Predicting Building Energy Efficiency Using New York City Benchmarking Data

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ABSTRACT

The reduction of risk and uncertainty with respect to post-retrofit performance and energy savings is a critical component to unlocking traditional capital markets for commercial building retrofits. This, in turn, is a necessary step in scaling up sustainable real estate markets and retrofit programs. While a range of factors influence actual energy savings, there remains a gap in our understanding of how building characteristics affect energy performance across a broad spectrum of variables. Using a unique database of energy benchmarking data resulting from New York City's Local Law 84, accessed and analyzed for the first time by the author, this paper examines energy performance across a range of building characteristics, including structural, mechanical, locational, and occupancy variables. The unprecedented data used in this paper allows for the analysis of over 10,000 large (over 50,000 square feet) commercial buildings and is the first significant, robust sample of non-voluntary energy performance reporting. Using robust regression techniques, this research then presents a predictive model of building energy efficiency. This work is particularly relevant to emerging policy initiatives relating to energy benchmarking, retrofit financing programs, and commercial lease structures designed to overcome split incentive barriers.

Introduction

Energy disclosure laws represent one of the most promising public policy tools to accelerate market transformation around building energy efficiency. Emerging from a rapidly evolving green building regulatory landscape, these laws require building owners to report energy consumption on an annual basis (Kontokosta 2011a). The first and most ambitious of these policies is New York City's Local Law 84 (hereafter LL84), 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.

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 producers/suppliers and consumers/end-users (Day 1976; Mathios 2000; 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, putting pressure on building owners to improve the relative energy efficiency of the building to make it more competitive.

There are, however, numerous impediments to energy efficiency improvements in existing buildings. 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 clearly defining how costs for energy efficiency improvements are passed-through from owner to tenant. 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.

This paper presents an analysis of the LL84 data and the determinants of energy efficiency in a diverse sample of large office and multi-family buildings in New York City. The next section discusses the data collection and cleaning effort, followed by descriptive statistics for the more 10,000 buildings included in the database. The methodology used to develop the predictive model is then presented and concludes with a discussion of the results and their implications for building energy benchmarking.

Data Description

This paper analyzes energy consumption and building data for commercial buildings over 50,000 square feet in New York City and develops a predictive model of building energy consumption and efficiency. 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 entered through the EPA's Portfolio Manager tool.

Initially, the database contained 10,201 observations. However, substantial cleaning was performed to remove errors and omissions in data entry by building owners and their representatives 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 (building use) was not indicated
- No (or insufficient) energy consumption information was provided
- Duplicate entries

After dropping buildings with energy use intensities below the 1st percentile and above the 99th percentile to eliminate 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.

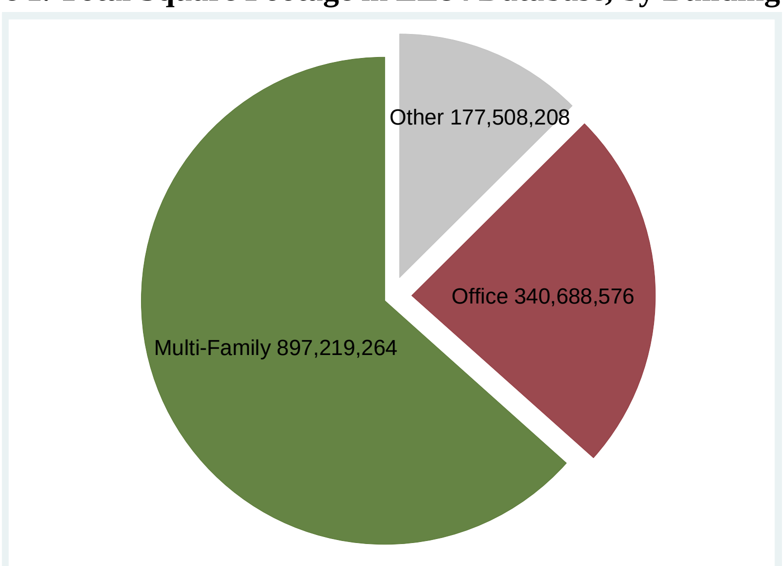
Descriptive Statistics

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 figures below provide a descriptive analysis of the type and quantity of space covered by the data and patterns of energy consumption and 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.

