Connecting the Dots: Mapping Building and Demographic Drivers of Energy Use in Commercial Buildings

Lili Yu, Haley Tong, Joshua Kace, Travis Walter
Lawrence Berkeley National Laboratory

ABSTRACT

Understanding where efficiency investments have the greatest impact requires connecting building technology, operational features, and socio-economic factors. This study develops a distributional impact analysis framework that combines the Commercial Buildings Energy Consumption Survey (CBECS) with U.S. Census demographic data to examine how building features and socio-economic conditions influence energy use intensity (EUI) across various property types and climate zones. Using advanced geospatial mapping techniques, CBECS building records were linked with neighborhood-level Census data, creating a nationally representative dataset that associates buildings with their social environments.

A series of weighted least-squares regression models was estimated for each combination of property type and climate zone to identify the effects of heating and cooling systems, building age, and conditioning strategies, while accounting for local demographic differences. Results show that system type and conditioning level are the primary drivers of energy performance, with consistent variations in EUI based on different heating and cooling technologies and levels of conditioning. Buildings with limited or uneven conditioning sometimes have higher EUI, pointing to inefficiencies in partial or backup systems. Socio-economic factors display context-dependent patterns. For example, some lower-income buildings show lower EUI linked to reduced operational activity, while others exhibit higher energy use associated with older buildings and maintenance challenges. The framework is intended as a first-stage program-planning tool. By identifying combinations of property type, climate, HVAC configuration, conditioning level, and neighborhood context associated with elevated EUI, it can help program administrators prioritize segments for audits, targeted outreach, incentive design.

1. Introduction

1.1 Background

Commercial buildings account for a large share of U.S. energy use, and efficiency programs have long targeted this sector because technical upgrades can yield persistent savings. However, a recurring challenge is to identify where investments have the greatest impact and ensure that benefits are not concentrated only in areas with stronger market uptake or easier access to capital. In the commercial sector, energy performance varies widely by building function, climate, and operational intensity. At the same time, building stock characteristics and reinvestment cycles can differ across socio-economic contexts, affecting both baseline performance and the feasibility of upgrades. These realities motivate analytical approaches that consider building technology and operations together with local context, rather than treating them as separate planning dimensions. Recent planning and program-design literature increasingly emphasizes the value of finer analysis by building segment, location, and implementation conditions, rather than relying only on aggregate savings estimates (Reyna, Wilson, and Fontanini 2019; Kramer, Leventis, and Deason 2024).

Despite growing interest in such analysis, commercial building evidence is often limited by data fragmentation. National datasets often capture one dimension well but not the other. CBECS provides nationally representative building-level energy and characteristics data, including system type, building vintage, and conditioning level. It is widely used for stock-level characterization when survey weights are applied appropriately (EIA 2020). In contrast, socio-economic and demographic indicators are typically available at neighborhood scales through Census and ACS (American Community Survey) products (U.S Census Bureau 2024), which are frequently used to define populations or evaluate distributional patterns in public policy. However, they include a limited number of building descriptors needed to interpret EUI differences.

1.2 Related Work and Remaining Gaps

Prior work using large-scale building datasets has shown that EUI distributions are wide and that comparisons can be misleading without consistent peer grouping by property type, climate, size, and operating characteristics. Studies based on CBECS and the Building Performance Database demonstrate both the value of narrowly defined peer groups and the limitations created by missing or unevenly populated system and operational variables (Mathew et al. 2015; Sohn and Dunn 2019; Walter and Mathew 2019). Building-stock modeling studies extend this approach by segmenting commercial buildings by property type, climate, vintage, end use, and HVAC configuration to support local retrofit and policy planning (Reyna, Wilson, and Fontanini 2019; Parker, Dahlhausen, and Wilson 2024). This literature establishes the importance of technical segmentation, but generally gives less attention to how neighborhood socioeconomic conditions may intersect with observed energy performance.

A parallel program-design and equity literature focuses on how customer and community context affects program reach and implementation. Reviews of small-commercial and comprehensive-retrofit programs find that participation depends on tailored outreach, trusted delivery partners, incentive structures, financing, and program designs suited to distinct customer segments (Nowak 2016; Srivastava and Mah 2022; Kramer, Leventis, and Deason 2024). For nonresidential community-serving institutions in low- and moderate-income areas, program administrators have also used targeted partnerships and delivery strategies to address resource and participation barriers (Drehobl and Tanabe 2019). More broadly, distributional equity frameworks call for demographic and socioeconomic indicators to be incorporated into assessments of who receives the benefits and bears the costs of energy-efficiency and distributed-energy investments (Woolf et al. 2024). Census-derived measures of poverty, income, housing, and population are already widely used to define populations and guide public-resource allocation (Reamer 2018; U.S. Census Bureau 2022, 2024).

Despite these advances, the technical building-performance and program-equity literatures remain only loosely connected. National commercial-building studies typically characterize energy use and technology at the building or stock level without attaching detailed neighborhood socioeconomic context. Conversely, program and equity studies often use community indicators to guide eligibility, outreach, or resource allocation without jointly modeling building-level EUI, HVAC systems, conditioning level, and climate. To our knowledge, limited work has integrated nationally representative commercial-building microdata with neighborhood-level socioeconomic indicators in a unified framework that supports segment-specific interpretation by both property type and climate. This study addresses that gap while treating neighborhood measures as contextual screening variables rather than direct measures of building-owner or tenant characteristics.

1.3 Research Question & Contribution

This study is focusing on two research questions that support targeted efficiency planning in the commercial sector.

First, what building characteristics are most strongly associated with variation in site energy use intensity (EUI)? The analysis focuses on HVAC (Heating, Ventilation, and Air Conditioning) heating and cooling system type, building vintage, and conditioning level because these variables represent actionable technology and operational dimensions.

