LOCAL LAW 84 ENERGY BENCHMARKING DATA

REPORT TO THE NEW YORK CITY MAYOR'S OFFICE OF LONG-TERM PLANNING AND SUSTAINABILITY

Prepared by:

Dr. Constantine E. Kontokosta, PE, AICP

New York University

Director, NYU Center for the Sustainable Built Environment

Deputy Director, NYU Center for Urban Science and Progress

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1.0 EXECUTIVE SUMMARY

At the request of New York City Mayor's Office of Long-Term Planning and Sustainability, this report provides an analysis of building energy consumption data as required by Local Law 84 (LL84). Following a description of the database, this report focuses on three primary areas. First, a predictive model of building energy consumption is developed, which builds on an analysis of the influence of several factors in determining energy use intensity (EUI) for office and multi-family properties. Second, a preliminary discussion of the underlying analytic foundations of a multi-family energy rating system is presented. Finally, this report analyzes the spatial distribution and patterns of energy consumption and efficiency across New York City.

The initial database included energy consumption information for 10,201 buildings. After data cleaning and validity testing, the final dataset includes 8,648 buildings. These buildings account for over 1.4 billion square feet of space, with multi-family buildings representing approximately 63 percent of the total space. For the 948 office buildings included in the sample, the median source EUI is 213.3 and the mean is 233.8 with a standard deviation of 111.0. The median EUI for office buildings is within 1.6 percent of the weather-adjusted primary energy use intensity for office buildings in the Northeast region, according to the 2003 Commercial Building Energy Consumption Survey. The median source EUI for the 6,671 multi-family buildings in the database is 132.2 and the mean is 136.5 with a standard deviation of 55.7. The median EUI for New York City multi-family properties is within 1.7 percent of the weather-adjusted primary energy use intensity for buildings with five or more units in the Northeast region as reported in the 2005 Residential Energy Consumption Survey.

The factors influencing building energy efficiency are analyzed using multivariate regression models with robust standard errors. The models include independent (explanatory) variables from both LL84 and PLUTO databases, together with new interaction variables. For office buildings, the results indicate that the significant drivers of building energy efficiency, as measured by changes in source EUI, are building age, fuel type, location and size of lot, building size, the amount of non-office space, operating hours, and worker density. For multi-family buildings, the primary determinants of building energy efficiency include building age, fuel type, location and size of lot, building size, laundry facilities per unit, and whether the building contains all subsidized units.

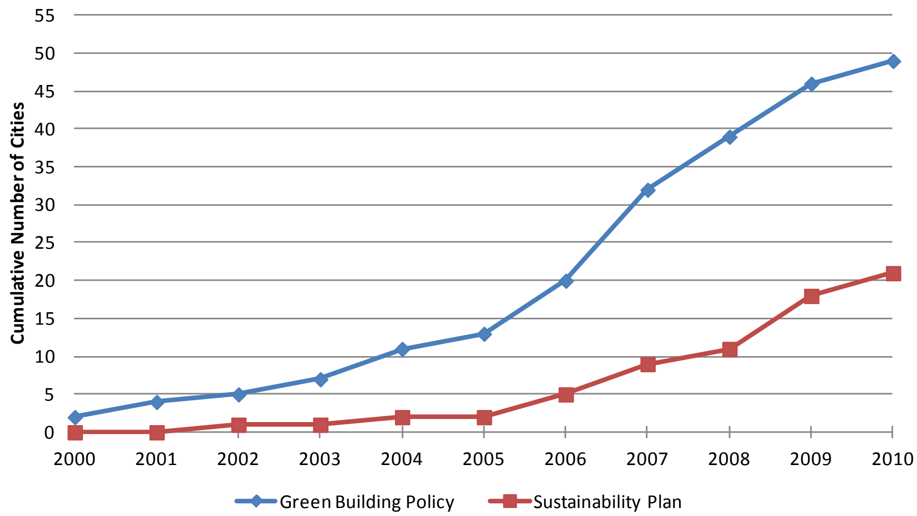
The spatial analysis of the data reveals some interesting findings with respect to patterns of energy efficiency across the five boroughs of New York City. In particular, of the zipcodes with the worst-performing buildings, on average, all are in Manhattan. For multi-family buildings, the worst-performing buildings are located in the poorest and wealthiest zipcodes based on median household income. As a preliminary test of neighborhood impacts of building energy efficiency, a positive correlation is found between asthma rates and high median energy use intensities, although this does not control for other neighborhood factors and should be interpreted only as an area for further exploration.

The LL84 data provides an important first look at a robust, heterogeneous sample of building energy consumption. As additional data are added to the database from the annual reporting requirements, time trends in energy efficiency and pre/post studies will become possible. Also, by merging the LL84 database with other relevant building and neighborhood data sources, the potential uses of the data, and hypotheses that can be tested and explored, will increase dramatically.

2.0 INTRODUCTION

The tenuous position of federal climate change policy in the U.S. has necessitated a more market-driven, city-focused approach to energy efficiency in the building sector. Strategies and policy initiatives involve a combination of local regulations to improve efficiency standards coupled with incentives and market-based mechanisms to catalyze innovation in the marketplace and create value around building energy performance. Cities have taken the lead in this respect, with more than 50 U.S. cities adopting some form of green building policy since 2001, as shown in Figure 2.0.1 (Kontokosta 2011a). These policies predominantly mandate or encourage newly constructed public sector and, in some cases, privately-owned buildings to achieve an eco-label certification – such as the U.S. Green Building Council's LEED certification or the Environmental Protection Agency's Energy Star label.

However, increasing attention is being placed on existing commercial buildings as an opportunity to reduce greenhouse gas (GHG) emissions, increase efficiencies, and create new investment and employment opportunities. Approximately 75 percent of commercial buildings in the U.S. were built more than 20 years ago, and 30 percent were built more than 50 years ago (U.S. Department of Energy 2008). In New York City, one of the oldest urban centers in the U.S., fully 85 percent of buildings that will be standing by 2030 have already been constructed (City of New York 2011). The existing building stock represents a significant opportunity to reduce total emissions through energy efficient retrofit strategies. However, substantial challenges remain to scaling up energy efficiency and GHG emission reduction measures in existing buildings, including regulatory, economic, technological, and behavioral constraints.



Source: Kontokosta 2011

Figure 2.0.1: Number of U.S. Cities with Green Building Policy and Sustainability Plan (Kontokosta 2011a)

Energy disclosure laws represent one of the most promising public policy tools to accelerate market transformation around building energy efficiency. These laws require building owners to report energy consumption on an annual basis. The first and most ambitious of these policies is New York City's Local Law 84 (hereafter LL84 and the subject of this report), adopted as part of Mayor Bloomberg's Greener, Greater Buildings Plan in 2009. Local Law 84 stipulates that all commercial (including multi-family) buildings of 50,000 square feet (approximately 4,645 square meters) or more must report energy and water consumption on an annual basis. The first deadline for reporting occurred in August of 2011.

This database represents one of the largest and most heterogeneous collections of non-voluntary building energy performance data in the nation. This information will allow New York City, and other cities with such policies including Seattle, San Francisco, and Washington DC, to understand the factors that influence building energy consumption, to create a benchmark for investment-quality comparisons across building types, and to provide the market with sufficient information to account for energy efficiency in investment decisions.

The potential for energy disclosure policies to shift market awareness of building energy efficiency is substantial. Research has shown that similar disclosure requirements in other industries, such fuel efficiency in the auto sector and nutrition labels for food served by "chain" restaurants, has led to changes in behaviors by both produces/suppliers and consumers/end-users (Day 1976; Vadiveloo, Dixon, and Elbel 2011). In the building sector, greater information on energy performance will allow tenants to incorporate energy efficiency metrics into leasing decisions. This, in turn, should create demand for more efficient buildings, thereby encouraging building owners to improve the relative energy efficiency of their building to make it more competitive.

There are, however, numerous impediments to energy efficiency improvements in existing buildings resulting from information asymmetries. One well-known challenge is the "split incentive" problem, defined as the mismatch between costs and benefits for owners and tenants in multi-tenant commercial buildings (Gillingham, Harding, and Rapson 2012; Schleich 2009). An emerging contractual tool known as the "energy-aligned lease" works to overcome this mismatch by clearing defining how costs for energy efficiency improvements are passed-through from owner to tenant (see Figure 2.0.2). Another challenge is the availability and cost of capital for energy efficiency improvements (Galuppo and Tu 2010; Kontokosta 2011b). Currently, uncertainty and risk around the potential energy savings from improvements has limited the sources of funds for building owners seeking to retrofit their buildings.

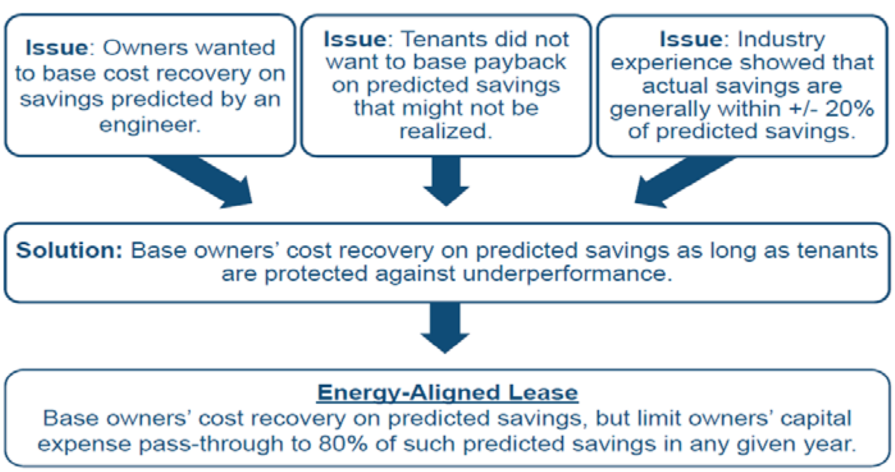


Figure 2.0.2: Energy-Aligned Lease Description (Source: NYC OLTPS)

There are a number of innovative financing mechanisms that have been developed, including performance contracts, on-bill financing, property-assessed clean energy (PACE) bonds, together with equity investors willing to fund what are perceived as high-yield, high-risk investments in energy efficiency improvements. Energy performance data collected through energy disclosure laws has the potential to increase the volume and quality of information on building energy efficiency and help to reduce uncertainty around patterns of building energy consumption and the savings expected from a building energy retrofit and specific energy conservation measures (ECMs). These data, together with pre/post studies of energy consumption in retrofitted buildings, will help to minimize risk and thus reduce the cost of capital for building owners seeking to optimize the efficiency of their property. By lowering the cost of capital for building retrofits, the yield on such investments will increase and shift the calculus of the business case for sustainable buildings.

More information and data on building energy consumption also has significant implications for infrastructure investment, particularly as it relates to the electricity grid and other sources of energy. By identifying clusters of poorly-performing or high consumption buildings, cities and utility companies can more efficiently determine where to focus their capital budgets and how best to target energy efficiency incentives. This type of information could also be used to locate potential areas for distributed generation facilities and other forms of shared renewable energy capabilities. Finally, understanding the spatial patterns of energy consumption can help neighborhoods to better plan future development and address issues of carbon emissions and potential negative externalities of inefficient buildings, including air quality and other public health concerns.

The growing availability, coverage, and granularity of building data have the power to transform real estate markets and investment decision-making around sustainability and energy efficiency. By properly collecting, analyzing, and disseminating this type of information, all of the key decision-makers in sustainable building markets – owners, tenants, lenders and investors, city agencies, utility companies – will have a robust source of data that will allow asset and portfolio-level decisions to include environmental impact as an important criterion in defining a suitable investment. By shifting market values to account for energy and emissions, the potential exists to catalyze a significant scaling up of energy efficiency initiatives in the global buildings sector.

3.0 DATA DESCRIPTION AND BACKGROUND

This report analyzes energy consumption and building data for commercial buildings over 50,000 square feet in New York City. These data were collected as per New York City LL84, which requires annual energy consumption reporting for large commercial buildings. This analysis includes all covered buildings for which information was submitted by August 31st, 2011. The LL84 database was then merged with building and lot information from the Primary Land Use Tax Lot Output (hereafter PLUTO) data file from the New York City Department of City Planning. The initial merged database contained 59 variables from PLUTO and 166 variables from the LL84 database enter through the EPA's Portfolio Manager tool.

3.1 Data Cleaning

Initially, the database contained 10,201 observations. However, substantial cleaning was performed to remove errors and omissions in data entry through the EPA Portfolio Manager interface. An observation was dropped from the analysis if it exhibited one of the following characteristics:

- Building located outside of the political boundaries of the five boroughs of New York City
- Facility Type was not indicated
- No Energy Use Intensity (EUI) value was provided
- Duplicate entries

In addition, the top and bottom one percent of buildings by EUI were omitted as outliers. The resultant cleaned database contains 8,648 observations. Additional measures were taken to ensure the accuracy and validity of the remaining observations, including mean testing with a quality-controlled sample of the dataset.

The dropped observations are indicative of a range of data entry errors and uncertainty in how to report certain unusual circumstances relating to building and meter configuration. For instance, two buildings on two separate parcels, but with a shared meter, might have been entered with all of the energy consumption attributed to just one building (and thus resulting in zero energy consumption for the other) or by arbitrarily allocating energy use between the two buildings.

3.2 Descriptive Statistics

The figures below provide a descriptive analysis of the type and quantity of space covered by the data and patterns of energy and water consumption and energy efficiency, as measured by source energy use intensity unless otherwise indicated. Source energy is the energy used during generation and transmission in addition to energy consumed at the site (EPA 2011).

In total, over 1.4 billion square feet of commercial space reported energy consumption by August 2011. A large majority, both by square footage and number of buildings, are multi-family properties. Office buildings represent the second largest amount of space reported.

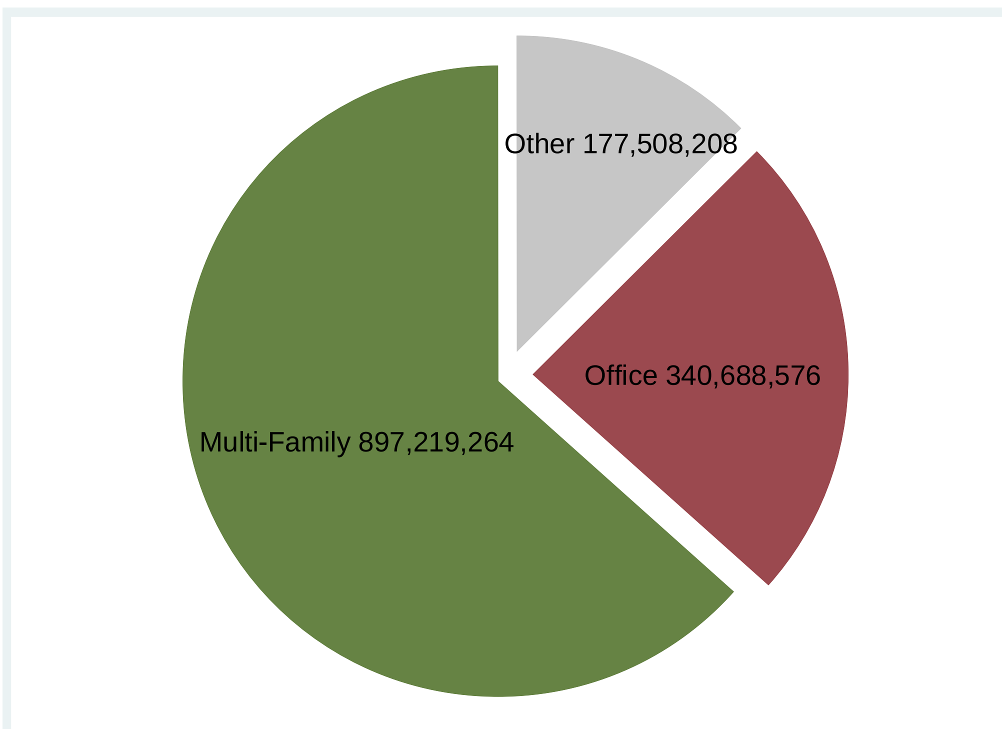


Figure 3.2.1: Total Square Footage in LL84 Database, by Building Type

Distribution of Building Energy Use Intensities

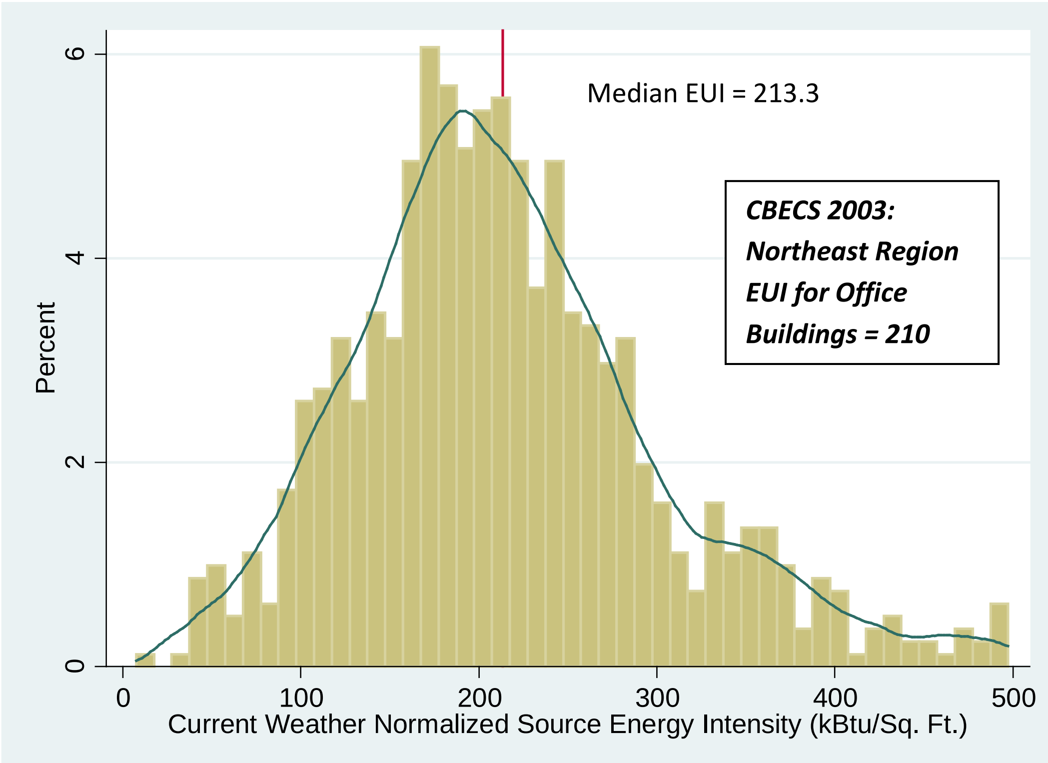


Figure 3.2.2: Histogram of Source EUI with Kernel Density Plot, Office Buildings Only

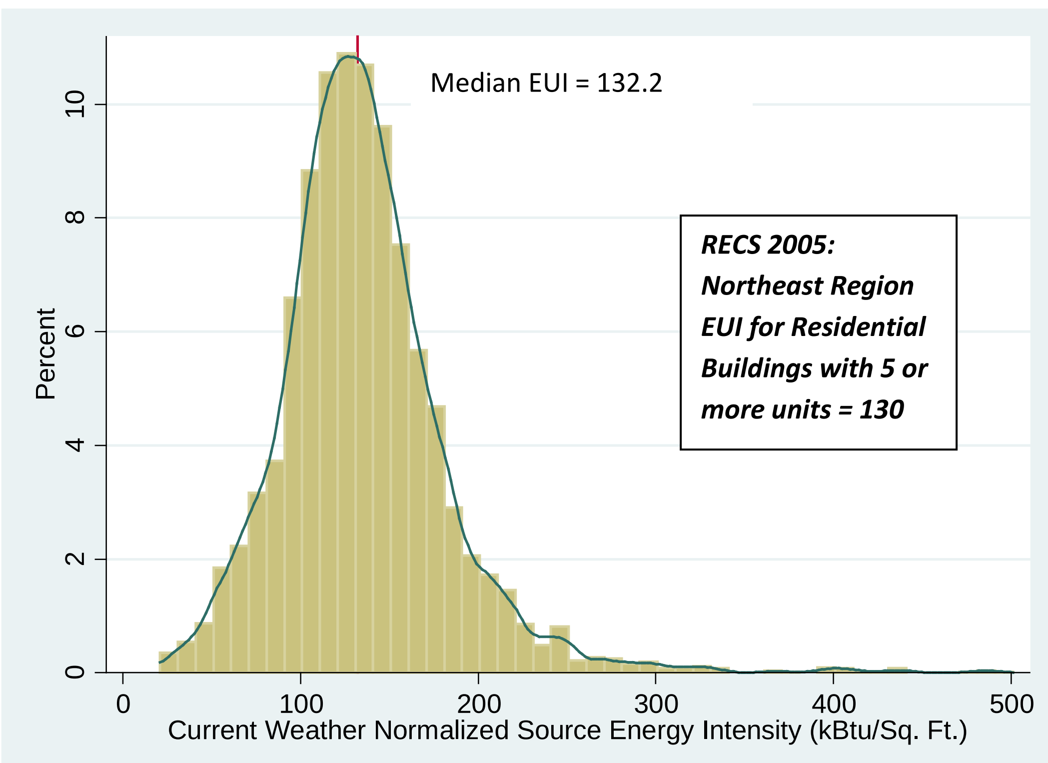


Figure 3.2.3: Histogram of Source EUI with Kernel Density Plot, Multi-Family Buildings Only

