Effect of Energy Benchmarking and Disclosure on Office Building Marketability

FINAL PROJECT REPORT

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by

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Acknowledgments

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Executive Summary

As commercial buildings form the main core of a city, the promotion of energy-efficient commercial buildings can significantly contribute to overall sustainability in a city. Recently, several U.S. cities and states have been trying to become more energy efficient by improving their energy consumption by adopting energy benchmarking and public disclosure of their consumption levels, which is expected to contribute to an increased awareness amongst tenants and investors especially among commercial properties as another measure of market comparison. An increasing sensitivity among corporate executives towards sustainability and the embracement of such practices by local, state, and federal agencies (e.g., US General Services Administration) has led to a growing demand for energy efficient buildings. Therefore, mandatory energy benchmarking and disclosure policies could possibly affect the leasing and purchasing decisions of real estate as the data become more readily available. Consequently, such policies are expected to motivate the owners of less energy efficient buildings to invest in energy retrofits with the goal of improving the short and long-term performance and marketability of their buildings.

However, there is a lack of studies specifically aimed at investigating the impact of such policies on office buildings of major cities. This study focuses on (1) assessing the real estate performance of sustainable buildings before and after the policy, while considering market cycles (e.g. seasonality); and (2) exanimating if different characteristics (e.g., building class level) of a building will affect the impact of the policy on its real estate performance.

Two interrupted time series analyses (ITSA), including one multiple-group ITSA and one single-group ITSA were used to serve for the research objectives. The multiple-group ITSA was conducted based on the annual average occupancy rates of the office buildings for each class and each city, in order to examine the change(s) after the policy implementation and then to infer the

impact of the benchmarking policy on real estate performance. In order to maximize the use of the collected data, and to avoid any loss of information caused by the aggregated-data-based analysis, we adopted the single-group ITSA to examine if the implementation of the policy resulted in a shift in the occupancy rate for each building.

Generally, the results revealed that for some cities, energy efficient buildings have better real estate performances for both analyses, but it is hard to conclude that the policy impacts on energy efficient buildings are more positive than less energy efficient buildings. Specifically, the results obtained from the multiple-group ITSA revealed that the energy policies might not immediately affect the real estate performance of office buildings. However, after the policy implementation, the real estate performances of energy efficient buildings exhibit continuously increasing trends, which is evidenced by the ITSA of all the four cities. The results are mixed for New York City, while Washington DC exhibited a decline in the real estate performance after the policy implementation. This effect may also have its roots in the financial crisis as the implementation happened in 2008 and 2009 for the first group of cities with rents being much higher in these properties. The result from the single-group ITSA is consistent with the result of the first analysis. For the cities of San Francisco and Chicago, energy efficient buildings have higher ratios of the 'positive and significant / significant', which implies that energy efficient buildings are more likely to be positively affected by the policy. However, such ratios are relatively low for New York and Washington DC, which may be caused by other confounding factors, such as the financial crisis.

This research is expected to contribute to the body knowledge in sustainability, public policy, and real estate. This study can also be viewed as a significant leap forward in facilitating informed decision making of building owners in future energy-efficiency improvement projects.

An important next step would be to analyze the disclosed energy performance in relationship to the real estate performance of properties, while also accounting for additional property amenities.

Chapter 1 Introduction

1.1 General Background

According to the Commercial Buildings Energy Consumption Survey (CBECS), the number of commercial buildings in the U.S. has increased from 3.8 million to 5.6 million between 1979 and 2012, with the footprint expected to increase to 124 billion square feet by 2050 (U.S. Energy Information Administration 2018). As commercial buildings form the main core of a city, the promotion of energy-efficient commercial buildings can significantly contribute to overall sustainability in a city (Cox et al. 2013). In recent years, several U.S. cities and states have been trying to become more energy efficient by improving their energy consumption through energy benchmarking and public disclosure of consumption levels (Institute for Market Transformation/Buildingrating.org, 2019), which is expected to contribute to an increased awareness amongst tenants and investors especially among commercial properties as another measure of market comparison.

Studies have shown that sustainable, energy-efficient buildings (e.g., LEED, Energy Star) commission higher rents and sale prices while achieving lower vacancies than comparable non-energy-efficient buildings (Dermisi 2013; 2014; Eichholtz et al. 2013; Dermisi and McDonald 2011). An increasing sensitivity among corporate executives towards sustainability and the embracement of such practices by local, state, and federal agencies (e.g., US General Services Administration) has led to a growing demand for energy efficient buildings. Therefore, mandatory energy benchmarking and disclosure policies could possibly affect the leasing and purchasing decisions of real estate customers as they become more aware of such data. Consequently, such policies are expected to motivate the owners of less energy efficient buildings to invest in energy retrofits with the goal of improving the short and long-term performance and marketability of their buildings.

However, there is a lack of studies specifically aimed at investigating the impact of such policies on office buildings of major cities. In view of the significance of the energy benchmarking and disclosure policy as well as their potential impacts on real estate markets, the research team examined previously the effectiveness of the benchmarking policy on the real estate performance of downtown Chicago office buildings with promising preliminary results, which led to this study which expanded the analysis to additional cities across the U.S.

1.2 Research Objectives

This research aims to expand the previous effort on assessing the effectiveness of the energy benchmarking and disclosure policy on real estate performance by 1) adding more major cities across the U.S. into the analysis and 2) conducting more comprehensive and robust analyses. Specifically, the objectives of the present research project include:

(1) assessment of the real estate performance of sustainable buildings before and after the policy, while considering market cycles (e.g. seasonality);

(2) examination if different characteristics (e.g., building class level) of a building will affect the impact of the policy on its real estate performance.

The present project focuses on four cities across the U.S., including New York City, Washington D.C., San Francisco, and Chicago, for the following reasons:

(1) Disclosure policy length and geographic location: the aforementioned cities have longer-term and more consistent data (Washington DC – since 2008, New York - since

2009, San Francisco - since 2011 and Chicago - since 2013) and are geographically disbursed;

(2) Level of sustainability awareness: This research targets to analyze the effect of the disclosure in a city with a population more sensitive to sustainable practices in comparison to other cities;

1.3 Report Organization

Chapter 2 of the report includes an extensive literature review regarding energy efficiency policies and their impacts on real estate performance. The literature review also showed that this project is the first of its kind. Therefore, the study of this nature can be viewed as a significant leap forward in facilitating informed decision making of building owners in future energy-efficiency improvement projects. Chapter 3 introduces the databases used in this research and describes the steps of data processing. Chapter 4 introduces the two interrupted time series analyses which are the main methods to examine the policy impact of this research. The results are discussed in Chapter 5, while the concluding remarks are provided in Chapter 6.

Chapter 2 Literature Review

Our research required the comprehensive exploration of literature in three areas relative to energy and buildings: (1) studies on energy efficient buildings; (2) studies on energy disclosure policies; and (3) studies on the impact of energy policies on real estate performance.

2.1 Energy Efficient Buildings vs. Non-Energy Efficient Buildings

Burr et al. (2010) suggested that the U.S. marketplace has been already factoring energy efficiency into its real estate decision-making. Additionally, Fuerst and McAllister (2009) compared the occupancy rates of LEED and Energy Star-labeled offices to those of non-certified/labeled offices by using OLS (Ordinary Least Squares) and quantile regression analyses. They found, a significant positive relationship between building occupancy rates and their eco-labels. Similarly, Harrison and Seiler (2011) investigated the effects of environmental certification on commercial real estate properties based on a sample of industrial warehouse facilities. They found that "green" certification (i.e., LEED and Energy Star) played an important, but contingent, role to the sector. Specific to the European Union, Bonde and Song (2013) examined the impact of the Energy Performance Certificate (EPC) on office revenues and found that better EPC ratings have a positive and significant effect on the revenues. In contrary, Zalejska-Jonsson (2013) found that energy and environmental factors have rather a minor impact on purchasing and renting decisions on a property. The finding indicated that when discussing the impact of energy and environmental factors of a buyer's decision on a real estate property, the availability (or disclosure) of the information should be considered as a major factor.

As a different approach to the subject, Dermisi (2014) investigated the spatial distributions of LEED and non-LEED buildings in downtown Chicago and concluded that LEED buildings are generally closer to each other when compared to the non-LEED buildings.

2.2 Building Energy Efficiency Policies

Kontokosata (2011) explored the determinants of green-building policy adoption and the spatial and temporal diffusion of such policies. The study indicated that economic, political, and climate factors are significant predictors of green-building policy adoption. The cities that are categorized as policy innovators and early adopters of green-building policies tend to have lower carbon emissions per capita, are better educated, and have more restrictive land use regulations. Kontokosata (2012) further examined energy performance across a range of building characteristics, such as structural, mechanical, locational, and occupancy variables and presented a model to predict energy savings by using the energy benchmarking data.

Specific to energy benchmarking and disclosure, Cluett and Amann (2013) summarized energy consumption disclosures in the U.S. and highlighted core elements adopted in such policies. In addition, a report by Better City and Meister Consultants Group, Inc. (2012) summarized the successful adoption of benchmarking policies in several cities. Lastly, Dunsky and Hill (2013) assessed the legal implications of such policies and provided recommendations for successful implementation of the policies.

2.3 Impact of Building Energy Efficiency Policies on the Real Estate Performance

The U.S. Department of Energy (2018) has highlighted that measuring and disclosing building energy use may drive their owners in making improvements to lower energy costs for their property, which can also be passed through to their tenants. The impacts of benchmarking and disclosure policies on energy savings have been studied by theoretical analyses (e.g., Cox et al. 2013; Palmer and Walls 2015) and by case studies (e.g., Kontokosata 2013; Meng et al. 2017). O'Keeffe et al. (2015) further summarized methods of quantifying such policies' impacts, including their effectiveness in reducing energy use.

The impacts of building energy efficiency policies were examined by various researchers, including Laposa and Villupuram (2010) who examined the Global Reporting Initiative (GRI)'s corporate sustainability reporting standards and concluded that there is a strong need for further disclosure and standardization of several corporate real estate-related reporting benchmarks, and increased transparency with respect to corporate-owned or leased properties in sustainability reports. Simons et al. (2009) found that the pro-green building policies (i.e., LEED and Energy Star) affected market penetration of green buildings in various commercial building markets in the U.S. Choi (2010) examined quantitatively the effect of municipal policies on commercial green office building designations by using the OLS regression. The findings revealed that municipal regulatory policies are effective in promoting green office building designations, whereas incentive-based policies are not effective in general. Furthermore, Cox et al. (2013) suggested that benchmarking policies increased the purchase of energy-efficient equipment. Similarly, Barrett et al. (2011) investigated the energy ordinances requiring energy retrofits for rental properties in Boulder, Colorado and found that early engagement of people committed to energy efficiency is conducive to the adoption of such requirements in an economically driven environment.

