

A Tale of Three Cities: Reducing Emissions with Building Performance Standards

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ABSTRACT

Many U.S. cities are implementing policies to reduce greenhouse gas (GHG) emissions of their building stock. These range from building energy benchmarking and disclosure ordinances, to audit and tune-up programs, to building performance standards (BPSs) that require buildings to meet specific energy use or emissions targets. As more cities collect data on their building stock and its energy consumption habits, there are opportunities to utilize these data to inform policy design. In this paper we discuss three projects involving building energy data analysis as a means to evaluate and design city-level policies for reducing emissions: 1) We analyzed the results of a tune-ups program implemented in Seattle, Washington to learn how much energy savings can be expected and which building and systems types may save the most. 2) We worked with Aspen, Colorado to quantify expected city-wide emissions reductions from a variety of potential BPS legislation setting energy use intensity (EUI) and/or emissions reduction targets. 3) We helped Berkeley, California investigate legislation requiring electrification of heating systems and the trade-offs between emissions reductions and the timing and scope of the policy. With all three cities, we focused on utilizing existing measured data to build predictive models allowing comparison of potential policy designs with respect to which buildings are most affected by the policies, how much emissions savings can be expected, and when the savings will occur. We summarize the lessons we learned during these projects, and offer advice for other cities interested in implementing BPS policies.

Introduction

Many U.S. cities are addressing climate change by setting goals to reduce their greenhouse gas (GHG) emissions. In most U.S. cities, the building sector is the largest contributor to the city's total GHG emissions. Many cities are passing legislation to target existing buildings through benchmarking, auditing, tune-ups, or energy or emissions performance standards. In the U.S., the most common policy mechanism so far has been the disclosure of benchmarking data. Required energy audits and building tune-ups are less common. While benchmarking and audits do not directly require energy or emissions reductions, the idea is that collecting and disclosing energy information can prompt action by building owners and operators (Meng, Hsu, and Han 2017; Palmer and Walls 2017; Kim and Lim 2018; Gui and Gou 2020). However, a study of New York City's mandatory audit policy found that the resulting reductions were not enough to meet the city's GHG reduction goals (Kontokosta, Spiegel-Feld, and Papadopoulos 2020).

Building tune-ups involve assessing and implementing operational and maintenance improvements to increase energy efficiency, such as changes to thermostat setpoints or lighting schedules (Sullivan, Baker, and Ringeisen 2020). Though sometimes considered different, in this paper, we treat tune-ups and retro-commissioning (RCx) to be largely synonymous. Tune-ups are low cost, typically do not require capital investment, and are therefore an important first step

toward reducing energy use and emissions prior to implementing higher-cost measures such as replacing lighting and HVAC equipment and envelope upgrades. Additionally, tune-ups can help ensure savings persistence from previously implemented energy efficiency measures. Several studies have documented energy savings due to tune-ups, including meta analyses across multiple projects (Mills et al. 2004; Mills 2011; Mills and Mathew 2014; Fernandez et al. 2015; Katipamula 2016; City of Seattle 2020a; Crowe et al. 2020), and simulation-based analyses (Fernandez et al. 2017). Crowe et al. showed median source energy savings ranged from 5% to 14%. However, these studies generally involve building-level savings, and there is limited information on the impacts of tune-ups across an entire building stock when implemented as a policy measure.

Recognizing that benchmarking, audits, and tune-ups are not aggressive enough to meet most climate goals, several cities and states have passed mandatory building performance standards (BPSs) that require buildings to meet a particular level of energy or emissions performance (Nadel and Hinge 2020).