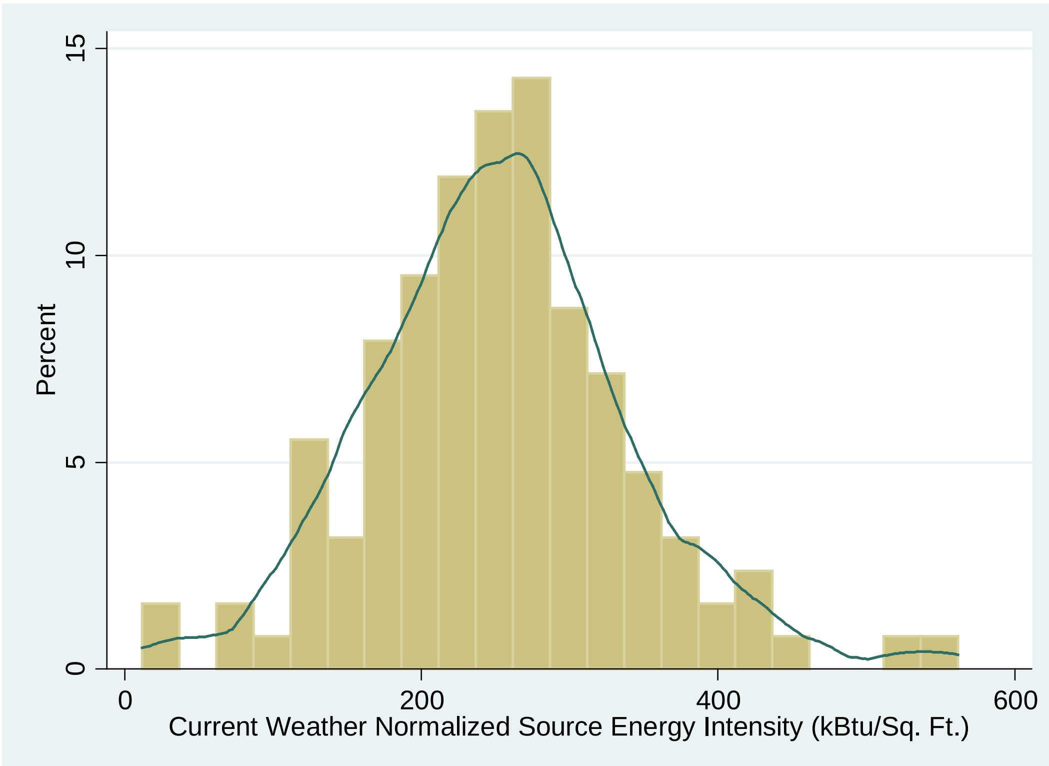


Figure 3.2.4: Histogram of Source EUI with Kernel Density Plot, Hotel/Lodging Buildings Only

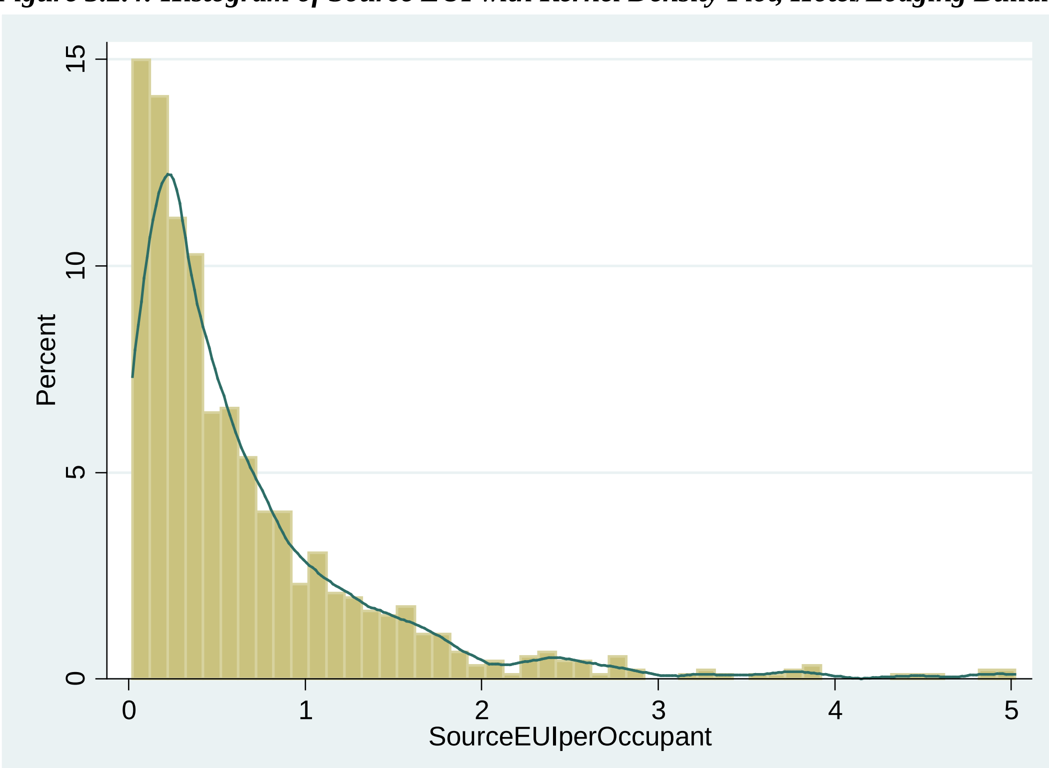


Figure 3.2.5: Histogram of Source EUI per Occupant, Office Buildings Only

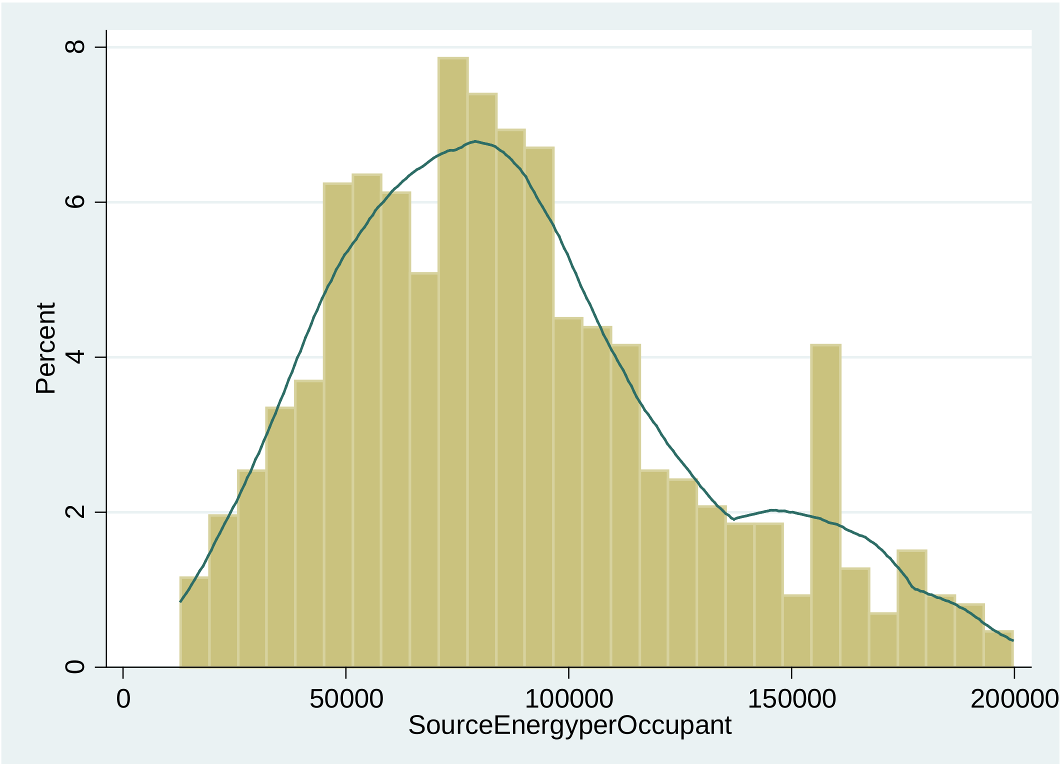


Figure 3.2.6: Histogram of Source Energy per Occupant, Office Buildings Only

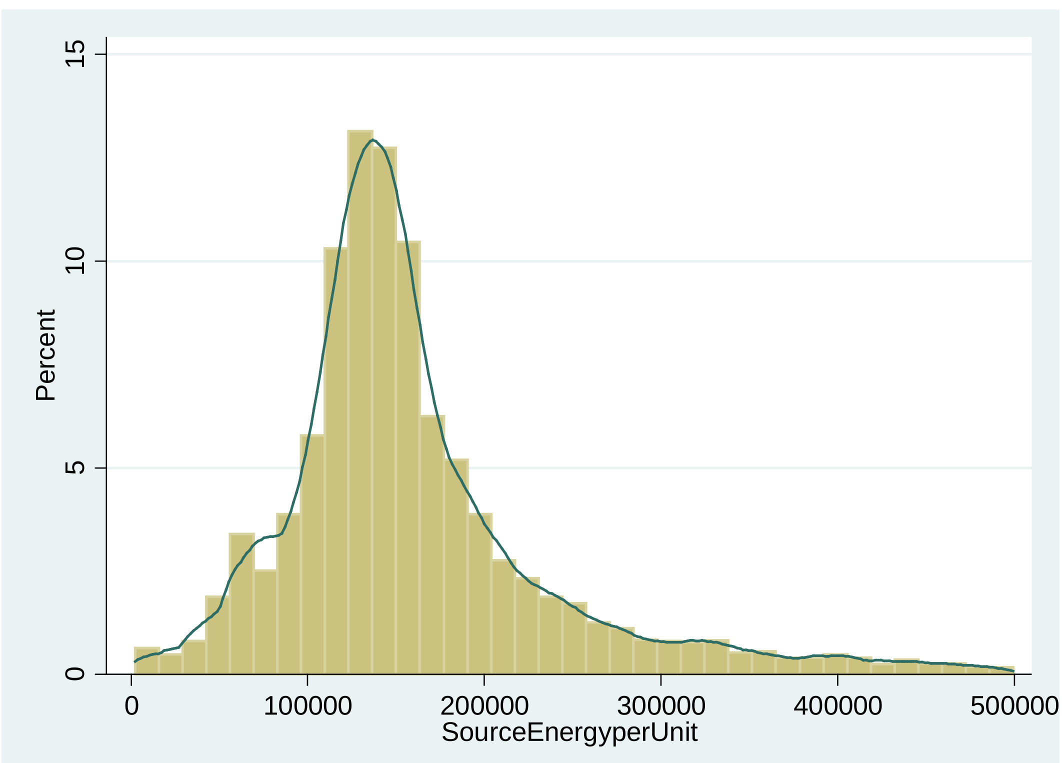


Figure 3.2.7: Histogram of Source Energy per Unit, Multi-Family Buildings

Building Energy Efficiency and Fuel Type

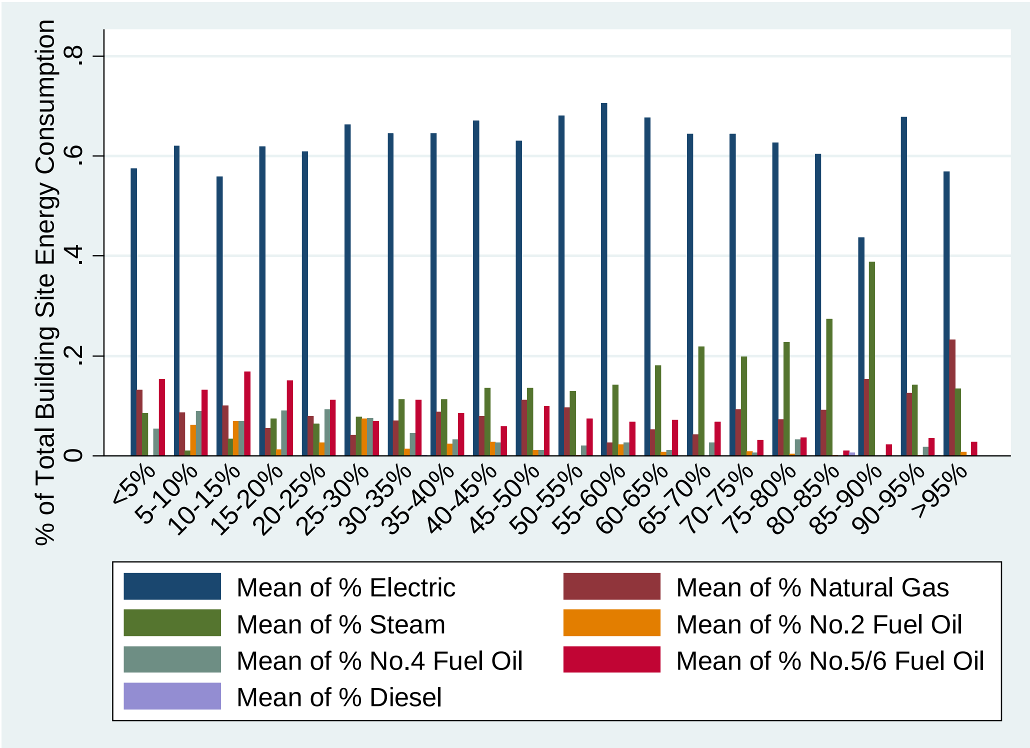


Figure 3.2.8: Average Percent of Total Site Energy Consumption by Fuel Type, 20-Quantile (Five-Percent Increments) based on Source EUI, Office Buildings

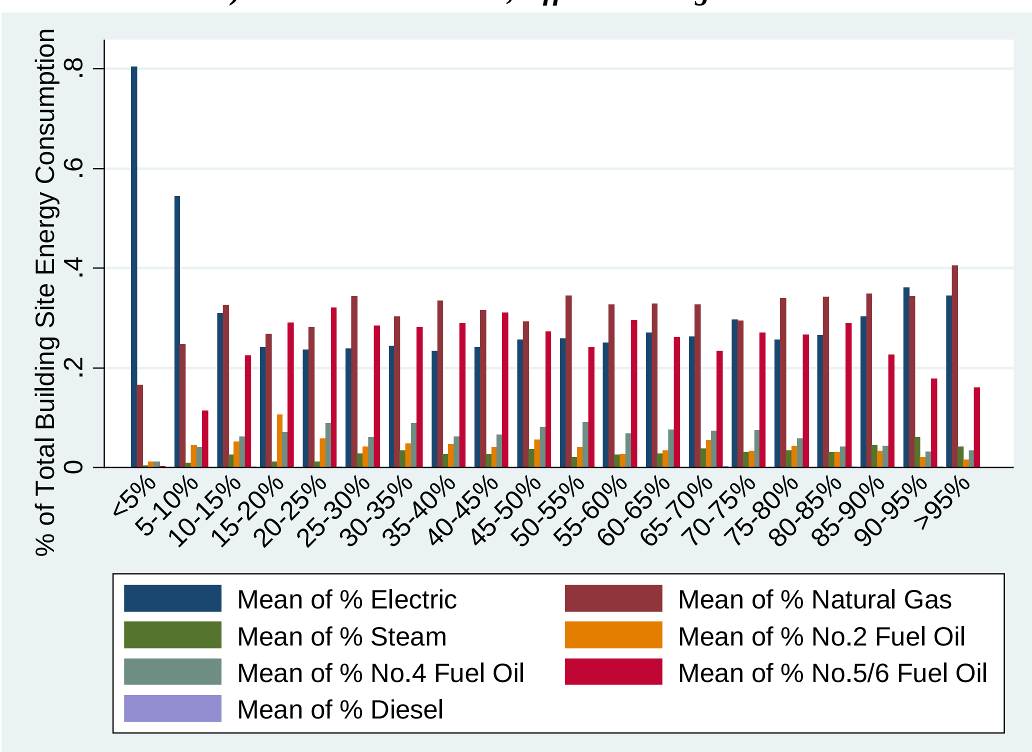


Figure 3.2.9: Average Percent of Total Site Energy Consumption by Fuel Type, 20-Quantile (Five-Percent Increments) based on Source EUI, Multi-Family Buildings