Second, how does neighborhood socio-economic context relate to EUI, and do observed patterns vary across property types and climates? Census-derived measures are widely used in public policy to describe local conditions and to support consistent screening and allocation decisions. Integrating these measures with building-system descriptors provides an empirical basis for examining whether context is associated with higher or lower EUI within comparable segments.

This study develops a distributional impact analysis framework that links building technology, operating characteristics, and neighborhood context to evaluate drivers of site EUI across property types and climate zones. The approach links CBECS building records with neighborhood-level Census attributes using reproducible crosswalk-based geospatial mapping methods. Weighted least-squares regression models are then estimated for each combination of property type and climate zone to isolate the effects of heating and cooling system type, building vintage, and conditioning level while accounting for local demographic variation. The resulting framework is designed to support targeted efficiency planning by distinguishing technology-driven differences in energy performance from context-dependent patterns that may reflect variation in usage intensity and building stock conditions.

2. Methodology

2.1 Data Source

The analysis integrates building-level energy and characteristics data with neighborhood-level demographic indicators to evaluate drivers of commercial building energy use intensity (EUI) across building segments and climates. Building records are drawn from the Commercial Buildings Energy Consumption Survey (CBECS), which provides nationally representative microdata on annual energy consumption, floor area, property type, climate zone, HVAC system characteristics, and conditioning coverage. Site EUI is used as the primary outcome metric and is computed as annual site energy consumption divided by floor area. Because CBECS is a complex survey designed for population inference, survey weights are retained and applied throughout estimation to preserve national representativeness within each modeled segment.

Neighborhood context is characterized using U.S. Census and American Community Survey (ACS) measures intended to capture socio-economic and demographic conditions that may correlate with building stock characteristics and operational intensity. The analysis includes indicators such as neighborhood poverty or income measures, minority percentage, English proficiency, and age-related measures. A neighborhood-level proxy for surrounding built-environment vintage is also included using Census housing "year built" distributions to represent the general age profile of the local building stock.

2.2 Geospatial Linkage

In this study, CBECS building records are first assigned a ZIP code geography using a combination of CBECS public-use microdata and restricted-access fields. Census demographic and socioeconomic attributes are available at Census tract resolution. To align these sources, HUD USPS ZIP Code Crosswalk Files [10] are used to map ZIP codes to Census tracts and to support reproducible geographic translation between the two units.

Figure 1 summarizes the linkage workflow. The CBECS building sample (public + private components) is mapped to ZIP code geography, while Census-based social indicators are represented at the tract level. HUD ZIP-tract crosswalk relationships provide the bridge between these geographies, enabling the merge of tract-level demographic attributes onto CBECS building records. The resulting analysis dataset combines building energy use and commercial building characteristics with neighborhood-level demographic and socioeconomic measures under a consistent geographic linkage, supporting segmented analysis by property type and climate zone.

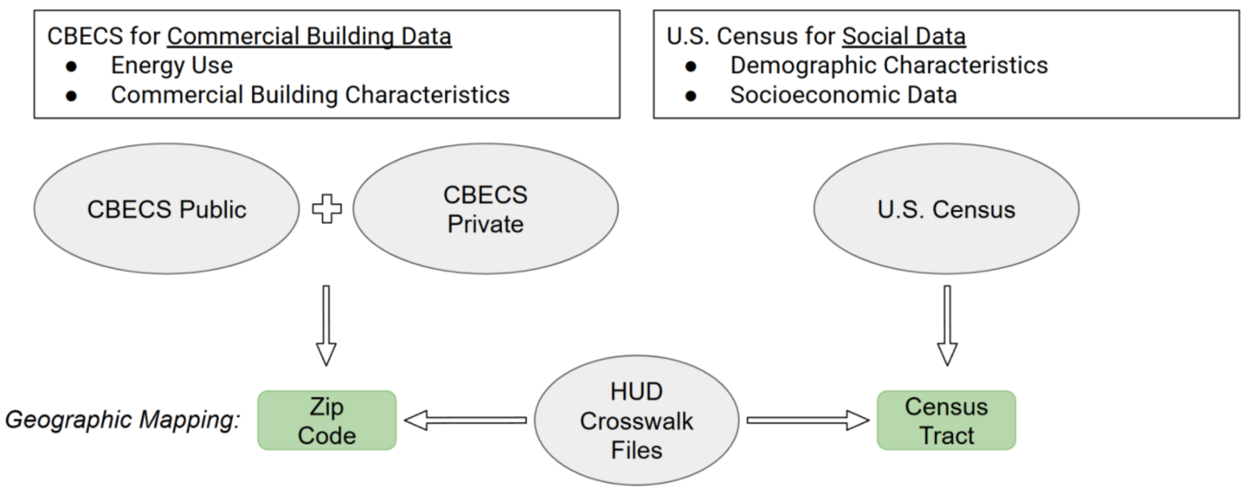

Figure 1. Geospatial linkage for constructing the analysis dataset.

2.3 Study Scope

The analysis is structured on property-type × climate-zone segments. The property type selections balance two considerations: energy impact and statistical support in the underlying CBECS data.

First, property types were screened based on their contribution to aggregate energy use. Figure 2 shows the weighted median EUI and total energy use by building type. The Office, Education, and Strip shopping center represent the largest contributors to total energy use among the building categories. They are also relatively heavy energy users when looking at the weighted median EUI of individual buildings within each category. These segments are therefore prioritized because they represent large opportunities.

Second, property types were screened for building volume and data availability in CBECS. Figure 3 summarizes building-type representation in CBECS, showing both raw row counts and weighted totals. The row counts reflect the variability, while the weighted totals represent the total number of buildings. Nonrefrigerated warehouse, Office, and Education appear as the most data-rich categories by row count, indicating stronger statistical support and broader variation in building characteristics available for segmented regression modeling. This consideration is especially important once the analysis is further stratified by climate zone, where sparsity may limit interpretability.