When designing a BPS policy, cities should consider the specific policy questions they are trying to answer, and select an analysis methodology suited to answering those questions with the necessary level of accuracy. Analyzing stock-level impacts of building policies is an established field and the literature shows a variety of approaches depending on the objectives of the analysis, data availability, and desired level of accuracy (Brøgger and Wittchen 2018; Langevin et al. 2020). For example, one approach is to use sector-level aggregate data and then determine sector-level impacts of an intervention by assuming a technical savings rate and adoption rate (Langevin, Harris, and Reyna 2019). At the other end of the spectrum are approaches that use data on individual buildings within a geographical area such as a city or a state. These include empirical approaches using energy benchmarking and audit data (Bergfeld et al. 2020; Kontokosta, Spiegel-Feld, and Papadopoulos 2020; Walter and Mathew 2021), as well as simulation-based approaches (Hong et al. 2016; Chen, Deng, and Hong 2020; Ferrando et al. 2020; Wang et al. 2021).

In addition, cities must consider the technical expertise, time, effort, and data required to conduct the analysis. For example, simulation-based methods can provide detailed results for individual buildings, but few cities have the required expertise to build, calibrate, and run simulation models for a significant portion of their stock. On the other hand, empirical approaches require less expertise and can provide results that are reasonably accurate for city-wide impacts, but may be limited by the availability of building-level data. Cities with benchmarking data can assess the impacts of requiring energy or emissions reductions, but cities that also have audit data can better understand what measures would need to be taken to achieve the reductions.

In this paper, we discuss three projects in which we used empirical data analysis to analyze and design city-level policies for reducing emissions:

1. We analyzed the results of a tune-ups program implemented in Seattle, Washington to learn how much energy savings can be expected and which building and systems types may save the most.
2. We worked with Aspen, Colorado to quantify expected city-wide emissions reductions from a variety of potential BPS legislation setting energy use intensity (EUI) and/or emissions reduction targets.
3. We helped Berkeley, California investigate legislation requiring electrification of heating equipment and the trade-offs between emissions savings and replacement age.

Each city had different policy questions and different data with which to analyze the policy impacts. We utilized measured data to understand which buildings are most affected by the policies, quantify the expected emissions savings, and predict when the savings will occur. In the following sections, we describe the data and methods used for each of these projects. We conclude by summarizing the lessons we learned and offering advice for other cities interested in implementing BPS policies.

Seattle, Washington: Energy savings from a tune-ups program

As a part of their climate action plan (City of Seattle 2013) that set a goal of zero net GHG emissions by 2050, the Seattle implemented a program requiring building tune-ups for large commercial buildings (City of Seattle 2020b). We analyzed data collected during Seattle's tune-ups program to better understand the impacts of implementing a city-wide building tune-ups program, and whether tune-ups should be targeted at particular buildings or systems (Walter and Mathew 2022).

Data

Seattle's tune-up program requires commercial buildings with floor area greater than 50k sqft to be assessed by trained specialists. The specialists recorded building characteristics (use type, floor area, year built, occupancy) and systems characteristics (type, age, and condition of lighting, heating, cooling, ventilation, distribution, and domestic hot water systems). Since energy use data was only available for the whole building, we aggregated space-level (e.g., building type) and system-level (types, ages, conditions, etc.) data to building-level using floor area weighting.

During the tune-up inspection, a tune-up specialist checked for 18 HVAC issues (10 related to operations, and 8 related to maintenance), 4 lighting issues, 2 domestic hot water issues, and 3 envelope issues. For each of these 27 issues, the dataset includes a flag for whether or not the issue was identified during the inspection, and another flag for whether the issue was fixed (either during the inspection, or afterwards). The dataset also includes the name and company of the tune-up specialist that conducted the inspection. When practical, issues were rectified during the inspection. Other issues were repaired after the inspection. See (Walter and Mathew 2022) for descriptions of each of the issues.

For this analysis, we used weather-normalized site energy use data that was collected using ENERGY STAR's Portfolio Manager (ENERGY STAR 2021) as part of a benchmarking program (City of Seattle 2020c) that was independent from the tune-ups program. For the pre-tune-up period, we used the annual energy total from the last year concluding before the tune-up took place. The full year of post-tune-up period data proved more difficult, due to many buildings drastically altering their operations and/or occupancy due to the COVID-19 pandemic. Since we did not consider pandemic operations to be representative, we required the post-tune-up time period to end before the pandemic started in March of 2020 (resulting in roughly 80% of buildings not having enough post-tune-up and pre-pandemic energy data).