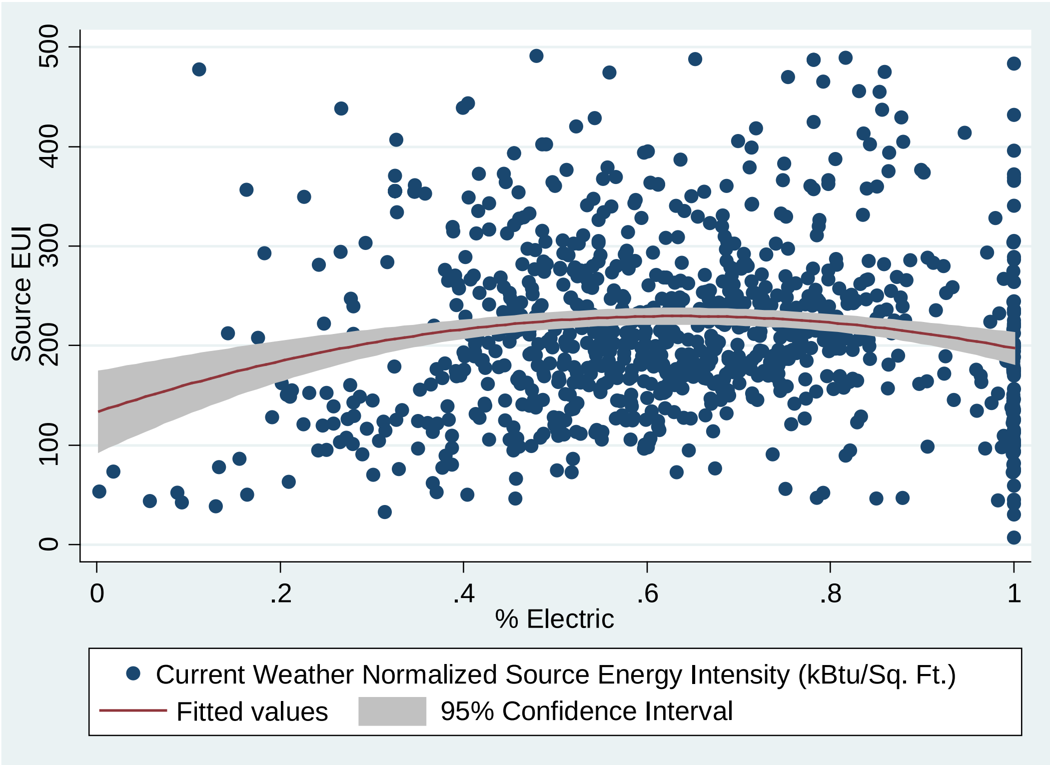


Figure 3.2.10: Source EUI by % Electric Energy Source, Office Buildings

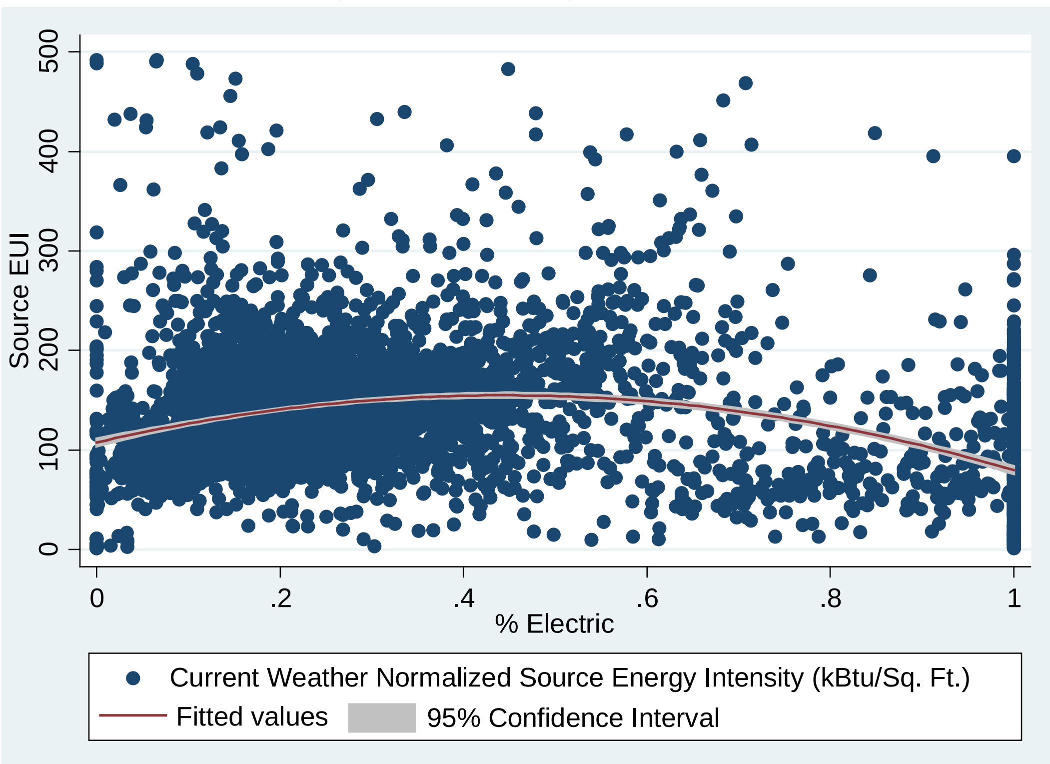


Figure 3.2.11: Source EUI by % Electric Energy Source, Multi-Family Buildings

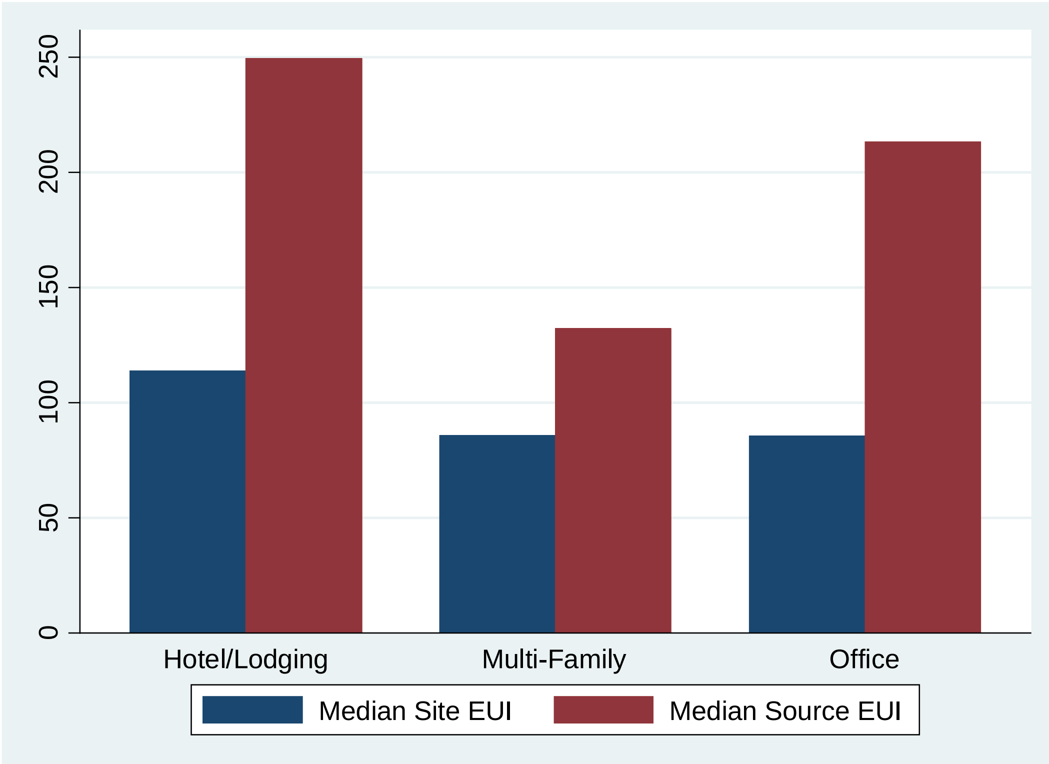


Figure 3.2.12: Bar Plot, Site EUI v. Source EUI

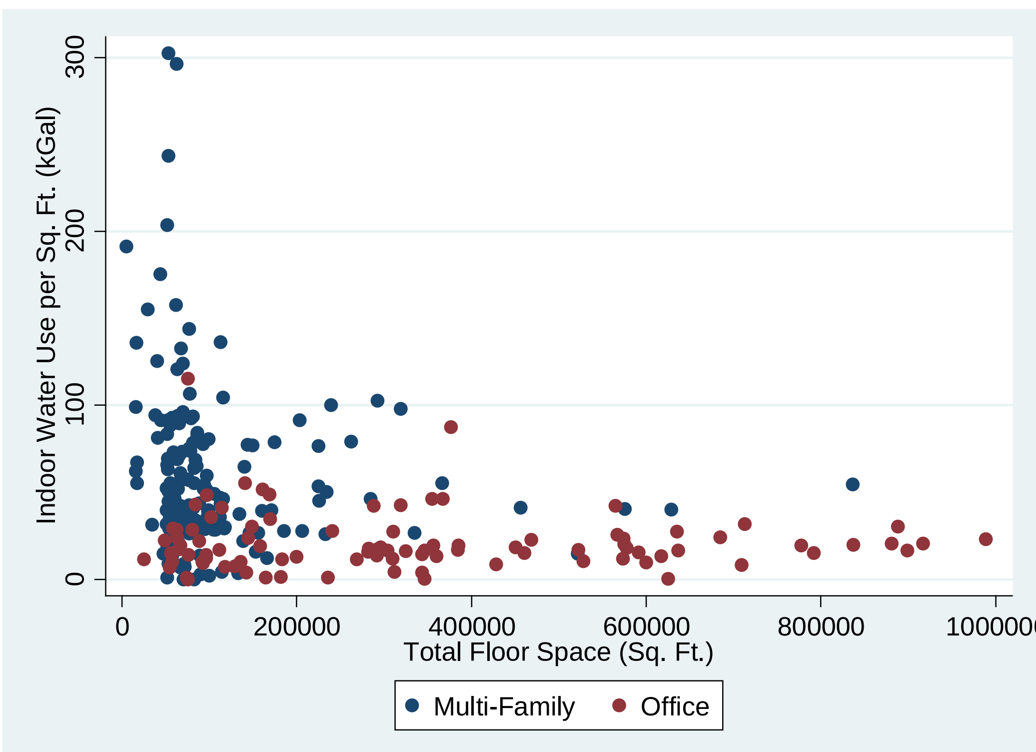


Figure 3.2.13: Combined Scatterplot of Water Consumption per Sq.Ft., Multi-Family and Office Buildings

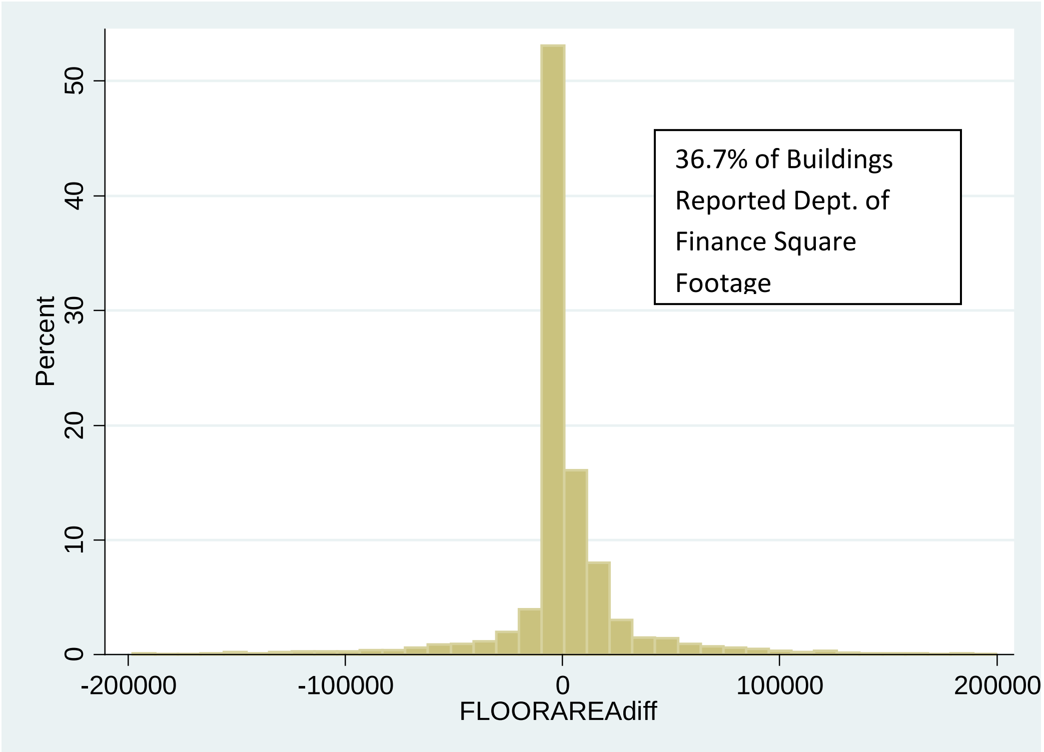


Figure 3.2.14: Histogram of Difference Between Self-Reported Total Square Footage and Department of Finance Total Square Footage (Multiple Buildings and Outliers excluded)

<u>Building Age and Energy Use Intensity</u>

The figures below present building EUI as a function of building age. For both office and multi-family buildings, older buildings, particularly those more than 80 years old, are found to be more efficient, on average. The data shown in the charts do not control for other building factors; this is discussed in Section 4.0. Figures 3.2.22 and 3.2.23 reveal clusters of building activity since 1900.

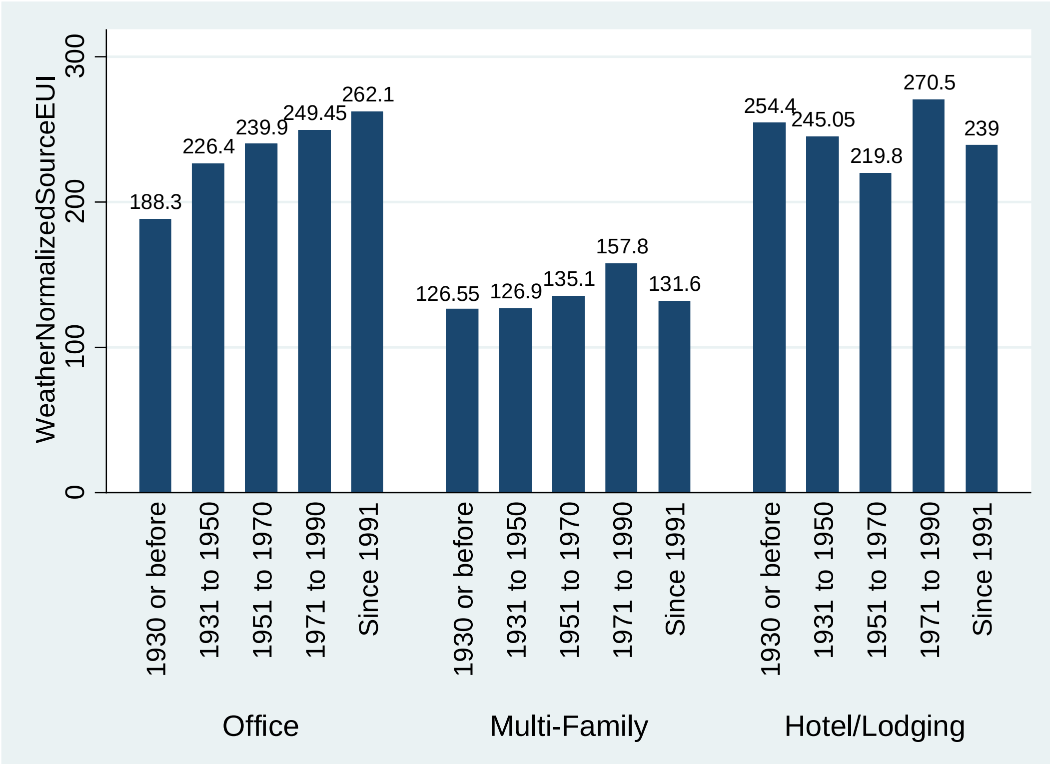


Figure 3.2.17: Source EUI by Building Age and Type

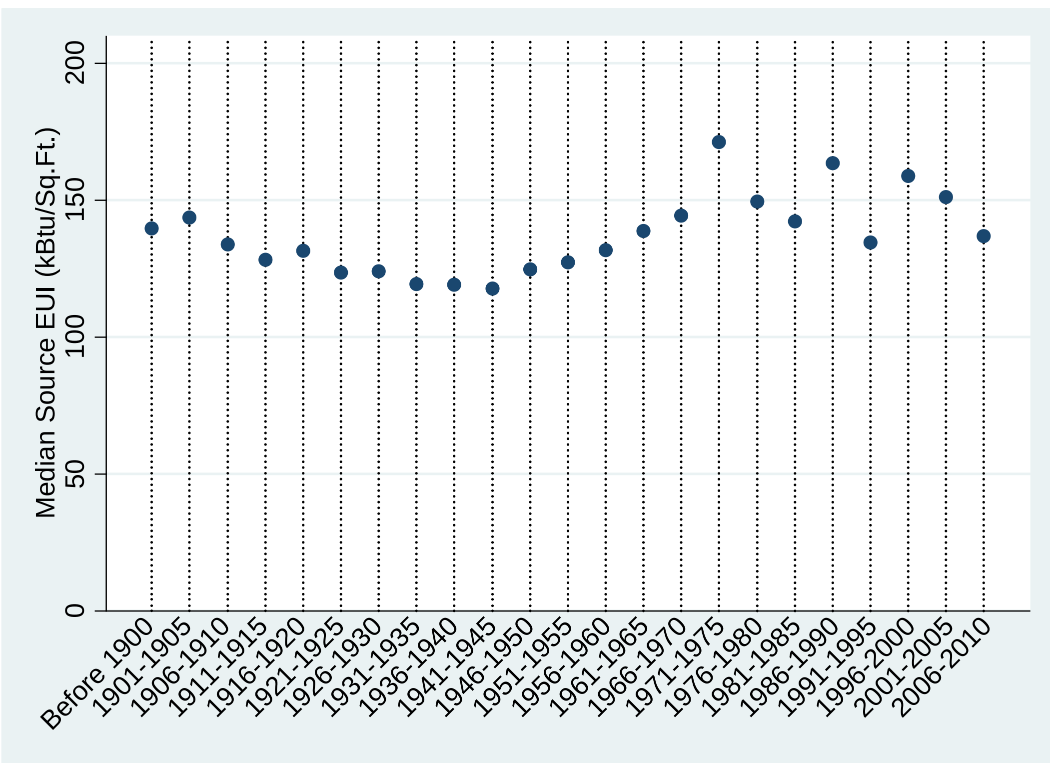


Figure 3.2.18: Median Source EUI by Building Age (Five-Year Increments), Multi-Family Buildings

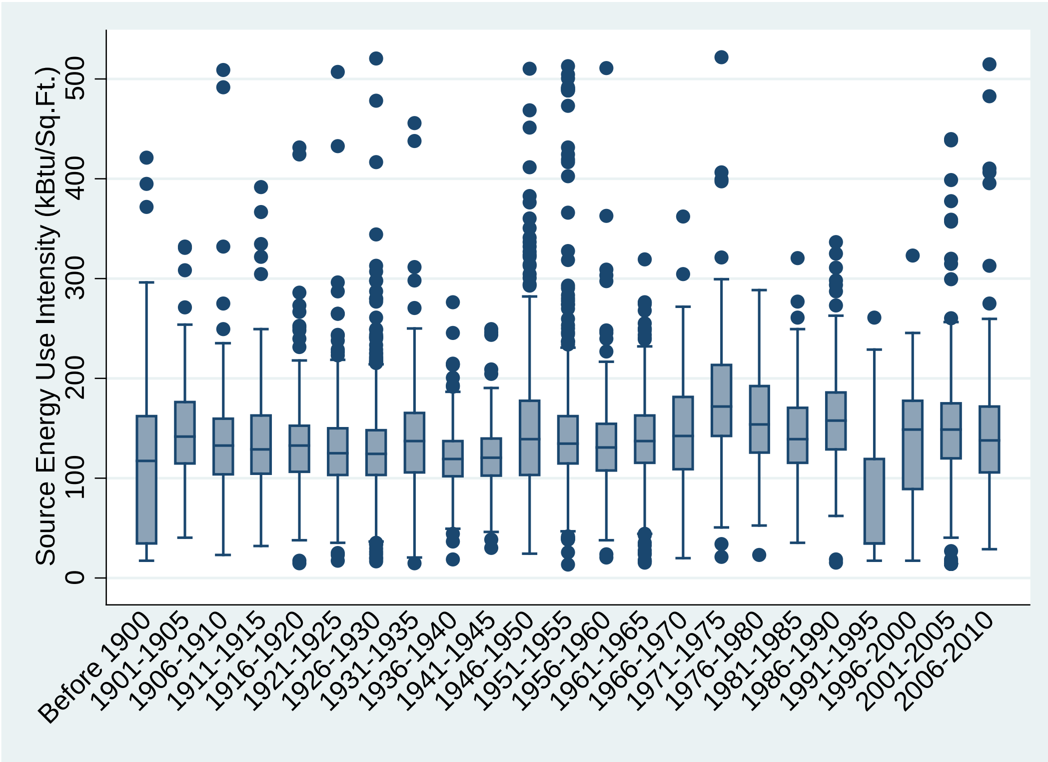


Figure 3.2.19: Box Plot of Source EUI by Building Age (Five-Year Increments), Multi-Family Buildings

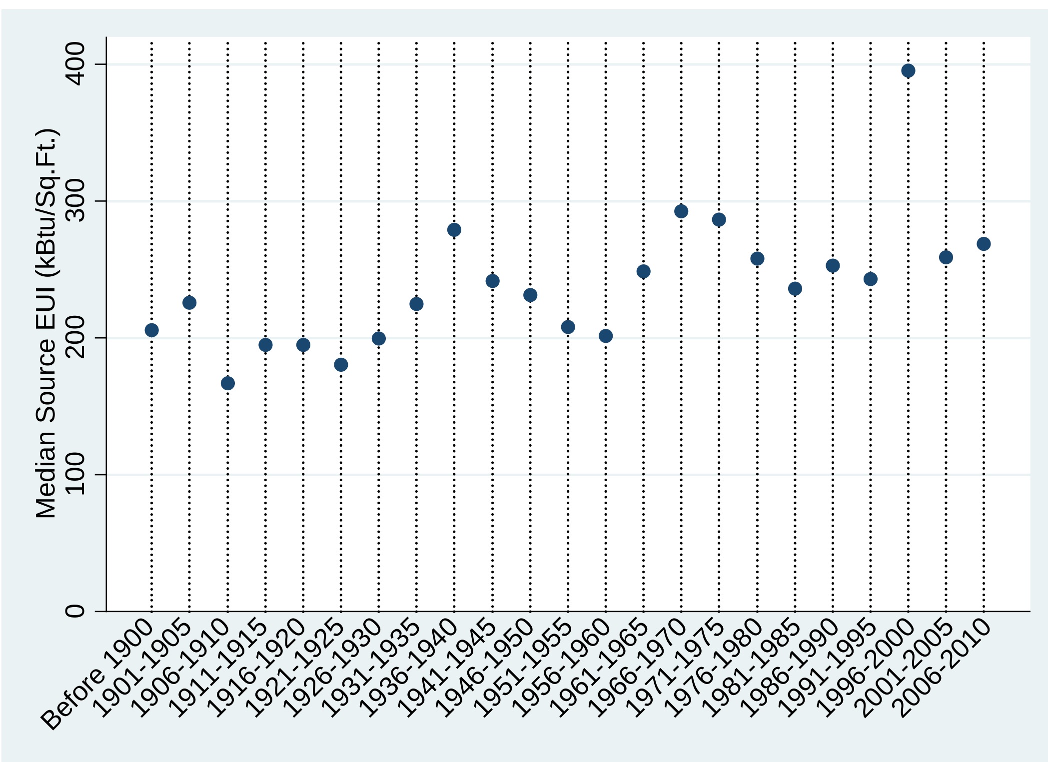


Figure 3.2.20: Median Source EUI by Building Age (Five-Year Increments), Office Buildings

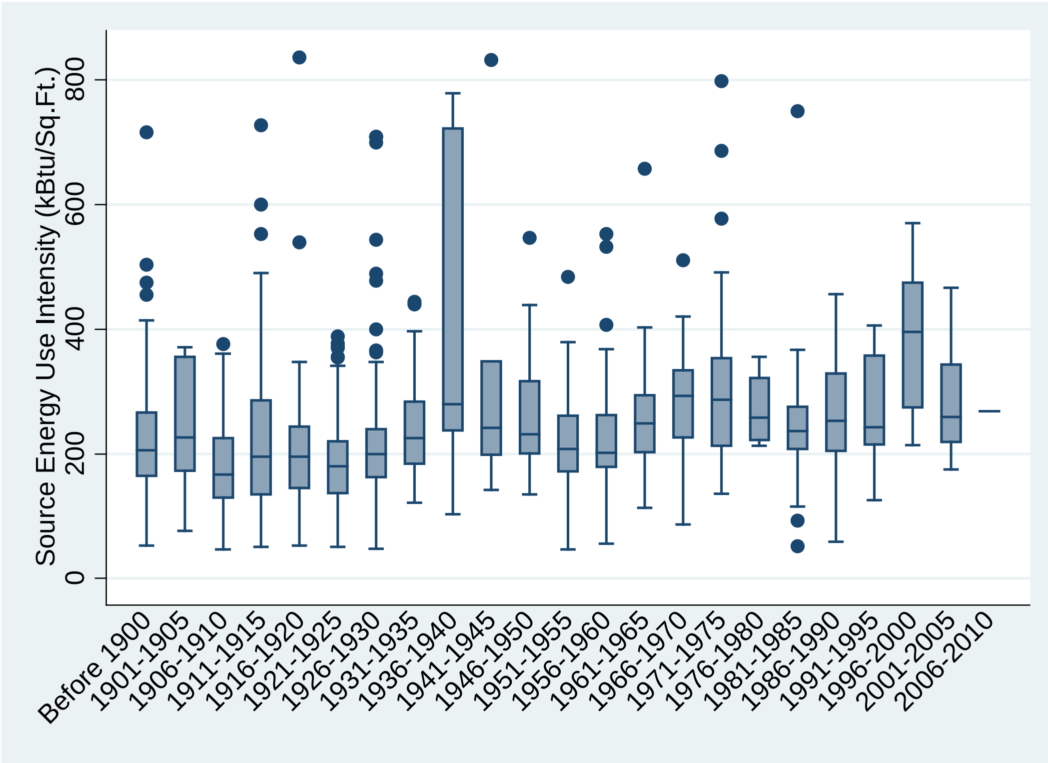


Figure 3.2.21: Box Plot of Source EUI by Building Age (Five-Year Increments), Office Buildings