Together, these two considerations support the final study set: Offices, Education, Strip shopping centers and Nonrefrigerated warehouses. Education is further split into subtypes: College/University, K-12 School, and Preschool/Daycare (Preschool/Daycare was later excluded from analysis due to insufficient sample sizes under this sub-category).

Climate zones are used to capture differences in heating and cooling demand and to support interpretation of HVAC technology impacts under different weather conditions. The segmented design therefore supports comparisons within consistent peer groups.

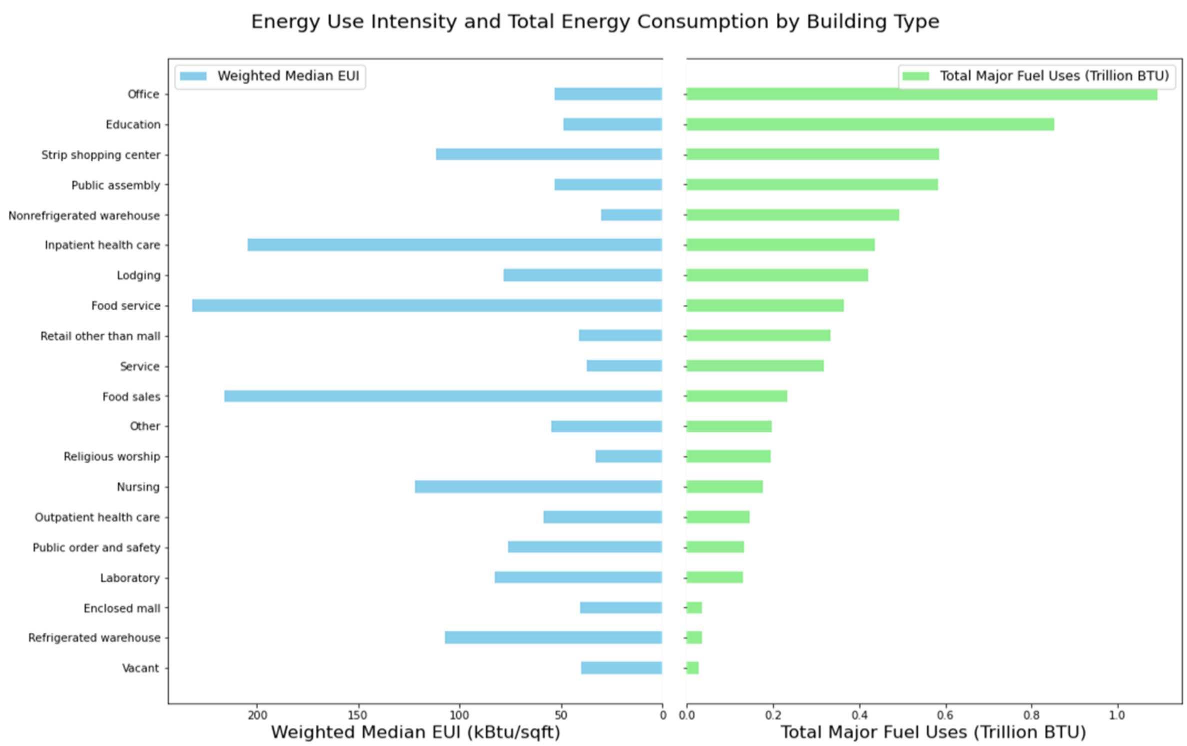

Figure 2. Property type screening by energy impact using CBECS: weighted median EUI and total major fuel consumption by building type.