The resulting dataset includes 420 buildings with information on building characteristics, systems information, and tune-up inspection results. Only 82 of the 420 buildings had a full year of post-tune-up weather-normalized site energy data and were included in the energy savings analysis.

Analysis

For energy savings analysis, we used weather-normalized site energy use because the tune-ups for different buildings were implemented at different times (sometimes in different years), and we wanted to separate the effects of the tune-ups from potential differences due to weather variations from year to year. We observed significant variation in savings from building to building, and many buildings actually had increased energy use. Increased energy use may be due to buildings increasing occupancy or changing their service levels for reasons unrelated to tune-ups, or they could be due to tune-ups: systems may have been operating incorrectly and correcting their operation during the tune-up increased energy use (e.g., adjusting ventilation flowrates to meet code). Figure 1 shows a histogram of weather-normalized site energy savings. Median savings are 4.1%, but 34% of buildings had negative savings (i.e., they used more energy after the tune-up than before). We performed a paired *t*-test on the savings with $p=0.05$ and accepted the hypothesis that savings are 2.1% or greater.

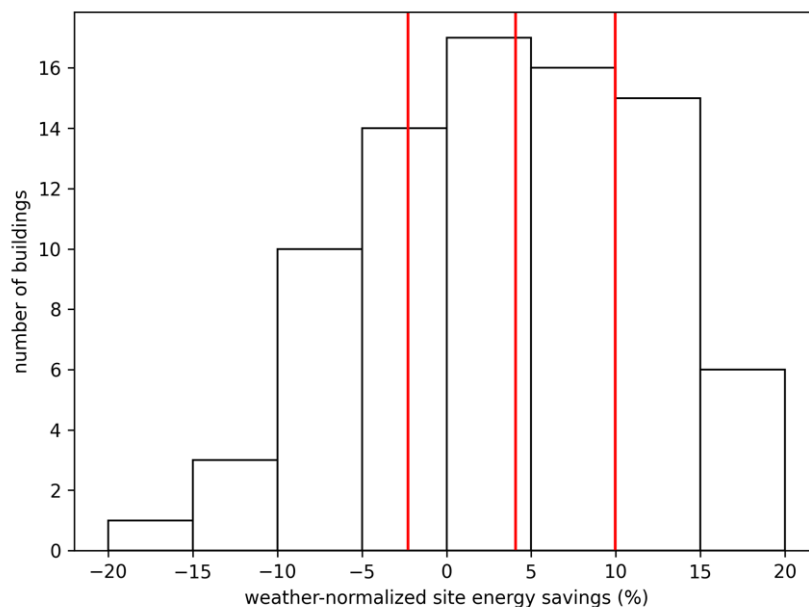


Figure 1. Histogram of weather-normalized site energy savings percentage for the 82 buildings with data. Red vertical lines indicate 25th, 50th, and 75th percentiles.

Next, we explored potential relationships between building and systems characteristics and energy savings due to tune-ups. We considered all of the building characteristics and system characteristics, and also considered the number of issues fixed due to the tune-up (including total number of issues, number of HVAC issues, number of lighting issues, etc.). Figure 2 shows boxplots of energy savings for buildings with each age of heating system. There is substantial scatter and significant overlap between subsequent boxplots. One might believe that an older heating system would have more problems, and thus more opportunities for energy savings, but we found no clear relationship.