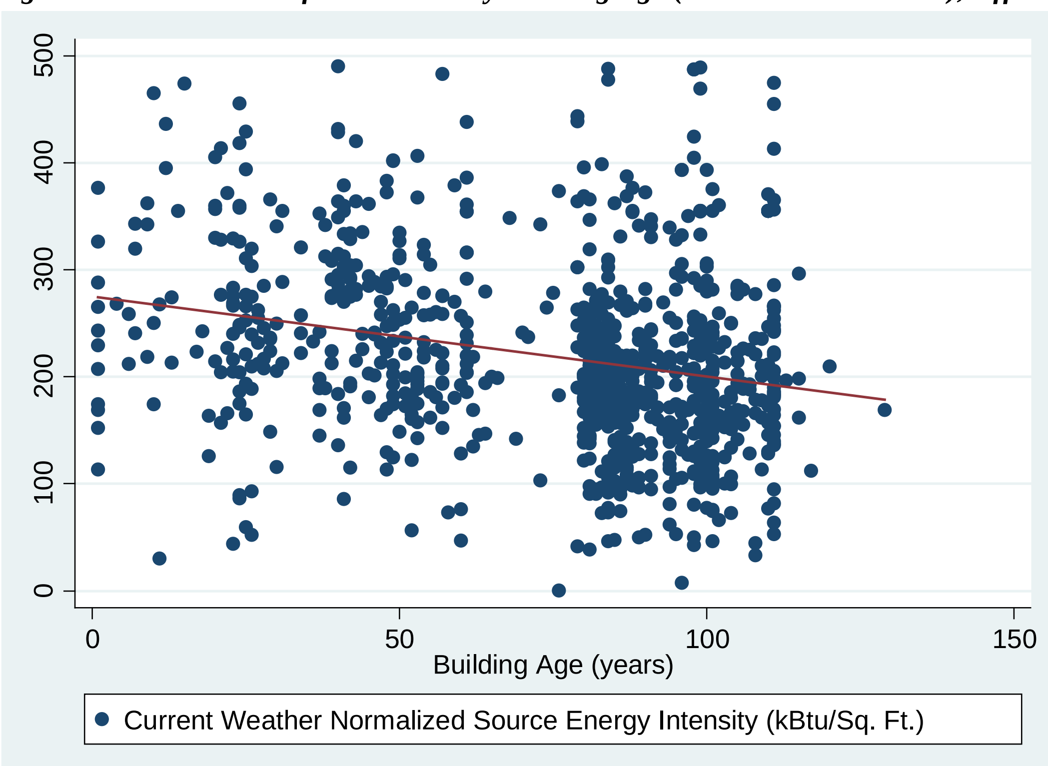


Figure 3.2.22: Scatterplot with Linear Fit Line of Building Age and Source EUI, Office Buildings

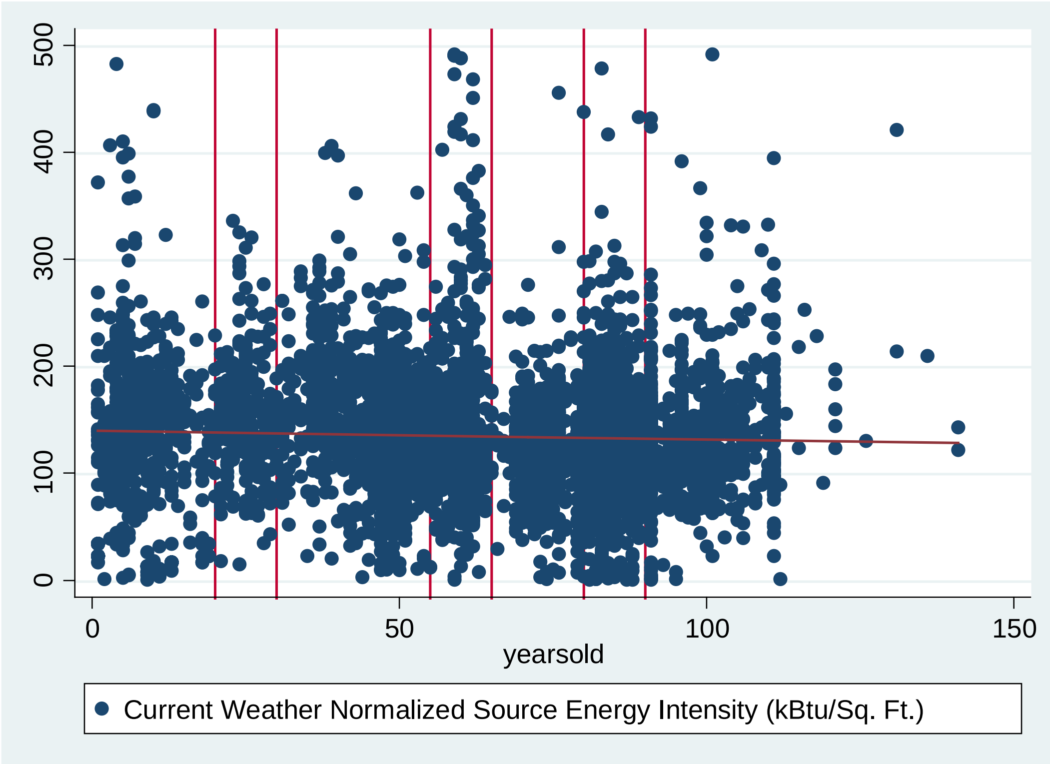


Figure 3.2.23: Scatterplot with Linear Fit Line of Building Age and Source EUI, Multi-Family Buildings

4.0 PREDICTIVE MODEL AND DETERMINANTS OF BUILDING ENERGY CONSUMPTION

This section analyzes the determinants of building energy consumption, based on the LL84 and PLUTO data, and develops a predictive model to create an energy performance benchmark or to estimate energy consumption for buildings where no actual data exists (Griffith et al. 2008). The predictive model can be used for several purposes, including:

1. Estimating energy consumption in noncompliant LL84 covered buildings
2. Estimating energy consumption in buildings less than 50,000 square feet, and those otherwise not subject to the requirements of LL84
3. Estimating energy consumption in buildings where actual energy consumption data is not available
4. Developing an energy benchmarking tool to identify more and less efficient buildings

4.1 Determinants of Building Energy Consumption

Building energy consumption is given by the following function:

$$\boxed{y = \alpha + \beta_1 SPATIAL_i + \beta_2 BULK_i + \beta_3 OCC_i + \beta_4 TYPE_i + \beta_5 ENERGY_i + \varepsilon}$$

where *SPATIAL* consists of geographic and locational variables, *BULK* includes variables that measure building size and placement on a given lot, *OCC* represents variables for occupant density and energy-consuming amenities, *TYPE* includes space type variables, *ENERGY* consists of variables for energy source, and ε is the error term.

Using robust multiple regression techniques, this section presents the factors that influence building energy efficiency (Griffith et al. 2008; Tso and Yau 2007; Turiel 1987). Based on the model coefficients and tests of significance, the model output is used to predict building energy consumption for use in creating an energy efficiency benchmark for commercial buildings in New York City (Chung, Hui, and Lam 2006; Hernandez, Burke, and Lewis 2008). It should be noted that there are potential limitations to multiple regression modeling for predicting building energy efficiency (Tso and Yau 2007). Potential bias in the coefficient estimates may result from collinearity between the explanatory variables.

Due to significant differences in energy consumption across building types, and the type-specific variables available in the LL84 database, individual models are created for each primary building type.

For all building types, the following independent (explanatory) variables are included in the base model:

Building Square Footage – Total building area as reported in PM

Building Age – Age of building based on year built from PLUTO database (new variable)

Number of Floors – Total number of floors in building from PLUTO database

FAR – As-built floor area ratio from PLUTO database

Lot Coverage – building footprint divided by lot area from PLUTO database. Building footprint approximated by multiplying building width by building depth (new variable)

Lot Location – a binary variable for whether the building is an inside lot or corner lot (based on variable from the PLUTO database)

Detached Building - a binary variable for whether the building is detached or attached to adjacent buildings (based on variable from the PLUTO database)

Primary Energy Source – a binary variable equal to 1 for the dominant fuel type in the building, and equal to 0 otherwise (new variable)

% non-Primary Space Type – percentage of non-primary space type (e.g. percentage of retail in a building with a majority office space) (new variable)

For Office buildings, the following variables are added to the base model:

Office Worker Density – Number of employees per 1,000 square feet (default value = 2.3)

Office Weekly Operating Hours – number of hours per week that a building is occupied by at least 75% of the tenant employees (default value = 65 hours per week)

Floor Plate Size – estimate of average floor plate size (new variable)

For Multi-Family buildings, the following variables are added to the base model:

Affordable or Market Rate – a binary variable equal to 1 if all units in building are affordable, and equal to 0 if market-rate (new variable); note that "affordable" is used here according to the EPA Portfolio Manager definition, which includes subsidized housing intended for low-income households.

Number of Laundry Facilities per Unit – total number of laundry facilities for each residential unit

Number of Dishwashers per Unit – total number of dishwashers for each residential unit

Percent Cooled – percent of gross floor space that is air conditioned

Average Unit Size = estimate of the average gross floor area per unit (new variable)

Individual models for office and multi-family buildings are estimated using ordinary least-squares (OLS) regression methods. Each building type model is run using both Weather Normalized Source EUI and its natural log as the dependent variable. The results are presented below.

Dependent Variable	Source EUI		log Source EUI	
	N = 824		N = 824	
	F-stat = 8.68		F-stat = 9.12	
	R^2 = .198		R^2 = .199	
	Coef.		*Coef.*	
Building Renovation				
Altered and Building 21 to 40 years old	-23.667		-0.0955	
Altered and Building 41 to 60 years old	-54.652	***	-0.2090	***
Altered and Building 61 to 80 years old	34.626		0.1521	
Altered and Building 81 or more years old	9.749		0.0523	
Building Age				
21 to 40 years old	-6.269		-0.0283	
41 to 60 years old	-14.936		-0.0350	
61 to 80 years old	-34.004		-0.1320	
81 or more years old	-61.021	***	-0.2542	***
Energy Source (> 50% site energy)				
Electric	18.699	*	0.1410	***
Steam	27.554	*	0.1663	**
Bulk and Area				
Lot Coverage	0.674		0.0040	*
Lot Area (000s of sq.ft.)	-0.093		-0.0002	
Detached Building	-9.406		-0.0827	
Inside Lot	-15.288	*	-0.0681	*
Number of Floors	-1.077	*	-0.0008	
Floor Area (000s of sq.ft.)	0.064	***	0.0002	**
% non-Office Space	82.017	**	0.3527	**
Floor Plate - 10k to 20k sq.ft	-0.216		0.0013	
Floor Plate - more than 20k sq.ft.	-8.514		-0.0269	
In Historic District?	-22.136	**	-0.0949	
Occupancy				
Weekly Operating Hours	0.447	**	0.0014	
Worker Density (workers per 1,000 sq.ft.)	10.482	***	0.0569	***
Value				
Assessed Value per Sq.Ft.	0.194	*	0.0005	
Constant	180.592	***	5.0284	***

Figure 4.1.1: Regression Results, Source EUI and natural log of Source EUI as dependent variable, Office Buildings **(excluding lots with multiple buildings)**

Dependent Variable	*Source EUI*		*log Source EUI*	
	N = 3642		N = 3642	
	F-stat = 21.04		F-stat = 23.12	
	R^2 = .1546		R^2 = .1594	
	Coef.		*Coef.*	
Building Renovation				
Altered and Building 21 to 40 years old	2.306		-0.002	
Altered and Building 41 to 60 years old	-2.888		-0.031	
Altered and Building 61 to 80 years old	-1.912		-0.021	
Altered and Building 81 or more years old	-0.151		0.001	
Building Age				
21 to 40 years old	11.530	**	0.075	**
41 to 60 years old	-5.127		-0.026	
61 to 80 years old	-22.025	***	-0.163	***
81 or more years old	-12.857	**	-0.105	***
Energy Source (> 50% site energy)				
Electric	-10.123	***	-0.192	***
Steam	1.238		0.005	
Natural Gas	5.987	***	0.029	**
Bulk and Area				
Lot Coverage	-0.012	***	-0.0001	***
Lot Area (000s of sq.ft.)	0.159	*	0.001	*
Detached Building	-0.913		-0.001	
Inside Lot	-3.082	**	-0.023	**
Number of Floors (7 or more)	-7.431	***	-0.046	***
Floor Area (000s of sq.ft.)	-0.027	**	-0.0002	**
% non-Residential Space	45.343	***	0.299	***
Gross Sq.Ft. per Unit	-0.004	*	0.000	*
In Historic District	-5.019	*	-0.029	
Amenities				
Dishwashers per Unit (1 or more)	1.838		0.017	
Laundry Facilities per Unit (1 or more)	7.668	**	0.053	**
% Space Cooled	8.679	*	0.061	***
Value				
Affordable Housing Only	7.819	**	0.035	
Assessed Value per Sq.Ft.	0.347	***	0.002	***
Constant	133.318	***	4.874	***

Figure 4.1.2: Regression Results, Source EUI and natural log of Source EUI as dependent variable, Multi-Family Buildings (excluding lots with multiple buildings)

4.2 Discussion of Results

On average, the models explain approximately 20 percent of the variation in energy efficiency across buildings. These models may, in fact, be more robust than those currently used in Energy Star benchmarking analysis, as the LL84 and PLUTO merged dataset provide a greater range of independent variables that have been shown to have a statistically significant effect on energy efficiency, including lot coverage, adjacent buildings, and other parcel-level characteristics (EPA 2011). For each building type, two models are estimated: one using source EUI as the dependent variable and the other using a semi-logarithmic transformation with the natural log of source EUI as the dependent variable. In this model, the coefficients can be approximated as the percent change in source EUI for a one unit change in the independent variable. However, it should be noted that the actual interpretation of the relationship between the independent and dependent variables is given by *exp(c)-1* where *c* is the coefficient value (Halvorsen and Palmquist 1980). The results and coefficient estimates for each model are discussed below.

4.2.1 Office Buildings

For office buildings (Figure 4.1.1), the age of the building is negatively correlated with EUI. Therefore, older buildings are found to be more efficient than those built more recently. Most notably, buildings over 80 years old have an almost 28 percent lower EUI than the average EUI for the entire sample. Buildings that are 41 to 60 years old and that have been altered (based on data contained in the PLUTO database) are also shown to be more energy efficient, controlling for the other variables included in the model.

Energy source is also a significant factor influencing source EUI, at least at the 90 percent confidence level. Buildings that primarily use either electric or district steam are shown to be less efficient than those using natural gas or fuel oil.

Looking at building size, space type, and location, several variables stand out. First, there is a positive correlation between EUI and building size, as measured by square footage. Larger office buildings, therefore, are shown to have higher EUIs (although it should be noted that buildings over 2,000,000 square feet are excluded from the model). Similarly, a larger amount of non-office space (based on a percentage of total space) is associated with a higher EUI. Specifically, for every additional 10 percent of non-office space, the building EUI increased by 8.2. Buildings on an inside lot (a lot with adjacent lots on either side) or in a historic district are found to have lower EUIs. This finding suggests the need for more detailed descriptions of the various uses in multi-use buildings.

Occupancy variables are a key driver of building energy efficiency. Worker densities vary considerably across usage and tenant types in office buildings, from relatively low-density law firm use, for example, to very high-density trading floors. Understanding and controlling for occupant density and the operational hours of a building are critical to the reliable and effective identification and comparison of peer groups of buildings. The regression results show that the coefficients for both weekly operating hours and worker density are positive and significant. As expected, this finding indicates that as operating hours or occupant density increases, so does the EUI of the building, after controlling for the factors included the model. The results in Figure 4.1.1 above reveal that for every additional hour the building is in operation, EUI increases by 0.45. Turning to the worker density variable, building EUI increases by a substantial 10.48 for every additional occupant added per 1,000 square feet. Therefore, it is shown that buildings with more people working longer hours have higher EUIs. This reinforces previous empirical evidence on building energy consumption from CBECS and highlights the importance of understanding building usage and occupant characteristics before attempting peer-to-peer building efficiency comparison.

4.2.2. Multi-Family Buildings

Many of the fundamental building characteristic variables – age, size, parcel location, fuel type – that are found to be significant for office buildings are also shown to be critical in understanding energy efficiency in multi-family buildings (Figure 4.1.2). Older buildings again shown to be correlated with lower EUIs, specifically for buildings more than 60 years old. Buildings that are more than 80 years old are much more efficient, controlling for the other factors in the model, than buildings built within the last twenty years. This finding is consistent with the results for office buildings, and reinforces the link between older buildings and energy efficiency. Interestingly, multi-family buildings built between 1970 and 1990 are found to be *less* efficient than similar buildings built since 1990. There are a number of possible explanations for this outcome, including the effects of building codes, construction materials, and building envelope.

Contrary to the findings for office buildings, larger multi-family buildings are found to be more efficient. Looking at the variables for number of floors (equal to 1 if the building has more than seven stories and 0 otherwise) and total building square footage, both are negative and significant, suggesting that as building size increases, building EUI decreases. The results demonstrate that buildings on inside lots, and thus with a high probability of adjacent structures, have lower EUIs. Similarly, buildings built more fully on a lot with, therefore, higher lot coverage ratios are more efficient than, for instance, a tower covering only a portion of the lot area. The coefficient estimates for both of these variables indicate the importance of adjacent buildings and the possible influence of shared party walls and less exposed building envelope area. Similar to office buildings, multi-family buildings located in historic districts have, on average, lower EUIs, after controlling for building age and other factors. This could reflect the building densities in these areas as well as the type of construction.

As with office buildings, energy source is a significant factor in determining source EUI. Multi-family buildings where electric is the dominant energy source (accounting for more than 50 percent of the total site energy consumption) have lower EUIs than buildings using fuel oil. Conversely, buildings where natural gas is the dominant energy source have slightly higher EUIs than comparable buildings using other energy sources.

For multi-family buildings with non-residential space, each additional ten percent of non-residential space equates to a 4.5 point increase in building EUI. This suggests non-residential space may occupied be higher intensity uses, such as retail and community facilities. It also raises issues of the availability of energy data for non-residential space in multi-family buildings.

The type of amenities in a multi-family building, including number of dishwashers, laundry facilities, and the amount of cooled space in the building, have a positive correlation with overall building EUI. Most notably, for buildings with one or more laundry facilities per unit, the building EUI is higher by 7.67. For the amount of cooled space, for every additional ten percent of cooled building area, the building EUI increases by 0.87.

Finally, buildings defined as "affordable" through the Portfolio Manager tool have, on average, a 7.82 higher EUI than mixed-income or market-rate buildings. Affordable buildings are defined as those buildings where all of the units are subsidized for occupancy by low-income households. Mixed-income buildings, such as 80/20 buildings, do not have a statistically significant difference in building EUI, controlling for other factors, as compared to market-rate buildings.

4.3 Predictive Model and Analysis

Using the coefficient estimates from the regression results, the predictive capacity of the models can be tested using actual data from observations in the LL84 database. Figures 4.3.1 and 4.3.2 below present the actual and predicted EUI for an office building in Manhattan and a multi-family building in Brooklyn.

As is shown below, the accuracy of the models is quite good and within a 15-20 percent range, although it must be noted that there is a wide variance in the predicted values. This reflects the explanatory power of the regression models presented above. The predictive models provide a solid foundation for developing a benchmark for office and multi-family buildings in New York City. It would be strengthened considerably by adding additional information on building systems and design characteristics. In the future, building energy audit data could be used to supplement the LL84 and PLUTO databases and create a more robust predictive model for building energy efficiency.

Figures 4.3.3 and 4.3.4 show the quantile-quantile (Q-Q) plots for office and multi-family buildings, respectively. These Q-Q plots display the relationship of actual EUI values to those predicted by the models for the entire LL84 sample. To clarify the interpretation of the graphs, if the predictive models were perfectly accurate in predicting building EUI, then all dots would fall on the upward-sloping diagonal line. Currently, the models are accurate in predicting EUI for buildings with actual EUIs around the respective medians for each building type, as would be expected given the relatively low explanatory power of the OLS models presented above. The models as specified tend to over-estimate EUI for more efficient (lower EUI) buildings and under-estimate EUI for less efficient (higher EUI) buildings.