Chapter 3 Study Data

3.1 The Original Data

To achieve the planned research objectives, the data were collected from three different databases:

a) Real Estate Data: Building characteristics (e.g., building class, size, etc.) and real estate performance data (e.g. occupancy rate) of New York City, Washington D.C., San Francisco, and Chicago were obtained from the CoStar Group database for office buildings of more than 10,000 square feet.

b) Sustainability Labeling Data: The sustainability data such as rating, certification level, and points are publicly available and were obtained from the U.S. Green Building Council (USGBC). The Energy Star label was obtained from the Energy Star building database.

c) Energy Consumption Data: The energy benchmarking and disclosure policy requires building owners publicly disclosure of their building's energy performance. Such data were obtained from the city web portals.

- New York City: https://www1.nyc.gov/html/gbee/html/plan/ll84_scores.shtml
- Washington D.C.: https://doee.dc.gov/page/energy-benchmarking-disclosure
- San Francisco: https://data.sfgov.org/Energy-and-Environment/Existing-Commercial-Buildings-Energy-Performance-O/j2j3-acqj
- Chicago: https://data.cityofchicago.org/Environment-Sustainable-Development/Chicago-Energy-Benchmarking/xq83-jr8c

3.2 Data Processing

The data processing consisted of two main tasks – data cleaning and database merging. In the task of data cleaning, incomplete, incorrect, inaccurate, and unreasonable data points were detected and carefully addressed (e.g., replacing, modifying, or deleting). For example, Figure 1 exhibits that some outliers exist in San Francisco's energy consumption database, and due to their irrationality, we decided to drop the data points that have the site EUI (i.e. the amount of heat and electricity consumed by a building) larger than 1000. We also compared the trend of mean site EUIs before and after the dropouts. As shown in Figure 2, the trend of site EUI after dropping out the outliers is consistent with that of the original data, which means the dropouts would not significantly impact our database. The complete process of data cleaning with the programming code is attached in Appendix 1.

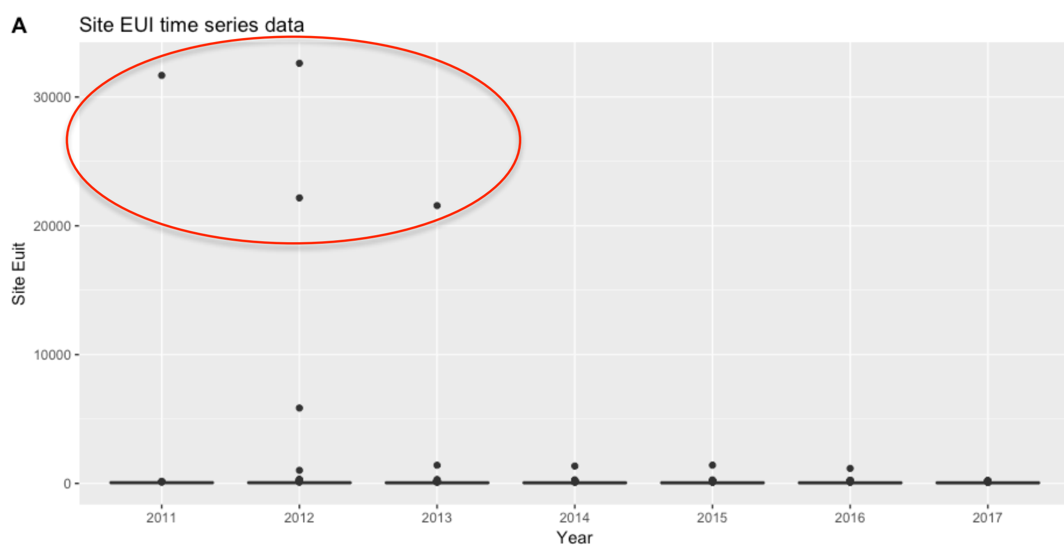


Figure 1. Boxplot of the Site EUI each year for the original database

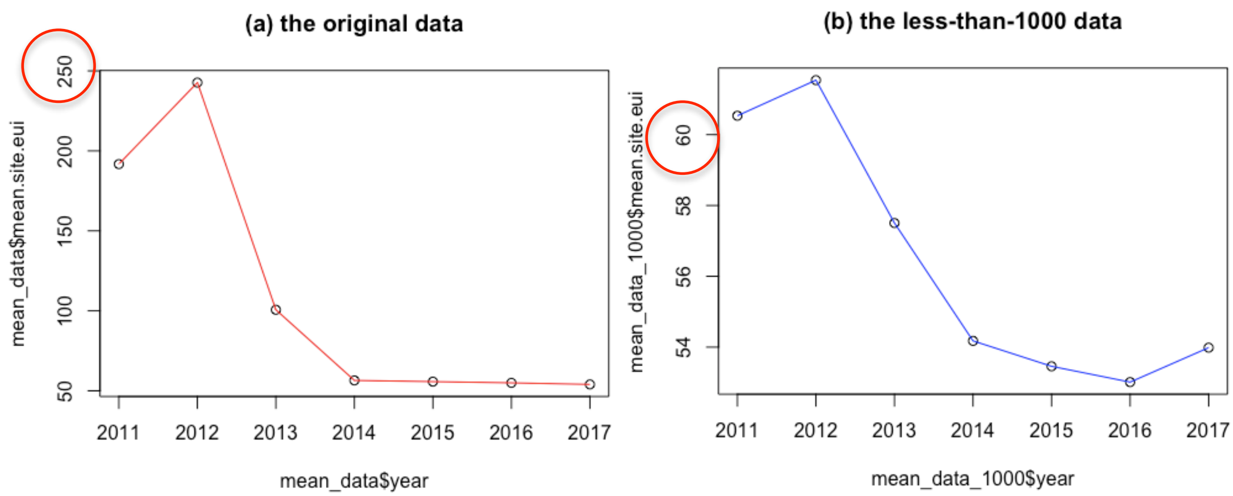


Figure 2. The mean Site EUI before and after data cleaning

In order to achieve the main objective (i.e., to examine the impact of energy policies on the real estate performance of office buildings), we needed to merge the aforementioned three separate data sets into an integrated dataset. Building addresses were used as the primary key (i.e., column) to merging the data sets, which could clearly distinguish one building from another. During the merging process, we first normalized the building addresses in different. A fuzzy merge method was then used to calculate the matching degree of the addresses in two different data sets, and the two addresses with the highest matching degree were identified as the same building and were merged. Figure 3 illustrates the merging process and the data size of each dataset before and after the merge is included. The complete process of data merging with the programming code is attached in Appendix 2.

It should be noted that since we were not able to automatically download all real estate information for each building, the real estate information of each building in the merged database had to be downloaded manually, which limits our flexibility to continually expand the database in the later phases of the study.

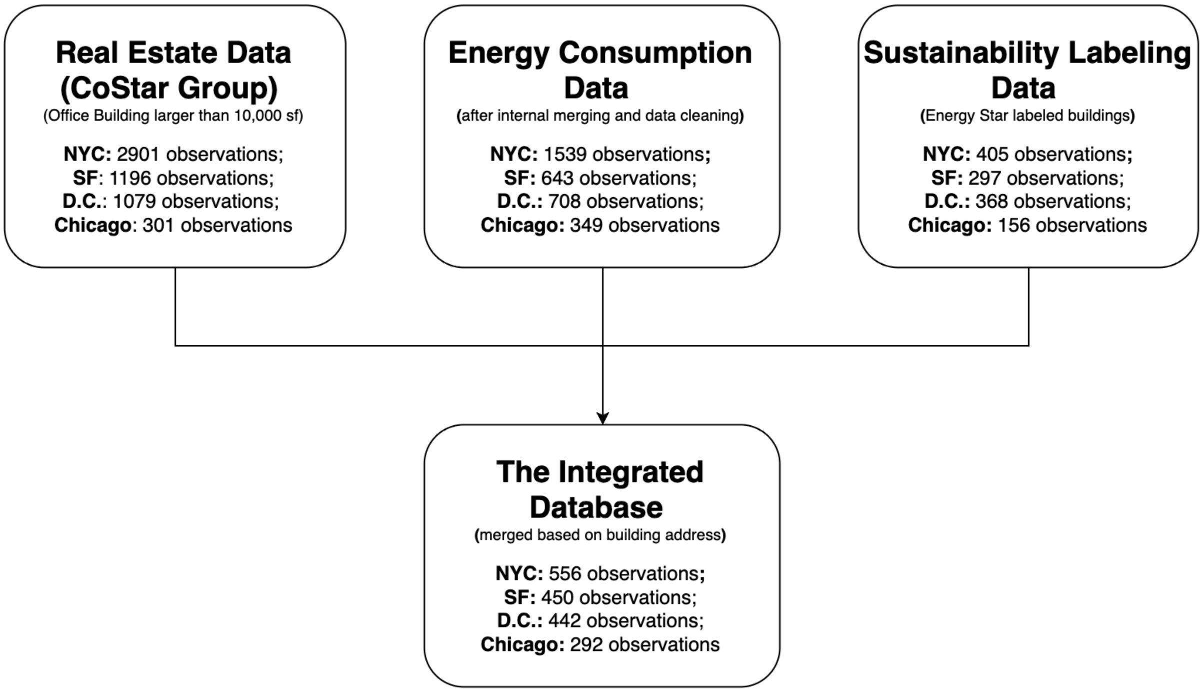


Figure 3. The data merging

The basic structure of the integrated database of each city has been summarized in Table 1. A variety of variables can be used to assess the real estate performance of office buildings. In this study, the annual occupancy was chosen in CoStar's database as it has the relatively high data quality (e.g., no missing variables) and reflects tenant demand for buildings that have or not embraced sustainability. The second column in Table 1 presents the available years of real estate data (i.e. occupancy) of each city. The third column shows the year the energy benchmarking policy was implemented in each city. In this project, the Energy Star label is the main feature we used to group the buildings as energy efficient (sustainable) buildings vs. less energy efficient buildings. Thus, Table 1 also summarizes the number of Energy Star label buildings and those without the Energy Star label. Note that we counted a building as Energy Star if it obtained the label at least once.

Table 1. The summary of the integrated database

City	Time Frame of Real Estate Data	Year of the Policy Implementation	Number of the ES Buildings	Number of non-ES Buildings	Total Number of Buildings
NYC	1994 - 2017	2009	160	396	556
D.C.	1993 - 2017	2008	254	188	442
SF	1997 - 2017	2011	144	306	450
Chicago	1996 - 2017	2013	145	147	292

Chapter 4 Methodology

4.1 Overview

This interdisciplinary research is at the interface of building energy efficiency, policy planning, and real estate economics, making contributions to each field. In order to achieve the research objective of assessing the impact of energy benchmarking policy on the real estate performance of office buildings, this study applied two Interrupted Time Series Analyses (ITSA) based on the occupancy rates of office buildings in the four cities. The general research process is summarized in Figure 4.