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 1. Total Square Footage in LL84 Database, by Building Type



Source: LL84 Database and Author's Calculations

Figure 2. Histogram of Source EUI with Kernel Density Plot, Office Buildings Only

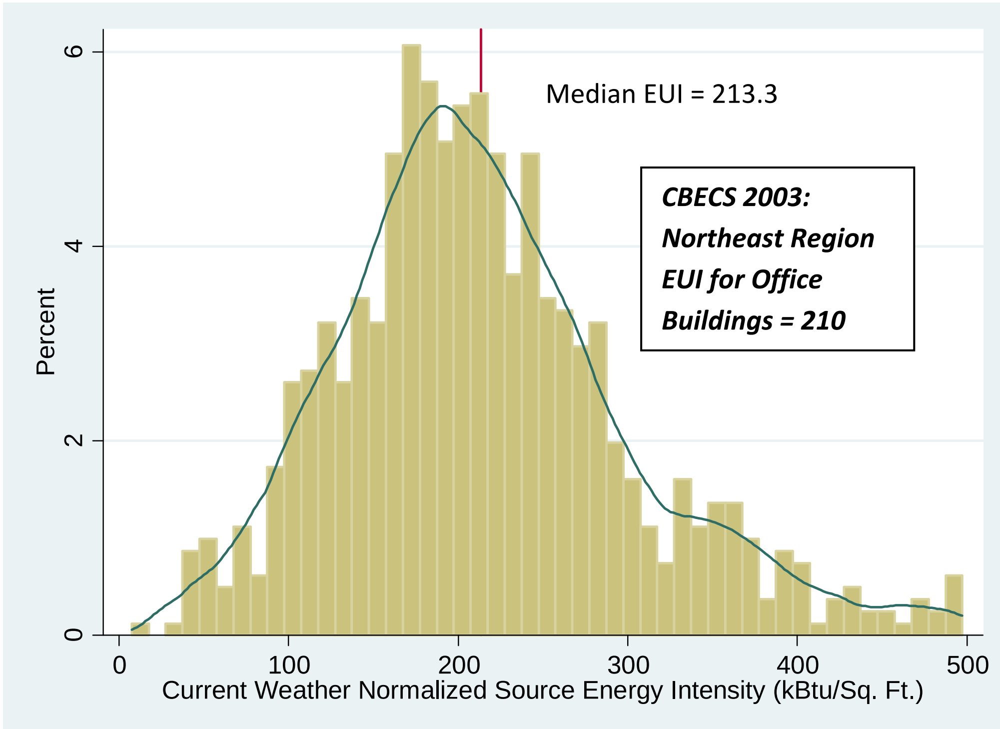
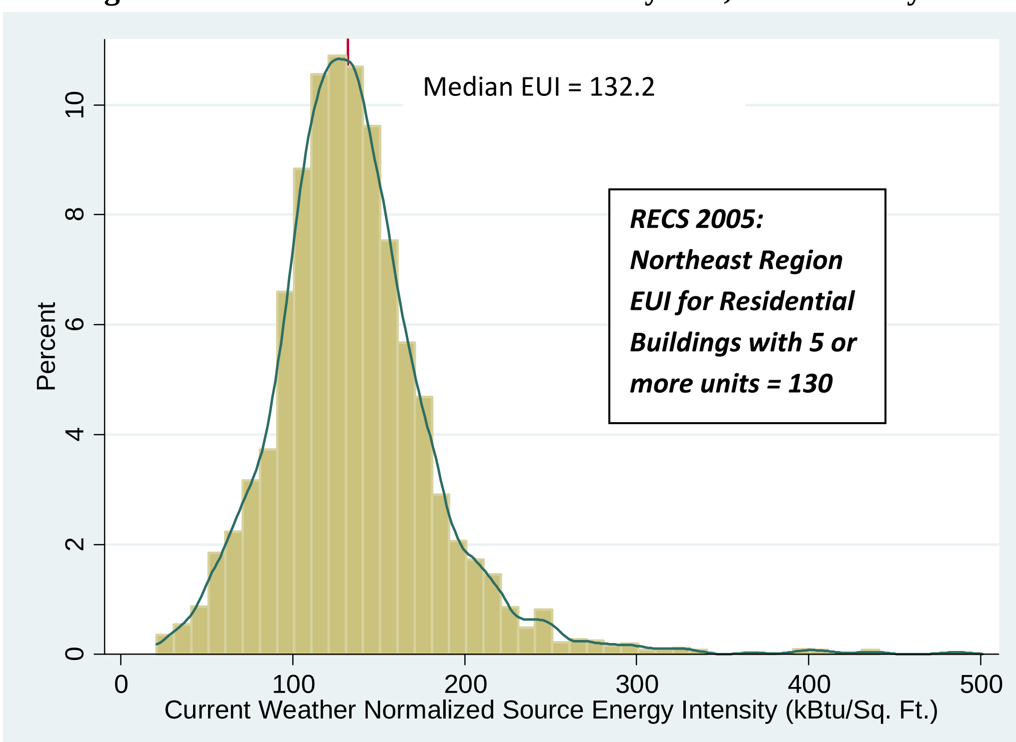


Figure 3. Histogram of Source EUI with Kernel Density Plot, Multi-Family Buildings Only



Methodology

This section presents an analysis of 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 data is not available
4. Developing an energy benchmarking tool to identify more and less efficient buildings

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, the factors that influence building energy efficiency are examined (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 limitations to multiple regression modeling for predicting building energy efficiency (Tso and Yau 2007). For example, potential bias in the coefficient estimates may result from collinearity between the explanatory variables. However, this method is found to be appropriate given the nature and extent of the database and the purpose of this analysis.