				1423569	
				Bldg 1	
Building Renovation	*Coef.*			*Actual Values*	*Coef. Values*
Altered and Building 21 to 40 years old	-23.667			0	
Altered and Building 41 to 60 years old	-54.652	***		1	-54.7
Altered and Building 61 to 80 years old	34.626			0	
Altered and Building 81 or more years old	9.749			0	
Building Age					
21 to 40 years old	-6.269			0	
41 to 60 years old	-14.936			0	
61 to 80 years old	-34.004			0	
81 or more years old	-61.021	***		0	0.0
Energy Source (> 50% site energy)					
Electric	18.699	*		0	0.0
Steam	27.554	*		1	27.6
Bulk and Area					
Lot Coverage	0.674			1	
Lot Area (000s of sq.ft.)	-0.093			17.05	
Detached Building	-9.406			0	
Inside Lot	-15.288	*		0	0.0
Number of Floors	-1.077	*		21	-22.6
Floor Area (000s of sq.ft.)	0.064	***		330	21.2
% non-Office Space	82.017	**		0.02	1.6
Floor Plate - 10k to 20k sq.ft	-0.216			1	
Floor Plate - more than 20k sq.ft.	-8.514			0	
In Historic District?	-22.136	**		0	0.0
Occupancy					
Weekly Operating Hours	0.447	**		65	29.1
Worker Density (workers per 1,000 sq.ft.)	10.482	***		2.39	25.1
Value					
Assessed Value per Sq.Ft.	0.194	*		52.7	10.2
Constant	180.592	***		1	180.6
				252	**218.0**
				Actual EUI	**Predicted EUI**
				34.0	*differential*

Figure 4.3.1: Actual v. Predicted EUI – Office Building Example

				2721900	
				Bldg 1	
	Coef.			*Actual Values*	*Coef. Values*
Building Renovation					
Altered and Building 21 to 40 years old	2.306			0	
Altered and Building 41 to 60 years old	-2.888			0	
Altered and Building 61 to 80 years old	-1.912			0	
Altered and Building 81 or more years old	-0.151			0	
Building Age					
21 to 40 years old	11.530	**		1	11.5
41 to 60 years old	-5.127			0	
61 to 80 years old	-22.025	***		0	0.0
81 or more years old	-12.857	**		0	0.0
Energy Source (> 50% site energy)					
Electric	-10.123	***		0	0.0
Steam	1.238			0	
Natural Gas	5.987	***		1	6.0
Bulk and Area					
Lot Coverage	-0.012	***		0.387	0.0
Lot Area (000s of sq.ft.)	0.159	*		38.8	6.2
Detached Building	-0.913			0	
Inside Lot	-3.082	**		1	-3.1
Number of Floors (7 or more)	-7.431	***		1	-7.4
Floor Area (000s of sq.ft.)	-0.027	**		139.2	-3.7
% non-Residential Space	45.343	***		0	0.0
Gross Sq.Ft. per Unit	-0.004	*		838	-3.1
In Historic District	-5.019	*		0	0.0
Amenities					
Dishwashers per Unit (1 or more)	1.838			0	
Laundry Facilities per Unit (1 or more)	7.668	**		0.03	0.2
% Space Cooled	8.679	*		0.1	0.9
Value					
Affordable Housing Only	7.819	**		1	7.8
Assessed Value per Sq.Ft.	0.347	***		53	18.4
Constant	133.318	***			133.3
				140.9	**167.0**
				Actual EUI	**Predicted EUI**
				-26.1	*differential*

Figure 4.3.2: Actual v. Predicted EUI – Multi-Family Building Example

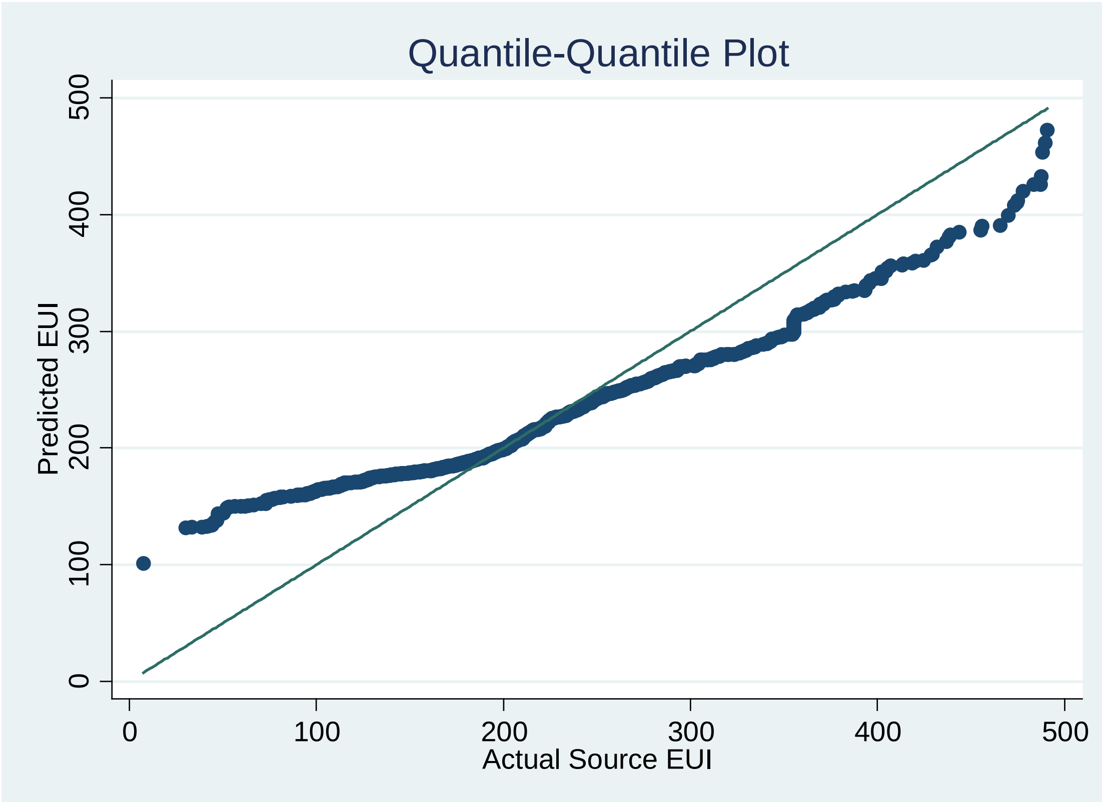


Figure 4.3.3: Quantile-Quantile Plot, Actual v. Predicted EUI, Office Buildings

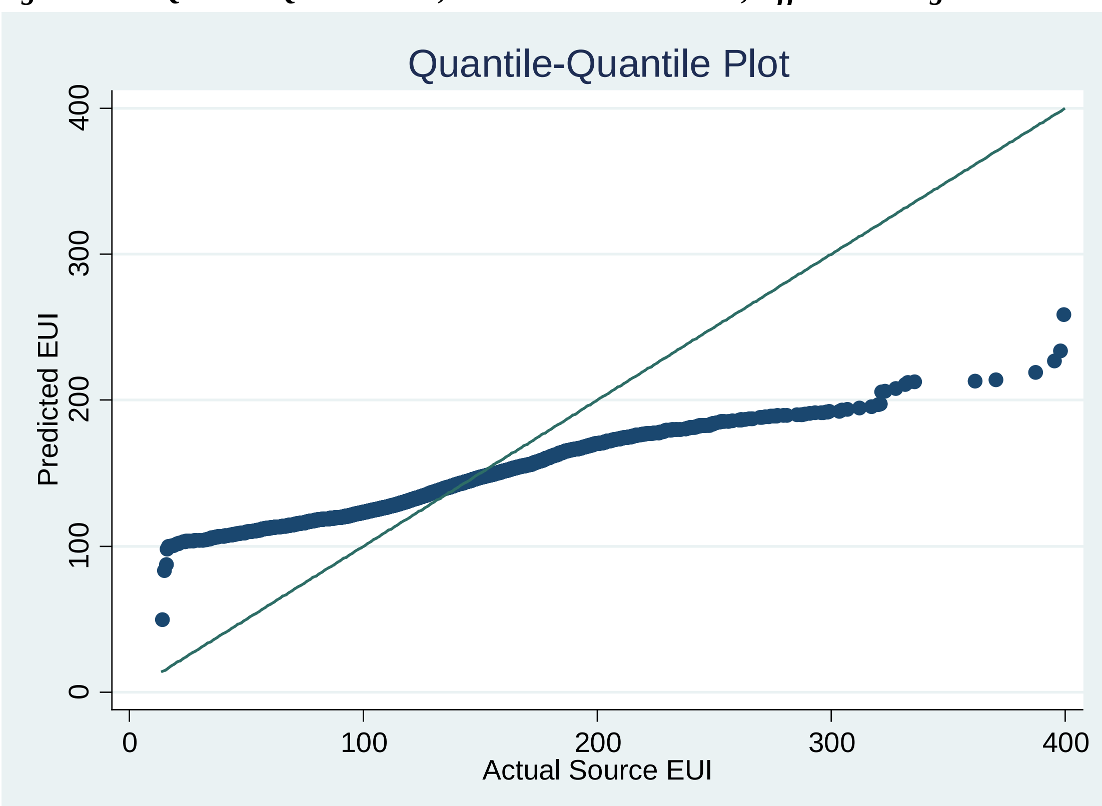


Figure 4.3.4: Quantile-Quantile Plot, Actual v. Predicted EUI, Multi-Family Buildings

5.0 MULTI-FAMILY BUILDING ENERGY RATING SYSTEM – A DISCUSSION

There are currently several initiatives underway to develop an energy rating/grading system for multi-family buildings (see, for example, Energy Star for Multifamily Housing; U.S. Department of Housing and Urban Development benchmark tool; Department of Energy Commercial Building Asset Rating Program). The LL84 database provides a rich source of information to build a rating system that controls for a number of observed building characteristics; however, additional data are needed on occupant/unit characteristics and consumption data collection methods. Possible foundations of a residential rating system include:

- Grading system based on 'A', 'B', and 'C' letter grades corresponding to building performance among some proportion cluster of energy performance. For example, the A-B-C letter grade scale could correspond to the 30% most efficient buildings, the 40% middle band of EUI, and the 30% least efficient buildings, respectively. Such a grading system would control for building and site characteristics as presented in the regression models in Section Four. In addition, data on building systems and operations would be useful in improving the reliability of the EUI predictive model and the accuracy of defining building comparison groups.

- Rating system tied to a benchmark for similar buildings, based off the predictive model presented in Section Four. This would function in a similar manner to the Energy Star measurement, but has the potential to improve the accuracy of the benchmark by controlling for additional building and site characteristics available through City of New York datasets.

Descriptive statistics for multi-family buildings in the sample are presented below.

5.1 Multi-Family Building Data Analysis

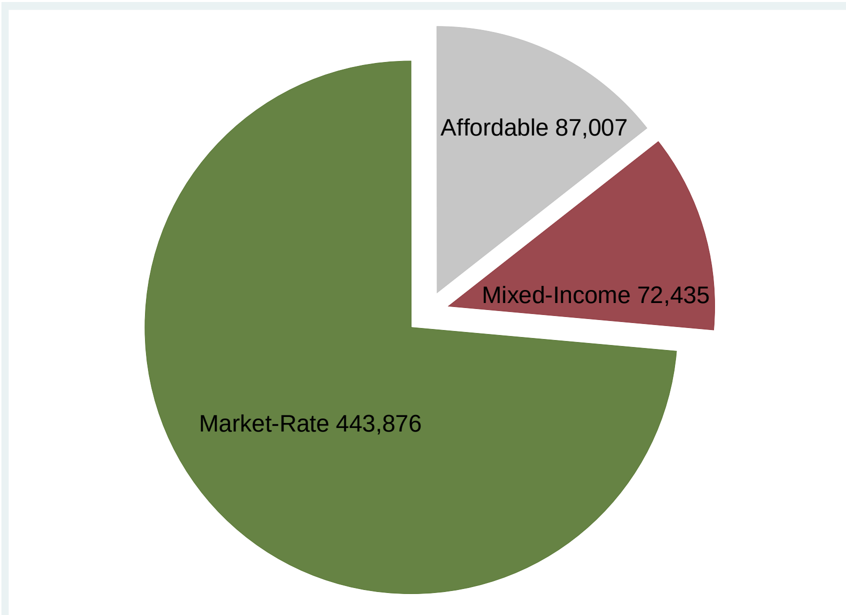


Figure 5.1.1: Number of Units by Type of Housing, Multi-Family Buildings (Note: Units in Mixed-Income Buildings are not allocated between Affordable and Market-Rate)

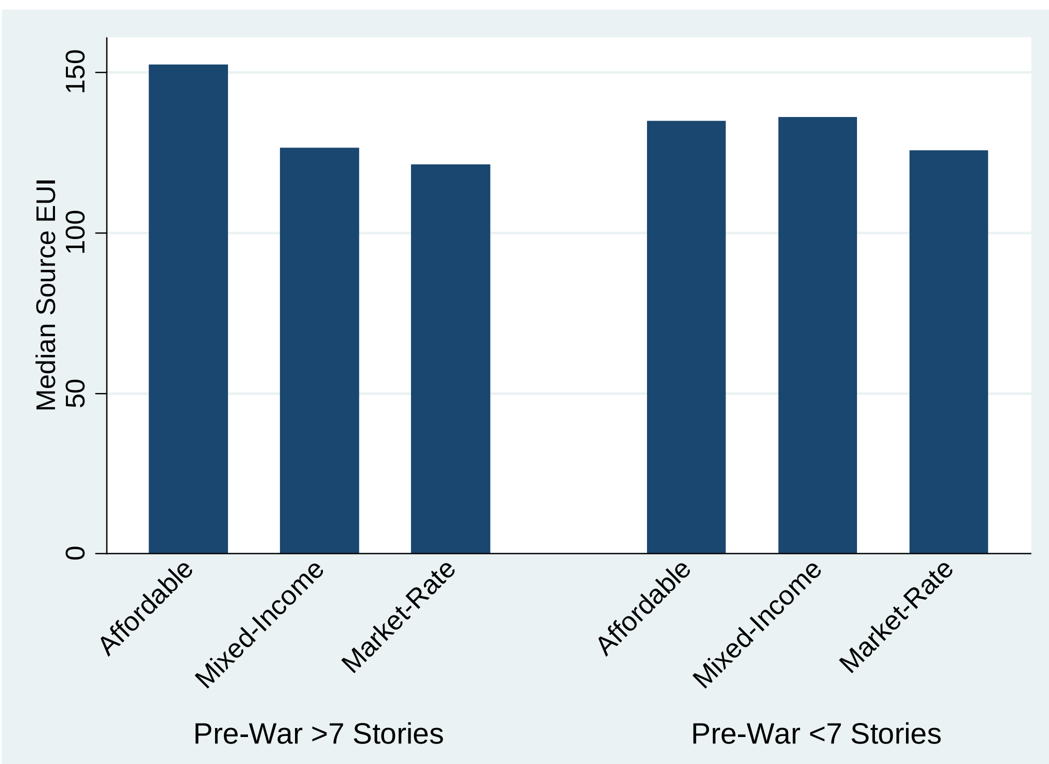


Figure 5.1.2: Comparison of Affordable, Mixed-Income and Market-Rate Multi-Family Buildings, Pre-War by Building Height

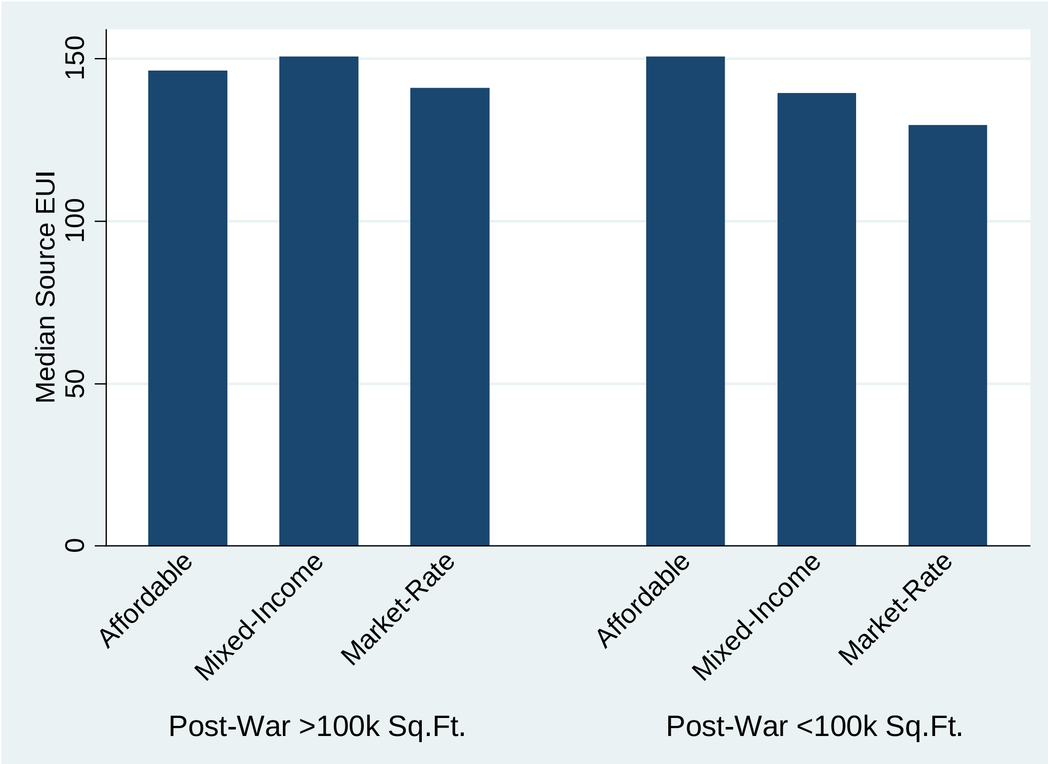


Figure 5.1.3: Comparison of Affordable, Mixed-Income, and Market-Rate Multi-Family Buildings, Post-War by Building Size

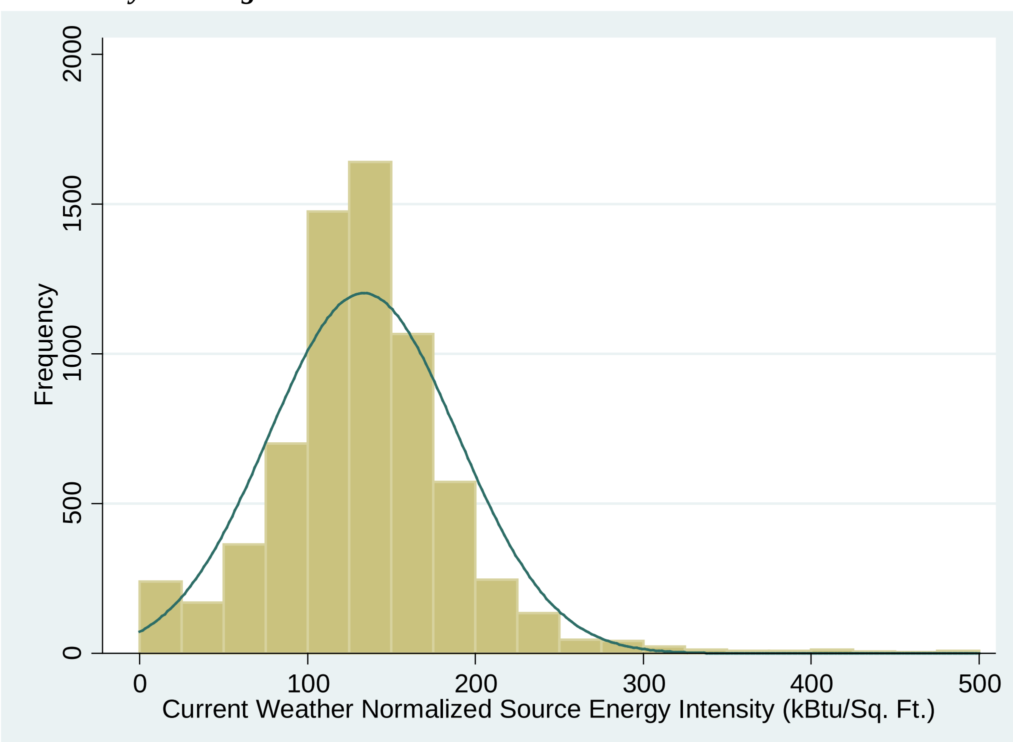


Figure 5.1.4: Histogram of Source EUI, Multi-Family Buildings (less than 2,000,000 sq.ft.)