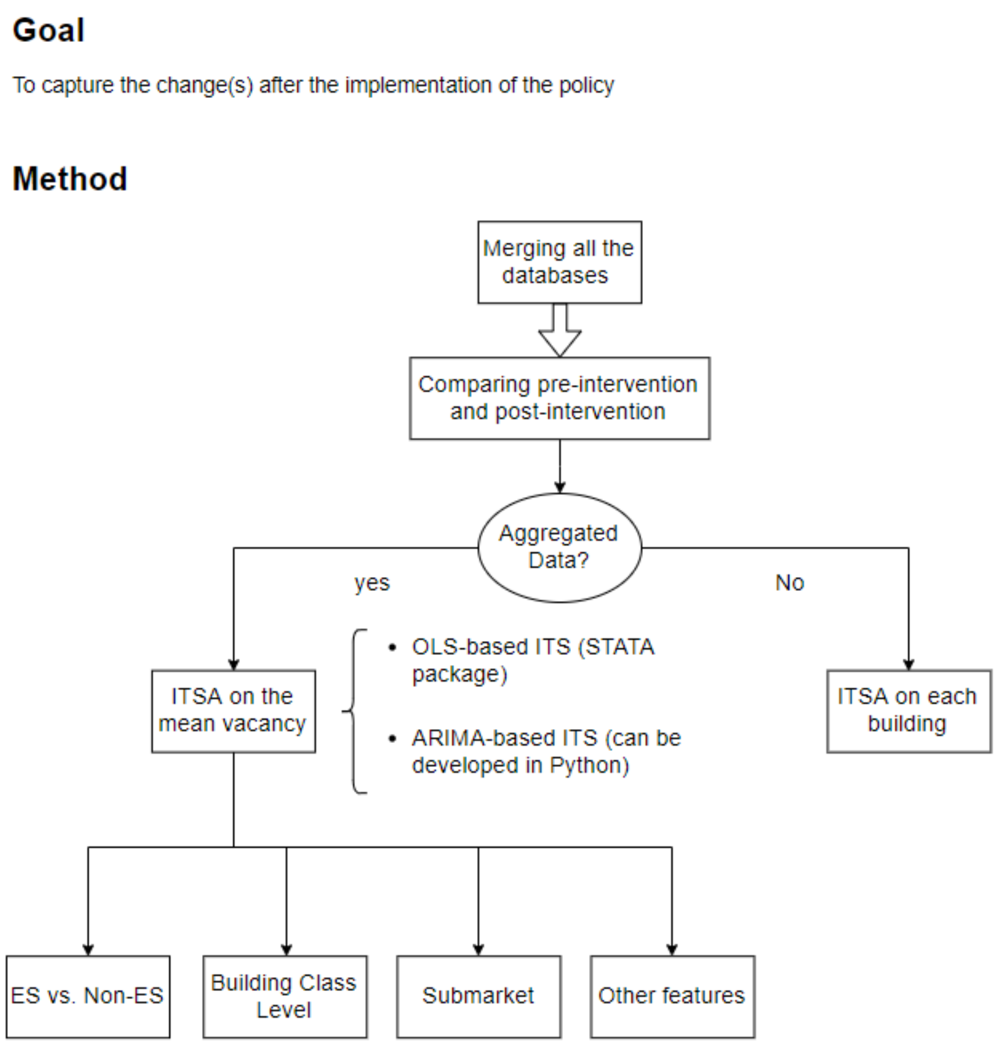


Figure 4. The summary of research methodology

To understand better our data, the next section introduces the exploratory data analysis based on the integrated database. After that, a single-group ITSA and a multi-group ITSA were conducted to serve the research objective.

4.2 Data Description

In addition to grouping buildings based on their sustainability status (i.e. Energy Star vs. non-Energy Star), we also used their building class. Office buildings are generally classified into three classes: A, B, and C, with Class A representing the highest quality buildings in each city. Buildings are rated based on such parameters as age, building systems (e.g. HVAC), location, how well the building is maintained, and amenities. Figure 5 exhibits the number of buildings in each class. As shown in Figure 5, except for DC, the other three cities have a similar distribution among the number of buildings for each class. The reason Washington DC is different from the other three cities for class C buildings is mainly due to data loss caused by data merging.

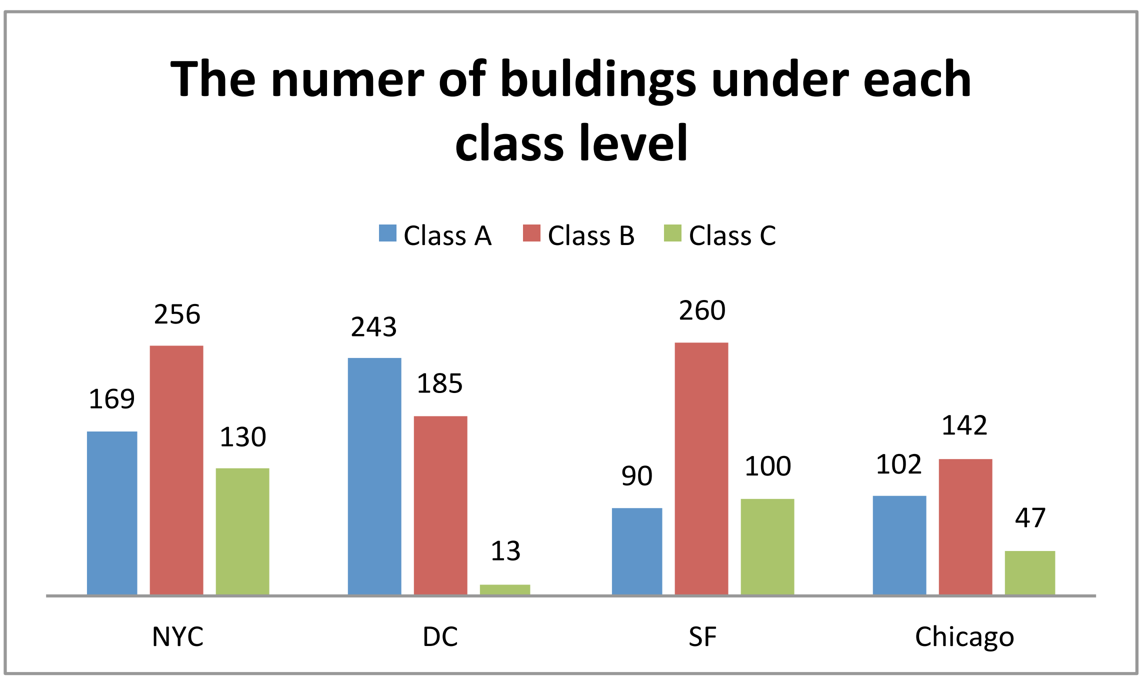


Figure 5. The number of buildings under each class level

We further compared the number of Energy Star buildings with the number of non-Energy Star buildings for each class level, as shown in Figure 6. In Class A, the proportion of Energy Star buildings is relatively higher, while the proportion of non-Energy Star buildings is higher for Class B buildings. Additionally, there are only a few Energy Star Class C buildings, which is expected as buildings with better energy efficacy are more likely to achieve a better classification level. The subsequent analysis focuses on A and B classes since the number of ES buildings in Class C group is very small.

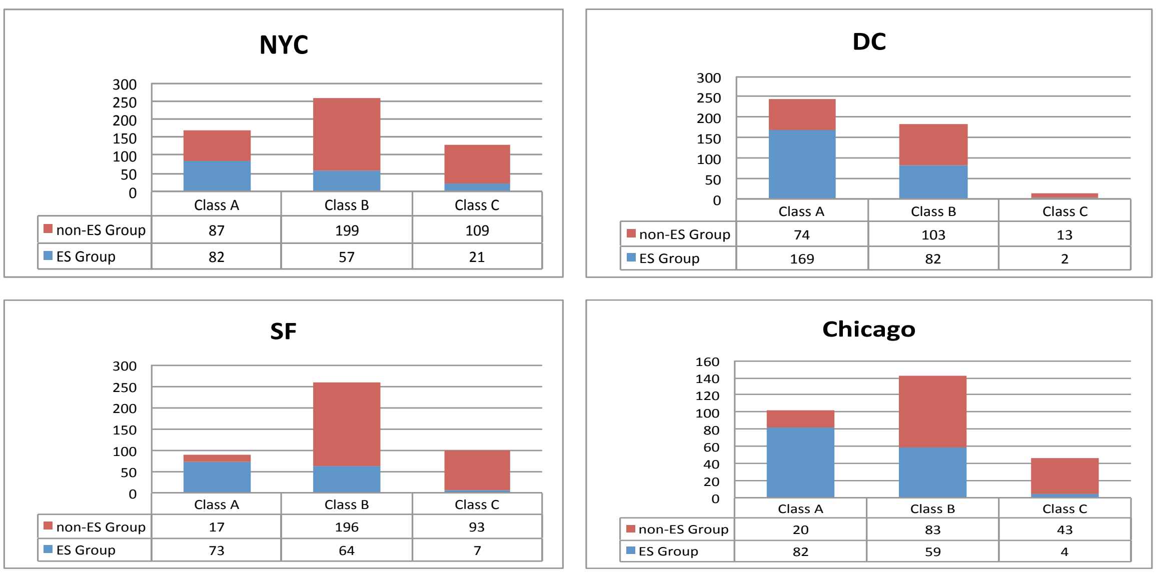


Figure 6. The number of ES buildings vs. the number of non-ES buildings under each class level

A variety of variables can be used to measure the real estate performance of office buildings. The occupancy rate was chosen because of the relatively high data quality (e.g., absence of missing variables) and its better reflection of tenant demand for properties that have or have not embraced sustainability. Figures 7 through 10 show the annual trends of average occupancy for each class in each city for Energy Star buildings and non-Energy Star buildings, respectively. For each city, the average occupancy rate of Energy Star buildings is lower than that of non-Energy Star buildings.