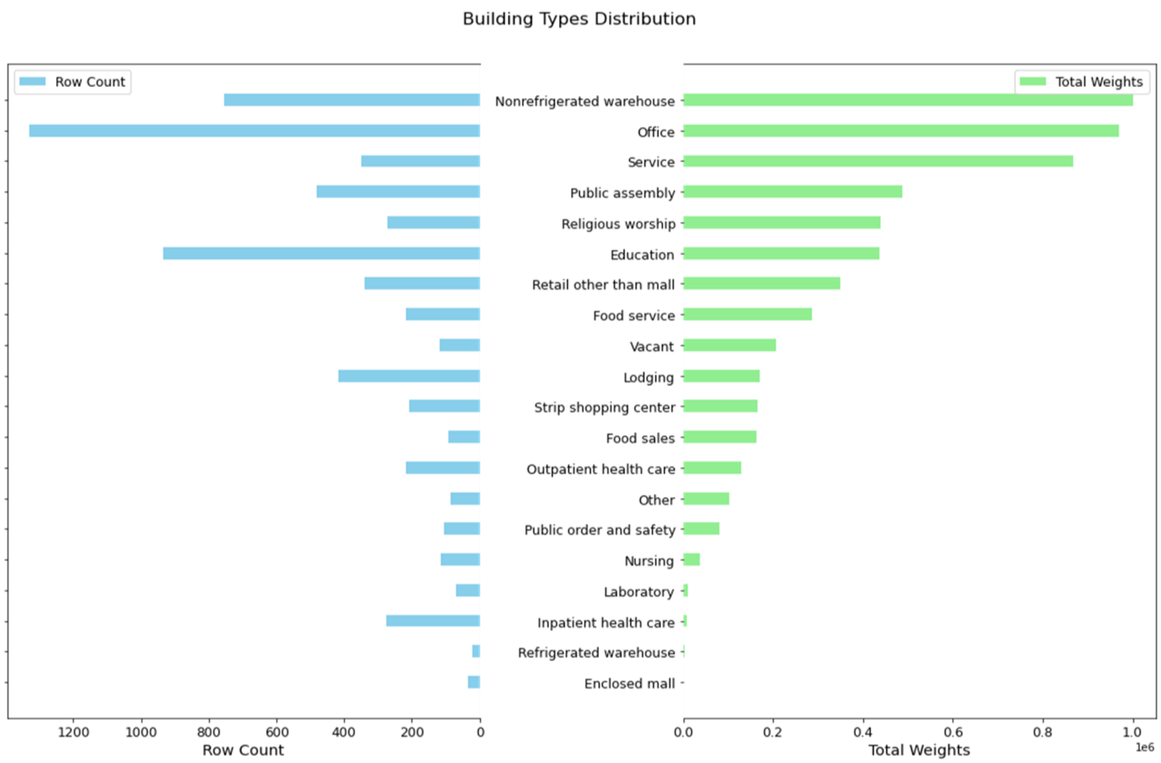

Figure 3. Property-type screening by statistical support using CBECS: sample row counts and weighted totals by building type.

2.4 Variable Construction and Modeling Approach

The analysis draws on two sources: (i) CBECS building records providing energy use and commercial building characteristics, and (ii) Census/ACS neighborhood indicators providing demographic and socioeconomic measures at the tract level. Table 1 summarizes the variables used in the integrated dataset.

Table 1. Variables of interest used in the datasets (source variables and derived measures)

Variable	Source	Type	Definition / Notes
Heating system type	CBECS	Raw	Main system serving space heating.
Cooling system type	CBECS	Raw	Main system serving space cooling.
Heated floor area (%)	CBECS	Raw	Percent of total building floor area that is heated.

Cooled floor area (%)	CBECS	Raw	Percent of total building floor area that is cooled.
Low-income % (poverty rate)	Census	Raw	Percent of all people below the Census poverty threshold.
Minority %	Census	Derived	Computed as (1 - White / Total population) × 100%.
Limited English proficiency share	Census	Raw	Percent of population speaking English less than "very well."
Median population age	Census	Raw	Median age of the population.
Median building vintage	Census	Derived	Derived median housing-vintage group from the "year structure built" distribution (used as a proxy for the age profile of the surrounding built environment).

Prior to modeling, several variables were recoded to support interpretability and comparability across segments. Several predictors are defined using grouped or categorical forms:

- HVAC system type is represented using consolidated heating and cooling categories that capture meaningful differences in technology and fuel use. Heating system type was grouped into district heating (reference), fuel-based, heat pump, and other electric. Cooling system type was grouped into district cooling (reference), heat pump, other electric cooling, other cooling types, and no cooling.
- Conditioning level was constructed by combining the reported percent heated and percent cooled into five categories: high conditioned (heating > 80% and cooling > 80%), heating dominant (heating > 80%, cooling ≤ 40%), cooling dominant (cooling > 80%, heating ≤ 40%), moderate conditioned (both 40–80%), and not/under Conditioned (both ≤ 40%; reference).
- Neighborhood median building vintage was represented using a binary indicator with 1980 as the threshold separating older vs. newer.
- Socio-economic indicators are represented using relative "high" versus "low" categories (defined within each segment) to enable within-context comparisons.

For each property-type × climate-zone segment, a weighted least-squares regression model is estimated with site EUI as the dependent variable. Models include HVAC heating system type, HVAC cooling system type, conditioning level, building vintage, and socio-economic indicators as predictors. CBECS survey weights are applied in estimation.

To support robustness and reduce sensitivity to extreme values, EUI observations below Q1 - 1.5×IQR or above Q3 + 1.5×IQR were excluded using Tukey's conventional boxplot rule. This procedure was applied within each modeled segment to reduce the influence of extreme observations on weighted coefficient estimates. Models with fewer than 40 unweighted CBECS observations were excluded. The threshold was selected as a pragmatic minimum to reduce instability in models containing multiple categorical predictors; it is not intended as a formal guarantee of statistical power. Future work should evaluate coefficient stability using resampling or alternative minimum-sample thresholds. Coefficients are interpreted as differences in EUI relative to reference categories within each segment, supporting direct comparison under consistent building-type and climate conditions.

3. Results and Discussion

Figure 4 summarizes statistical significance patterns across the full set of segmented regressions. Each row represents a property-type × climate-zone combination, and each column represents a predictor. The figure highlights that no single variable is significant in every segment; instead, effects are segmented and context-dependent. Two predictors stand out showing frequent, strong signals across many segments: HVAC system type and conditioning level. In contrast, socio-economic predicators show more mixed patterns, with fewer consistently significant relationships across segments. Figure 5 provides the corresponding coefficient heatmap, showing the direction and relative magnitude of effects compared to the defined reference categories.

Together, Figures 4 and 5 provide an overview of where relationships are robust enough to interpret. They motivate a variable-by-variable analysis of results.