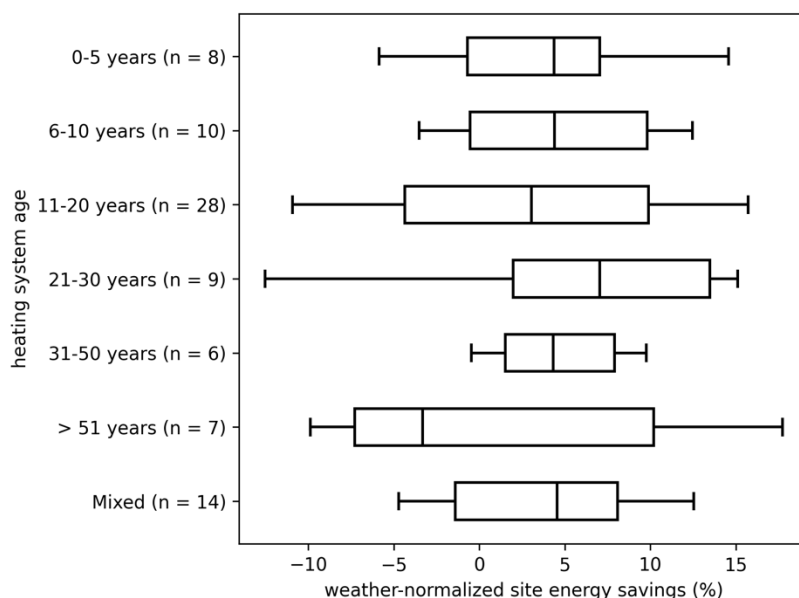


Figure 2. Boxplots of weather-normalized site energy savings percentage for buildings with each age of heating system. Values in parentheses are the number of buildings with that age (82 buildings total). Boxplots show 5th, 25th, 50th, 75th, and 95th percentiles.

In addition to visual inspection of relationships, we fit roughly 20 linear regression models to energy savings as a function of each of the building and system characteristics. We found very few statistically-significant coefficients, and those that were significant were for coefficients for very few buildings. We found no evidence that building or system characteristics could be used to reliably predict energy savings due to tune-ups. We suspect this is due to a combination of factors: the dataset is relatively small (82 buildings), and savings are both relatively small (median site energy savings were 4.1%) and highly variable. In short, there is likely too little "signal" and too much "noise".

Next, we looked at how building and system characteristics relate to the issues found during the tune-ups. Here, we consider the full dataset of 420 buildings, not only the 82 buildings with energy data. We started by considering the number of issues found during the tune-up. We fit roughly 20 linear regressions models to the number of issues found (total issues, HVAC issues, lighting issues, etc.) as a function of each of the building and system characteristics. We found roughly 10 regression coefficients that were statistically significant (with $p=0.05$). For example, we found that having a 100% outside air ventilation system is associated with 1.83 fewer issues being found, while having natural ventilation instead is associated with 3.60 fewer issues found. The large majority of the effects were intuitive (e.g., systems being in worse condition and being older are associated with more issues found). However, all coefficients except one had magnitude less than 3, indicating the effect building and system characteristics have on how many problems a building has is small.

We also explored the relationship between particular building or system characteristics and whether or not individual issues were found during the tune-up. We fit a logistic regression model to a binary indicator (i.e., 1 = issue found, 0 = not found) as a function of each of the building and system characteristics (plus the name and company of the tune-up inspector). In total, we fit over 500 models (corresponding to over 2500 model coefficients). Roughly one third of the statistically-significant ($p < 0.05$) coefficients were highly non-intuitive and deemed statistical anomalies not worth consideration (e.g., coefficients for lighting system type in a

model that predicts the probability of finding an HVAC issue). We also excluded from consideration the many cases in which the building or system characteristic has a weak effect on whether the issue is found. After those exclusions, we found only 8 cases where the model predicts a probability ≥ 0.8 of the issue being found for buildings with a particular characteristic. All 8 of these cases involved HVAC-related issues. One of the 8 cases shows an intuitive result: a relationship between distribution system age and the probability of finding equipment near the end of its service life.. In the other 7 cases, the predictor was either the name of the tune-up specialist or the specialist's company (i.e., a couple of inspectors and companies are very likely to find some particular HVAC issues during a tune-up).

Lessons Learned

We looked at changes in weather-normalized site energy use before and after tune-ups were completed, and found median savings of 4%. While tune-ups can be a cost-effective way to improve energy efficiency in individual buildings, a tune-ups program applied at a city-wide level is unlikely to yield the level of energy savings need to reach climate change goals.