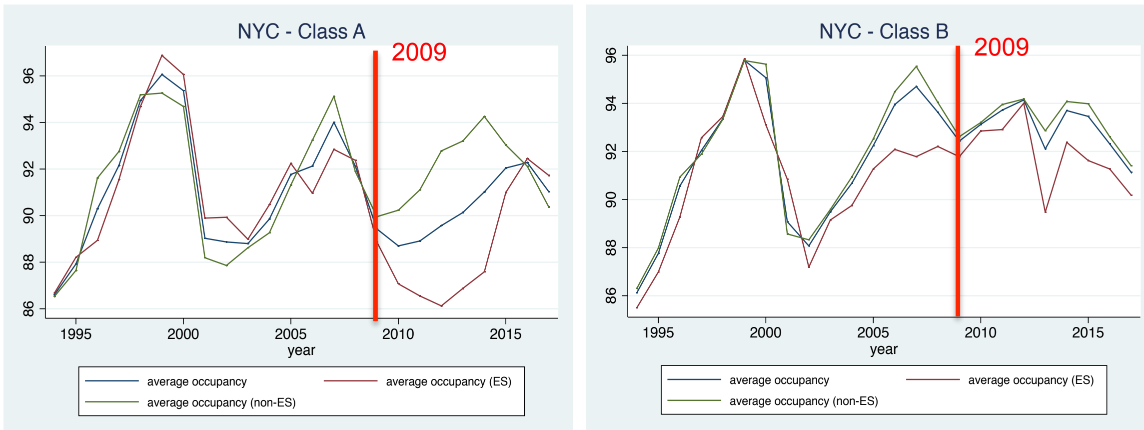


Figure 7. The trend in the average occupancy of ES buildings vs. non-ES buildings in NYC

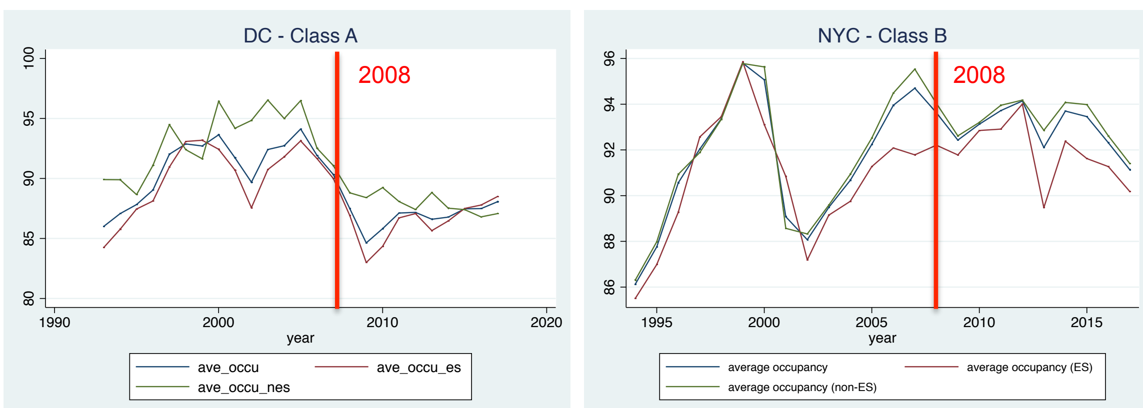


Figure 8. The trend in the average occupancy of ES buildings vs. non-ES buildings in D.C.

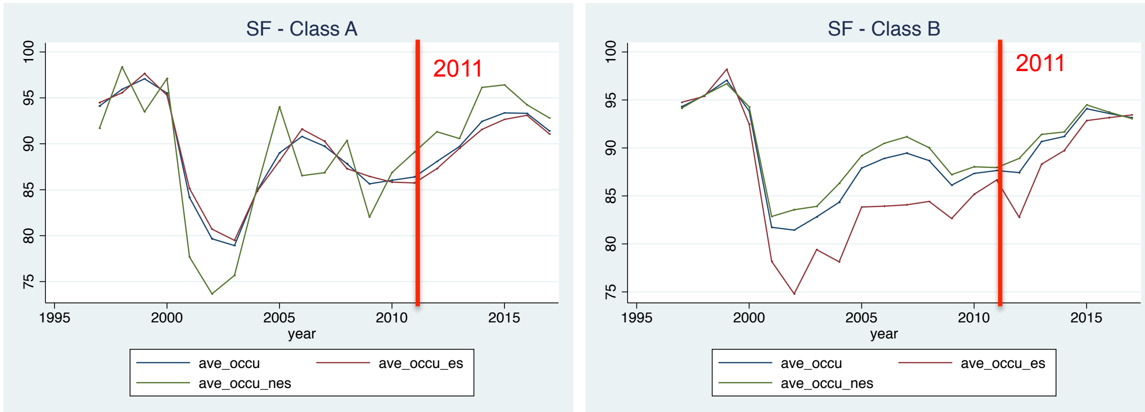


Figure 9. The trend in the average occupancy of ES buildings vs. non-ES buildings in SF

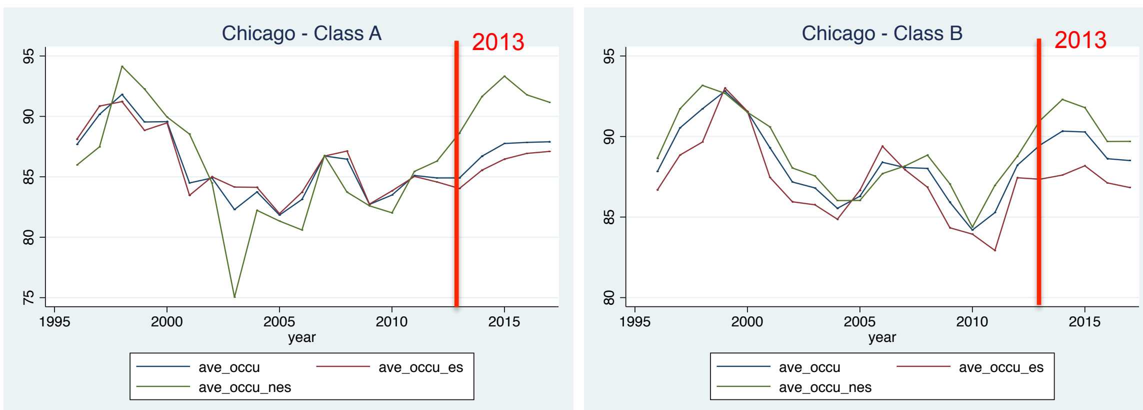


Figure 10. The trend in the average occupancy of ES buildings vs. non-ES buildings in Chicago

4.3 Interrupted Time Series Analysis (ITSA)

Once the real estate performance variable such as the occupancy was decided, the next step was to set up hypotheses regarding how the policy would impact the variable. The policy impacts have three main scenarios, including if the trend of the performance variable had a change in level (i.e., an immediate change) after the policy, a change in gradient (i.e., a continuous change), or both. It is difficult to draw conclusions as to whether such impacts exist or not by simply observing the trends shown in Figures 7 through 10. This study applied the Interrupted Time Series Analysis (ITSA).

ITSA is a quasi-experimental method that is widely used to assess if a time series of a specified outcome (e.g., occupancy rate) was affected by intervention(s) at a known point(s) in time (Bernal et al. 2017; Grimshaw et al. 2000; Harris et al. 2006; Wagner et al 2002). It has become increasingly popular in political science, which aims to evaluate the impact of changes in laws or regulations on the behavior of people or market (Biglan, Ary and Wagenaar 2000; Briesacher et al. 2013; Muller 2004). ITSA is based on the key assumption that data trends remain unchanged without interventions. In other words, if there were no interventions, an expected trend can be predicted based on the pre-existing trend. A comparison between the expected trend and the actual trend observed in the post-intervention period reveals the difference, which provides evidence for the impact of the intervention. However, the assumption of the unchanged data trends has the risk of yielding biased results, if the time series data is seasonal. As such, the result of ITSA may be affected by seasonality. For example, ITSA may detect changes after the policy implementation but it is difficult to determine if that change is caused by policy or seasonality. Therefore, we need to first adjust the seasonality in our time series data before the ITSA.

4.3.1 Seasonality Adjustment

The process of adjusting seasonality can be divided into two main steps. In the first step, we used Fourier transformation to detect seasonality (Kandlikar 2007). The main purpose of this step is to detect the seasonal cycle of our time series data (i.e., occupancy rate). For instance, Table 2 shows the detection results based on the non-Energy Star data in Chicago. It shows that the data has two seasonal cycles, and the main one is 8 years.

Table 2. Seasonality of the occupancy of non-ES buildings in Chicago

Order	Spec	Freq	Seasonality (1/freq)
1^{st}	0.600	0.125	8 years
2^{nd}	0.325	0.042	24 years

The next step is to extract seasonality from the time series data through decomposition. Seasonality may exist in time series data through two forms – an additive way or a multiplicative way. Figure 11 shows how these two forms work in time series data.

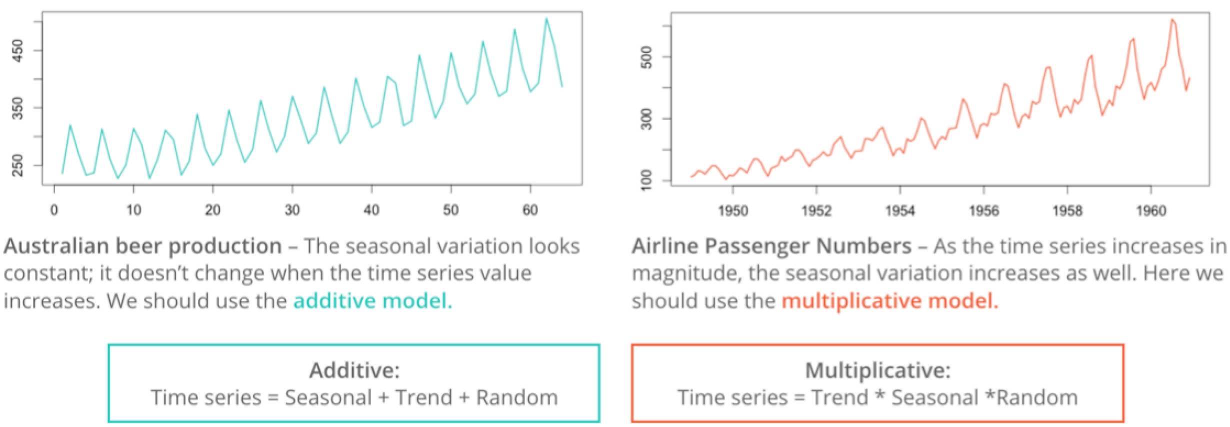


Figure 11. The two forms of time series data decomposition (figure from https://anomaly.io/seasonal-trend-decomposition-in-r/)

According to the occupancy rate trends shown in Figures 7 through 10, our time series data shows an additive pattern. Based on the seasonal cycle determined from the previous step, the original time series data can be decomposed into three parts (i.e., seasonal, trend, and random), and we can simply remove the seasonal part from the original data. Figures 12 through 15 show the annual trends of the average occupancy for each city after the seasonality adjustment, which can be compared with the original trends shown in Figures 7 through 10. A detailed process of seasonality adjustment (with code) is included in Appendix 3.

