Energy benchmarking in New York City:

Trends in Building Energy Consumption and Efficiency Pre and Post COVID-19

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A Senior Thesis submitted to the Economics Department of Fordham University,

In Partial Fulfillment of the Requirements for the Honors Program at

Fordham College at Rose Hill

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May 8th, 2025

Abstract

Energy benchmarking and disclosure policies have been widely adopted in major U.S. cities since the early 2010s to promote transparency and encourage energy efficiency improvements in large buildings. These policies aim to raise property owner awareness while enabling public and private entities to assess and compare building energy performance. While previous studies found efficiency gains in the years following implementation, few have examined trends since then, or how the COVID-19 pandemic affected energy usage patterns. This study analyzes benchmarking and land use data from New York City buildings between 2014 and 2023 to evaluate changes in energy trends. All major building categories saw improvement, with less efficient building types seeing the largest gains. In terms of raw energy reduction, multifamily housing and offices combined for 83.2% of total savings. This study also applies an Interrupted Time Series model, revealing that energy performance shifted most significantly in offices, K-12 schools, and hotels, sectors with large occupancy changes during lockdowns. Additionally, a Random Forest regression model predicted Source EUI with approximately 70% accuracy, identifying assessed value per square foot, total square footage, and building age as the most influential predictors. These results highlight the importance of tailoring policy to specific property types and demonstrate the value of integrating machine learning into benchmarking frameworks.

Introduction

Improving building energy efficiency has increasingly become a focus of climate policy in the 21st century. With buildings in the United States accounting for about 40% of total energy consumption and nearly 75% of electricity demand, making them essential to include in any strategy to lessen the effects of climate change.[1] Major cities have an even greater proportion of energy come from buildings, with their energy consumption reaching levels as high as 75%.[2] This makes improving building energy performance a necessity for cities that have set emission reduction targets, such as New York committing to reduce greenhouse gas emissions by 80 percent by 2050.[3] In order to do so, policies that can effectively improve building energy efficiency without incurring major costs as a necessity.[4]

One such policy that has gained widespread adoption in major US cities is energy benchmarking. Under energy benchmarking, building operators submit annual energy data on their total energy usage breakdown, which is subsequently released to the public. Additionally, buildings receive an ENERGY STAR score from 1 to 100 based on their relative energy efficiency compared to similar buildings in the United States, with buildings above a 75 eligible to receive an ENERGY STAR certification. By mandating energy usage reporting, policymakers seek to increase property operators' awareness of their building's energy usage and encourage the implementation of cost-effective energy usage improvements. Public access to benchmarking data also enables markets to better account for energy efficiency when viewing buildings, with buyers, tenants, and investors able to incorporate energy efficiency into property valuations and

[1] "Data and Analysis for Buildings Sector Innovation."
[2] "Building Energy Benchmarking and Disclosure in US Cities."
[3] "NYC Greenhouse Gas Inventories."
[4] Hesselink and Chappin, "Adoption of Energy Efficient Technologies by Households – Barriers, Policies and Agent-Based Modelling Studies."

leasing decisions.[5] Furthermore, energy-efficient buildings contribute to lower air pollution, more comfortable living conditions, and improved public health outcomes, benefiting the public as a whole.[6] Given these factors, proponents of energy benchmarking argue that its implementation benefits both the public as a whole and the private sector. Despite these benefits and the relatively low cost of many energy efficiency improvements, adoption and implementation of energy efficient measures are often slow, and disparities persist, particularly across building types and income levels.

A substantial body of research has studied the early effects of energy benchmarking in New York City, which became one of the first US cities to adopt such policies with the passage of Local Law 84 in 2009. However, the recent trajectory of energy usage across building types, particularly the effects during and following the COVID-19 pandemic, deserves more attention. This paper uses publicly available energy benchmarking and land use data from New York City to: (1) assess long-term trends in building energy performance, (2) evaluate how different property types responded to COVID-related disruptions, and (3) model the building characteristics most associated with energy usage intensity. Through this analysis, the study aims to assess what building efficiency trends have seen progress and where additional attention is needed.

2. Literature Review

2.1 Energy Benchmarking Overview

The concept of energy benchmarking gained prominence in the United States in the late 1990s and early 2000s, with the introduction of the U.S. Environmental Protection Agency's

[5] Popescu et al., "Impact of Energy Efficiency Measures on the Economic Value of Buildings."
[6] Baniassadi et al., "Co-Benefits of Energy Efficiency in Residential Buildings."

ENERGY STAR Portfolio Manager. Originally a voluntary tool, Portfolio Manager allows property owners to input building data, such as energy use, building size, occupancy, and usage type. Portfolio Manager then uses this data to generate a standardized performance score from 1 to 100, called ENERGY STAR Scores, comparing a building's energy efficiency to similar properties nationwide by adjusting for key characteristics. A score of 50 represents median performance, while buildings scoring 75 or above are eligible for ENERGY STAR certification, following the EPA's approach on energy-efficient labels for household appliances.[7]

Building upon the Portfolio Manager framework, local governments began adopting energy benchmarking mandates in the late 2000s. New York City was a pioneer in doing so, becoming the third major city to require annual energy reporting with the passage of Local Law 84 (LL84) in 2009. LL84 required buildings over 50,000 square feet to benchmark and publicly disclose their energy and water usage data each year through the Portfolio Manager platform. The goal was not just to gather data, but to increase energy consumption transparency, improve awareness among property owners, and lay the groundwork for future energy efficiency policies. Most US major cities, including San Francisco, Washington D.C., Seattle, Chicago, and Los Angeles, have passed similar benchmarking policies throughout the 2010s.[8] These policies vary in scope, but most target large commercial and multifamily housing buildings and require public disclosure of performance data. Many cities also now tie benchmarking to energy grading systems, retrofit requirements, or emissions caps, making it an integral part of local decarbonization strategies.

[7] Brown, Webber, and Koomey, "Status and Future Directions of the Energy Star Program."
[8] Seyrfar, Ataei, and Derrible, "A Review of Building Energy Benchmarking Policies Across the U.S. Cities."

Despite its widespread adoption, the ENERGY STAR methodology has faced criticism. Researchers have raised concerns about the tool's reliance on self-reported data, the inaccuracy of its scoring algorithm, and its limited ability to reflect building-specific or regional factors such as climate zones or usage variability. These limitations have resulted in calls for alternative grading systems, such as quantile-focused approaches, machine learning-based models, or more localized benchmarking tools.[9] [10] Regardless, benchmarking continues to serve as an essential component of building energy policy in the United States. It allows for increased energy transparency, providing the data infrastructure necessary for performance-based regulation, market transformation, and further research into building energy consumption. As the need for energy reduction and savings becomes greater, energy benchmarking serves not just as a reporting tool but as a catalyst for improving energy performance of buildings.

2.2 Benefits of Energy Benchmarking

Various studies examine the effectiveness of energy benchmarking policies at improving energy usage intensity (EUI) in buildings. Meng, Hsu, and Han examined NYC office building EUIs from between the first full year of released public data in 2011 to 2014, comparing office buildings required to submit energy consumption data to offices exempt from the policy. They found that benchmarking was responsible for a 6 percent EUI improvement from 2011 to 2013, which increased to 14 percent in 2014.[11] In a similar study, Hamad similarly found the policy effective at improving EUI, with a 10 percent source EUI improvement in commercial buildings from 2011 to 2016. However, her report contrasted Meng's in that almost all of the gains came

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[9] Arjunan, Poolla, and Miller, "EnergyStar++."

[10] Yalcintas and Aytun Ozturk, "An Energy Benchmarking Model Based on Artificial Neural Network Method Utilizing US Commercial Buildings Energy Consumption Survey (CBECS) Database."

[11] Meng, Hsu, and Han, "Estimating Energy Savings from Benchmarking Policies in New York City."

within the first year of the policy, with no noticeable changes caused by the policy in following years.[12]

Additional research studies have established a positive correlation between energy efficiency in buildings and improved economic performance. Buildings that implement energy-saving measures have seen financial benefits as a result, with improved energy efficiency resulting in lower utility bills and savings for property owners. Even when including the initial cost to install improvement, property owners generally see returns on investments within a 5 year period.[13] Additionally, energy-efficient properties had 6.7% fewer vacancies than non-energy efficient buildings, indicating that energy efficient buildings are more attractive to buyers.[14] [15] Estimates suggest that by 2035, energy benchmarking initiatives could lead to energy savings of 2.2–2.4%, surpassing implementation costs for both the public and private sectors.[16] These findings support the value of energy benchmarking from a financial perspective in addition to an environmental one.