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 and presented here for office and multi-family buildings.

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 with robust standard errors. 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.

Results and Discussion

On average, the models explain approximately 20 percent of the variation in energy efficiency across buildings, as shown in the regression output in Figures 4 and 5. These models may, in fact, be more robust than those currently used in Energy Star benchmarking analysis, as the LL84 and PLUTO datasets contain a greater range of explanatory variables, although limited building-level system information impacts the explanatory power of the models. 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 the latter 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).

Office Buildings

Examining the results of the regression analysis presented in Figure 4, several variables are found to be statistically significant at or above the 95 percent confidence level for office buildings. Building age 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 30 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 provided in the PLUTO databases) are also shown to be more energy efficient, controlling for the other variables included in the model.

Figure 4. Regression Results, Source EUI and log Source EUI as Dependent Variables, Office Buildings (Excluding Lots with Multiple Buildings)

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	***

***Significant at the 99% confidence level
**Significant at the 95% confidence level
*Significant at the 90% confidence level

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, on average, 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, controlling for other factors (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 in a building identified primarily for office use, 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.

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 below 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 (Santin, Itard, and Visscher 2009).

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 (as shown in Figure 5). Older buildings are 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 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, building envelope, and architectural style.

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 higher lot coverage ratios are more efficient than buildings covering a smaller 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 development densities in these areas as well as the type of construction.

Figure 5. Regression Results, Source EUI and log Source EUI as Dependent Variables, Multi-Family 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	***

***Significant at the 99% confidence level
**Significant at the 95% confidence level
*Significant at the 90% confidence level

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 be occupied by higher intensity uses, such as retail and community facilities. It also raises issues of the availability of actual energy data for non-residential space in multi-family buildings, which may have been difficult for owners to acquire. 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 (on average), 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.

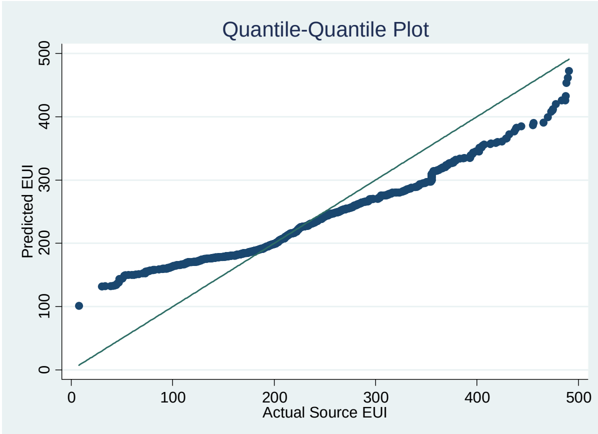
Predictive Model Analysis

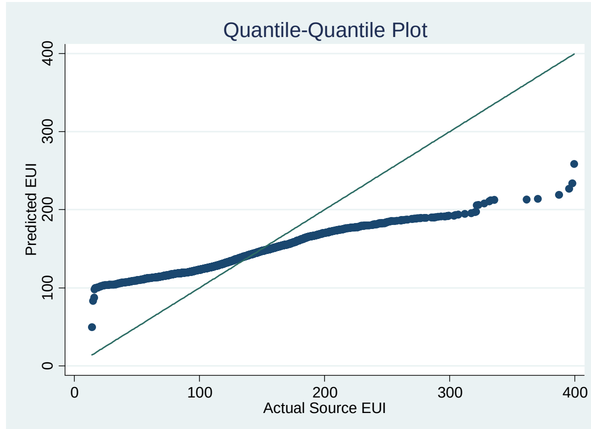
Using the coefficient estimates from the regression results, the predictive capacity of the models can be tested using actual data from observations in the LL84 database. The model was tested using the actual building characteristics for an office building in Manhattan and a multi-family building in Brooklyn.

In these specific cases, 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 6 and 7 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. The models tend to over-estimate EUI for more efficient (lower EUI) buildings and under-estimate EUI for less efficient (higher EUI) buildings.

Figures 6 (left) and 7 (right). Quantile-Quantile Plot, Actual v. Predicted EUI, Office Buildings and Multi-Family Buildings, Respectively





Implications and Conclusions

The growing availability of data on buildings and energy consumption has the tremendous 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.

The next reporting date for New York City's LL84 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 by the author will include:

- The analysis of year-over-year changes in energy consumption and efficiency and discrepancies in data entry and reporting
- Merging of the LL84 data with additional datasets
- 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

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.

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