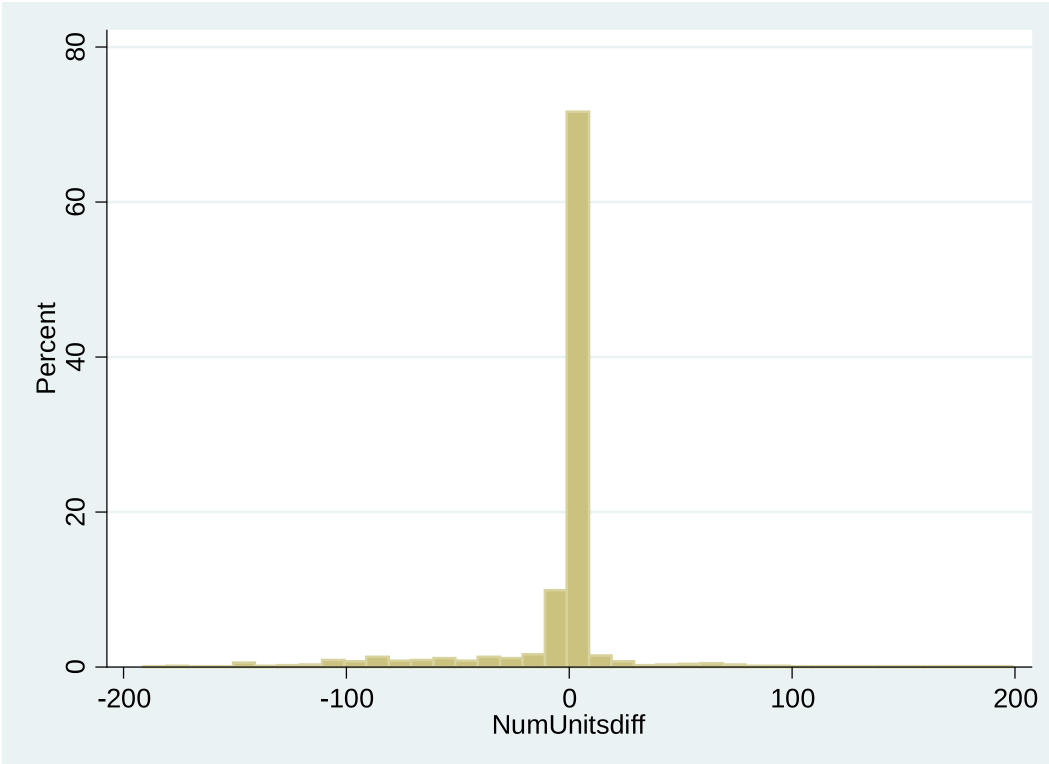


Figure 5.1.5: Difference between Number of Residential Units as Reported in PM and PLUTO

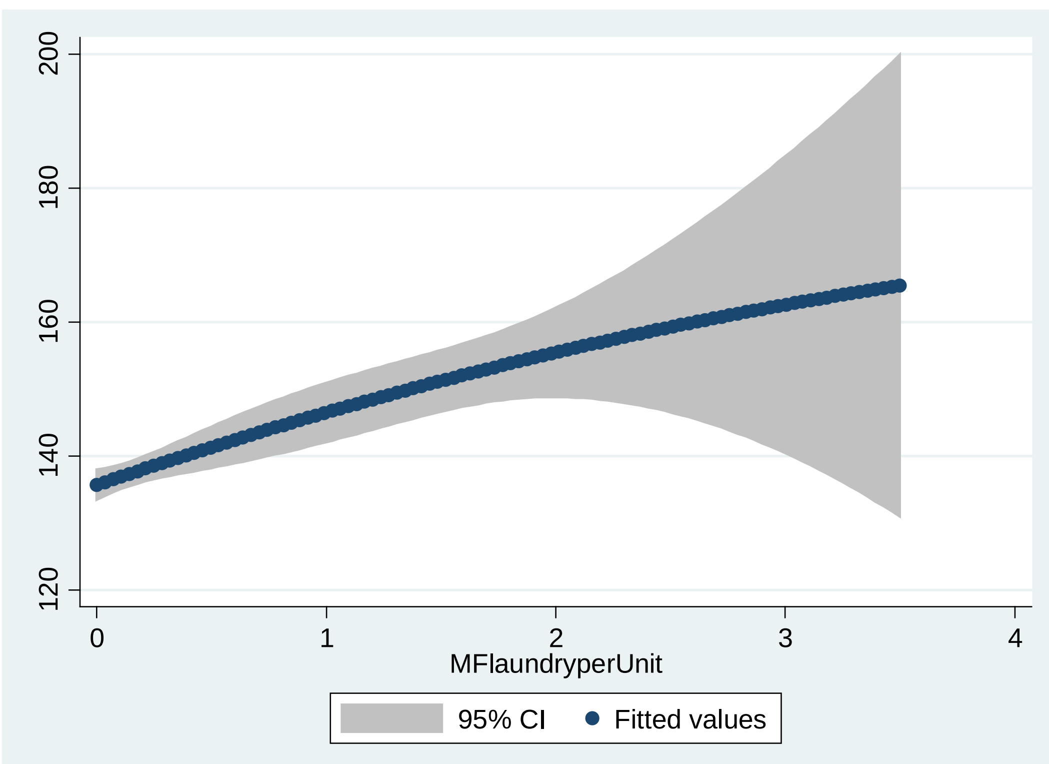


Figure 5.1.6: Source EUI by Number of Laundry Facilities per Unit, Multi-Family Buildings

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	6312	141.8408	1.611691	128.0458	138.6814	145.0003
1	554	195.417	14.19319	334.0679	167.5378	223.2961
combined	6866	146.1637	1.880319	155.8058	142.4777	149.8498
diff		-53.57614	6.874093		-67.05149	-40.10079

diff = mean(0) - mean(1) t = -7.7939
Ho: diff = 0 degrees of freedom = 6864

Figure 5.1.7: T-test of Difference of Means, Affordable (=1) v. Market and Mixed-Income Housing (=0)

6.0 BUILDING ENERGY CONSUMPTION REDUCTION POTENTIAL

Energy performance disclosure can be an important mechanism to shift market demand and behavior with respect to building energy efficiency. In New York City, buildings account for 76 percent of total energy use. The LL84 data reveal that a targeted strategy, focusing on the 20 percent least efficient buildings, can have a dramatic impact on total energy consumption in New York. In summary, a 30 percent reduction in energy consumption in the City's least efficient buildings could result in an annual energy savings of over 11,000 GBtu.

The figures below present the median source EUI, total site and source energy consumption, and GHG emissions per square foot for multi-family and office buildings, by five percent increments based on source EUI. Reduction potentials in the worst-performing 20 percent of buildings are also shown. Clearly, the best performing buildings (those in the <5% increment) and the worst performing buildings (those in the >95% increment) capture noticeable deviations from the distribution of the remaining 90 percent of buildings.

6.1 Multi-Family Buildings

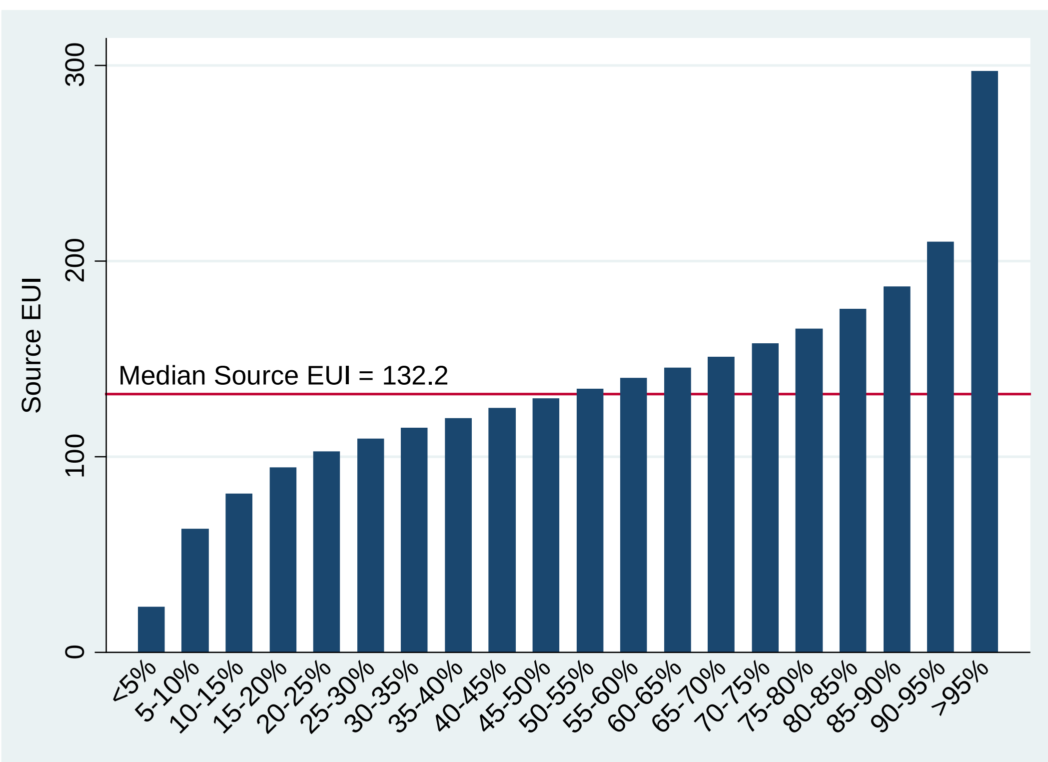


Figure 6.1.1: Source EUI by Five-Percent Increment, Multi-Family Buildings

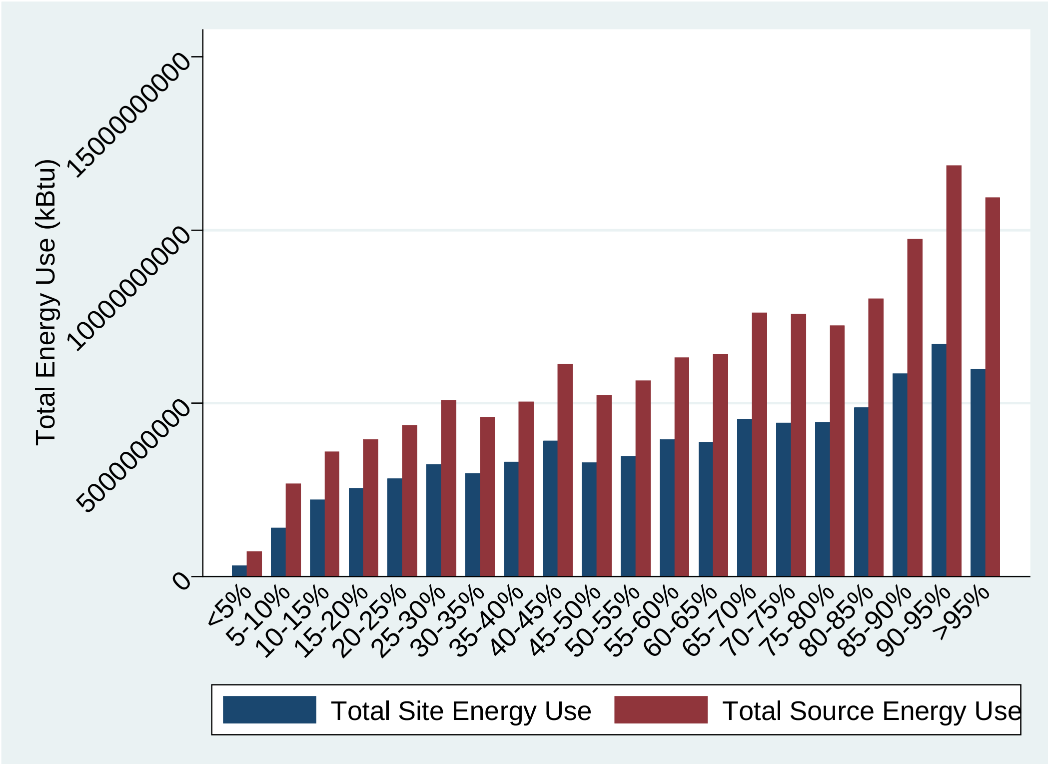


Figure 6.1.2: Total Site and Source Energy Consumption (kBtu) by Five-Percent Increment, Multi-Family Buildings

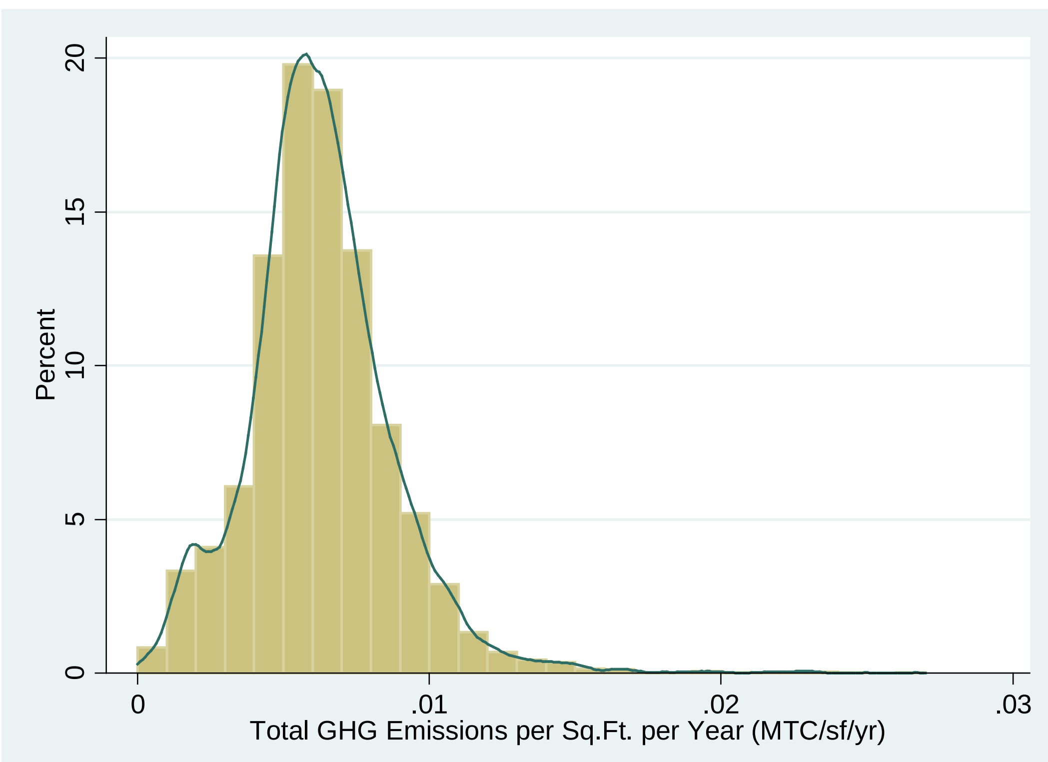


Figure 6.1.3: Total GHG per Square Foot per Year, Metric Tons CO2e, Multi-Family buildings

Figure 6.1.2 above shows the total energy consumption in multi-family buildings by five-percent increment. The figure reveals that the 20 percent worst-performing buildings consume more than six times the total energy as the 20 percent best-performing buildings. The 20 percent worst-performing buildings collectively account for more than 6,470.427.724 kBtu annually in total site energy consumption.

What is apparent from the figure above is the potential to achieve significant energy use reductions by targeting the worst-performing 20 percent of multi-family buildings. The following calculation provides an estimate the potential impact of a 30 percent reduction in energy consumption in the worst-performing buildings, and graphically depicted in Figure 6.1.4:

- **Total Energy Consumption – 20% Best-Performing Buildings = <u>6,470,427,724 kBtu</u>**
- **Total Energy Consumption – 20% Worst-Performing Buildings = <u>25,672,900,000 kBtu</u>**
- **30% Efficiency Improvement in Worst-Performing Buildings = <u>7,701,870,000 kBtu use reduction</u>**

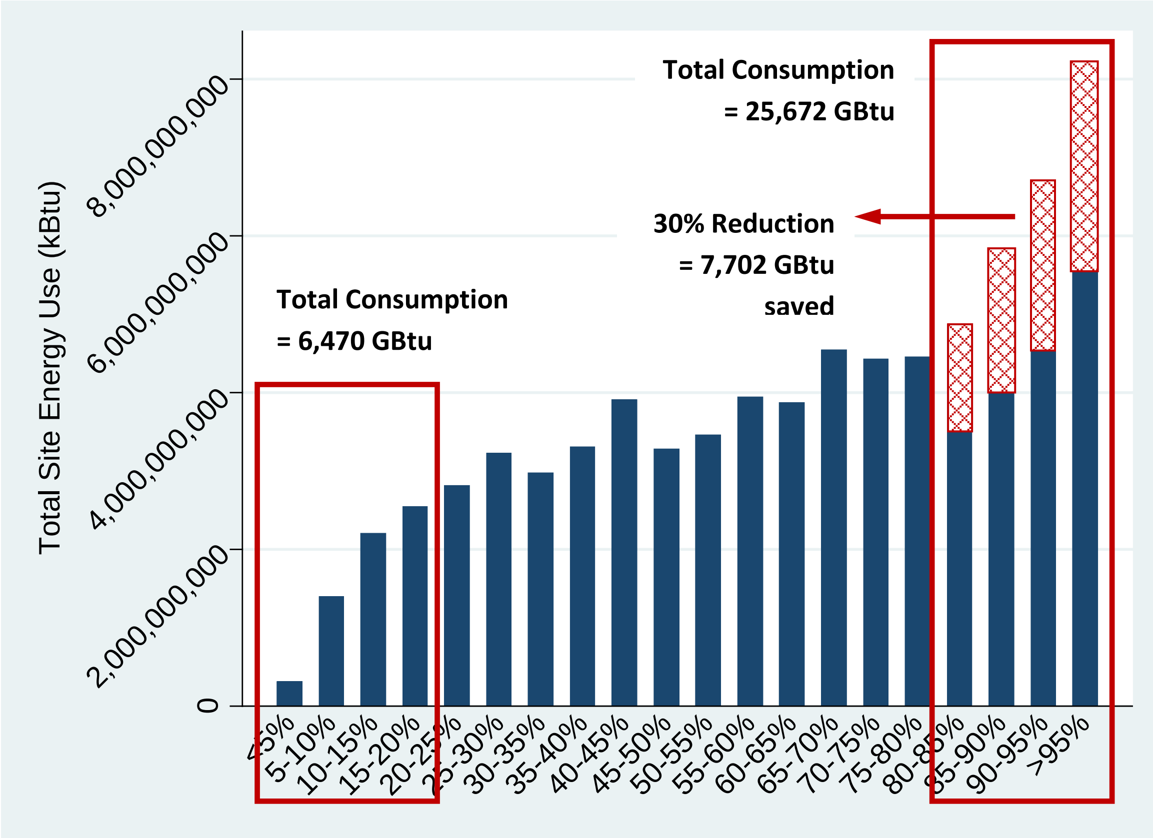


Figure 6.1.4: Illustration of Potential Savings in Multi-Family Buildings

6.2 Office Buildings

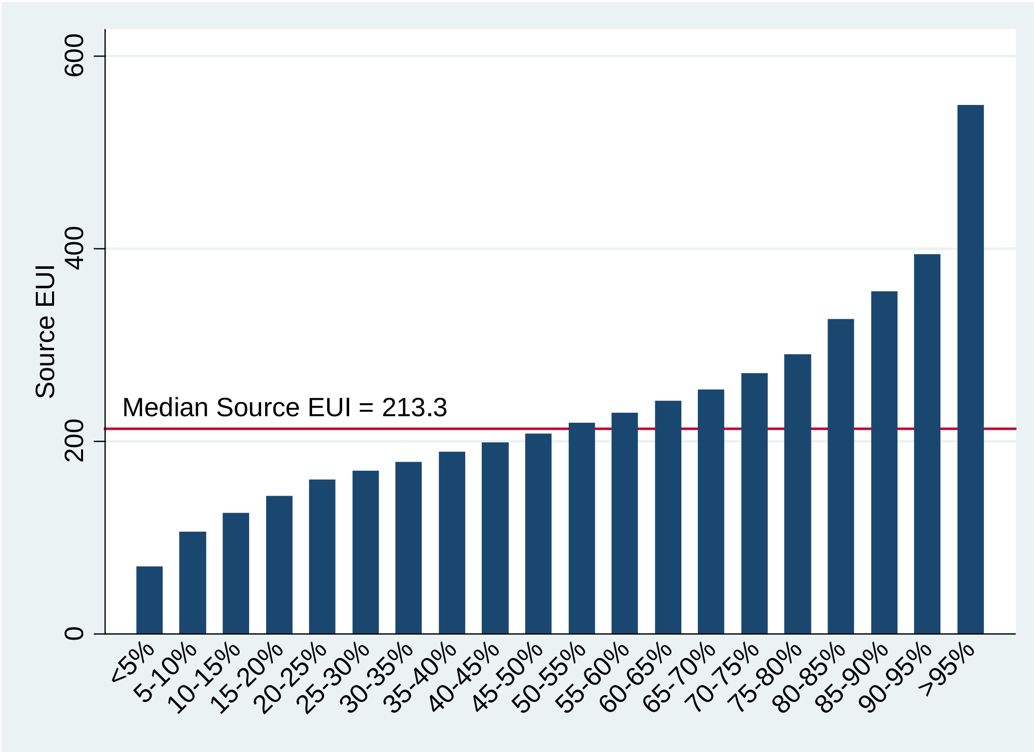


Figure 6.2.1: Source EUI by Five-Percent Increment, Office Buildings

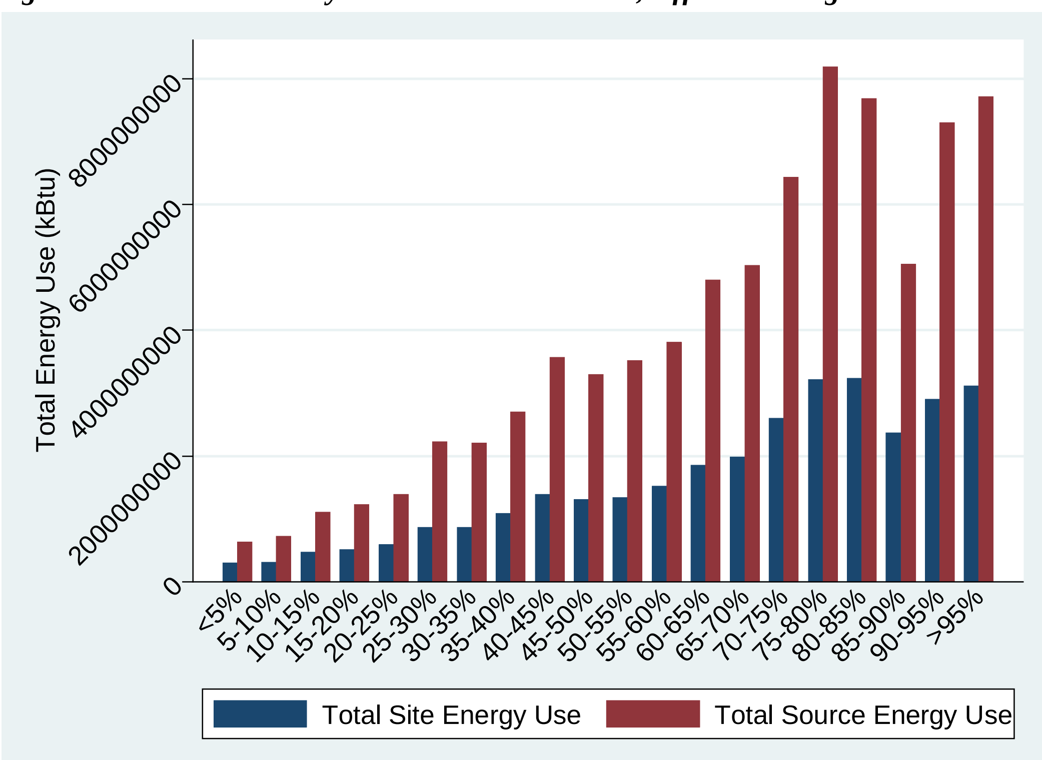


Figure 6.2.2: Total Site and Source Energy Consumption (kBtu) by Five-Percent Increment, Office Buildings