Moreover, potential efficiency and financial gains appear even greater in lower-income and underserved communities. Buildings classified as 'affordable' tend to be less energy efficient than their 'expensive' counterparts.[17] These buildings often lack basic, low-cost energy improvements that can generate substantial savings. Estimates for adding these improvements in low-income and minority households see utility bills for buildings reduce by as much as $1,500

[12] Hamad, "Influence of Energy Benchmarking Policies on the Energy Performance of Existing Buildings."
[13] Tarquinio, "The Cost of Saving Energy."
[14] Shang et al., "Impact of Energy Benchmarking and Disclosure Policy on Office Buildings."
[15] Shang et al., "Assessing Office Building Marketability before and after the Implementation of Energy Benchmarking and Disclosure Policies—Lessons Learned from Major U.S. Cities."
[16] Cox, Brown, and Sun, "Energy Benchmarking of Commercial Buildings."
[17] Kontokosta, "Predicting Building Energy Efficiency Using New York City Benchmarking Data."

annually.[18] This disparity underscores both an environmental and social equity dimension in the push for building energy reform, suggesting that targeting efficiency improvements in these areas could deliver outsized benefits.

2.3 Energy Usage and the COVID-19 Pandemic

Given the profound impact that the COVID-19 pandemic had on most aspects of human life, research on its impact on building energy consumption patterns across the world naturally followed. Following the implementation of lockdowns and fall of occupancy levels in commercial and institutional buildings, energy usage in many of these facilities dropped substantially. Vacated university buildings saw energy consumption drop to 46.9% of pre-pandemic levels.[19] Commercial buildings in Manchester saw a 90% decrease in occupancy, resulting in a 20% decrease in electricity costs.[20] These studies underscore the significant role occupancy plays in driving building energy consumption, but they also reveal that even unoccupied or minimally used buildings continue to consume substantial amounts of energy due to baseline operational needs.

Studies have found similar trends across the world. Observing overall trends in the European Union illustrated a similar story on a national level: overall energy consumption fell across nearly every economic sector, regardless of country. The exception to this trend were households, which saw an increase in energy consumption. While overall energy consumption dropped, when accounting for GDP Europe used more energy per GDP, saying that energy usage

[18] Kontokosta and and Bonczak, "Energy Cost Burdens for Low-Income and Minority Households."
[19] Gaspar et al., "Assessing the Impact of the COVID-19 Lockdown on the Energy Consumption of University Buildings."
[20] Jogunola et al., "Energy Consumption in Commercial Buildings in a Post-COVID-19 World."

was less efficient when accounting for economic output.[21] South Korea saw similar energy consumption trends; electricity and gas energy consumption decreased 4.46% and 10.35% respectively, with the only increase coming from residential buildings.[22] These trends highlight the correlation between energy consumption and human activity, with the pandemic greatly altering normal patterns. For building energy benchmarking, this presents challenges in comparing performance during these years and identifying genuine efficiency improvements versus occupancy-driven changes.

3. Materials and Methods

In this section the following is covered: first, an overview of the datasets utilized for this study and an explanation of the preprocessing methods used to clean the dataset; second, a conceptual overview of the study; third, an overview of the models selected for the study.

3.1 Data Sources and Preparations

This paper draws from two publicly available datasets provided by the City of New York: the last decade of Portfolio Manager (PM) benchmarking data for buildings and the Primary Land Use Tax Lot Output (PLUTO) dataset. The PM dataset contains annual energy usage metrics for both public and private buildings in New York City that exceed 50,000 square feet in floor area, as mandated by Local Law 84. These records include detailed information on energy consumption, primary property use, and physical building characteristics. The PLUTO dataset

[21] Rokicki et al., "Changes in Energy Consumption and Energy Intensity in EU Countries as a Result of the COVID-19 Pandemic by Sector and Area Economy."
[22] Kang et al., "Changes in Energy Consumption According to Building Use Type under COVID-19 Pandemic in South Korea."

complements this by providing additional data not present in the PM, including number of floors and assessed property value. The Building Identification Number (BIN), a standardized column across NYC building datasets, allowed for merging the two together.

The primary energy performance metric analyzed in this study is Weather Normalized Source Energy Use Intensity (Source EUI), measured in kBTU per square foot. Unlike total energy consumption, EUI adjusts for building size by expressing energy use on a per-square-foot basis, allowing for more accurate comparisons across buildings of different scales. This study focuses on Source EUI rather than Site EUI, as Source EUI reflects the total upstream energy required, including generation and transmission losses. It also better captures the environmental impact of different fuel types, accounting for whether a building relies on cleaner or more carbon-intensive energy sources. Additionally, the EUI values are weather-normalized using EPA standards to account for variations due to temperature or weather differences across years.

In addition to the energy outcome dependent variable, the final dataset includes a range of building-level features to serve as predictors in the modeling process. Physical characteristics of the building included the total square footage area of each building, the year of construction. For energy variables, the model uses the proportion of each fuel type relative to a building's total energy use. Next, the model includes the building's primary property type (e.g., Multifamily Housing, Office) as a categorical feature to capture sector-specific differences that may influence energy usage. Additionally, the assessed total property value and assessed total property value per square foot provide an economic perspective on the building's scale and quality. Together, these features represent a comprehensive view of the physical, operational, and economic attributes of each building to enable prediction of Source EUI across NYC buildings.

The raw datasets contained missing, duplicate, and misreported values, so I applied several preprocessing steps before analyzing the data. First, because NYC frequently changes column names from year to year, I standardized all column names in the PM datasets to ensure accurate merging across different years. I also translated all property type entries submitted in French into English to prevent duplicate category entries. Next, I removed any yearly building entry that did not report Source EUI. For buildings that submitted multiple PM entries in a single year, I retained only the most recent report and discarded the others. To reduce the influence of extreme outliers, I excluded entries in the 1st and 99th percentiles. I also removed any yearly building entry that fell more than three standard deviations from the building's average Source EUI over the past decade, as these values appeared to result from metering or reporting errors.

The initial dataset contained 256,662 rows with information from 52,978 unique buildings. After the preprocessing procedures, the cleaned dataset contained 200,225 rows from 26,773 buildings.

3.2 Descriptive Statistics

Prior to conducting any modeling, I computed a variety of descriptive statistics to better understand the dataset's key features and provide a basic understanding of the distributions, trends, and variability of the variables.[23] This exploratory step allowed for clearer interpretation of the data and informed subsequent modeling decisions.

[23] Ding and Liu, "A Comparative Analysis of Data-Driven Methods in Building Energy Benchmarking."

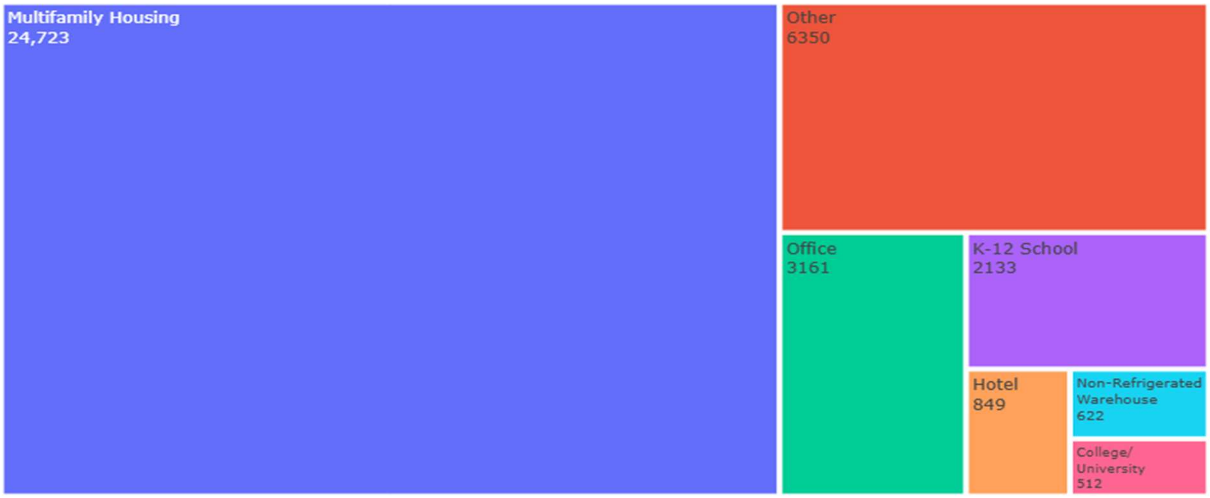

Figure 1: Counts of unique buildings that reported for each building type

While many buildings may share similar physical characteristics, their primary use plays a significant role in determining energy consumption patterns. Operational demands, occupancy schedules, and equipment loads vary widely across property types and affect average energy consumption. The majority of properties were multifamily housing buildings, making up 64.47% of all buildings in the cleaned dataset. Other property types with over 500 entries were offices (8.24%), K-12 schools (5.56%), hotels (2.21%), non-refrigerated warehouses (1.62%), and colleges/universities (1.34%).