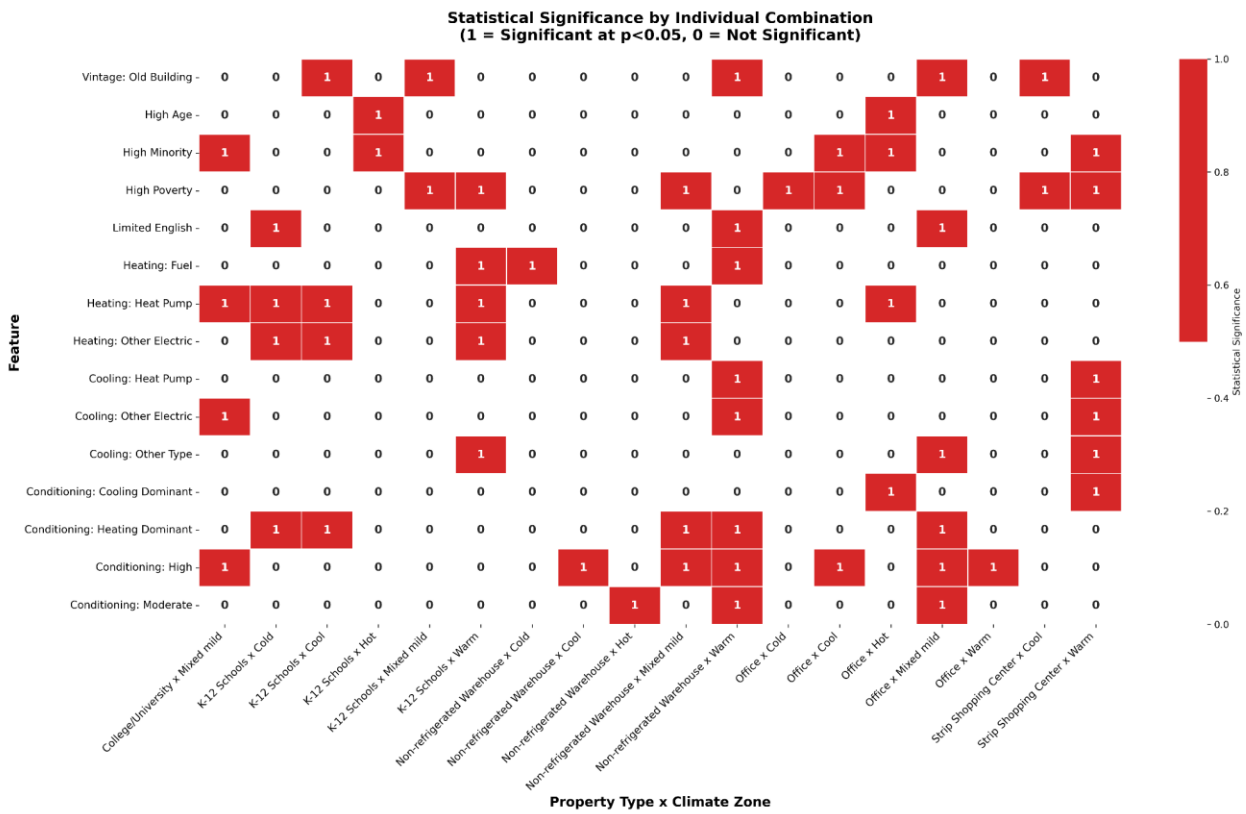

Figure 4. Statistical significance (p-value) heatmap across property-type × climate-zone regression models.

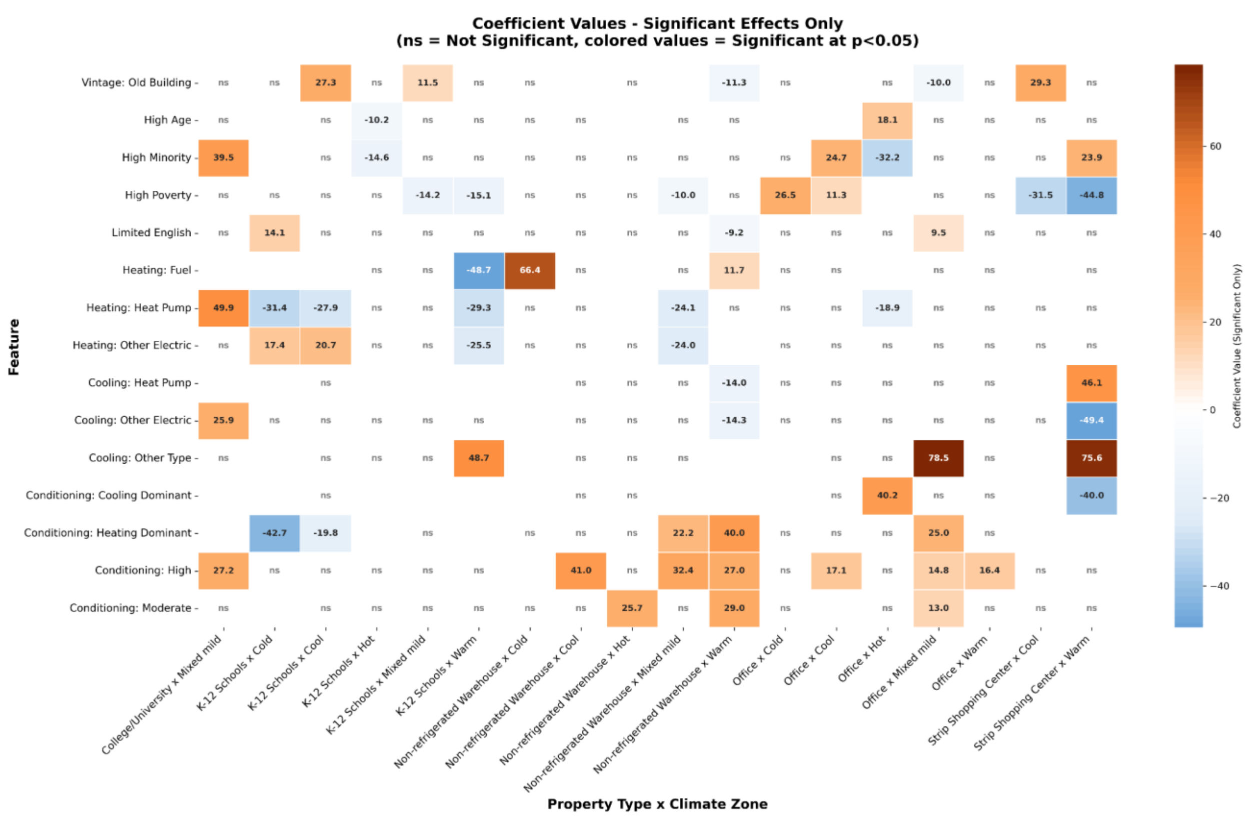

Figure 5. Coefficient heatmap (sign and magnitude) across property-type × climate-zone regression models.