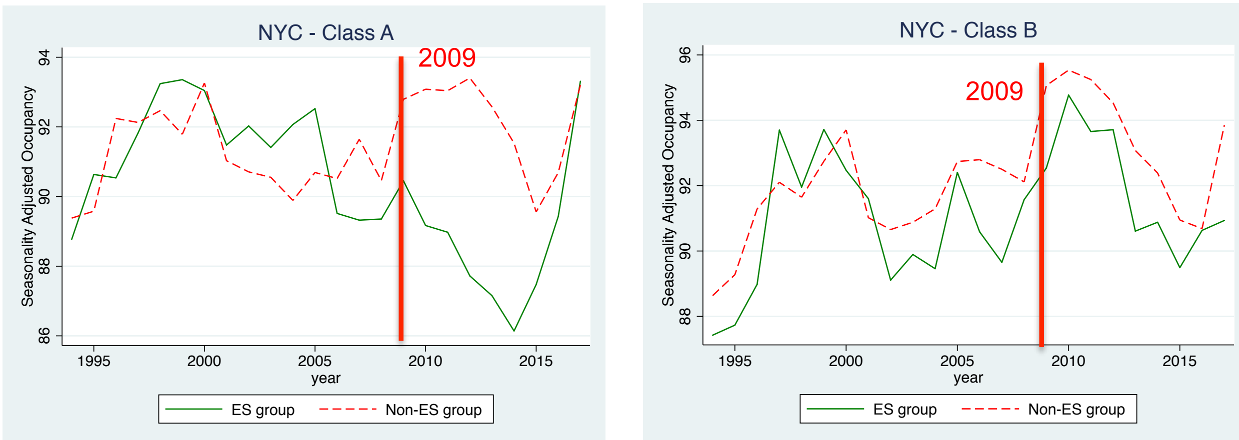


Figure 12. The seasonality adjusted trend in the average occupancy of ES buildings vs. non-ES buildings in NYC

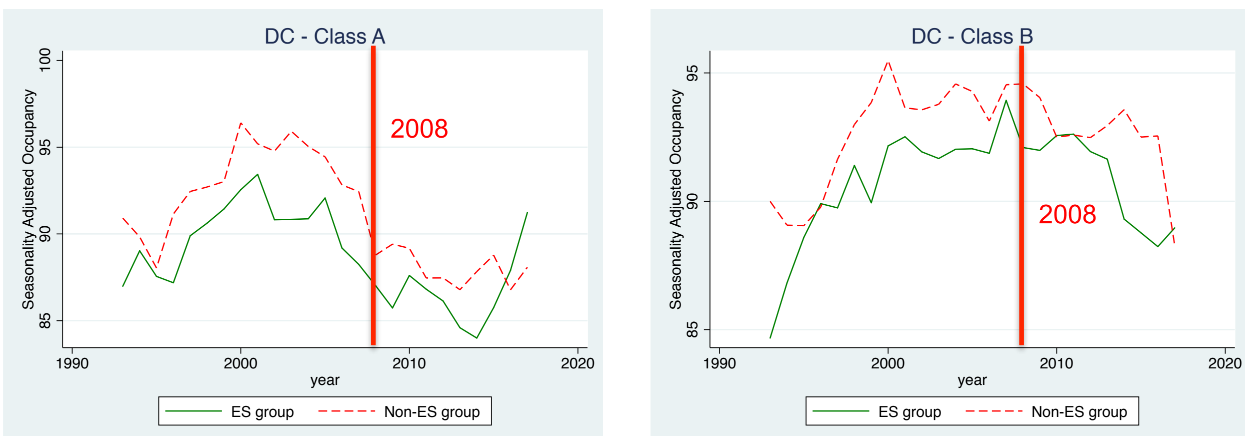


Figure 13. The seasonality adjusted trend in the average occupancy of ES buildings vs. non-ES buildings in D.C.

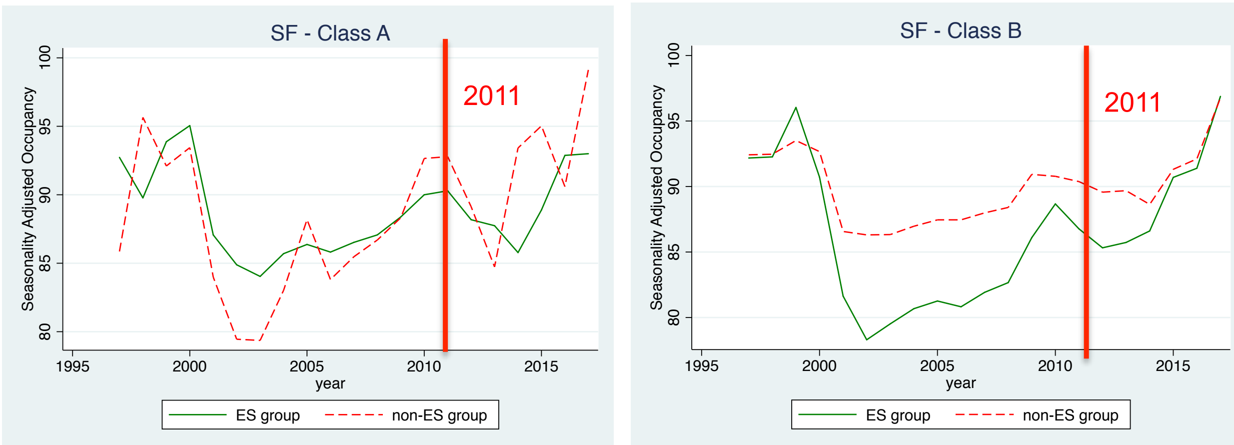


Figure 14. The seasonality adjusted trend in the average occupancy of ES buildings vs. non-ES buildings in SF

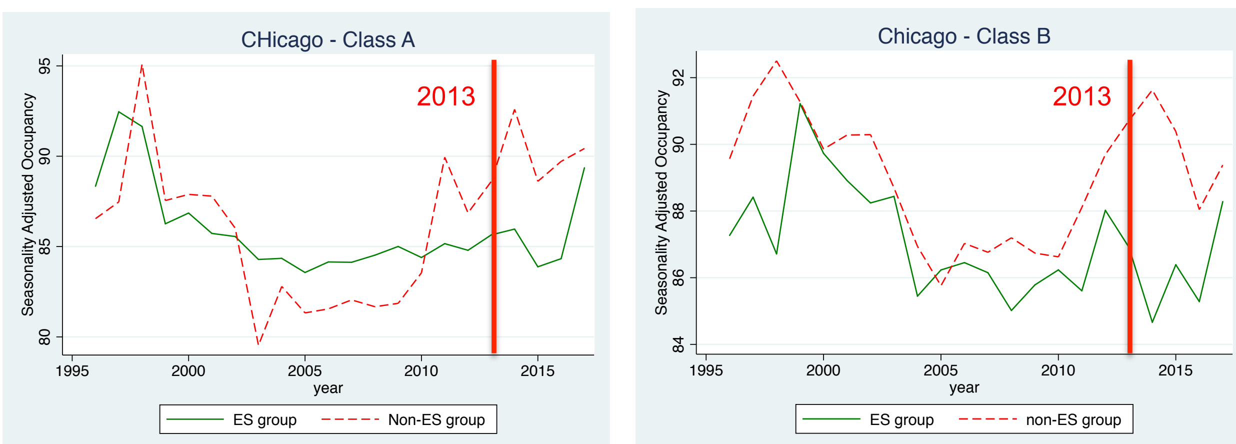


Figure 15. The seasonality adjusted trend in the average occupancy of ES buildings vs. non-ES buildings in Chicago

4.3.2 The multi-group ITSA on two groups of buildings

When studying the impact of a large-scale intervention (e.g., a policy affecting all buildings in a city), researchers often have an effective sample size of N = 1 (treatment group) or N = 2 (treatment group with a control group) (Linden 2015), and it is common to use an aggregated value (e.g., median or mean) to represent the sample in the ITSA. In the present study, the treatment group consists of all the Energy Star buildings of each class for each city, and the mean occupancy rate is used as the aggregated outcome variable for the ITSA.

In addition to the energy policy, many unobserved factors could potentially affect occupancy rates. Including a control group in the ITSA can help account for the other confounding factors when an exogenous intervention affects all the groups, which is called multiple-group ITSA (Linden 2015). The multiple-group ITSA hypothesizes that the level or trend of the outcome variables remains unchanged for all groups if no intervention occurs. It assumes the unobserved factors affect both groups at the same extent. This study conducted multiple-group ITSA's for each city based on two comparable groups – one control group consisting of the non-Energy Star buildings and one treatment group consisting of the Energy Star buildings. By accounting for confounding factors, this grouping enables us to focus on investigating how the benchmarking policy affected occupancy rates differently between the energy-efficient buildings and their non-energy-efficient counterparts. The multiple-group ITSA with two groups is based on the following regression model (Linden and Adams 2011; Simonton 1977):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 T_t X_t + \beta_4 Z + \beta_5 Z T_t + \beta_6 Z X_t + \beta_7 Z T_t X_t + \varepsilon_t, \qquad (1)$$

where Y_t is the aggregated outcome variable (average occupancy rate) at each equally spaced (annual) time point t, and Z is the dummy variable to indicate the group (0 = control and 1 = treatment). In Eq. 1, the first four coefficients, β_0 through β_3, refer to the control group, while the last four coefficients, β_4 through β_7, refer to the treatment group. Specifically, β_0 = the intercept of the outcome variable; β_1 = the coefficient to represent the initial trend before the intervention; β_2 = the level change that occurs immediately after the intervention; β_3 = the continuous change of the trend after the intervention. And, β_4 is the difference in the intercept of the outcome variable between treatment and control groups before the intervention. β_5 is the difference in the trend between the two groups before the intervention. β_6 is the difference between the two groups in the level change immediately after the intervention. Lastly, β_7 is the difference between the two groups in the continuous change of the trend after the intervention. ε_t is a random error term.

To ensure the comparability between the groups, the control and treatment groups should not be significantly different in either the initial intercept or the trend of the outcome variable *before* the intervention. Thus, the appropriate control group should have p-values for both β_4 and β_5 greater than the required threshold (i.e., 0.05). The p-values of β_2 and β_3 show if there are significant changes (immediate and continual) of the control group (non-Energy Star group) after the intervention. The p-values for β_6 and β_7 then provide statistical evidence on whether the policy affects the treatment group differently from the control group.

4.3.3 The single-group ITSA on each building

There is a potential issue of information loss by using the aggregated data (i.e., average occupancy rate). This is because we used the average data to represent the whole sample, which limited us in analyzing the policy impacts on each building. To deal with this challenge, we expanded the aforementioned analysis by conducting ITSA on each building. In this case, a single-group ITSA is used.

