the CEC AB3232 analysis. Albeit this work is also forward looking but provides foundational research in considering costs of fuel substitution. Otherwise, the efforts used in the emerging technology space can offer lessons learned when projecting costs of new or enhanced penetration of technologies.

6. **Identifying how the prototype top-down analysis could be further enhanced through the use of high-frequency individual customer AMI data.**

   In keeping with the project development philosophy of using only data already in possession of the CPUC or publicly available, Guidehouse did not use participant AMI data in this analysis. Though such data were considered, Guidehouse's team considered that it made sense to first prove the concept through the use of coarser (though simpler and faster to use) participant billing data.

   Having demonstrated that a top-down potential projection can deliver valuable insights and provide a reasonably transparent estimate of future energy efficiency potential, it is now appropriate to consider how such analysis could be enhanced through the use of high frequency (hourly or sub-hourly) AMI data, and the value such enhancements could offer. One clear use-case for AMI data in the top-down process is the development of more granular customer segmentation.

   Guidehouse noted in Chapter 2 that heterogeneity within a given segment can be a confounding factor when trying to develop and "apples-to-apples" comparison of customer energy intensity (see section 2.2.4, in particular). This issue was particularly apparent with the Grocery segment, and can be remedied through additional segmentation to control for any systematic differences between Grocery customers that may also be correlated with consumption.

   Guidehouse understands that certain machine-learning techniques (in particular support vector machines – SVM) can allow for robust customer segmentation of a population provided there is a reasonable starting sample of survey data identifying the segment characteristics of interest, and that these survey data can be combined with the AMI data. It seems likely that data collected by the CEUS could be such to allow machine learning classification techniques to be deployed to more finely segment existing customers and therefore more reliably identify the potential energy intensity improvements available.

Guidehouse would further recommend that any such incremental segmentation be developed in close collaboration with staff from the CEC to ensure consistency with the forecasting segmentation used to deliver the IEPR, and the calibration of segment load profiles across the two pieces of work.

4.2.2 Medium-Term Recommendations

In the medium term, if the data identified in the short-term recommendations above are found to be sufficient to expand the scope of the top-down analysis to all other commercial segments and/or to other non-residential sectors (industrial and agricultural) and to allow for a more confident extrapolation of estimated potential from the core sample to the population, Guidehouse would make the following recommendations.

Guidehouse recommends that the CPUC consider:

1. **Replacing the commercial sector bottom-up approach with a top-down approach that reflects the enhancements identified in the short-term recommendations above.**

   The mechanics of a bottom-up approach demand a comprehensive characterization of efficient measures and baseline technologies. Without an estimate of the unit savings for a particular widget, its EUL, the penetration of the technology it replaces and the saturation of efficient measures in that particular category of equipment it cannot be included in the analysis and does not contribute to the estimated potential.

   This is not an unreasonable assumption for the residential sector, where the number of technologies and end-uses is (relatively) limited but is an unsustainable approach in the longer term for a commercial sector in which efficiency opportunities are more diverse. To properly characterize the energy efficiency opportunities in the commercial sector, a bottom-up approach must be constantly expanding the stable of measures it considers or else include measures that are so broad in definition (e.g., retro-commissioning) that they are effectively not very different from a top-down assumption.

   In the medium-term, a top-down approach reflecting the enhancements identified immediately above will provide a more transparent, if necessarily higher-level, estimate of commercial sector energy efficiency potential than the bottom-up. Reducing the number of inputs (i.e., those required for measure characterization) and the complexity of deterministic model mechanics (i.e., modeled consumer behaviour and market dynamics) means that it is clearer to all stakeholders at which hinge-points of the analysis the professional judgement of the analyst is most important. With a much smaller number of inputs, it is then easier for all stakeholders to identify how sensitive projected potential may be to changes in any of the assumptions applied by the analyst.

   Put more simply: at the cost of reduced precision (e.g., measure-level savings), the projection of potential can be accomplished more transparently. A more transparent process should be expected to lead, through debate undertaken in good faith amongst stakeholders over time, to a more accurate result.

2. **Developing a prototype top-down approach suitable for the agricultural and industrial sectors and develop a top-down projection of potential in these sectors in parallel with the bottom-up.**

   Conditional on the completion of the short-term recommendation related to the development of a source of data that can be used to normalize agricultural and industrial customer demand data as an intensity (e.g., agricultural electricity per acre-foot of water withdrawn from reservoirs, etc.), Guidehouse would recommend developing an estimate of the energy efficiency potential for these sectors using a top-down approach. This approach should take advantage of the methodological lessons learned as a part of this current (commercial sector) top-down approach, as well as in the course of implementing the recommendations above.

   As with the commercial sector, but more so, a widget-based approach is, over the longer term, unsuitable for both these sectors given the general lack of homogeneity of energy use even within the sub-sectoral segments. Guidehouse would recommend that in addition to the types of data used for the prototype commercial top-down potential estimation approach, the CPUC consider ensuring that segment-level potential setting takes advantage of any market reports specific to these segments.[60] These could be further enhanced on the basis of information and qualitative data obtained through include interviews or Delphi panels with stakeholders, including industry and agriculture associations and utility account representatives, all of whom might be expected to be familiar with the types of opportunities available to their members or customers.