3.1 Heating and Cooling System Type

Across the segmented models, heating system type shows the most consistent relationship with EUI. In the coefficient heatmap (Figure 5), the heat pump heating category frequently appears with negative coefficients relative to the heating reference configuration, indicating lower EUI across many property-type × climate-zone combinations. Fuel-based heating coefficients are more often positive, indicating underperforming especially in colder climate segments.

Figure 6 presents boxplots of EUI distributions by heating system type for a subset of segments where heating-type effects are statistically significant. While the boxplots represent unadjusted distributions (one variable at a time) rather than multivariable partial effects, the distributions generally reinforce the regression results: heat pump groups tend to cluster at lower EUI relative to other heating categories. Fuel-based heating has higher medians and wider spreads especially in colder climates.

Cooling system type shows fewer consistently significant effects across segments. The grouped “other cooling types” category tends to be associated with higher EUI. This category includes nonstandard or less common cooling configurations, such as evaporative cooling, natural gas chiller, etc.

Overall, these findings indicate that system configuration is a primary driver of EUI variation within comparable peer groups. Heating technology differences are most visible in climates where heating demand is high, and nonstandard cooling configurations can be associated with higher EUI in selected contexts.

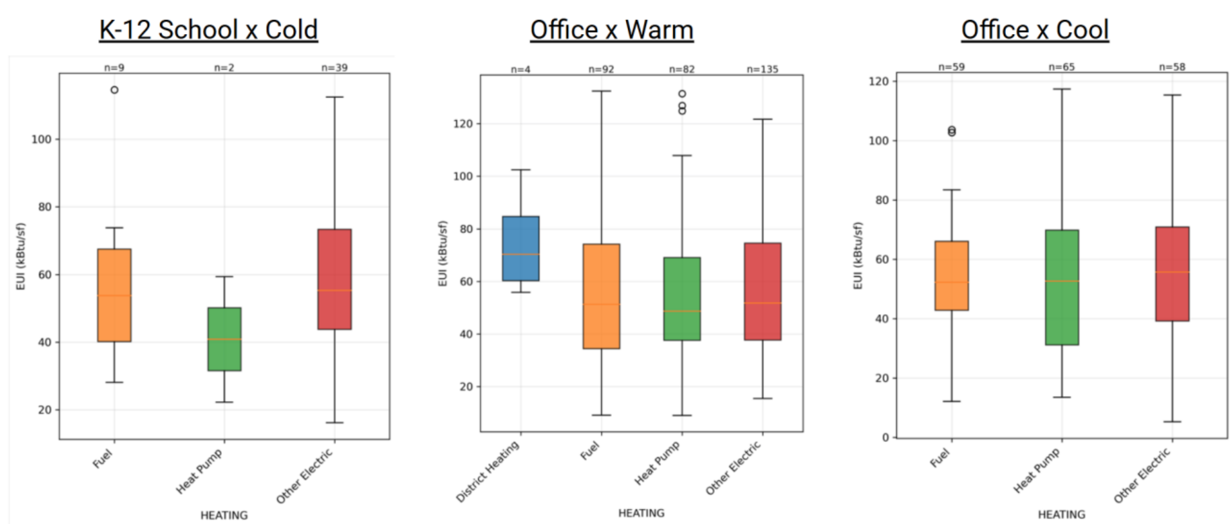

Figure 6. EUI distributions by heating system type for selected property type x climate zone segments with significant heating-type effects.

3.2 Conditioning Level

Conditioning level is frequently significant as observed in Figure 4. In many segments, greater conditioning coverage is associated with higher EUI. In the coefficient heatmap (Figure

5), this appears as positive coefficients for more conditioned categories relative to the low/under-conditioned reference.

However, one notable exception appears in K-12 schools in cold climates, where a heating-dominant conditioning level is associated with lower EUI relative to the under-conditioned reference. Figure 7 highlights this contrast. For most segments shown, the expected ordering is visible: high-conditioned buildings have higher EUI than under-conditioned buildings. In the K-12 x cold-climate case, the pattern is reversed, suggesting that under-conditioned buildings can have higher EUI despite lower conditioning coverage. One hypothesis is that some under-conditioned schools rely on localized or supplemental heating, poorly coordinated equipment, or control sequences that provide inconsistent thermal coverage while still consuming substantial energy. For example, localized space heaters or poorly controlled auxiliary systems can increase energy use without providing consistent conditioning at the building scale. This result suggests that conditioning coverage does not map directly to energy use in all segments. Uneven or partial conditioning can be associated with operational inefficiencies.