The single-group ITSA is a simple version of the multiple-group ITSA, which only examines the changes for the treatment group (i.e. occupancy rate of each building). It is based on the following model (Huitema and Mckean 2000a; Linden and Adams 2011):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 T_t X_t + \varepsilon_t, \qquad (2)$$

where Y_t is the occupancy rate of each building at year *t*; T_t is the time since the starting year of the database; X_t = the dummy variable to indicate the pre- or post-intervention period (0 = pre-intervention period and 1 = post-intervention period). It is noted that if we set Z in Eq.1 to 0, the two functions become the same. The meanings of the coefficients (i.e. β_1 to β_3) in Eq.2 are the same as those in Eq.1.

Chapter 5 Results

5.1 The result of the multiple-group ITSA on two groups of buildings

The multiple-group ITSA was conducted based on the annual average occupancy rates of the office buildings for each class and each city, in order to examine the change(s) after the policy implementation and then to infer the impact of the benchmarking policy on real estate performance. This multi-group analysis specified Energy Star buildings as the treatment group and non-Energy Star buildings as the control group.

5.1.1 New York City results

For Class A buildings, as shown in Table 3(a), the starting level of difference between the treatment group and the control group (β_4: z) was not significant (P=0.80), and the initial trend difference (β_5: z_t) was not significant either (P=0.87). As mentioned earlier, the groups with *p*-values greater than a specified threshold (i.e., 0.05) for both β_4 and β_5 in Eq. 1 are preferred, to ensure the comparability. Thus, for NYC Class A buildings, the Energy Star group (i.e. treatment group) and non-Energy Star group (i.e. control group) behave similar before the policy intervention. After the intervention, the occupancy rate of the non-Energy Star group increases by 2.28% immediately (β_2; P=0.001), while that of the Energy Star group drops immediately by 2.50% ($\beta_2 + \beta_6$; P=0.01). The policy was implemented following the beginning of the financial crisis with Class A buildings commissioning the highest rents and the crisis could lead to tenant flight to Class B. For the continuous trends (β_3 and β_7), there is a slightly increasing trend for the Energy Star group's occupancy rate and a decreasing trend of the non-Energy Star group's occupancy rate, but neither is statistically significant. Note that β_6 and β_7 represent the differences between the Energy

Star group and non-Energy Star group rather than the changes of the Energy Star group before and after the policy implementation. The results were verified upon the visual display of Figure 16(a).

For Class B buildings, in Table 3(b), the occupancy rate of the non-Energy Star group increases by 2.28% immediately after the policy implementation with a continuously decreasing trend (-0.21% per year). The p-values of β_6 and β_7 show that there is no significant difference of the trend between the Energy Star and non-Energy Star groups after the intervention. It indicates that the occupancy rate of the Energy Star group has also an immediate increase with a continuous decreasing trend. The results were also exhibited in Figure 16(b).

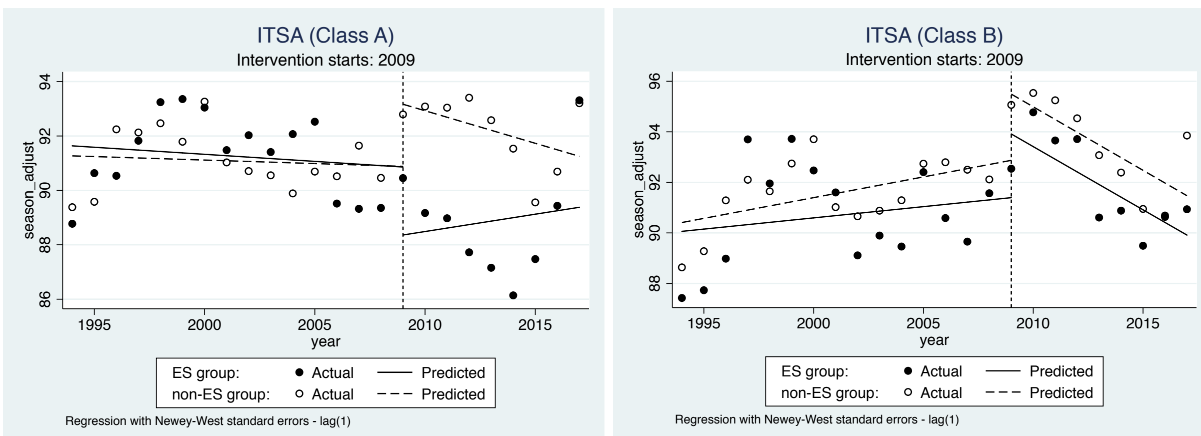


Figure 16. (a) ITSA for Class A and (b) ITSA for Class B in New York City

Table 3(a). Multiple-Group ITS Regression Model for Class Level A Buildings in New York City

Regression with Newey-West standard errors	Number of obs = 48
Maximum lag: 1	F (7, 40) = 5.70
	Prob > F = 0.001

Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf.**	**Interval]**
β_1: t	-0.026	0.087	-0.30	0.769	-0.20	0.15
β_4: z	0.368	1.446	0.25	0.800	-2.55	3.29
β_5: z_t	-0.026	0.159	-0.17	0.870	-0.35	0.29
β_2: x2013	2.283	0.662	3.45	**0.001**	0.95	3.62
β_3: x_t2013	-0.214	0.189	-1.13	0.265	-0.60	0.17
β_6: z_x2013	-4.782	1.912	-2.50	**0.017**	-8.65	-0.92
β_7: z_x_t2013	0.393	0.415	0.95	0.349	-0.45	1.23
β_0 (cons)	91.269	0.892	102.29	0.000	89.47	93.07

Table 3(b). Multiple-Group ITS Regression Model for Class Level B Buildings in New York City

Regression with Newey-West standard errors	Number of obs = 48
Maximum lag: 1	F (7, 40) = 10.90
	Prob > F = 0.001

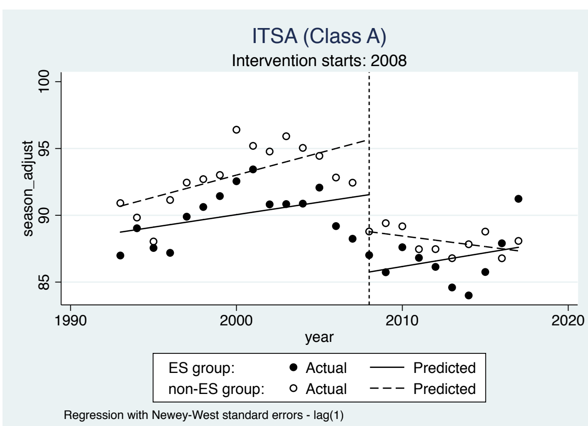
Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf.**	**Interval]**
β_1: t	0.164	0.080	2.06	0.046	0.00	0.33
β_4: z	-0.350	1.726	-0.20	0.840	-3.84	3.14
β_5: z_t	-0.075	0.165	-0.46	0.651	-0.41	0.26
β_2: x2013	2.619	0.722	3.63	**0.001**	1.16	4.08
β_3: x_t2013	-0.666	0.201	-3.31	**0.002**	-1.07	-0.26
β_6: z_x2013	-0.010	1.360	-0.07	0.942	-2.85	2.65
β_7: z_x_t2013	0.077	0.286	0.27	0.788	-0.50	0.66
β_0 (cons)	90.411	0.835	108.23	0.000	88.72	92.10

5.1.2 Washington D.C. results

Table 4 (a) and (b) summarizes the analysis results of the two class levels respectively for Washington D.C. For Class A buildings, there is a significant drop of occupancy rate for the non-

Energy Star group (-6.89%) after the policy implementation. Although the immediate change of the Energy Star group is slightly different (1.10%) from that of the non-Energy Star group, it is not statistically significant. Thus, the occupancy rate of the Energy Star group also had an immediate drop after the policy. Similar to New York City, these drops might also be caused by the financial crisis. However, after the policy implementation (year 2008), the occupancy of the Energy Star group shows an increasing trend, while the non-Energy Star group has a decreasing trend (statistically significant). The results are visualized in Figure 17(a).

For Class B buildings, the occupancy rates have significant decreasing trends after the policy implementation for both groups. However, there is no significant difference between the two groups, which implies that the policy affects both Energy Star and non-Energy Star buildings to the same extent. Visualization is shown in Figure 17(b).



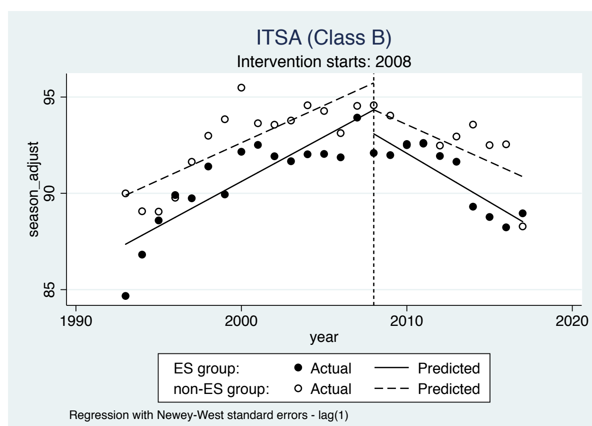


Figure 17. (a) ITSA for Class A and (b) ITSA for Class B in Washington DC

Table 4(a). Multiple-Group ITS Regression Model for Class Level A Buildings in Washington D.C.

Regression with Newey-West standard errors Maximum lag: 1				Number of obs = 50 F (7, 42) = 12.26 Prob > F = 0.0000		
Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf.**	**Interval]**
β_1: t	0.332	0.147	2.27	0.029	0.04	0.63
β_4: z	-1.944	1.451	-1.34	0.188	-4.87	0.99
β_5: z_t	-0.145	0.199	-0.73	0.469	-0.55	0.26
β_2: x2013	-6.895	1.509	-4.57	**0.000**	-9.94	-3.85
β_3: x_t2013	-0.492	0.161	-3.05	**0.004**	-0.82	-0,17
β_6: z_x2013	1.107	2.304	0.48	0.633	-3.54	5.76
β_7: z_x_t2013	0.510	0.325	1.57	0.124	-0.15	1.17
β_0 (cons)	90.683	1.072	84.61	0.000	88.52	92.85

Table 4(b). Multiple-Group ITS Regression Model for Class Level B Buildings in Washington D.C.

Regression with Newey-West standard errors Maximum lag: 1				Number of obs = 50 F (7, 42) = 17.65 Prob > F = 0.0000		
Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf.**	**Interval]**
β_1: t	0.389	0.086	4.52	0.000	0.22	0.56
β_4: z	-2.545	1.244	-2.05	0.047	-5.06	-0.04
β_5: z_t	0.077	0.135	0.57	0.573	-0.20	0.35
β_2: x2013	-1.395	0.934	-1.49	0.143	-3.28	0.49
β_3: x_t2013	-0.774	0.178	-4.36	**0.000**	-1.13	-0.42
β_6: z_x2013	0.150	1.355	0.11	0.913	-2.58	2.88
β_7: z_x_t2013	-0.197	0.228	-0.87	0.392	-0.66	0.26
β_0 (cons)	89.902	0.797	112.74	0.000	88.29	91.51

5.1.3 San Francisco results

As shown in Table 5(a) and Figure 18(a), for Class A buildings, both groups have an increasing trend of occupancy rate (but not statistically significant) after the policy implementation.