   Likewise, this effort should include – if possible given commercial data privacy concerns – an attempt at a more granular segmentation of customers using AMI data, as identified in the short-term recommendations above.

3. **Developing a segment-specific set of cost curves the structure of which reflect some adaptation of the economic theory of the firm, and address issues related the manner in which the marginal cost of achieving energy savings for an individual firm are likely to increase at increasing rate as the lowest-cost opportunities are exhausted.**

   As noted above, the existing CEDARS data set provides a rich and immensely useful data set for assessing the costs of energy efficiency potential. The key short-coming of these data is that they are, by and large, derived principally from deemed savings and cost measure profiles. This effectively limits the consideration of costs (e.g., LCOEs) of potential to linear analyses.

   Extending the microeconomic theory of the firm to DSM programing could allow for the development of a cost function that more realistically captures the intuitively obvious idea of the “low-hanging fruit”. If each firm is assumed to have some production function that outlines the production of savings (“negawatts”) as opposed to products and

[60] For example, Measure, Application, Segment, Industry (MASI) reports completed in 2015. The food processing industry is documented with this report: http://www.calmac.org/publications/MASI_Food_Processing_Final_Report.pdf.

services, and energy efficiency actions and measures are the inputs to that production, then it seems reasonable to suppose that the cost function for the “production” of such savings is convex: that the cost of obtaining savings increases at an increasing rate as the lowest cost opportunities are exhausted.

If AMI data (required in order to better isolate the purchase of the energy efficiency measures) can be combined with the (admittedly imperfect, but immensely useful) incremental cost data included in the CEDARS database, it may be possible to develop a more robust estimate of the relationship between energy efficiency potential and savings.

One potential limiting factor that should be considered in determining whether to proceed (or not) with this recommendation is the fact that to properly apply such a function on a forward-looking basis is that some assumption must be made regarding the magnitude of savings acquired by individual firms. If costs are a function of the savings already “purchased”[61] by an individual firm, then projection of costs requires some assumption (or estimate) of how many savings each individual firm has already acquired.

Guidehouse would note that undertaking the estimation of such a cost function would require considerable effort and expertise. Though such a cost function would, if appropriately estimated and applied, deliver a more (potentially much more) accurate estimate of the longer-term costs of energy efficiency adoption, the incremental value of such improved accuracy will depend in large degree on the precision of the estimated potential. The more precise (i.e., the narrower the band of uncertainty around the estimate) that projected potential can be, the greater the value of an improved approach to estimating the cost of that potential.

4.2.3 Long-Term Recommendations

In the long term, if the transition of the commercial sector potential estimation from a bottom-up to a top-down approach delivers acceptable and satisfactory results, and the parallel estimation of industrial and agricultural top-down potential (alongside the bottom-up estimation of such potential) is determined to be a success, Guidehouse would make the following recommendations.

Guidehouse recommends that the CPUC consider:

Transitioning the residential sector energy efficiency potential estimation to a top-down approach, making use of more granular segmentation in all sectors, and aligning such segmentation with the longer-term forecasting practices of the IOUs (if possible) and the CEC.

Of all the sectors, the bottom-up approach to potential estimation (comprehensively characterizing energy efficiency measures and market dynamics) is best-suited to the Residential sector. Customers tend to be reasonably homogenous, and the number of potential end-uses (and the efficiency improvements available for those end-uses) is relatively circumscribed.

[61] That is, if the cost of any additional savings for an individual firm is a function of the dollars already spent on energy efficiency technologies and actions by that particular firm.

However, if, as many industry experts predict, residential customers are expected to become more active participants in grid management (through DERs, including vehicle-to-grid storage dispatch), the existing approach may face the issues presented by the commercial, industrial, and agricultural sectors, in particular the heterogeneity of individual end-use consumption patterns. As this occurs, the benefit of transitioning the residential sector to a top-down approach, and in particular the development of more granular AMI and cross-sectional data driven segmentation, may be able to improve the accuracy of potential projection and ultimately allow for the integration of potential estimation as part of long-term load forecasting exercises.

If CPUC finds that the first two medium-term recommendations can be executed with success, Guidehouse would recommend, over the longer-term, transitioning the residential sector to a top-down approach as well.

In summary, the above recommendations describe, at a high level, the path forward for developing a top-down approach across all sectors. The next steps would be to develop some operational guidance to consider for the implementation of these recommendations. The CPUC and the stakeholder community may wish to explore what the future potential and goals study might look like if these recommendations are fully implemented.

As part of such an exploration, stakeholders should describe their existing and ideal use cases of the potential and goals study output. Currently, the study attempts to first prioritize goal setting and secondarily to provide input and analysis for stakeholders with various requirements. As a result, the balancing of the advantages and disadvantages of the potential study approach should optimize the value the study provides to the community, as well as maintaining independence, transparency, and integrity to the process and results. Therefore, alternate solutions may be required depending on the use case. This result could be studied further to ensure a cost effective, robust solution that meets multiple needs.

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