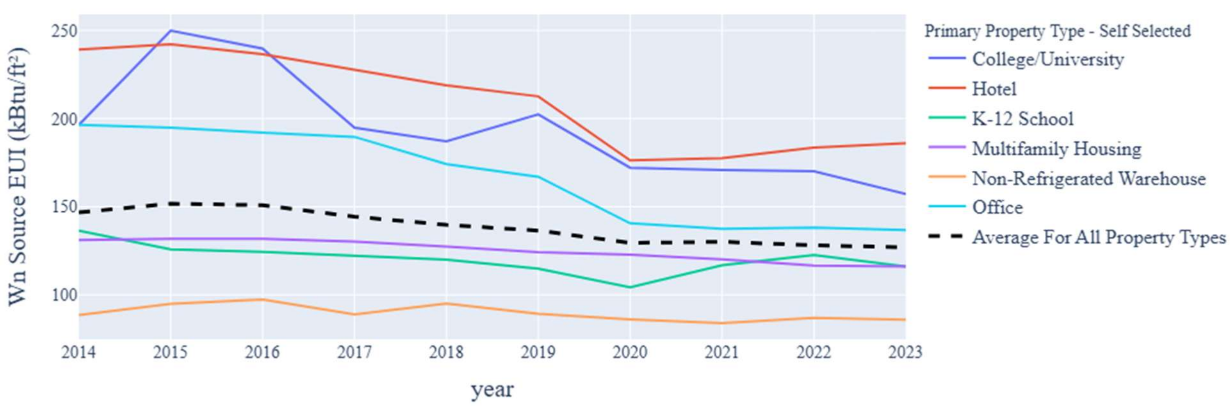

Figure 2: Average Source EUI per property type (2014-2023)

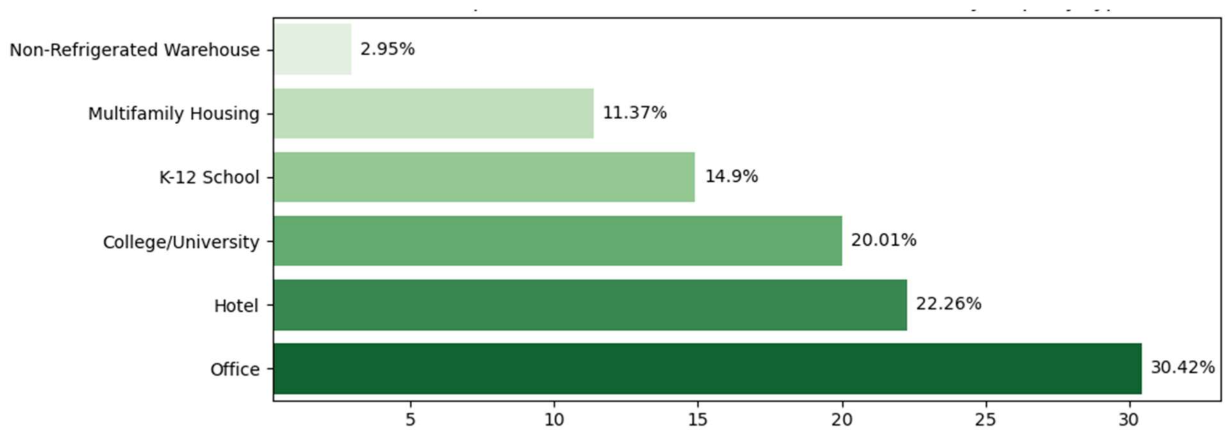

Figure 3: Percent decrease in Source EUI per property type (2014-2023)

Examining the Source EUI trends across each property type shows significant differences between them. When observing percent improvement in Source EUI over the last decade, the biggest gains have come from less efficient buildings. Offices had the largest improvement of 30.42%. Their Source EUI went from 33.9% more energy intensive than the average building in 2014 to just 7.6% higher than average in 2023. Besides offices, the most improved buildings were hotels and colleges/universities, the other property types with Source EUIs above average. They both started with Source EUIs higher than offices, signifying that it is not purely a matter of high EUI buildings being easier to make more efficient. Multifamily buildings, which started more energy efficient than the average building, saw a decrease of 11.37% Source EUI. Due to the sheer number of multifamily homes in the dataset, this decrease saw the largest total reduction of energy per square foot, although it was lower percentage wise than all other building types besides non-refrigerated warehouses.

Analysis of Source EUI trends across property types reveals substantial variation in both initial energy intensity and improvement over time. When examining percent reductions in Source EUI over the past decade, the most significant gains occurred among property types that were initially less efficient. Offices had the greatest improvement, with a 30.42% reduction in Source EUI from 2014 to 2023. In 2014, offices consumed 33.9% more energy per square foot than the average building, but by 2023, they were only 7.6% above average. Hotels and colleges/universities also achieved notable reductions, although not as great as offices despite beginning with even higher Source EUIs. This suggests that while less efficient buildings seem more susceptible to improvement, this was not uniform across all property types.

Multifamily housing started the period more efficient than the citywide average and recorded an 11.37% decline in Source EUI. While their Source EUI improvement was smaller than that of the other large categories (with the exception of non-refrigerated warehouses), their sheer volume in the dataset meant that this drop was the most significant when considering the raw amount of kBTU saved, emphasizing the importance of targeting specific policies at housing. These trends underscore the importance of considering building type when conducting energy policy, as different property classes follow distinct trends.

Trends in Source EUI between 2020 and 2023 illustrate how different property types responded to the COVID-19 pandemic. Office buildings, hotels, K–12 schools, and colleges/universities all saw a decline in EUI in 2020 relative to 2019, with decreased occupancy and operational hours during lockdowns leading to temporary improvements in energy performance.[24] However, these trends varied by building type. K–12 schools and hotels saw their Source EUIs increase in subsequent years, likely reflecting the resumption of normal activity. In contrast, office buildings and colleges/universities maintained much of their initial energy reductions through 2023, potentially from the continued adoption of remote/hybrid work or other

[24] Doma et al., “Towards Post-Pandemic Occupancy Patterns.”

shifts in occupancy.[25] Multifamily housing and non-refrigerated warehouses showed comparatively little change in Source EUI from 2019 to 2020, suggesting their energy usage was less sensitive to the COVID pandemic.[26] This may be due to these buildings maintaining higher levels of activity than the previously mentioned building types, due to their more essential functions of living space and providing goods.