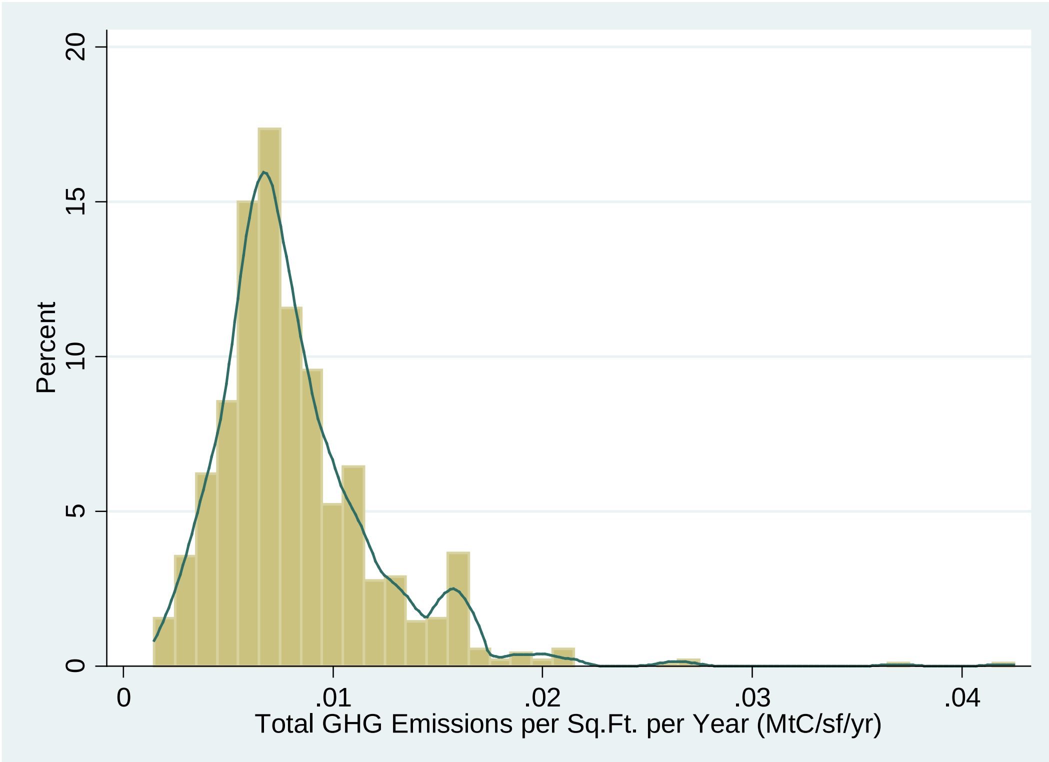


Figure 6.2.3: Total GHG per Square Foot per Year, Metric Tons CO2e, Office buildings

As with multi-family buildings, there is significant energy use reduction potential embedded in the 20 percent worst-performing buildings. The following calculation provides an estimate the potential impact of a 30 percent reduction in energy consumption in the worst-performing office buildings and is shown graphically in Figure 6.2.4:

- **Total Energy Consumption – 20% Best-Performing Buildings**
  = <u>1,597,000,000 kBtu</u>
- **Total Energy Consumption – 20% Worst-Performing Buildings**
  = <u>11,640,000,000 kBtu</u>
- **30% Efficiency Improvement in Worst-Performing Buildings**
  = <u>3,492,000,000 kBtu use reduction</u>

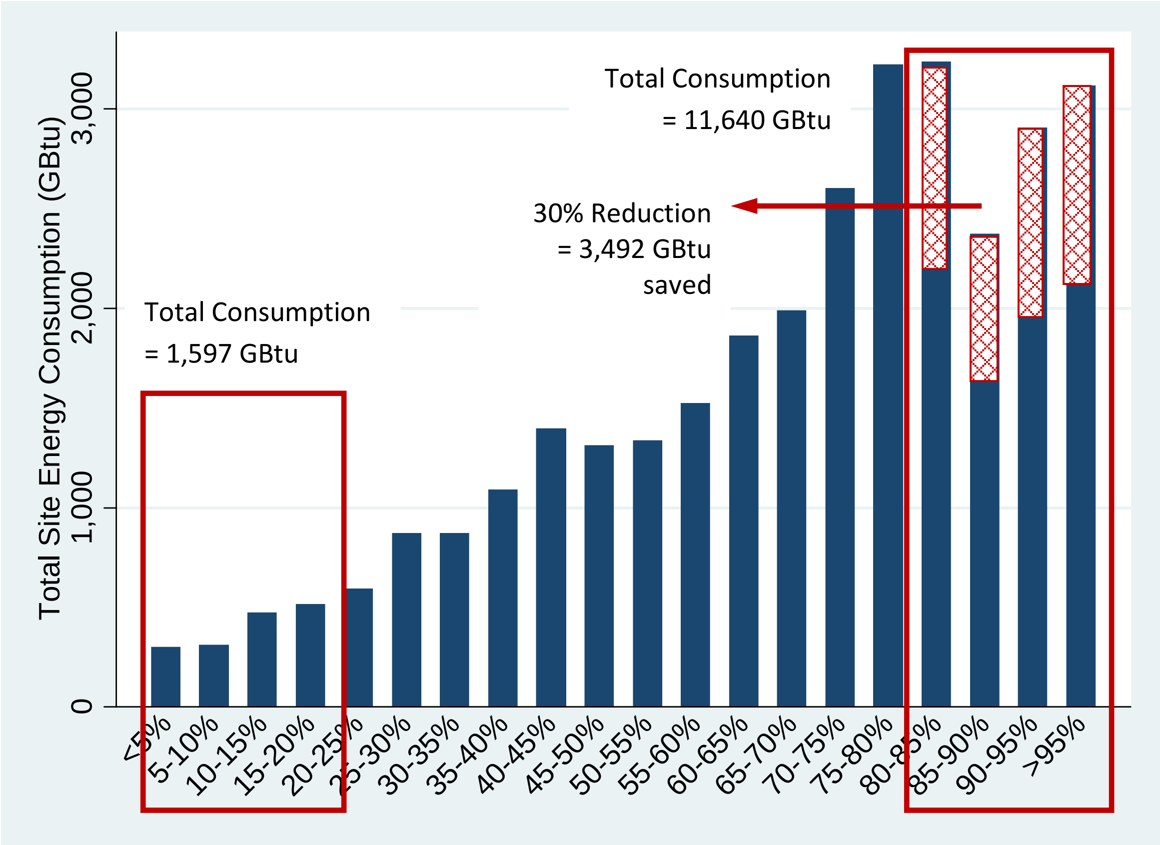


Figure 6.2.4: Illustration of Potential Savings in Office Buildings

7.0 SPATIAL ANALYSIS OF BUILDING ENERGY CONSUMPTION

Understanding the spatial patterns of energy consumption and efficiency in New York City provides an important level of analysis for directing infrastructure investment, targeting outreach for incentives and place-based policies, and informing community organizations and residents regarding neighborhood-level energy issues. Figure 7.0.1 presents basic descriptive statistics by borough for office and multi-family buildings. Figure 7.0.2 shows the median source EUI by borough for the three primary space types contained in the LL84 database. It should be noted that the median EUI values do not control for differences in building inventory or characteristics, so the figure is intended to provide only a relative indication of typical energy efficiencies across the five boroughs.

Office	*# of Buildings*	*Avg. Number of Floors*	*Average Size (Sq.Ft.)*	*Average Age (years old)*
Bronx	11	7	136,798	62
Brooklyn	38	10	213,031	73
Manhattan	864	20	372,269	76
Queens	45	6	195,622	58
Staten Island	10	3	59,298	33
Multi-Family	*# of Buildings*	*Avg. Number of Floors*	*Average Size (Sq.Ft.)*	*Average Age (years old)*
Bronx	1,139	7	102,643	64
Brooklyn	1,309	7	108,377	57
Manhattan	2,902	15	159,919	65
Queens	1,386	6	113,597	60
Staten Island	73	5	120,490	50

Figure 7.0.1: Descriptive Statistics by Borough

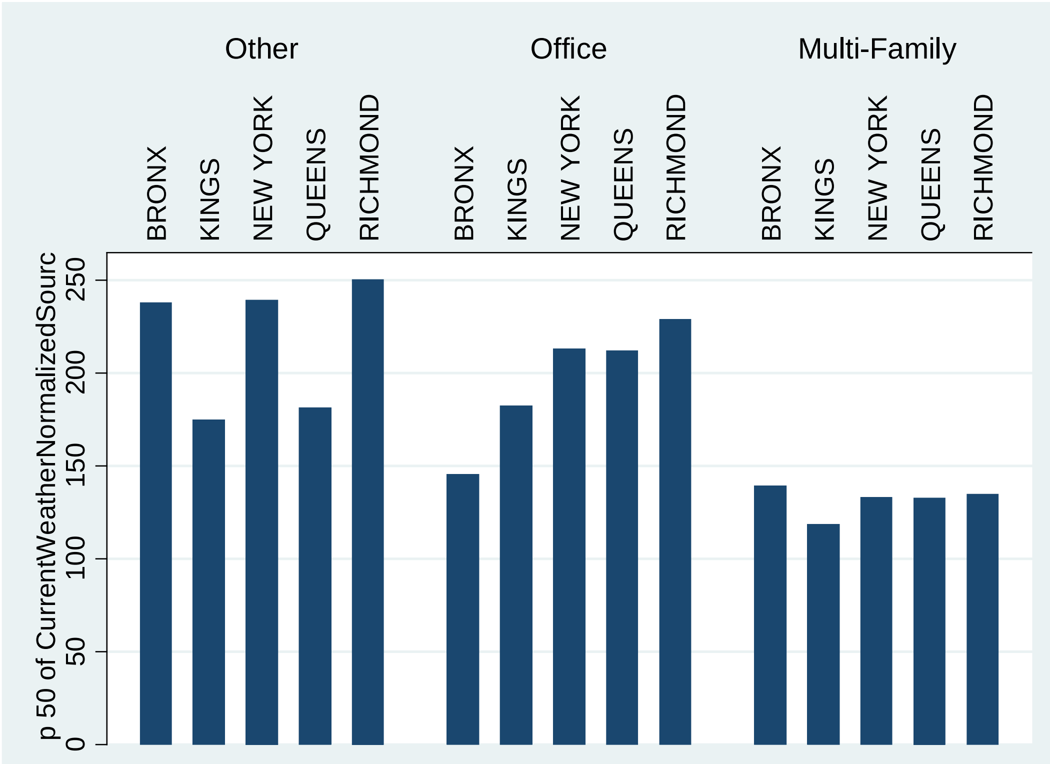


Figure 7.0.2: Median Source EUI by Borough and Building Type

Figure 7.0.3 shows the ten zipcodes in the five boroughs with the highest total energy consumption, together with the total number of buildings in the zipcode and the aggregate square footage. All ten zipcodes are located in Manhattan, primarily a function of the distribution of large commercial buildings covered by Local Law 84 requirements.

Figure 7.0.4 maps the mean total energy consumption per building by zipcode. Given the variations in building types and sizes across the five boroughs, each borough is mapped using its own scale.

	Zip Code	Total Site Energy Consumption	# of Bldgs.	Total Square Footage
1	10019	6,130,000,000	173	58,100,000
2	10022	5,770,000,000	232	59,200,000
3	10017	4,980,000,000	145	47,900,000
4	10036	4,520,000,000	102	41,600,000
5	10016	4,440,000,000	218	45,900,000
6	10001	3,650,000,000	167	39,600,000
7	10023	3,540,000,000	180	39,100,000
8	10065	3,120,000,000	145	25,800,000
9	10021	2,530,000,000	193	30,500,000
10	10025	2,380,000,000	207	29,700,000

Figure 7.0.3: Top 10 zipcodes with largest total energy consumption

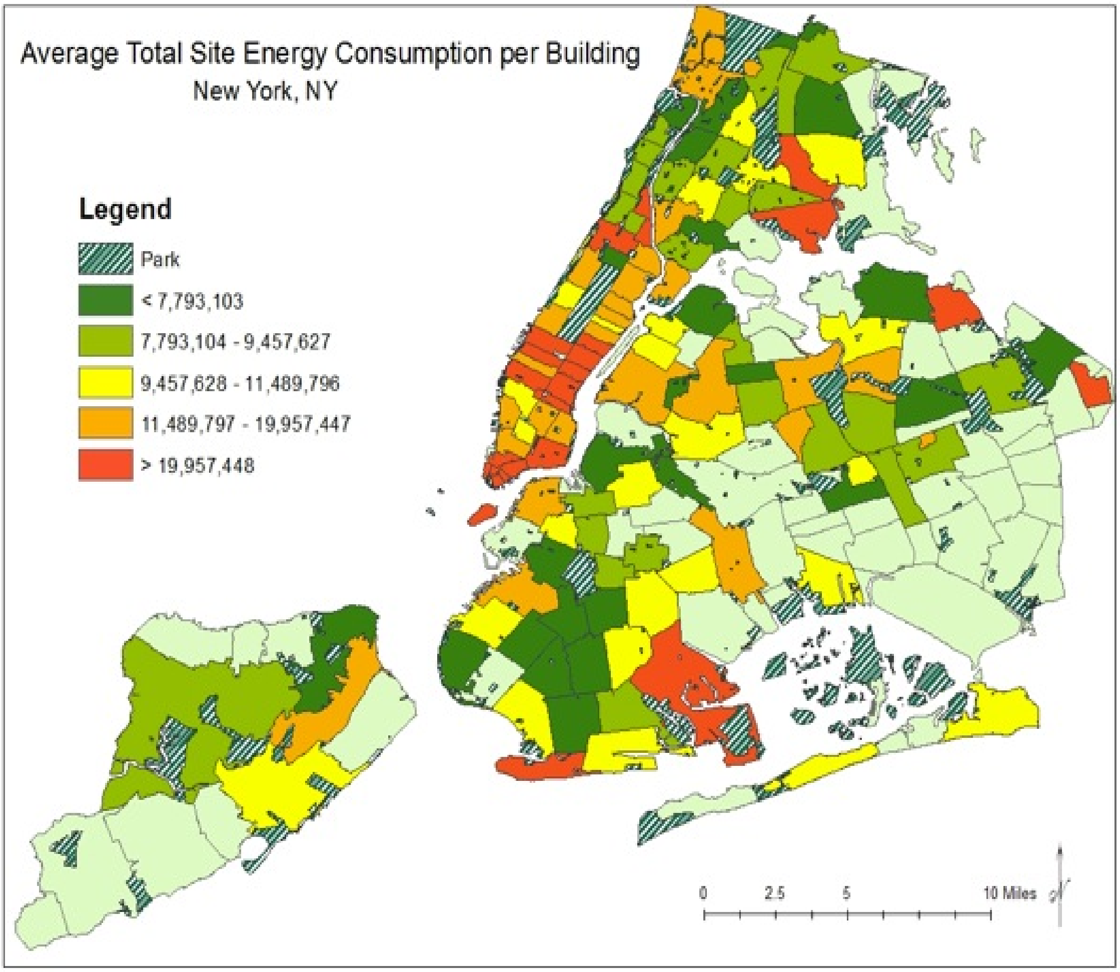


Figure 7.0.4: Map of Mean Total Source Energy Use per Building by Zipcode, Office and Multi-Family Buildings

7.1 Office Buildings

The following two sections (7.1 and 7.2) present geographic information system (GIS) maps of the median EUI for office and multi-family buildings, respectively, by zipcode. Although maps depicting a much more granular level of detail are possible, down to the individual parcel, confidentiality concerns prohibit the presentation of such analysis at this time. Following the maps, tables are included that identify the ten zipcodes with the least efficient buildings (based on median EUI) for the respective building type.

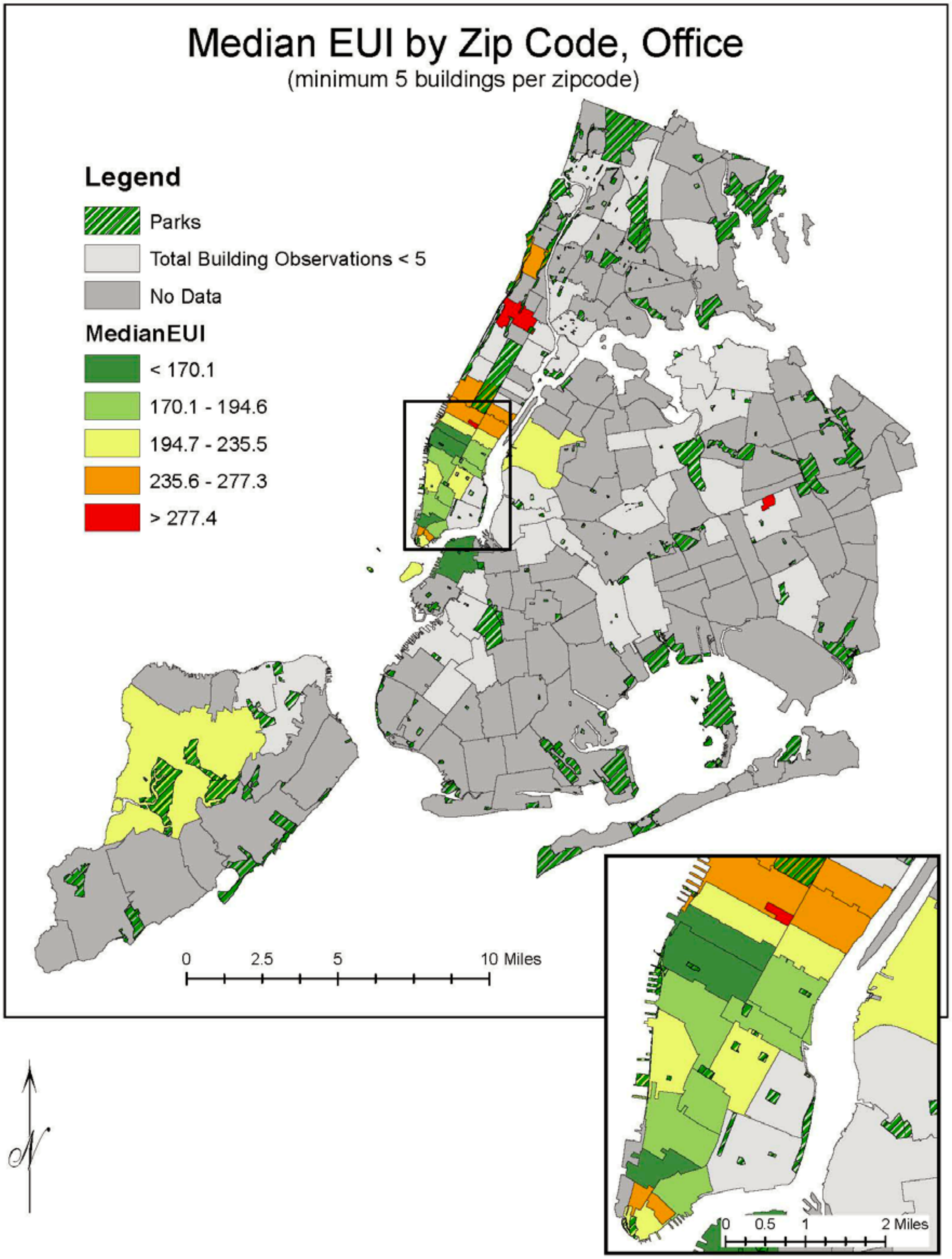


Figure 7.1.1: Map of Source EUI by Zipcode, Office Buildings Only (Green = Lower EUI; Red = Higher EUI) (All Zipcodes)

	Zip Code	Median Source EUI	Bldgs.	Avg. Age
1	10467	708.7	3	69.0
2	10024	391.0	4	78.8
3	10301	356.5	4	49.5
4	10027	355.3	30	90.7
5	11439	354.7	8	61.0
6	10020	323.7	5	51.6
7	10065	277.3	5	56.2
8	10023	268.5	9	58.0
9	10005	258.5	17	55.7
10	10022	249.9	75	53.3

Figure 7.1.2: Ten Zipcodes with Highest Median EUI, Office Buildings (min. four observations)