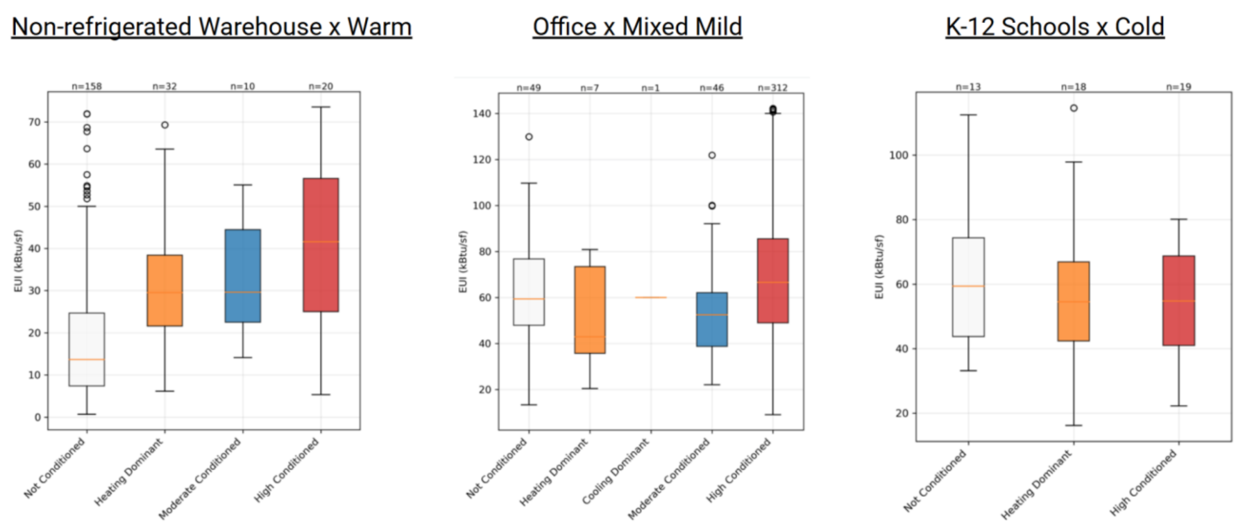

Figure 7. EUI distributions by conditioning level for selected property type x climate zone segments

3.3 Poverty Level

Among the socio-economic indicators, poverty level shows the clearest segmented pattern. The regression coefficients indicate that offices in higher-poverty areas tend to have higher EUI, while K-12 schools and strip shopping centers in higher-poverty areas often show lower EUI. Figure 8 illustrates this using boxplots for the corresponding segments. The boxplot direction generally aligns with the regression, even though the boxplots represent unadjusted comparisons (one variable at a time) rather than multivariable partial effects.

For K-12 schools and strip shopping centers, several modeled segments show lower EUI in higher-poverty neighborhoods. The available data do not identify the mechanism underlying this relationship. One possible explanation is lower operating intensity, such as fewer occupied hours, lower plug and process loads. In retail buildings, the reason would be differences in vacancy or tenant mix. However, these operating characteristics are not directly measured in the integrated dataset and should therefore be treated as hypotheses for future validation rather than explanations established by the present analysis. The opposite pattern appears in several office segments, where buildings in higher-poverty neighborhoods exhibit higher EUI. Potential explanations include differences in building condition, reinvestment cycles, HVAC efficiency, envelope performance, or operating practices. The concentration of some of these effects in colder climates is consistent with a possible heating-related contribution, but the regression results do not isolate the specific physical or organizational mechanism. Additional information

on operating schedules, ownership, tenancy, equipment age, maintenance practices, and end-use consumption would be needed to evaluate these hypotheses.

Figure 8. EUI distributions by neighborhood poverty level (High vs Low) for selected property type x climate zone segments

3.4 Other Socio-economic Factors

Additional socio-economic factors, including minority percentage, median population age, and limited English proficiency, show fewer significant relationships across the full set of segmented models. Where effects appear, they are not consistent across building segments. The limited consistency across these indicators suggests that these socio-economic factors contribute less explanatory strength for EUI differences in this dataset. Or, other relationships may be mediated by segment-specific factors not captured by the available descriptors.

4. Program Design and Implementation Implications

The analytical framework developed in this study can support program planning by combining two forms of segmentation that are often considered separately: the technical characteristics that influence energy performance and the neighborhood context in which buildings are located. The results should not be interpreted as a stand-alone method for determining program eligibility or estimating project-level savings. Rather, they provide a first-stage screening approach that program administrators can use to prioritize market segments for more detailed assessment, customer engagement, and program delivery.

First, the strong and recurring relationships between HVAC configuration and EUI suggest that program targeting can be improved by moving beyond property type and total consumption alone. For example, offices in colder climates with fuel-based heating and comparatively high EUI may warrant targeted HVAC assessments, building-envelope screening, or comprehensive retrofit offerings. Conversely, segments in which heat pump systems are associated with lower site EUI may provide useful peer groups for identifying candidate buildings with older or less efficient heating configurations. These associations do not estimate measure-level savings, but they can help narrow a large customer population to segments where audits and engineering analysis are more likely to identify substantial opportunities.

Second, the conditioning-level results indicate that low conditioned floor area should not automatically be interpreted as low efficiency-program potential. In some segments, including K-12 schools in cold climates, under-conditioned buildings exhibited higher EUI than more consistently conditioned peer buildings. Program administrators could use this pattern as a screening signal for operational assessments, retrocommissioning, control improvements, and investigation of supplemental or poorly coordinated heating equipment. Additional building-level investigation would be needed to determine the underlying equipment and operating conditions.

Third, neighborhood socioeconomic indicators can be used as an implementation overlay rather than as direct measures of building owner financial capacity. For example, a technically promising segment located in a higher-poverty area may warrant enhanced outreach, no- or low-cost technical assistance, higher incentive levels, streamlined participation requirements, or financing options that reduce upfront cost. However, neighborhood resident characteristics do not necessarily describe the financial resources or decision-making authority of commercial building owners and tenants. Program administrators should therefore combine neighborhood screening with ownership, tenancy, and business size before establishing eligibility or incentive levels.

The framework may also support program evaluation. Participation, incentive expenditures, completed projects, and realized savings could be compared across the property type, climate, technology, and neighborhood segments defined here. Such comparisons could reveal whether high-opportunity segments are being reached proportionately or whether particular groups remain underserved.

5. Limitations

Several limitations should be considered when interpreting the results.

First, the analysis is observational and cross-sectional. The estimated relationships represent associations rather than causal impacts.