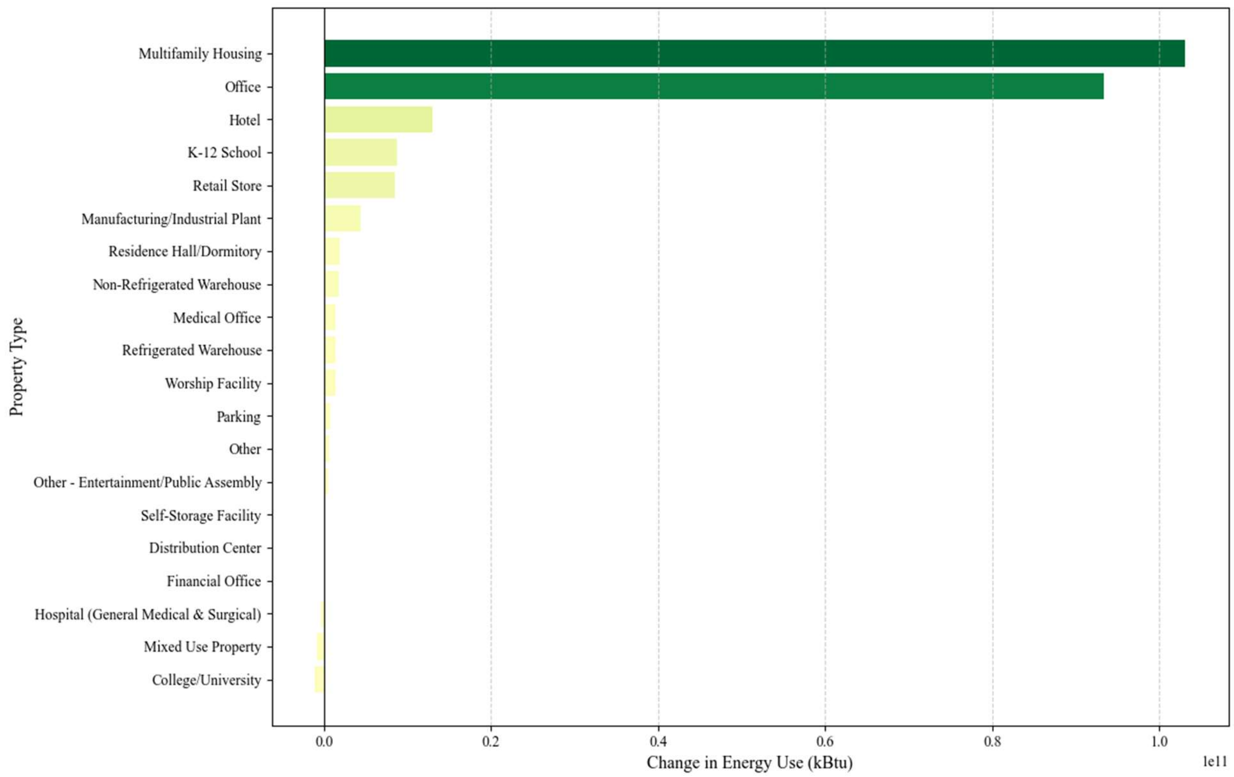

Figure 4: Estimated Total Source Energy Use Reduction by Property Type (2014-2023)

Examining estimated total source energy savings without adjusting for square footage provides an additional angle for understanding which property types saw the greatest decrease in

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[25] Motuzienė et al., “Office Buildings Occupancy Analysis and Prediction Associated with the Impact of the COVID-19 Pandemic.”

[26] Dong et al., “Trends and Changes in U.S. Residential Occupancy and Activity Patterns Across Demographics During and Post-COVID.”

energy consumption. Among property types with at least 10 buildings reporting in both 2014 and 2023, multifamily housing and offices accounted for the largest absolute declines in energy use. Multifamily housing led with total savings of 43.2% of total savings, largely due to its sheer volume of the dataset, despite a more modest percentage reduction in Source EUI. Despite having far fewer buildings, offices achieved similar total energy savings of 39.1%, driven by a much steeper decline in energy intensity. Other property types that had notable reductions were hotels (5.4%), K–12 schools (3.6%), and retail stores (3.6%), though their impacts were significantly smaller in comparison.

3.3 Model Selection

To analyze whether there was a statistically significant change in NYC building Source EUI trends associated with the COVID pandemic, an interrupted time series (ITS) is utilized. ITS is a statistical method used to evaluate the impact of an intervention or event that occurs at a specific point in time. It does so by modeling the pre-intervention trend, the immediate effect of the intervention, and the post-intervention trend, allowing for the detection of both level shifts and changes in trajectory due to the event. This methodology has been extensively applied in policy analysis and public health research, and has been utilized in building energy studies for assessing the effects of benchmarking policies, incentive programs, and regulatory changes on real estate performance.[27] [28]

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[27] Hategeka et al., "Use of Interrupted Time Series Methods in the Evaluation of Health System Quality Improvement Interventions."

[28] Shang et al., "Impact of Energy Benchmarking and Disclosure Policy on Office Buildings."

This study uses 2020 as the interruption point, aligning with the onset of COVID-19-related lockdowns in mid-March. The analysis began by applying the ITS model to the full dataset to evaluate trends in Source EUI across all NYC buildings. It then ran separate ITS models for the six most common property types (Multifamily Housing, Offices, K-12 Schools, Hotels, Non-Refrigerated Warehouses, and Colleges/Universities) to assess how the interruption impacted each category differently.

In addition to the ITS models, this study applies a Random Forest regression model to predict buildings' Source EUI. A separate model also uses the natural logarithm of Source EUI as the dependent variable to account for the wide range of values and reduce the influence of outliers.[29] Random Forests, an ensemble learning method built on decision trees, handle nonlinear relationships, feature interactions, and mixed data types effectively. Unlike traditional linear regression, Random Forests make no assumptions about the functional form of relationships, allowing them to capture complex drivers of energy consumption. These advantages have consistently enabled Random Forests to outperform linear models in predicting building EUI scores.[30]

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[29] "Statistical Model and Benchmarking Procedure for Energy Use by US Public Water Systems | Journal of Sustainable Water in the Built Environment | Vol 4, No 4."

[30] Kaskhedikar, Reddy, and Runger, "Use of Random Forest Algorithm to Evaluate Model-Based EUI Benchmarks from CBECS Database."

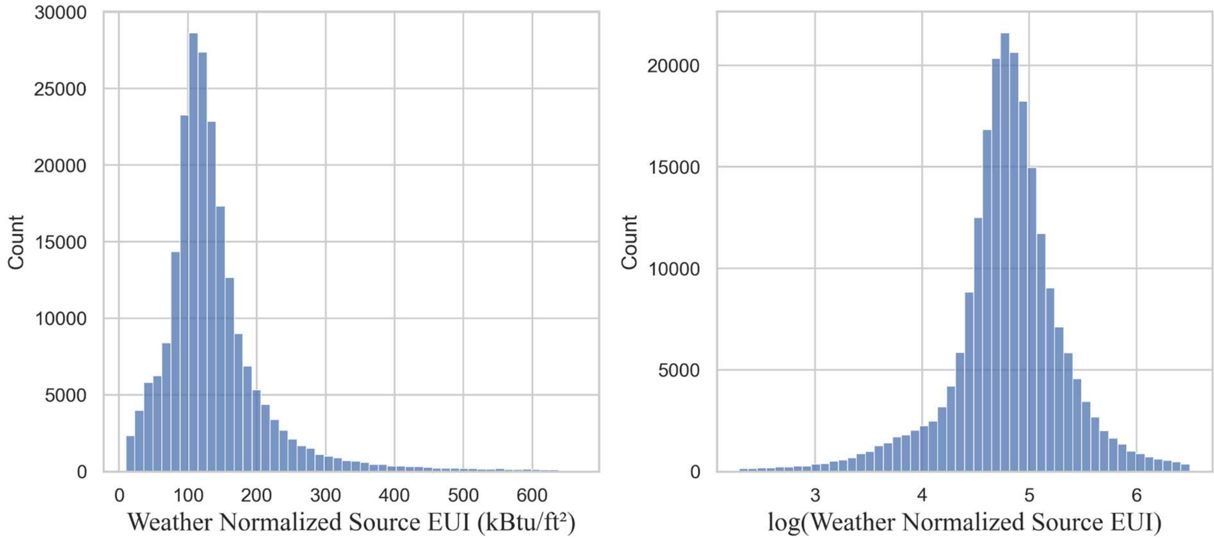

Figure 5: Histograms of Energy Usage in NYC Buildings (2014-2023)

The model uses a broad set of building attributes for training, including physical characteristics, energy consumption ratios, and tax valuation. The table below lists all selected features. To improve interpretability and reduce noise from infrequent categories, the analysis uses only data from buildings from the six most common property types in the dataset. This approach avoids the effects of over 100 less-represented categories that could introduce variability and weaken model performance. By narrowing the scope to the most prevalent property types, the model more effectively captures meaningful patterns and produces more accurate insights into the factors that influence Source EUI.

While Random Forests are less interpretable than linear models in terms of direct coefficient estimates, they offer feature importance scores that provide insight into which variables are most predictive of building performance. These scores highlight key characteristics associated with high or low energy usage, guiding future benchmarking and policy targeting efforts.