We explored relationships between energy savings and building and system characteristics, but found no evidence that those characteristics could reliably predict energy savings. We also investigated relationships between tune-ups findings (i.e., quantity of issues found, and which particular issues were found) and building and system characteristics. We found no evidence that a tune-ups program should be limited to particular types of buildings, ages of buildings and systems, or buildings with particular systems installed. Similarly, we found no evidence that tune-ups should be limited to only checking for particular issues or types of issues.

Aspen, Colorado: Emissions reductions from EUI and GHGI targets

Aspen is planning to implement BPS legislation in order to meet their community GHG reduction goal of zero carbon emissions by 2050. We modeled city-wide emissions reductions from a variety of potential BPS legislation implementations based on setting energy use intensity (EUI) and/or GHG emissions intensity (GHGI) reduction targets and buildings meeting the targets through either efficiency or electrification.

Data

We used Aspen's tax assessor data to compile a list of all buildings in the city, along with their gross floor area and use type. Due to limited detail in the tax assessor data, we combined all commercial buildings into a single category, but were able to separate residential buildings into single family, multifamily with 2-4 units, and multifamily with 5 or more units. We checked that each building's use type was consistent with its floor area, and made corrections when necessary. Since the assessor data contained many condominiums, we aggregated multiple records representing individual units into a single unit representing the whole building.

No measured energy use was available for Aspen's buildings. Instead, we used energy data from the CBECS (EIA 2012) and RECS (EIA 2015) datasets. We selected only buildings from CBECS and RECS that were located in the mountain census division and were located in cold or very cold climate regions, since this is most representative of Aspen's location. From the CBECS and RECS datasets, we generated distributions of two key energy consumption parameters: site EUI and the proportion of site EUI that is electricity. For each building in Aspen, we sampled site EUI and the electric to site ratio from the CBECS or RECS distribution,

then, using the sampled values and the Aspen building's actual floor area (from the tax assessor data), computed the building's site, electric, and natural gas energy use.

This left us with a dataset including building type, floor area, electric energy use, and natural gas energy use for each building in Aspen. We also used future projections of CO₂e grid emissions factors for each year from 2020 to 2050 from NREL's Cambium tool (NREL 2022a).

Analysis

To quantify the impacts of potential BPS policy implementations, we constructed a model of how each building's energy use changes over time as the building becomes subject to different policy targets. In 5-year cycles, new targets are set, and each building reduces its energy use to meet its target. Targets are either particular values of site EUI or of GHGI and are specific to each building type. During each 5-year cycle, buildings reduce their energy use to meet their targets either by increasing efficiency (i.e., reducing electric and gas use proportionally), or by electrifying (i.e., replacing natural gas energy use with electric energy use).

We exercised our model on several different policy scenarios, as described in Table 1. For each scenario, we computed each building's electric and gas energy use and GHG emissions in each year from 2020 to 2050, then combined the results into city-wide totals.

Table 1. Descriptions of scenarios for Aspen

Scenario name	Description
Basecase	No energy reduction. Emissions only change due to grid emissions factors changing over time.
EUI	Buildings reduce energy use proportionally (electric/gas ratio stays the same) to meet EUI targets every 5 years. Single Family exempt.
EUI + Single Family	Same as "EUI" scenario, except Single Family is included.
GHGI	Buildings reduce energy use proportionally to meet GHGI targets every 5 years. Single Family exempt.
Electrify (COP=2)	Buildings replace gas energy use with electric (with coefficient of performance = 2) to meet GHGI targets every 5 years. Single Family exempt.
Electrify (COP=3)	Same as "Electrify (COP=2)" scenario, except coefficient of performance = 3. Single Family exempt.