The results show that there is no significant difference in the trend between these two groups. For Class B buildings, after the policy implementation, the occupancy rates of both groups have statistically significant increasing trends, and there is no significant difference between the two groups, as shown in Table 5(b) and Figure 18(b).

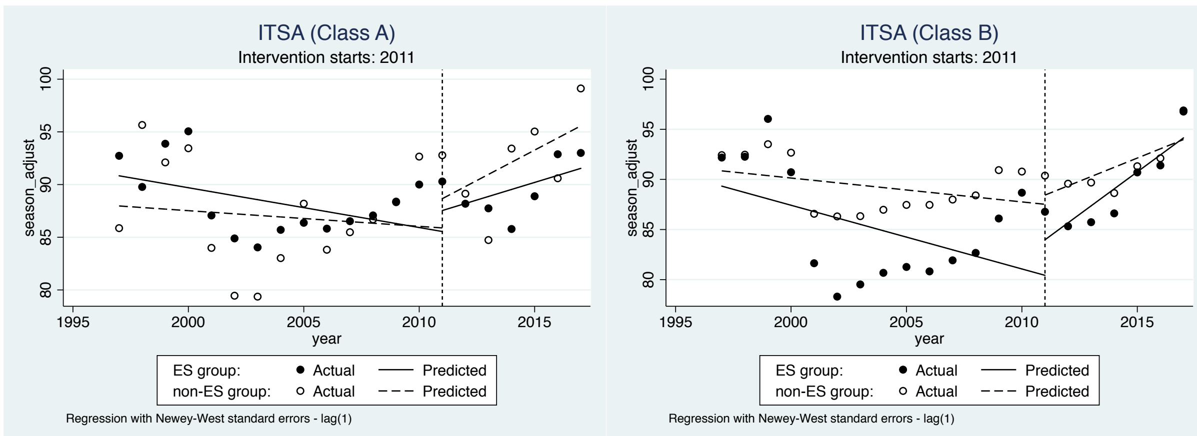


Figure 18. (a) ITSA for Class A and (b) ITSA for Class B in San Francisco

Table 5(a). Multiple-Group ITS Regression Model for Class Level A Buildings in San Francisco

Regression with Newey-West standard errors Maximum lag: 1				Number of obs = 42 F (7, 34) = 2.98 Prob > F = 0.0152		
Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**T**	**P > |t|**	**[95% Conf. Interval]**	
β_1: t	-0.149	0.388	0.38	0.704	-0.94	0.64
β_4: z	2.863	3.986	0.72	0.478	-5.24	10.96
β_5: z_t	-0.229	0.452	-0.51	0.616	-1.15	0.69
β_2: x2013	2.776	3.393	0.82	0.419	-4.11	9.67
β_3: x_t2013	1.300	0.820	1.59	0.122	-0.37	2.97
β_6: z_x2013	-0.785	4.018	-0.20	0.846	-8.95	7.38
β_7: z_x_t2013	-0.226	0.977	-0.26	0.795	-2.24	1.73
β_0 (cons)	87.969	3.471	25.34	0.000	80.91	95.02

Table 5(b). Multiple-Group ITS Regression Model for Class Level B Buildings in SF

Regression with Newey-West standard errors Maximum lag: 1				Number of obs = 42 F (7, 34) = 4.12 Prob > F = 0.0023		
Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf. Interval]**	
β_1: t	-0.238	0.215	-1.11	0.276	-0.675	0.199
β_4: z	-1.524	4.023	-0.38	0.707	-9.70	6.65
β_5: z_t	-0.397	0.496	-0.80	0.429	-1.41	0.61
β_2: x2013	0.919	1.945	0.47	0.640	-3.03	4.87
β_3: x_t2013	1.162	0.470	2.48	**0.018**	0.21	2.17
β_6: z_x2013	2.626	4.051	0.65	0.521	-5.61	10.86
β_7: z_x_t2013	1.168	0.834	1.40	0.171	-0.53	2.86
β_0 (cons)	90.853	1.751	51.90	0.000	87.29	94.41

5.1.4 Chicago results

As shown in Table 6(a) for Class A buildings, both groups have an increasing trend of occupancy after the policy implementation. However, there is a significant difference in the immediate change between the two groups. The non-Energy Star group has an immediate jump after the implementation. Also, Figure 19(a) visualizes the results. For Class B buildings, the non-Energy Star group has a significant jump of occupancy after the policy implementation, which is different from the Energy Star group. However, the continual trend of non-Energy Star group is decreasing after the policy implementation, while the Energy Star group has an increasing trend, as shown in Table 6(b) and Figure 19(b).

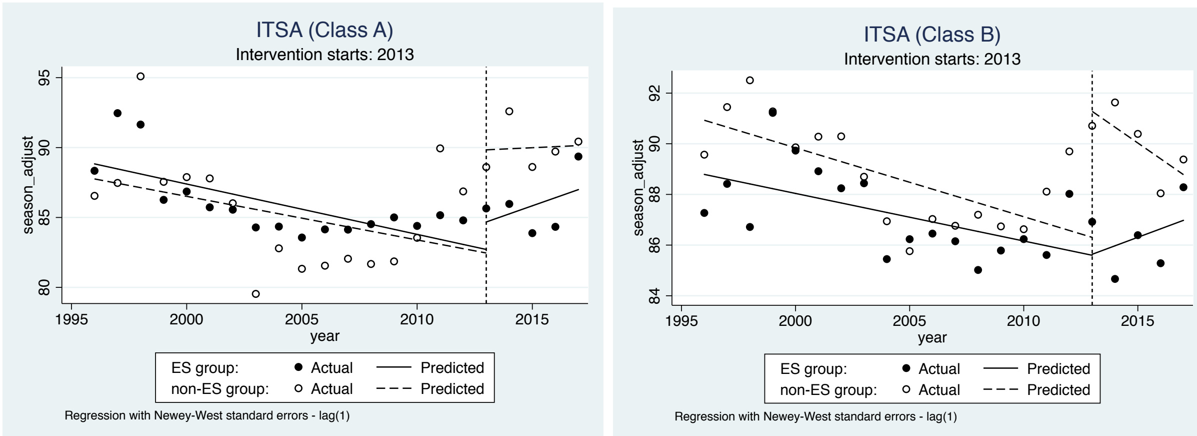


Figure 19. (a) ITSA for Class A and (b) ITSA for Class B in Chicago

Table 6(a). Multiple-Group ITS Regression Model for Class Level A Buildings in Chicago

Regression with Newey-West standard errors — Number of obs = 44
Maximum lag: 1 — F (7, 36) = 11.32
Prob > F = 0.000

Ave_vacant (log_transformed)	**Coef.**	**Newey-West Std. Err.**	**t**	**P > |t|**	**[95% Conf. Interval]**	
β_1: t	-0.312	0.245	-1.27	0.212	-0.81	0.19
β_4: z	1.076	2.463	0.44	0.665	-3.82	6.07
β_5: z_t	-0.048	0.277	-0.17	0.862	-0.61	0.51
β_2: x2013	7.378	2.991	2.47	**0.019**	1.31	13.44
β_3: x_t2013	0.388	0.347	1.12	0.270	-0.31	1.09
β_6: z_x2013	-5.412	3.293	-1.64	0.109	-12.09	1.27
β_7: z_x_t2013	0.551	0.648	0.85	0.401	-0.76	1.86
β_0 (cons)	87.757	2.037	43.09	0.000	83.63	91.89

Table 6(b). Multiple-Group ITS Regression Model for Class Level B Buildings in Chicago

Regression with Newey-West standard errors — Number of obs = 44
Maximum lag: 1 — F (7, 36) = 11.59
Prob > F = 0.000

Ave_vacant (log_transformed)	Coef.	Newey-West Std. Err.	t	P > |t|	[95% Conf. Interval]	
β_1: t	-0.272	0.102	-2.66	0.012	-0.48	-0.06
β_4: z	-2.138	1.182	-1.81	0.079	-4.54	0.26
β_5: z_t	0.084	0.131	0.64	0.523	-0.18	0.35
β_2: x2013	4.974	1.357	3.67	**0.001**	2.22	7.73
β_3: x_t2013	-0.353	0.190	-1.86	0.072	-0.74	0.03
β_6: z_x2013	-4.935	1.589	-3.11	**0.004**	-8.16	-1.71
β_7: z_x_t2013	0.875	0.423	2.07	**0.046**	0.02	1.73
β_0 (cons)	90.928	0.828	109.78	0.000	89.25	92.61

5.2 The result of ITSA on each building

In order to maximize the use of the collected data, and to avoid any loss of information caused by the aggregated-data-based analysis, we adopted the single-group ITSA to examine if the implementation of the policy resulted in a shift in the occupancy rate for each building. Based on the analysis results, we counted the number of buildings with a statistically significant shift (i.e. p-value < 0.05) in the occupancy rate after the policy implementation. Also, among the buildings with statistically significant changes, we further counted the number of them with positive changes (i.e., the occupancy rate increases after the policy implementation). Table 7 summarized the numbers for each city. Note that in Table 7, the column of “Total” means the total number of buildings under each group (Energy Star vs. non-Energy Star); the column of “Significant” means the number of buildings that have statistically significant changes (either immediately or continuously) after the year the policy was implemented; and the columns of “sign & pos” means the number of buildings with statistically significant and also positive changes (increase in occupancy rate) after the year of policy implementation.

By comparing these totals (i.e., significant and sign & pos) with the total number of buildings under the Energy Star group and the non-Energy Star group respectively, two ratios can be derived. The first ratio (significant / total) indicates the percentages of buildings that have changes in occupancy rate after the policy implementation, and the second ratio (significant and positive / significant) indicates the percentage of the buildings that are positively affected by the policy among the buildings that have significant changes. The results can be used to infer if the policy has different impacts on the real estate performance between the Energy Star and non-Energy Star groups. Figure 20 shows the corresponding ratios.