Table 1: Descriptive Statistics Summary (N=127,816 observations; or 26,773 buildings)

Variable name (Unit)	**Mean**	**Std.**	**Min.**	**Max.**
Weather Normalized Source EUI (kBtu/ft^2)	129.14	584.74	10.40	631.20
Physical Features				
Age of Building	70.53	3.328	0	200
Number of Floors	9.14	8.07	1	102
Building Area (ft^2)	1.33 x 10^5	2.92 x 10^5	1289.0	2.79 x 10^7
Energy Usage Ratios				
Electricity Ratio	0.4598	0.2365	0	1
Natural Gas Ratio	0.4209	0.2966	0	1
District Steam Ratio	0.0193	0.0902	0	1
Primary Building Use				
Multifamily Housing - dummy	0.7735	0.4186	0	1
Hotel - dummy	0.0218	0.1461	0	1
K-12 School - dummy	0.0783	0.2687	0	1
College/University - dummy	0.0109	0.1038	0	1
Non-Refrigerated Warehouse - dummy	0.0162	0.1263	0	1
Tax Valuation				
Assessed Total Value of Property	1.24 x 10^7	5.63 x 10^7	0	8.01 x 10^9
Assessed Total Value of Property per total sqft	116.71	4357.35	0	8.01 x 10^5

4. Results and Discussion

4.1 Interrupted Time Series Results

The ITS model applied to the cleaned NYC dataset yielded an R^2 value of 0.929, indicating a strong overall fit to the average Source EUI trends from 2014 to 2023. The model estimated a substantial immediate drop in Source EUI from 2019 to 2020 of 17.6750 kBtu/ft^2, consistent with expectations surrounding the impact of the COVID-19 pandemic on building energy usage. Interestingly, the model also found a deceleration in the rate of improvement for building energy efficiency. Prior to 2020, Source EUI was decreasing by an average of 2.6879 per year, whereas post-2020, the rate of improvement slowed to just 0.9452 annually. This decline may be the result of occupancy rates rising for many buildings in 2021/2022, counteracting some of the initial drop from COVID-19 and causing the Source EUI numbers to rise more than expected.

Despite these meaningful directional shifts, the associated p-values for both the level change (0.203) and slope change (0.315) exceeded the conventional threshold of statistical significance ($p < 0.05$) by a significant margin. This result suggests that, although the observed changes align with pandemic-related expectations, the model cannot definitively attribute them to the COVID-19 intervention. The likely cause of this statistical insignificance is the limited sample size of the dataset, which includes only 10 annual observations, reducing the statistical power of the ITS model.

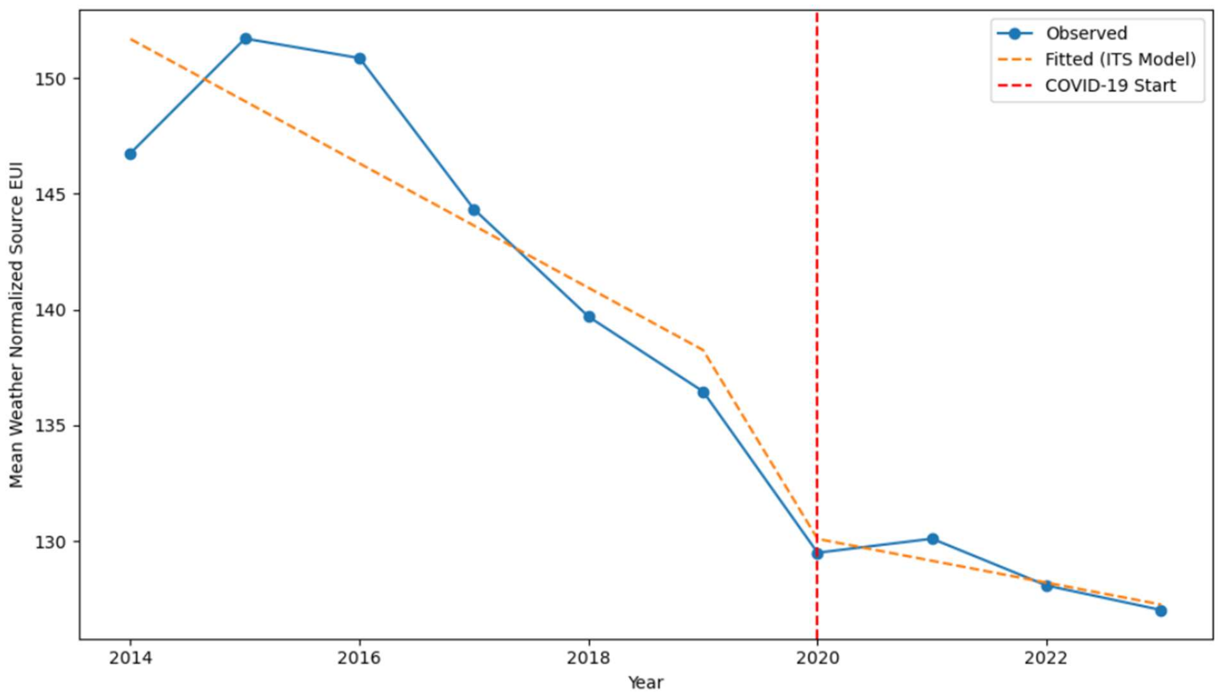

Figure 6: ITS graph for year vs mean Source EUI, with the interruption year of 2020

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Dep. Variable:     Weather Normalized Source EUI (kBtu/ft²)   R-squared:                   0.929
Model:                                                  OLS   Adj. R-squared:              0.893
Method:                                       Least Squares   F-statistic:                 26.06
Date:                                      Wed, 30 Apr 2025   Prob (F-statistic):       0.000771
Time:                                              00:07:34   Log-Likelihood:            -23.064
No. Observations:                                        10   AIC:                         54.13
Df Residuals:                                             6   BIC:                         55.34
Df Model:                                                 3
Covariance Type:                                  nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const            154.3780      2.919     52.881      0.000     147.235     161.521
time              -2.6879      0.750     -3.586      0.012      -4.522      -0.854
post_covid       -17.6750     12.372     -1.429      0.203     -47.949      12.599
time_post_covid    1.7427      1.590      1.096      0.315      -2.148       5.634
==============================================================================
Omnibus:                        1.035   Durbin-Watson:                   1.453
Prob(Omnibus):                  0.596   Jarque-Bera (JB):                0.020
Skew:                          -0.086   Prob(JB):                        0.990
Kurtosis:                       3.131   Cond. No.                         101.
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Figure 7: ITS model results for all NYC buildings (2014-2023)

The ITS results across individual property types revealed differences in both the magnitude and statistical significance of changes in Source EUI before and after the COVID-19 pandemic. Multifamily housing was the only category to experience a post-intervention increase in EUI, with an estimated rise of 4.4482 kBtu/ft^2. While this result was not statistically significant, it is consistent with behavioral shifts during the pandemic, as residents spent more time at home. Similarly, non-refrigerated warehouses and colleges/universities also exhibited statistically insignificant results, suggesting either a limited impact from pandemic-related disruptions or greater variability in their energy consumption patterns. Both the property types saw decreases in EUI as opposed to multifamily housing however.

By contrast, K-12 schools and hotels were the only property types where both the immediate level drop and subsequent trend change were statistically significant. These findings likely reflect the dramatic reductions in building occupancy during the early pandemic period, as in-person schooling and travel came to a near halt. The eventual rebound in EUI for these categories may be due to the return to more traditional activity as in-person activity resumed.

Office buildings also showed a statistically significant immediate decline in Source EUI, estimated at 59.4805 kBtu/ft^2 ($p = 0.010$), highlighting a clear disruption in energy use in 2020. The subsequent trend shift, however, narrowly missed statistical significance ($p = 0.053$), suggesting the possibility of a long-term structural change that merits further investigation. Given the persistence of remote and hybrid work arrangements, it is plausible that office energy demand did not fully return to pre-pandemic levels, distinguishing it from the post-COVID trajectories from schools and hotels.

These results underscore the importance of disaggregating analysis by building type when evaluating the effects of large-scale shocks. The pandemic's energy implications were highly dependent on the function and usage patterns of each building category, reinforcing the need for tailored policy strategies.