Second, neighborhood socioeconomic characteristics describe residents living near a building and do not necessarily characterize the building owner, business operator, tenants, employees, or customers. Commercial properties may be owned by corporations or investors located outside the neighborhood, and tenants rather than owners may control equipment operation while owners control capital investment. Consequently, neighborhood indicators should be interpreted as contextual screening variables, rather than direct measures of decision-maker income, investment capacity, or program eligibility.

Third, variable grouping choices in this analysis are to support interpretability and stable estimation within segmented models. Grouping HVAC system categories reduces sparsity; however, it may mask heterogeneity within grouped classes. Converting continuous socio-economic measures into “high” vs “low” indicators reduces sensitivity to gradients and nonlinear relationships.

Finally, segments by property type and climate zone improve comparability; however, it reduces sample sizes to be analyzed. The segments with limited observations were excluded from regression analysis, which limits coverage for some building-type × climate combinations.

These limitations motivate future work to incorporate additional operational proxies where available, refine system classifications, and evaluate the robustness of results under alternative variable constructions.

6. Conclusions

This study develops a distributional impact analysis framework that links building technology, operational characteristics, and socio-economic context to examine drivers of commercial building EUI across property types and climate zones. Using geospatial mapping methods, CBECS building records were linked with neighborhood-level Census attributes to create a nationally representative dataset connecting buildings with surrounding social environments. Weighted least-squares regression models were estimated for each property-type × climate-zone combination to isolate the effects of heating and cooling technologies, building vintage, and conditioning strategies while accounting for local demographic variation.

Results indicate that system type and conditioning level are the strongest drivers of energy performance across segmented models, with consistent differences in EUI across heating and cooling technologies and levels of conditioning. Buildings with limited or uneven conditioning in some contexts exhibit higher EUI, suggesting inefficiencies in partial or backup configurations. Socio-economic indicators show context-dependent patterns that differ by building segment, highlighting the importance of peer-group interpretation and the need to distinguish technology-driven performance differences from patterns associated with operating intensity and stock condition. Overall, the framework demonstrates how integrating technical and neighborhood datasets can reveal new opportunities for targeted efficiency investment in the commercial sector.

References

Drehobl, A., and K. Tanabe. 2019. Extending the Benefits of Nonresidential Energy Efficiency to Low-Income Communities. Washington, DC: American Council for an Energy-Efficient Economy. Report U1910. www.aceee.org/research-report/u1910.

Kramer, C., G. Leventis, and J. Deason. 2024. Driving Uptake for Energy Efficiency Financing Programs: Marketing and Outreach, Partnership Networks, and Program Design Considerations. Berkeley, CA: Lawrence Berkeley National Laboratory. eta-publications.lbl.gov/publications/driving-uptake-energy-efficiency.

Mathew, P. A., L. N. Dunn, M. D. Sohn, A. C. Mercado, C. Custudio, and T. Walter. 2015. "Big-Data for Building Energy Performance: Lessons from Assembling a Very Large National Database of Building Energy Use." Applied Energy 140: 85-93.

Nowak, S. 2016. Big Opportunities for Small Business: Successful Practices of Utility Small Commercial Energy Efficiency Programs. Washington, DC: American Council for an Energy-Efficient Economy. Report U1607. www.aceee.org/research-report/u1607.

Parker, A., M. Dahlhausen, and E. Wilson. 2024. Commercial Building Stock Segmentation for Decarbonization Planning. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5500-88947.

Reamer, A. 2018. Census-Derived Datasets Used to Distribute Federal Funds. Counting for Dollars 2020, Report No. 4. Washington, DC: George Washington Institute of Public Policy.

Reyna, J., E. Wilson, and A. Fontanini. 2019. Preparing for a City-Scale Building Energy Upgrade Analysis: A Case Study for New York City. Golden, CO: National Renewable Energy Laboratory.

Sohn, M. D., and L. N. Dunn. 2019. "Exploratory Analysis of Energy Use across Building Types and Geographic Regions in the United States." Frontiers in Built Environment 5: 105.

Srivastava, R., and J. Mah. 2022. Moving the Needle on Comprehensive Commercial Retrofits. Washington, DC: American Council for an Energy-Efficient Economy. Report B2203. www.aceee.org/research-report/b2203.

U.S. Census Bureau. 2022. "Small Area Income and Poverty Estimates (SAIPE) Program." Accessed February 2026. www.census.gov/programs-surveys/saipe.html.

U.S. Census Bureau. 2024. "Census Bureau Data Portal." Accessed October 2025. data.census.gov.

U.S. Department of Housing and Urban Development. n.d. "HUD USPS ZIP Code Crosswalk Files." Accessed February 2026. www.huduser.gov/portal/datasets/usps_crosswalk.html.

U.S. Energy Information Administration. 2020. "2018 Commercial Buildings Energy Consumption Survey (CBECS)." Accessed February 2026. www.eia.gov/consumption/commercial/.

Walter, T., and P. Mathew. 2019. Is the BPD Nationally Representative? A Comparison of the Building Performance Database to the Commercial Buildings Energy Consumption Survey. Berkeley, CA: Lawrence Berkeley National Laboratory. bies.lbl.gov/sites/default/files/is-the-bpd-nationally-representative.pdf.

Wang, N., S. Goel, and A. Makhmalbaf. 2013. Commercial Building Energy Asset Score Program Overview and Technical Protocol (Version 1.1). Richland, WA: Pacific Northwest National Laboratory.

Woolf, T., A. Napoleon, N. Mims Frick, L. C. Schwartz, and J. Michals. 2024. Distributional Equity Analysis for Energy Efficiency and Other Distributed Energy Resources: A Practical Guide. Berkeley, CA: Lawrence Berkeley National Laboratory. eta-publications.lbl.gov/publications/distributional-equity-analysis.