Figure 3 shows the total GHG emissions from 2020 to 2050 resulting from the each of the different policy scenarios in Table 1. In the two electrification scenarios, emissions are the same as in the basecase scenario until 2030 because before 2030, Aspen's electric grid is more carbon-intensive than natural gas. After 2030, many buildings fully electrify, but still do not meet the GHGI targets (due to a combination of a carbon-intensive electric grid and high site energy use, likely due to heating during the winter). Thus, the two electrification scenarios do not yield significantly more emissions savings than the basecase. In the EUI and GHGI scenarios, all buildings meet their individual targets (because the model allows as much electric and gas energy reduction as is necessary), but the city-wide goal of zero emissions by 2050 is not met. We set EUI and GHGI targets as low as we estimated to be technically and economically feasible, but these limits are not well known.

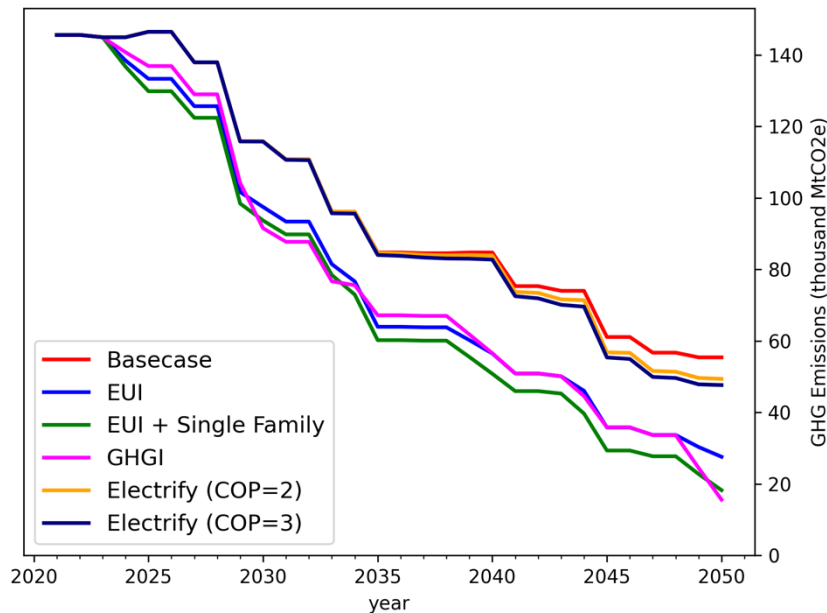


Figure 3. City-wide GHG emissions from 2020 to 2050 resulting from the different policy scenarios in Table 1.

Lessons Learned

We created a model of Aspen's building stock based on tax assessor data and on energy use data from CBECS and RECS. The tax assessor data did not contain specific use type for commercial buildings, so we sampled energy use for all commercial buildings from the same distributions. Also, it is not clear how representative the CBECS and RECS energy use distributions are of Aspen's actual building stock. In order to increase confidence in the applicability of our results to Aspen's expected outcomes, we recommend implementing a benchmarking program that will both record more precise use types for commercial buildings, and will measure actual energy use by buildings in Aspen.

We modeled several different potential BPS policy implementations and the resulting emissions from 2020 to 2050. We found that EUI and GHGI targets largely have the same effect, and thus recommend using EUI targets in BPS legislation because it is easier for building owners and operators. In all modeled scenarios, we found that the reduced carbon intensity of the electric grid was a major driver of emissions reductions, and that BPS policies had a smaller impact in comparison, although BPS can drive reductions sooner than other policies (resulting in less cumulative emissions). Finally, we found that electrification alone is not sufficient to meet Aspen's emissions goals; energy use reductions are required as well.

Berkeley, California: Emissions reductions from electrification

Berkeley has set a goal to eliminate their GHG emissions from buildings using legislation requiring electrification. Since essentially all of the city's electricity will come from renewable generation in the very near future, full electrification of the building stock will effectively meet this goal. Berkeley is considering legislation that will require electrification of space and/or water heating systems at the end of the equipment's life, or sooner. We modeled Berkeley's GHG

emissions due to these alternate BPS implementations to better understand the emissions reductions due to different potential policy implementations.