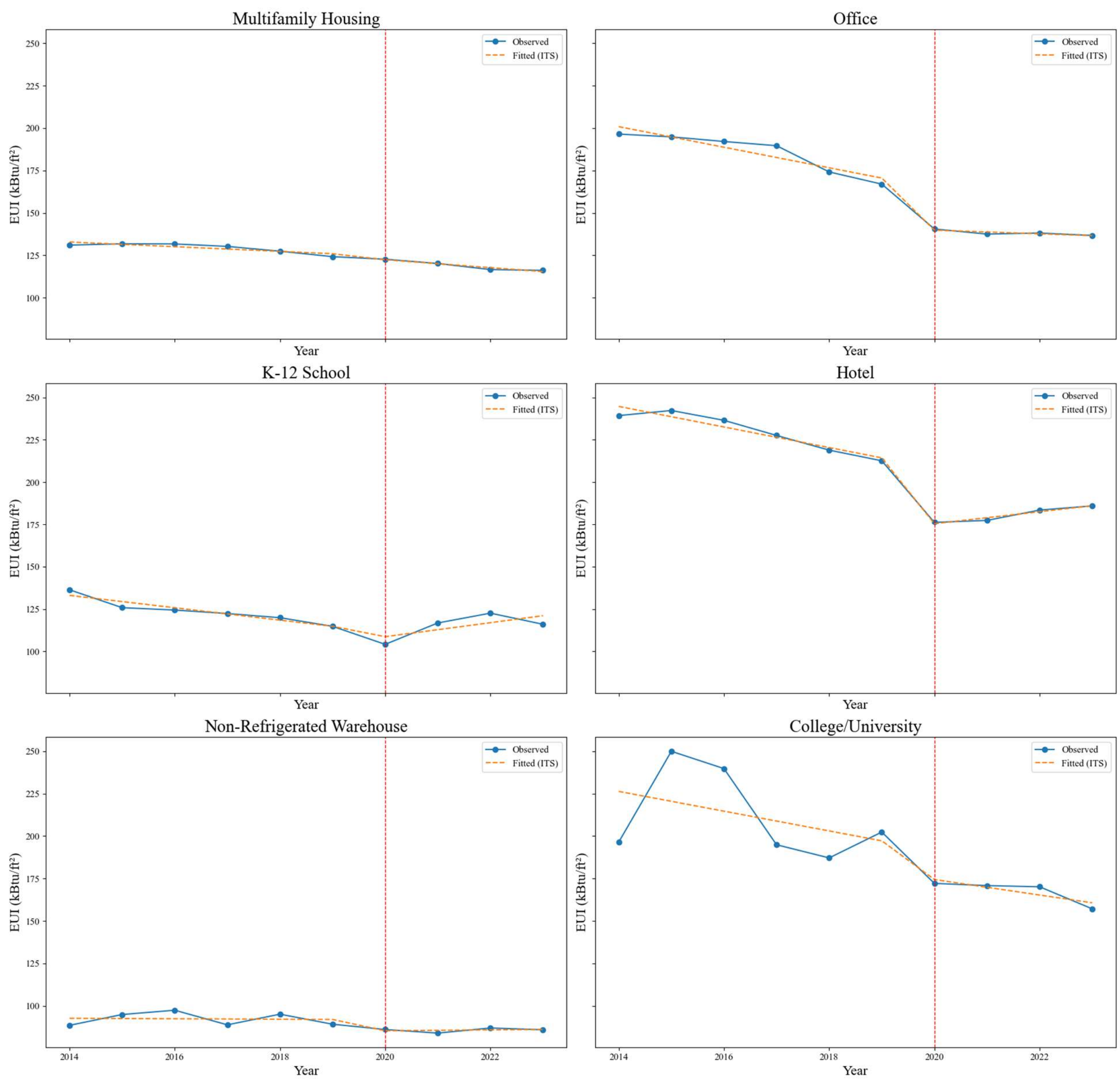

Figure 8: ITS model results for individual property types (2014-2023)

Figures 9-14: ITS model results per property type

Multifamily Housing

	coef	std err	t	P>|t|	[0.025	0.975]
const	134.2842	1.389	96.658	0.000	130.885	137.684
time	-1.3878	0.357	-3.890	0.008	-2.261	-0.515
post_covid	4.4482	5.888	0.755	0.479	-9.959	18.855
time_post_covid	-0.9429	0.757	-1.246	0.259	-2.795	0.909

Offices

	coef	std err	t	P>|t|	[0.025	0.975]
const	206.9136	3.797	54.493	0.000	197.622	216.205
time	-6.0578	0.975	-6.213	0.001	-8.444	-3.672
post_covid	-59.4805	16.093	-3.696	0.010	-98.857	-20.104
time_post_covid	4.9771	2.068	2.406	0.053	-0.084	10.038

K-12 Schools

	coef	std err	t	P>|t|	[0.025	0.975]
const	136.6901	4.177	32.722	0.000	126.469	146.911
time	-3.6405	1.073	-3.394	0.015	-6.265	-1.016
post_covid	-56.8174	17.704	-3.209	0.018	-100.137	-13.498
time_post_covid	7.7629	2.275	3.412	0.014	2.195	13.331

Hotels

	coef	std err	t	P>|t|	[0.025	0.975]
const	250.7407	3.143	79.776	0.000	243.050	258.431
time	-6.0648	0.807	-7.515	0.000	-8.040	-4.090
post_covid	-99.8325	13.321	-7.495	0.000	-132.427	-67.238
time_post_covid	9.5866	1.712	5.600	0.001	5.397	13.776

Non-Refrigerated Warehouses

	coef	std err	t	P>|t|	[0.025	0.975]
const	92.8099	3.421	27.131	0.000	84.440	101.180
time	-0.1358	0.878	-0.155	0.882	-2.285	2.014
post_covid	-9.2522	14.498	-0.638	0.547	-44.727	26.222
time_post_covid	0.3922	1.863	0.211	0.840	-4.167	4.952

Colleges/Universities

	coef	std err	t	P>|t|	[0.025	0.975]
const	232.1274	20.480	11.335	0.000	182.015	282.239
time	-5.8198	5.259	-1.107	0.311	-18.687	7.048
post_covid	-25.7379	86.795	-0.297	0.777	-238.117	186.642
time_post_covid	1.2521	11.155	0.112	0.914	-26.044	28.548

4.2 Random Forest Results

The trained Random Forest models proved effective at predicting on both the Source EUI and its natural logarithm, earning R^2 scores of 0.6870 and 0.6950 respectively. This explains almost 70% of variance in the dataset. These values indicate that the models are able to explain nearly 70% of the variance in building energy usage intensity across the dataset, which is encouraging given the variety of factors that go into a building’s energy usage.

Factors outside the scope of the model’s features may include the property owner's awareness of or commitment to energy efficiency, the presence (or absence) of recent renovations, differences in occupant behavior, variations in operational schedules, and building maintenance practices. Additionally, variables not captured in the dataset, such as building system functionality, equipment age, and tenant occupancy, may influence energy use in ways the model does not fully account for. These omitted factors introduce noise that are difficult to adjust for, given the difficulty of acquiring or quantifying these factors.

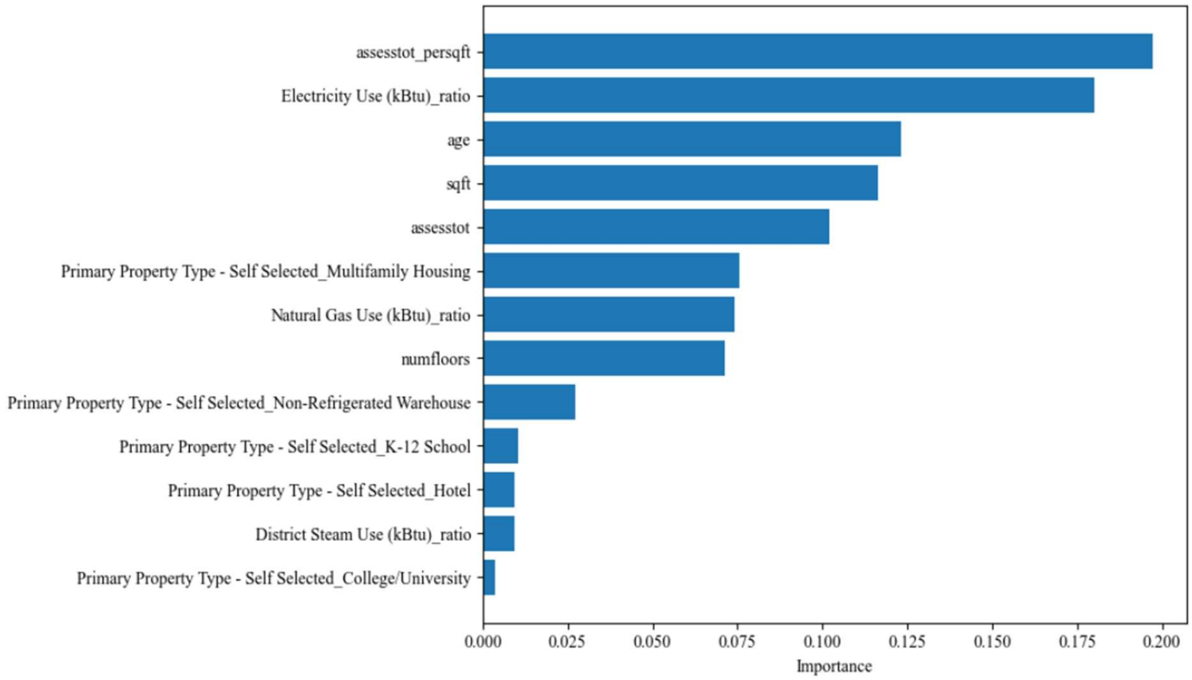

Figure 15: Random Forest Feature Importance for Source EUI model (R^2: 0.6870)