Table 7. The number of buildings that are affected (and positively affected) by the policy

	ES			Non-ES		
	Total	Significant	Sign & Pos	Total	Significant	Sign & Pos
NYC_a	82	41	16	87	45	29
NYC_b	57	23	12	199	83	41
DC_a	169	75	22	74	27	5
DC_b	82	36	9	103	39	9
SF_a	73	29	22	17	6	3
SF_b	64	27	23	196	57	44
Chi_a	82	49	33	20	15	11
Chi_b	59	38	24	83	43	28

Figure 20. The ratios of the buildings that are affected (and positively affected) by the policy

The first ratio (significant/total) can be used to check which type(s) of buildings are more likely to have a change in real estate performance after the policy implementation. As shown in Figure 20, in New York City, overall the ratios of both groups (Energy Star and non-Energy Star) are very close. For Class A buildings, the ratios are approximately 0.5, which implies the real estate performances of about half of Class A buildings have significantly changed after the policy implementation. For Class B, these ratios are slightly smaller, around 0.4. In Washington D.C. and San Francisco, the significant/total ratio of the Energy Star group is higher than that of the non-Energy Star group, while the difference in this ratio between Class A and Class B is not obvious. This indicates that for Washington D.C. and San Francisco, the real estate performance of the Energy Star buildings may be more sensitive to the energy policy (i.e. more prone to change) compared to the non-Energy Star buildings. For Chicago, both the Energy Star and non-Energy

Star Class A buildings have a relatively high significant/total ratio (close to and over 0.7 respectively), which means occupancy rates of a large proportion of Class A buildings significantly changed after the policy implementation. For Class B buildings, the ratio of the Energy Star group is very close to that of the Energy Star group in Class A. This implies that for Energy Star buildings, the class level may not affect the sensitivity of their real estate performance to the policy. However, for non-Energy Star buildings, the ratio of Class A buildings and that of Class B buildings are obviously different (0.75 vs. 0.53), which implies that the sensitivity of non-Energy Star buildings' real estate performance to the policy may depend on the building class.

The second ratios (positive and significant / significant) can be used to check which type(s) of buildings are more likely to be positively affected by the energy policy. From Figure 20, in New York City, among the buildings that have statistically significant changes in occupancy rate after the policy, Class A non-Energy Star buildings have a higher ratio showing positive changes (0.64). However, only 39% of Class A Energy Star buildings exhibit an increase in occupancy rate after the policy implementation, which means, after the policy implementation, more Class A Energy Star buildings have a decreasing trend in occupancy rate. For Class B buildings, the occupancy rates of 52% of Energy Star buildings increased after the policy implementation, which is slightly higher than non-Energy Star buildings (49%). In Washington D.C., the 'significant and positive / significant' ratios of both Energy Star and non-Energy Star groups are relatively low, which implies that more buildings experienced declines in occupancy rate after 2008 (the year of the energy policy implementation). This low ratio might have been caused by other confounding factors, such as the financial crisis. However, it is noted that the ratio of the Energy Star group is higher than that of non-Energy Star group for Class A buildings, which implies that Energy Star buildings are more likely to be positively affected by the policy. For Class A buildings in San

Francisco, the ‘significant and positive / significant’ ratio of the Energy Star group is approximately 0.76, while that of the non-Energy Star group is only 0.5. This implies that after the policy implementation, Energy Star buildings tend to have better improvement in real estate performance. In Chicago, the ‘significant and positive / significant’ ratios of both groups for Class A buildings are relatively high, which shows that the policy generally has a positive influence on Class A buildings, with the influence not being substantially different between the Energy Star and non-Energy Star groups. For Class B buildings, 53% of Energy Star buildings exhibit an increase in occupancy rates after the policy implementation, which is lower than the ratio of non-Energy Star buildings (68%).

5.3 Discussion

According to the multiple-group ITSA on the average occupancy rate, the results are mixed with New York City and Washington D.C., showing that the occupancy rate of Class A Energy Star buildings fell immediately after the policy implementation and then recovered with a gradual upward trend. In contrast, the Class A non-Energy Star buildings exhibited a gradually decreasing trend after the policy implementation. According to the ITSA, however, there was no statistical evidence of a continuous occupancy rate trend difference between the two groups after the policy implementation. These effects may have their roots in the financial crisis as the implementation happened in 2008 and 2009 respectively and rents are much higher in these properties. On the other hand, the Class A buildings (both Energy Star and non-Energy Star) in San Francisco and Chicago show an increase of occupancy after the policy implementation. For Class B buildings, the multiple-group ITSA shows that New York City and Washington DC experienced a decreasing trend in occupancy rate after the policy implementation, while San Francisco experienced an increase. There is also no evidence to indicate that occupancy rates performed differently between Energy Star and non-Energy Star groups for the aforementioned cities. Chicago is the only city with statistically significant differences between the two groups (Figure 19(b) and Table 6(b)).

The results from the single-group ITSA complemented the previous analysis. For Class A buildings, the grouping of Washington D.C. with New York City as well as San Francisco with Chicago are maintained with the former showing a slower occupancy increase than the latter. For Class B buildings, in contrast to all other cities, Washington D.C. maintains a smaller ratio of the buildings that have the increasing occupancy. Again, the financial crisis may be a confounding factor for the result.

As a preliminary study, limitations of this study should be acknowledged. Due to the limited data availability, the established model may not fully capture the trend of occupancy rate before the policy implementation and therefore will limit the forecast of the trend after the policy implementation. With more available data points in the future, a more sophisticated ARIMA (autoregressive integrated moving average) model could improve the forecast accuracy. Additionally, an external confounding factor such as the financial crisis may have affected our analysis results significantly.

Chapter 6 Conclusion and Future Research

6.1 Future Research

The current study was limited to assessing the effectiveness of energy policies on the real estate performance of office buildings, but not on the energy consumption performance. This is because the energy consumption data is publicly available only after the policy implementation, and data prior to the policy implementation are not disclosed. As such, ITSA is not applicable. However, we have already done a series of exploratory analyses based on the available energy consumption database. For example, we compared the energy consumption among different sizes of buildings (Figure 21 shows an example of New York City). A full exploratory analysis of the energy consumption database is included in Appendix 4. In the next phase, an analysis of energy consumption data will be included to assess the relationship between the policy and the energy performance.

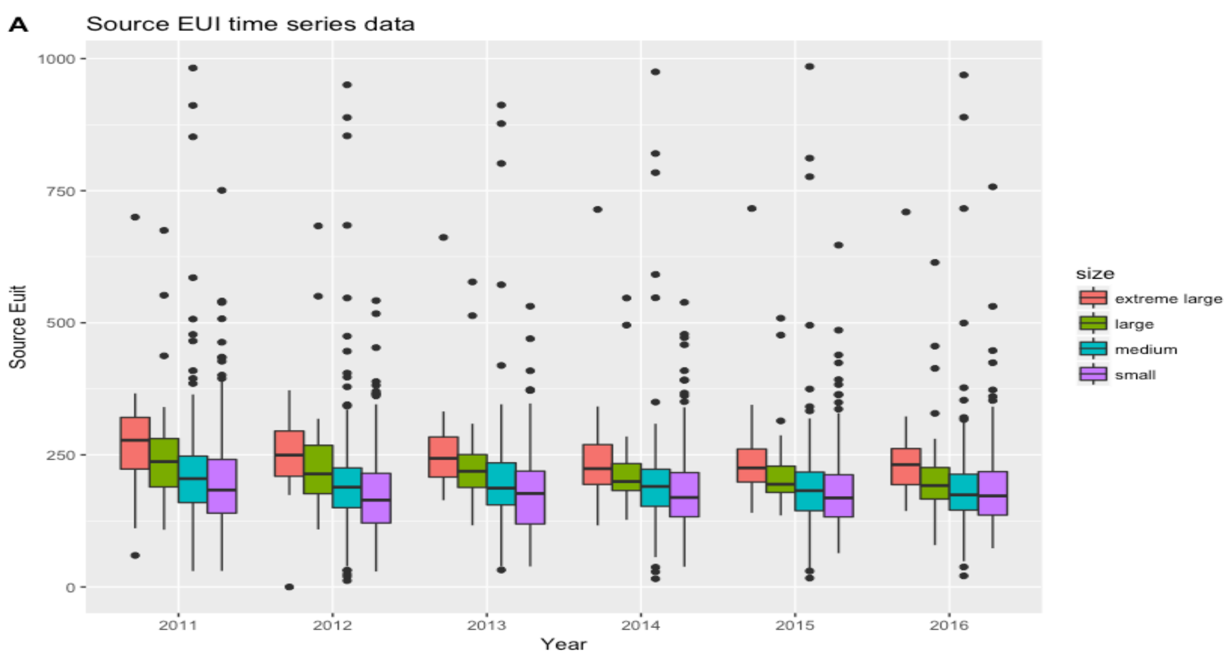


Figure 21. Boxplots of the Source EUI for each year grouped by building area size in NYC

Additionally, more building features, such as rents and/or sale prices, frequency of transactions, and type of owner, can be added to the current regression model to increase the prediction accuracy of the model. Also, in order to deal with the confounding effects, a more sophisticated analysis can be performed by comparing the real estate performance of buildings that do not disclose energy performance with those that do.

6.2 Conclusion

The implementation of energy benchmarking and disclosure policies aim to raise awareness of energy-efficient properties among owners, investors, and tenants. Consequently, they are expected to motivate owners of less energy efficient buildings to invest in energy retrofits to improve the energy and sustainability performance of their buildings. However, there has been no study on assessing the impact of such policies in relation to the real estate performance of office buildings.

To contribute to the body of knowledge in sustainability, public policy, and real estate, this research investigated the impacts of the benchmarking policy on real estate performances by applying two ITSAs to office buildings in four cities across the U.S., namely, New York City, Washington D.C., San Francisco, and Chicago. The first analysis assessed the impact of the policy on real estate performances between energy-efficient and non-energy-efficient buildings based on the aggregated data (i.e. the mean of occupancy rates) by using the multi-group ITSA. To avoid the potential issue of information loss due to the use of aggregated data, the second analysis focused on the impact of the policy on real estate performance of *each* building using the single-group ITSA and counted how many buildings under each group showed statistically significant and positive results.

Generally, the results revealed that for some cities, the Energy Star buildings have better real estate performances for both analyses, but it is hard to conclude that the policy impacts on Energy Star buildings are more positive than non-Energy Star buildings. Specifically, the results obtained from the first analysis revealed that the energy policies might not immediately affect the real estate performance of office buildings. However, after the policy implementation, the real estate performances of energy-efficient buildings exhibit continuously increasing trends, which is evidenced by the ITSA of all the four cities. The results are mixed for New York City, while Washington DC exhibited a decline in the real estate performance after the policy implementation. This effect may also have its roots in the financial crisis as the implementation happened in 2008 and 2009 for the first group of cities with rents being much higher in these properties.

The result from the single-group ITSA is consistent with the result of the first analysis. For the cities of San Francisco and Chicago, the energy-efficient buildings have higher ratios of the 'positive and significant / significant', which implies that the energy-efficient buildings are more likely to be positively affected by the policy. However, such ratios are relatively low for New York and Washington DC, which may be caused by other confounding factors, such as the financial crisis. In the future, more sophisticated analyses are needed to account for the confounding effects, such as including control-group cities without disclosure policies in the analyses.

Chapter 7 Reference

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