Data

We used tax assessor data to compile a list of all buildings in Berkeley, along with their use types and floor area. We used Berkeley's benchmarking data (City of Berkeley 2022) to learn the current distribution of electric and gas consumption for each building use type, and imputed missing data by sampling from San Francisco's benchmarking data (City of San Francisco 2021), CBECS (EIA 2012), and RECS (EIA 2015). We used audit data provided by Berkeley to understand the types, ages, and efficiencies of space heating and hot water heating systems currently installed in Berkeley's buildings, and imputed missing data using San Francisco's audit data and engineering judgement. Since very few buildings have data on the amount of energy used specifically for space and water heating in the audit data, we imputed missing data using CBECS (EIA 2012).

Analysis

We constructed a model of Berkeley's building stock that includes building type, floor area, electric and natural gas consumption, and the type, age, fuel, and efficiency of each space and water heating system. The model forecasts each building's energy use and GHG emissions each year as the buildings are subject to the BPS policy under consideration: When a system reaches a specified age, it is replaced by an electric system with efficiency dictated by the current year (we assumed COP=2 for 2020-2030, COP=3 for 2030-2040, and COP=4 for 2040-2050). Systems that were initially electric are replaced with a more efficient electric system. We assumed grid emissions factors did not change over time, since they are already effectively zero. To mirror the legislation currently being considered by Berkeley, the model only replaces equipment for buildings (both commercial and multifamily) with floor area > 20k sqft. We used the model to compute emissions savings under the different policy scenarios described in Table 2.

Table 2. Descriptions of scenarios for Berkeley

Scenario name	Description
Baseline	Space heating equipment replaced when age is 30 years (for furnaces), 20 years (for packaged systems), or 25 years (all other systems). Water heating equipment replaced when age is 20 years.
5 years earlier	Same as baseline, except all systems are replaced 5 years earlier.
5 years later	Same as baseline, except all systems are replaced 5 years later.
Space heating only	Same as baseline, except only space heating systems are replaced.
Water heating only	Same as baseline, except only water heating systems are replaced.

Figure 4 shows the total emissions for all buildings in Berkeley with floor area > 20k sqft resulting from the policy scenarios in Table 2. Replacing equipment 5 years earlier results in the same emissions in 2050 as the baseline, but replacing equipment 5 years later results in slightly higher emissions in 2050 than the baseline (because some equipment doesn't get replaced by 2050). However, when considering cumulative emissions from 2020 to 2050, replacing equipment 5 years earlier results in 22% more savings than the baseline and replacing equipment 5 years later results in 24% less savings than the baseline (Figure 5). Figure 4 also shows the

emissions savings to be expected when replacing only space heating equipment (75% of the baseline) or only water heating (25% of the baseline).

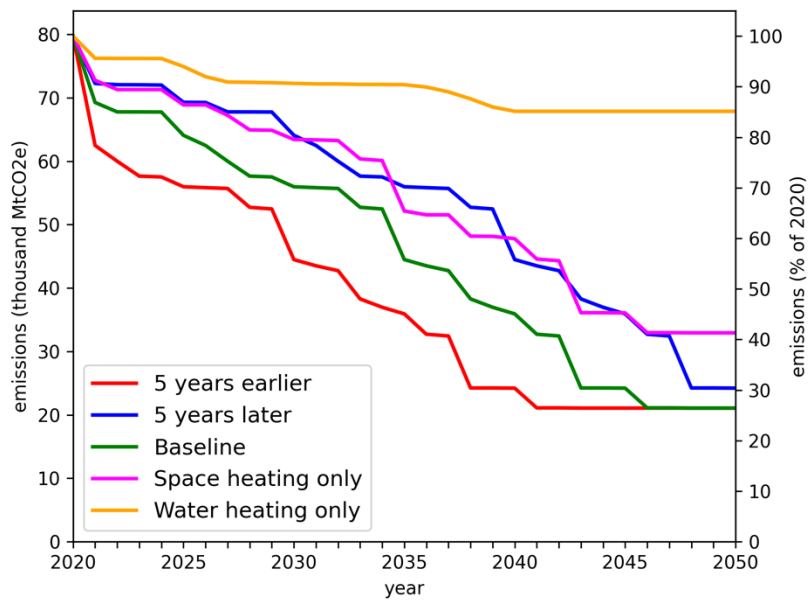


Figure 4. GHG emissions for buildings > 20k sqft from 2020 to 2050 resulting from the policy scenarios in Table 2.