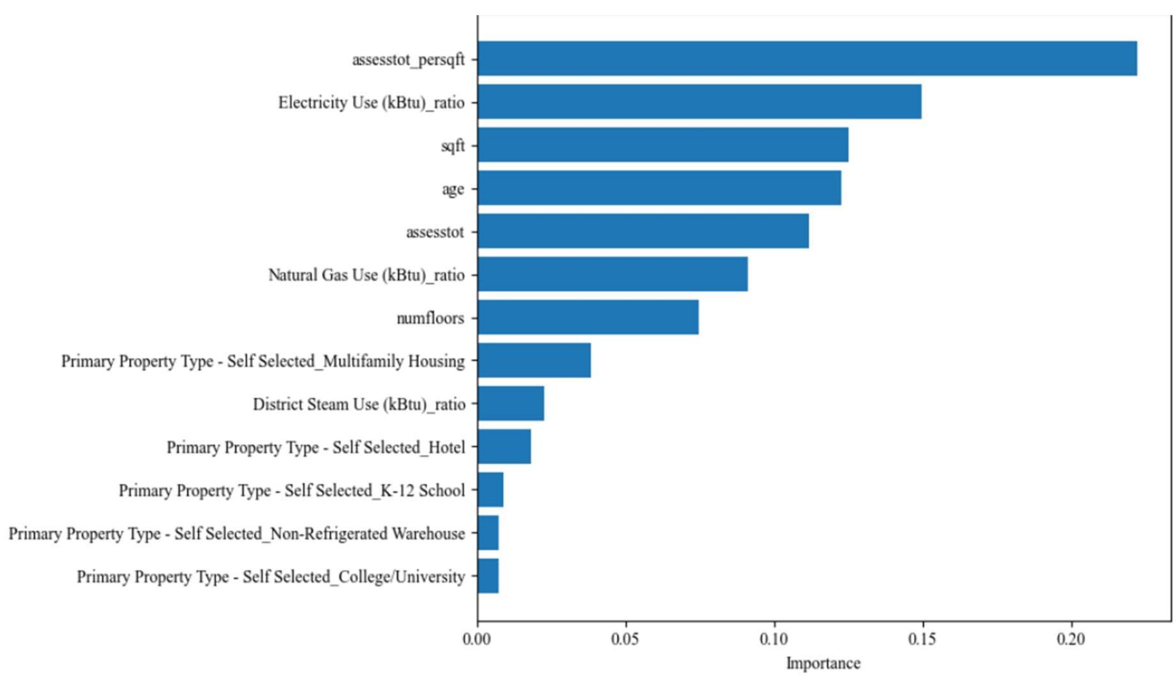

Figure 16: Random Forest Feature Importance for Log(Source EUI model) (R^2: 0.6950)

The Random Forests produced similar feature importance rankings across both the Source EUI model and its logarithmic counterpart. The most influential predictor was the assessed total value per square foot, suggesting a strong relationship between a building's market valuation and its energy efficiency. Other key features included building age and total square footage, reinforcing the importance of a building's physical characteristics in shaping its efficiency. Among the energy-specific variables, feature importance appeared to align with usage prevalence. Electricity use, the most common energy source in the dataset, emerged as the second most important predictor. In contrast, less frequently used sources like steam had significantly lower importance scores, likely due to their limited representation across building types. This pattern suggests that the model draws more predictive power from energy types that are both widespread and more variable across buildings, while niche or infrequently reported fuel sources contribute less to distinguishing energy performance.

6. Conclusion and Policy Implications

This analysis of a decade of New York City energy benchmarking data reveals several key conclusions. First, buildings have seen notable improvements in energy efficiency from 2014 to 2023, both before the COVID-19 pandemic and after it. Offices, hotels, and colleges/universities had the largest relative improvements in Source EUI over the past decade, suggesting that buildings with greater initial inefficiency have more room for efficiency gains. In terms of total energy reduction, multifamily housing, though already more efficient than average and seeing a smaller EUI improvement, contributed the largest absolute reductions in energy consumption due to its dominance in the building stock. Offices were the second notable contributor. These results underscore the value of property-type-specific policy approaches that reflect the differing operational and structural characteristics of various building sectors.

This analysis of a decade of New York City energy benchmarking data reveals several key conclusions. First, buildings improved significantly in energy efficiency between 2014 and 2023, both before and after the COVID-19 pandemic. Offices, hotels, and colleges/universities achieved the largest relative reductions in Source EUI, suggesting that buildings with higher initial inefficiency have the most room for performance gains. Multifamily housing, despite already operating at above-average efficiency and showing a smaller percentage improvement, contributed the largest absolute reduction in total energy use due to its overwhelming presence in the dataset. Offices followed closely behind. These findings highlight the value of property-type-specific policies that recognize the distinct characteristics of each building class.

From these results, multifamily housing and offices stand out as the highest-priority targets for further research and policy action. These two categories accounted for the largest share of buildings in the dataset and the majority of energy savings observed over the study period. Investigating which retrofits, incentive programs, or policies drove those improvements can help improve future interventions. Additionally, policies tailored to these property types are likely to produce the greatest returns in both energy savings and emissions reductions.

Secondly, the impact of COVID-19 on building energy use appears to have been closely tied to changes in occupancy. Property types EUI drops and rebounds generally fit with building occupation trends documented by other studies. Although the NYC benchmarking dataset includes some occupancy-related fields, these columns are largely empty, making them ineffective for including in a model. Given the strong connection between occupancy and energy consumption patterns observed during the pandemic, further research into the role of building usage levels is warranted, particularly through supplemental data sources or case-specific studies.

Regardless, the ITS analysis revealed significant disruptions to typical energy consumption patterns caused by the COVID-19 pandemic, especially in building types that experienced the most substantial drops in occupancy during lockdowns, such as K-12 schools, offices, and hotels. In contrast, warehouses and multifamily housing showed relatively stable Source EUI values with no statistically significant changes detected. These findings emphasize the need for care in interpreting benchmarking data during tumultuous periods and should continue to be monitored in the continuing years to better understand post-pandemic trends.

Finally, The Random Forest models developed in this study proved effective at predicting building energy usage intensity, explaining approximately 70% of the variance in Source EUI. Key predictive variables included assessed property value per square foot, total square footage, and building age. The results support the idea that both economic factors and physical building characteristics play important roles in building energy performance. Testing with additional financial features would be a good next step. The use of machine learning models such as Random Forests presents a promising avenue for supplementing existing benchmarking scores to ensure more accurate assessments of energy trends.

In conclusion, energy benchmarking remains a critical tool for decarbonizing buildings. Its capacity to monitor energy performance over time enables policymakers, researchers, and property owners to track progress, identify underperforming buildings, and assess the impact of external events like the COVID-19 pandemic. Strengthening these systems, through improved data quality, continuing reporting, and predictive modeling, will help cities like New York craft more effective, equitable, and forward-thinking energy policies.

References

Arjunan, Pandarasamy, Kameshwar Poolla, and Clayton Miller. “EnergyStar++: Towards More Accurate and Explanatory Building Energy Benchmarking.” *Applied Energy* 276 (October 15, 2020): 115413. https://doi.org/10.1016/j.apenergy.2020.115413.