7.2 Multi-Family Buildings

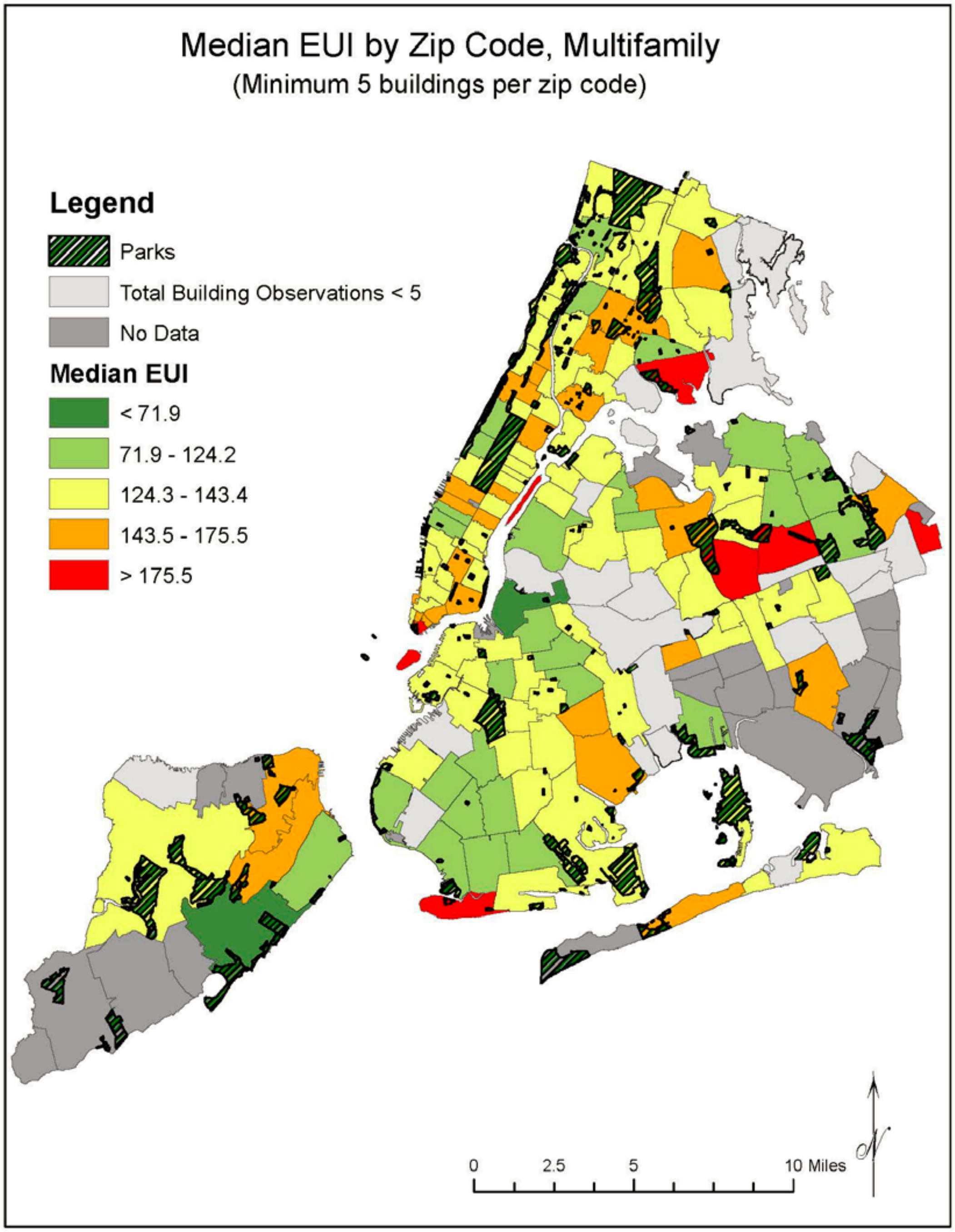


Figure 7.2.1: Map of Source EUI by Zipcode, Multi-Family Buildings Only (Green = Lower EUI; Red = Higher EUI)

	Zip Code	Median Source EUI	Bldgs.	Total Units	Avg. Age (years)
1	11224	196.8	16	7241	168.3
2	11367	193.0	68	3983	58.6
3	11365	183.6	48	288	61.7
4	10473	178.7	24	4256	42.3
5	11362	174.1	43	2425	56.7
6	10454	173.0	22	1343	74.9
7	10469	168.0	116	1523	75.9
8	10304	162.7	14	460	41.8
9	10005	162.0	15	4229	71.3
10	10038	161.3	25	2234	151.1

Figure 7.2.2: Ten Zipcodes with Highest Median EUI, Multi-Family Buildings (min. ten observations)

Figure 7.2.3 shows a scatterplot of median EUI by zipcode and childhood asthma emergency room visit rates (based on data from the New York State Department of Health for ages 0 to 17). The positive slope of the linear best-fit line indicates a correlation between poorly performing neighborhoods and potential air quality issues. Please note that this graph does not control for other variables that may affect asthma rates and does not suggest causation. However, the visual relationship between EUI and asthma rates suggests that neighborhoods where public health concerns are greatest are also home to energy inefficient buildings, a finding that should be explored more rigorously.

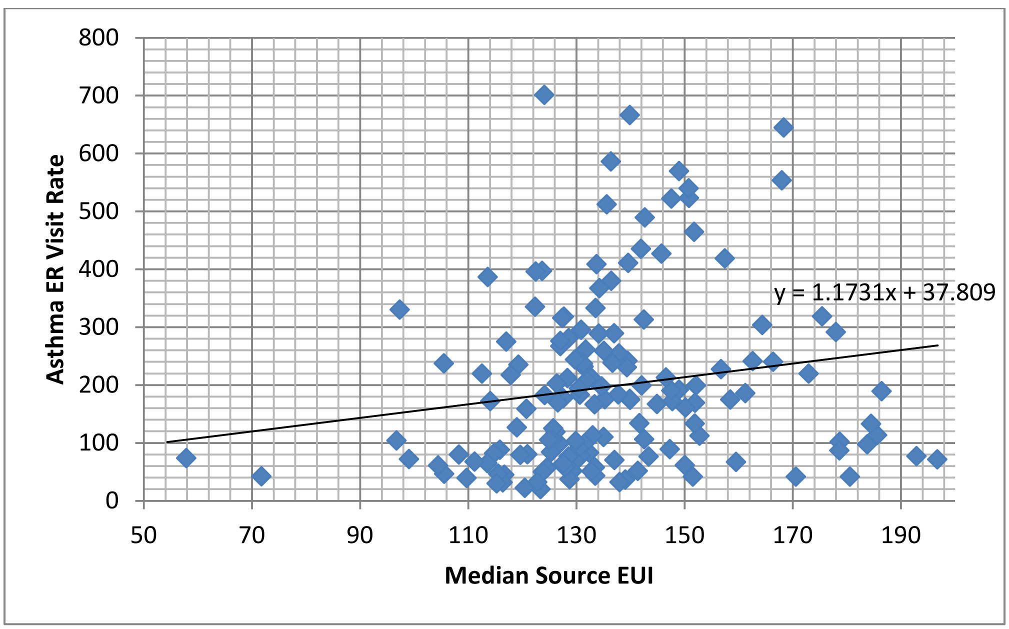


Figure 7.2.3: Median Source EUI and Asthma ER Visit Rate, Multi-Family Buildings, by Zipcode

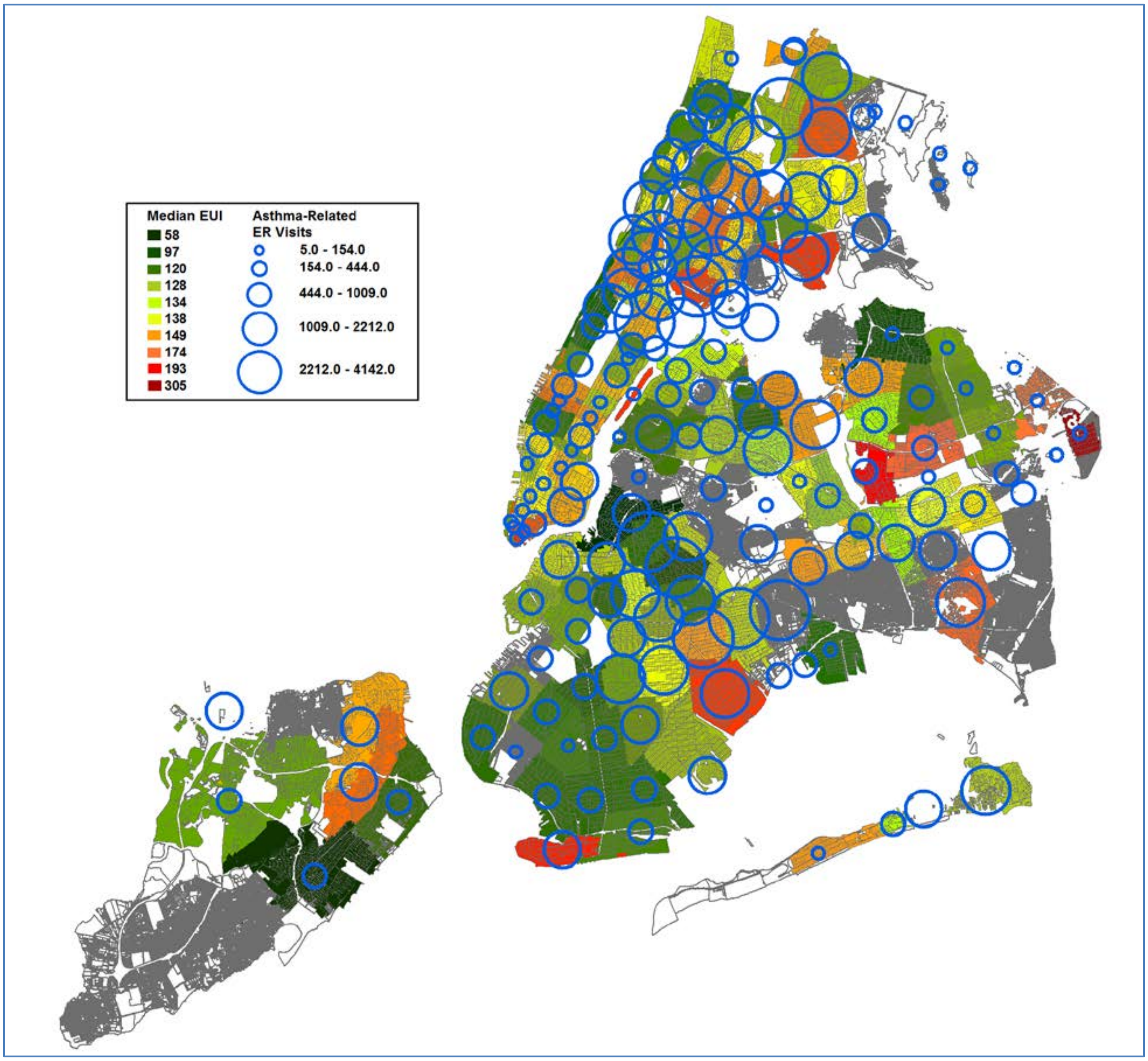


Figure 7.2.4: Map of Source EUI by Zipcode, Multi-Family Buildings Only (Green = Lower EUI; Red = Higher EUI) and Asthma Emergency Room Visit Rate by Zipcode (minimum 10 buildings)

8.0 CONCLUSIONS AND NEXT STEPS

Local Law 84 has provided the first look at a large sample of non-voluntary (and thus non-self-selected) building performance data. The uses of this information are numerous, and the analysis of the initial data collection effort presented here offer some examples of the potential for building energy disclosure to catalyze shifts in market demand, tenant and building owner behavior, and building and infrastructure investment criteria.

The next reporting date is scheduled for May 2012. As additional data become available, a panel or cross-section time-series dataset can be created, allowing for future analysis of program and policy evaluation and changes in consumption and efficiency over time. The next steps in analysis of the data should include:

- Extension of the predictive models to include cluster and factor analyses
- The analysis of year-over-year changes in energy consumption and efficiency
- The analysis of discrepancies in other indicators when comparing first-year data and subsequent submissions
- Merging of the LL84 data with additional datasets, particular those with systems-level information
- The use of the models presented here to estimate energy consumption and efficiency patterns in buildings under 50,000 square feet
- The use of the models presented here to estimate energy consumption and efficiency patterns in other cities

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Appendix A – Additional Charts and Graphs

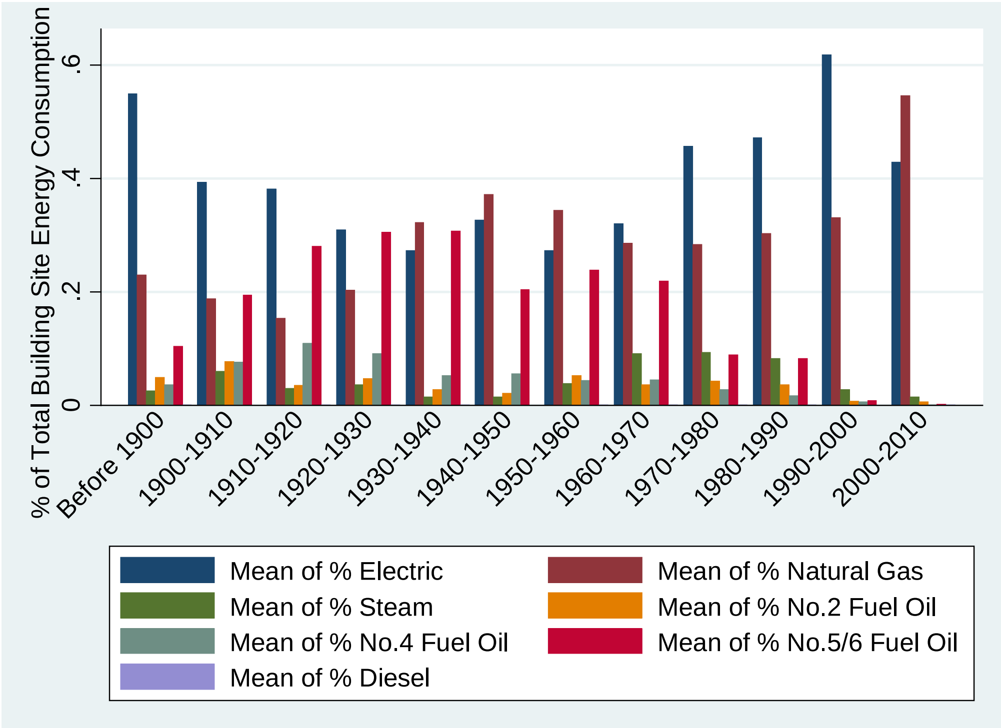

Figure A.1: Mean of % Building Site Energy Consumption By Fuel Type by Building Age, Office and Multi-Family Buildings

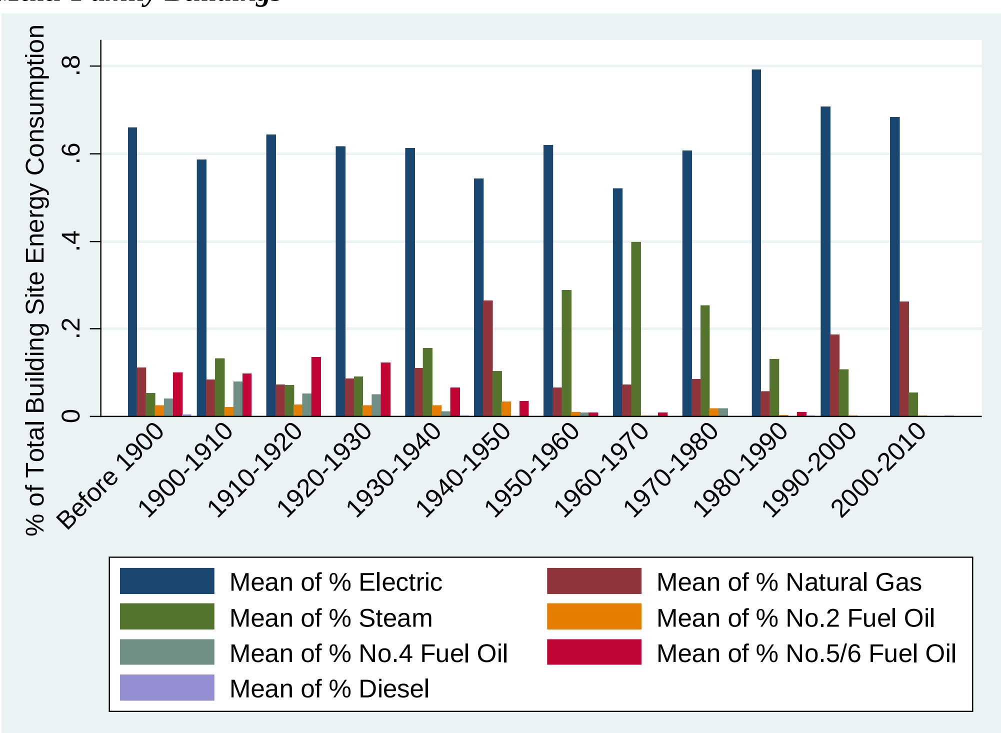

Figure A.2: Mean of % Building Site Energy Consumption By Fuel Type by Building Age, Office Buildings Only

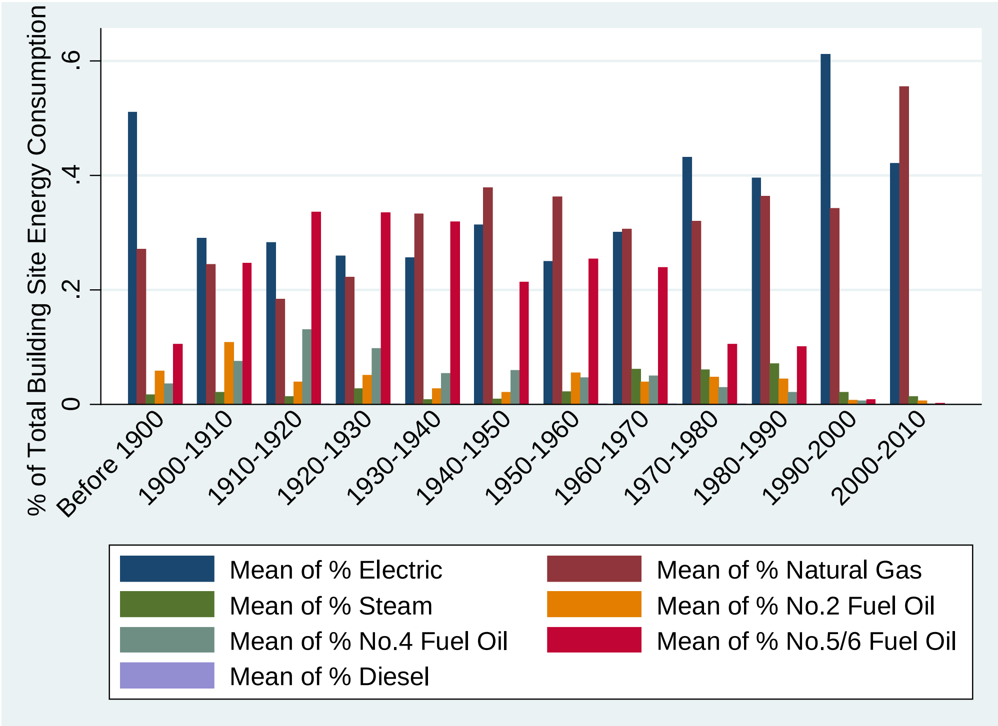

Figure A.3: Mean of % Building Site Energy Consumption By Fuel Type by Building Age, Multi-Family Buildings Only

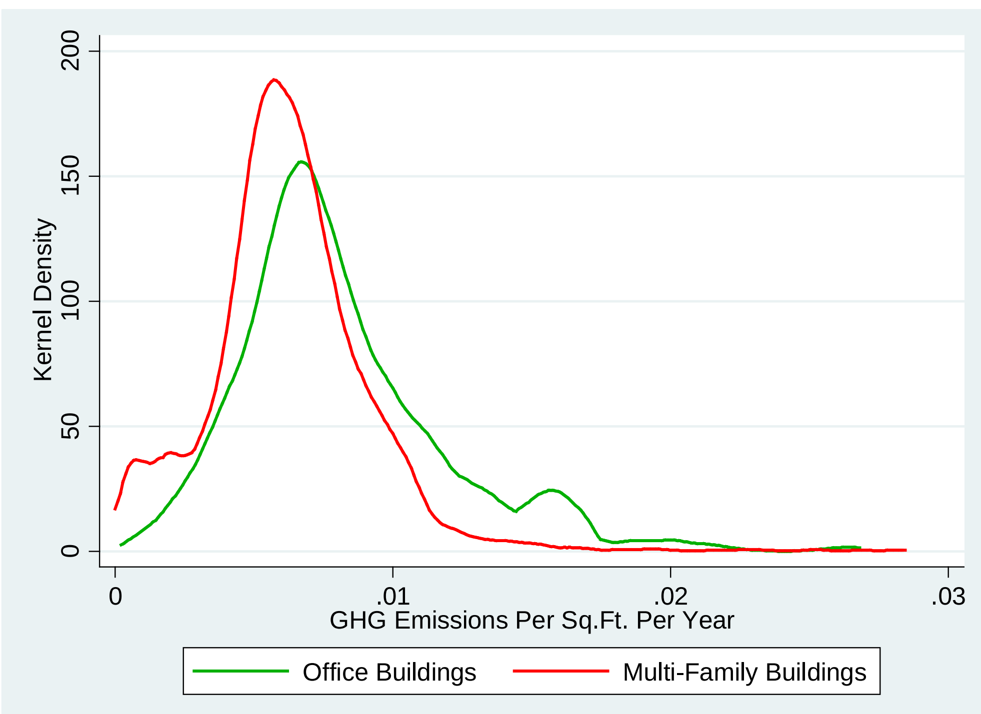

Figure A.4: Kernel Density Plots of GHG Emissions Per Sq.Ft. Per Year, Office and Multi-Family Buildings (Overlay of Figures 6.1.3 and 6.2.3)