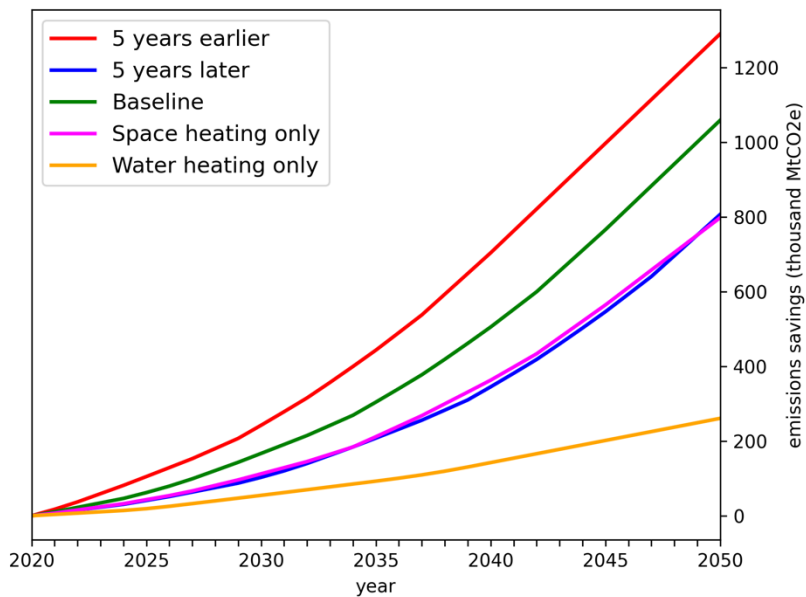


Figure 5. Cumulative GHG emissions for buildings > 20k sqft from 2020 to 2050 resulting from the policy scenarios in Table 2.

Lessons Learned

While Berkeley provided detailed audit data for this analysis, it included a very small portion of the buildings in the city, and even after utilizing San Francisco's audit data as well, a large portion of the systems data was imputed using engineering judgement. Detailed systems data was required for this electrification analysis, and more of it would improve confidence in the modeling results. We learned that electrification of space heating systems results in roughly three times the emissions savings as electrification of water heating systems, so they should be prioritized. We also learned the large impact that replacing equipment earlier has on cumulative emissions. However, our analysis did not include cost-effectiveness and it's not clear whether the additional emissions reductions are worth replacing equipment earlier than necessary (i.e., there are increased costs associated with replacing equipment that is still functioning).

Conclusions

In this paper, we summarized lessons learned during analyses of planned BPS policies by three cities using empirical building data. Empirical analysis of building data can provide reasonably accurate stock-level results without significant expertise, making it an effective method for cities considering BPS policies. While many cities have the same broad goal to reduce emissions, one size does not fit all when it comes to analyzing the impacts of specific BPS policies. The three cities have different climate goals, policy objectives, and data availability, thus different analyses were conducted and different lessons were learned.

From Seattle's tune-ups data, we learned that tune-ups, while low cost, provide relatively small (a few percent) reductions at the city-wide level, and that tune-ups programs need not be targeted at particular buildings or systems. In Aspen's case, we learned that the electric grid's carbon intensity has a large effect on emissions goals, that electrification alone is not sufficient, and that collecting city-specific benchmarking data would improve confidence in analysis results. From Berkeley's analysis, we learned that detailed audit data, though difficult to measure, is crucial for analyzing the impacts of electrification, and that electrifying sooner can have a large impact on cumulative emissions.

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