Baniassadi, Amir, Jannik Heusinger, Pablo Izaga Gonzalez, Stephan Weber, and Holly W. Samuelson. “Co-Benefits of Energy Efficiency in Residential Buildings.” *Energy* 238 (January 1, 2022): 121768. https://doi.org/10.1016/j.energy.2021.121768.

Brown, R., C. Webber, and J. G. Koomey. “Status and Future Directions of the Energy Star Program.” *Energy* 27, no. 5 (May 1, 2002): 505–20. https://doi.org/10.1016/S0360-5442(02)00004-X.

Cox, Matt, Marilyn A Brown, and Xiaojing Sun. “Energy Benchmarking of Commercial Buildings: A Low-Cost Pathway toward Urban Sustainability.” *Environmental Research Letters* 8, no. 3 (July 2013): 035018. https://doi.org/10.1088/1748-9326/8/3/035018.

Ding, Yong, and Xue Liu. “A Comparative Analysis of Data-Driven Methods in Building Energy Benchmarking.” *Energy and Buildings* 209 (February 15, 2020): 109711. https://doi.org/10.1016/j.enbuild.2019.109711.

Doma, Aya, Mohamed Osman, Ahmed Zaalouk, Hamidreza Karimian, Mazdak Nik-Bakht, and Mohamed Ouf. “Towards Post-Pandemic Occupancy Patterns: Investigating Building Occupancy in New York City.” *ASHRAE Transactions* 128, no. 1 (January 2022): 323–30.

Dong, Hao, Roohany Mahmud, Debrudra Mitra, and Kristen Cetin. “Trends and Changes in U.S. Residential Occupancy and Activity Patterns Across Demographics During and Post-COVID.” In *2024 ASHRAE Winter Conference*. ASHRAE, 2024. https://doi.org/10.63044/w24don043.

Energy.gov. “Data and Analysis for Buildings Sector Innovation,” December 30, 2024. https://www.energy.gov/eere/buildings/data-and-analysis-buildings-sector-innovation.

Gaspar, K., M. Gangolells, M. Casals, P. Pujadas, N. Forcada, M. Macarulla, and B. Tejedor. "Assessing the Impact of the COVID-19 Lockdown on the Energy Consumption of University Buildings." *Energy and Buildings* 257 (February 15, 2022): 111783. https://doi.org/10.1016/j.enbuild.2021.111783.

Hamad, Samar. "Influence of Energy Benchmarking Policies on the Energy Performance of Existing Buildings." Ph.D., Walden University, 2018. https://www.proquest.com/docview/2042391356/abstract/7B06025FE5DE4661PQ/1.

Hategeka, Celestin, Hinda Ruton, Mohammad Karamouzian, Larry D. Lynd, and Michael R. Law. "Use of Interrupted Time Series Methods in the Evaluation of Health System Quality Improvement Interventions: A Methodological Systematic Review." *BMJ Global Health* 5, no. 10 (October 14, 2020). https://doi.org/10.1136/bmjgh-2020-003567.

Hesselink, Laurens X. W., and Emile J. L. Chappin. "Adoption of Energy Efficient Technologies by Households – Barriers, Policies and Agent-Based Modelling Studies." *Renewable and Sustainable Energy Reviews* 99 (January 1, 2019): 29–41. https://doi.org/10.1016/j.rser.2018.09.031.

Jogunola, Olamide, Craig Morley, Ikpe Justice Akpan, Yakubu Tsado, Bamidele Adebisi, and Li Yao. "Energy Consumption in Commercial Buildings in a Post-COVID-19 World." *IEEE Engineering Management Review* 50, no. 1 (2022): 54–64. https://doi.org/10.1109/EMR.2022.3146591.

Kang, Hyuna, Jongbaek An, Hakpyeong Kim, Changyoon Ji, Taehoon Hong, and Seunghye Lee. "Changes in Energy Consumption According to Building Use Type under COVID-19 Pandemic in South Korea." *Renewable and Sustainable Energy Reviews* 148 (September 1, 2021): 111294. https://doi.org/10.1016/j.rser.2021.111294.

Kaskhedikar, Apoorva, T. Agami Reddy, and George Runger. "Use of Random Forest Algorithm to Evaluate Model-Based EUI Benchmarks from CBECS Database." *ASHRAE Transactions* 121 (2015): 17–28.

Kontokosta, Constantine. “Predicting Building Energy Efficiency Using New York City Benchmarking Data.” In *Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings*, 2012.

Kontokosta, Constantine E., Reina ,Vincent J., and Bartosz and Bonczak. “Energy Cost Burdens for Low-Income and Minority Households: Evidence From Energy Benchmarking and Audit Data in Five U.S. Cities.” *Journal of the American Planning Association* 86, no. 1 (January 2, 2020): 89–105. https://doi.org/10.1080/01944363.2019.1647446.

Meng, Ting, David Hsu, and Albert Han. “Estimating Energy Savings from Benchmarking Policies in New York City.” *Energy* 133 (August 15, 2017): 415–23. https://doi.org/10.1016/j.energy.2017.05.148.

Motuzienė, Violeta, Jonas Bielskus, Vilūnė Lapinskienė, Genrika Rynkun, and Jolita Bernatavičienė. “Office Buildings Occupancy Analysis and Prediction Associated with the Impact of the COVID-19 Pandemic.” *Sustainable Cities and Society* 77 (February 1, 2022): 103557. https://doi.org/10.1016/j.scs.2021.103557.

NYC Mayor’s Office of Climate and Environmental Justice. “NYC Greenhouse Gas Inventories,” October 17, 2022. https://climate.cityofnewyork.us/initiatives/nyc-greenhouse-gas-inventories/.

Popescu, Daniela, Sven Bienert, Christian Schützenhofer, and Rodica Boazu. “Impact of Energy Efficiency Measures on the Economic Value of Buildings.” *Applied Energy*, Special issue on Thermal Energy Management in the Process Industries, 89, no. 1 (January 1, 2012): 454–63. https://doi.org/10.1016/j.apenergy.2011.08.015.

Rokicki, Tomasz, Radosław Jadczak, Adam Kucharski, Piotr Bórawski, Aneta Bełdycka-Bórawska, András Szeberényi, and Aleksandra Perkowska. “Changes in Energy Consumption and Energy Intensity in EU Countries as a Result of the COVID-19 Pandemic by Sector and Area Economy.” *Energies* 15, no. 17 (January 2022): 6243.

https://doi.org/10.3390/en15176243.

Seyrfar, Abolfazl, Hossein Ataei, and Sybil Derrible. “A Review of Building Energy Benchmarking Policies Across the U.S. Cities.” Volume 8: Advances in Energy Innovation and Development, December 16, 2020. https://doi.org/10.46855/energy-proceedings-7016.

Shang, Luming, Sofia Dermisi, Youngjun Choe, Hyun Woo Lee, and Yohan Min. “Assessing Office Building Marketability before and after the Implementation of Energy Benchmarking and Disclosure Policies—Lessons Learned from Major U.S. Cities.” *Sustainability* 15, no. 11 (January 2023): 8883. https://doi.org/10.3390/su15118883.

Shang, Luming, Hyun Woo Lee, Sofia Dermisi, and Youngjun Choe. “Impact of Energy Benchmarking and Disclosure Policy on Office Buildings.” *Journal of Cleaner Production* 250 (March 20, 2020): 119500. https://doi.org/10.1016/j.jclepro.2019.119500.

SlideShare. “Building Energy Benchmarking and Disclosure in US Cities,” January 2, 2014. https://www.slideshare.net/slideshow/energy-benchmarking-in-us-cities/29645706.

“Statistical Model and Benchmarking Procedure for Energy Use by US Public Water Systems | Journal of Sustainable Water in the Built Environment | Vol 4, No 4.” Accessed April 30, 2025. https://ascelibrary.org/doi/full/10.1061/JSWBAY.0000864.

Tarquinio, J. Alex. “The Cost of Saving Energy.” *The New York Times*, July 15, 2007, 1(L)-1(L).

Yalcintas, Melek, and U. Aytun Ozturk. “An Energy Benchmarking Model Based on Artificial Neural Network Method Utilizing US Commercial Buildings Energy Consumption Survey (CBECS) Database.” *International Journal of Energy Research* 31, no. 4 (2007): 412–21. https://doi.org/10.1002/er.1232.