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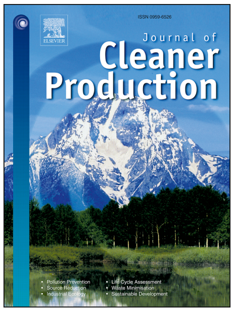

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Impact of Energy Benchmarking and Disclosure Policy on Office Buildings

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Word Count: 6908

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ABSTRACT

Building energy benchmarking policies require owners to publicly disclose their building's energy performance. In the US, the adoption of such policies is contributing to an increased awareness among tenants and buyers and is expected to motivate the owners of less efficient buildings to invest in energy efficiency improvements. However, there is a lack of studies specifically aimed at investigating the impact of such policies on office buildings among major cities through quantitative analyses. In response, this study evaluated the effectiveness of the benchmarking policy on energy efficiency improvements decision-making and on real estate performances, by applying two interrupted time series analyses to office buildings in downtown Chicago. The initial results indicate a lack of statistically strong evidence that the policy affected the annual vacancy trend of the energy efficient buildings (represented by ENERGY STAR labeled buildings). However, the use of interrupted time series in a more in-depth analysis shows that the policy is associated with a 6.7% decrease in vacancy among energy efficient buildings. The study proposed a method to quantitatively evaluate the impact of energy policies on the real estate performance of office buildings, and the result confirms the positive impact of energy-efficient retrofits on the real estate performance. The study findings support the reasoning behind the owners' decision in implementing energy efficiency improvements in their office buildings to remain competitive in the market.

Word Count: 6908

Keywords: Building energy benchmarking and disclosure policies; building energy efficiency; office buildings; time series modeling

1. INTRODUCTION

The Commercial Buildings Energy Consumption Survey (CBECS) highlights that the number of commercial buildings in the U.S. has increased from 3.8 million to 5.6 million between 1979 and 2012 (EIA 2012), with the footprint (square footage; sf) expected to increase to 124 billion square feet by 2050 (U.S. Energy Information Administration 2017). As commercial buildings form the main core of a city, the promotion of energy-efficiency among them significantly contributes to the overall sustainability of cities (Cox et al. 2013), as energy efficient measures are known to reduce the energy consumption of commercial buildings by 20 to 30% (Kneifel 2010). However, studies have shown that energy consumption information asymmetry has been prevalent in commercial buildings, leading to *energy-efficiency gaps* between the availability of cost-effective measures for energy efficiency and the lack of implementation of those measures realized in buildings (Jaffe and Stavins 1994). In recent years, an increasing number of cities and states have attempted to overcome the energy-efficiency gap by mandating energy benchmarking and disclosure policies for commercial buildings, which focuses on the disclosure of energy consumption information to the public. As a result, this benchmarking and disclosure is expected to contribute to an increased awareness and appreciation of energy-efficient properties amongst tenants, owners and investors.

Cross-sectional studies showed that sustainable and energy-efficient buildings (e.g., LEED, ENERGY STAR) commission higher rents and higher sale prices while achieving lower vacancies than comparable non-energy-efficient buildings (Dermisi, 2014, 2013; Eichholtz et al.

2013 and Dermisi and McDonald 2011). Demand for energy-efficient buildings is growing due to an increasing sensitivity among corporate executives towards sustainability and the embracement of such practices by local, state, and federal agencies. Therefore, energy benchmarking and disclosure policies should not only impact leasing and purchasing decisions but they should also motivate owners of less efficient buildings to invest in energy-efficiency improvements to maintain market competitiveness of their properties.

Despite the significance of energy benchmarking and disclosure policies as well as their potential impacts on real estate markets, there is a lack of studies specifically aimed at investigating the impact of policies on office buildings of major cities. In response, this study aims to develop a statistical approach to examine the effectiveness of a benchmarking policy on energy efficiencies and real estate performances of downtown Chicago office buildings by applying interrupted time series analysis. From a theoretical perspective, this study provides quantitative measures to gauge the impact of the energy-related policies on the real estate market. In addition, from a practical point of view, the obtained results could be used as evidence to support decision-makings on energy-efficient improvements.

The remainder of the paper is organized as follows. First, a literature review on relevant energy policies is presented. Second, to help readers have a better understanding of the study context, the benchmarking policy used in Chicago is described. Third, the study data and the quantitative approach used to assess the policy impact are described in detail. Lastly, the study results and conclusions are presented.

2. LITERATURE REVIEW

A. Energy efficient buildings vs. non-energy efficient buildings

Burr et al. (2010) suggest that the U.S. marketplace has been already factoring energy efficiency into its real estate decision-making. For example, Fuerst and McAllister (2009) compared the occupancy rates of "green" (LEED and ENERGY STAR-labeled) versus non-"green" office buildings by using OLS (Ordinary Least Squares) and quantile regression analyses. A significant positive relationship was found between the occupancy rate and the eco-label. 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 within this sector. Specific to the European Union, Bonde and Song (2013) examined the impact of the Energy Performance Certificate (EPC) on office revenues. They found that better EPC ratings have a positive and significant effect on the revenues. However, Zalejska-Jonsson (2013) found that energy and environmental factors have rather a minor impact on the purchasing and renting decision on a property. The author further indicated that when discussing the impact of energy and environmental factors on 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 aspect 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 comparing to the non-LEED buildings.

B. Building energy efficiency policies

The recent studies demonstrate that the rapid development of energy conservation projects and strategies provides a positive control in carbon emissions (Ma et al. 2019; Liang, Cai, and Ma 2019). Kontokosata (2011) explored the determinants of green-building policy adoption and the spatial and temporal diffusion of such policies. The study suggested that economic, political, and climate factors are significant predictors of green-building policy adoption. 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. Furthermore, Kontokosata's (2012) model to predict energy savings by using energy benchmarking data suggests that the disclosure of energy consumption positively impacts on energy savings while examining the energy performance across a range of building characteristics, such as structural, mechanical, locational, and occupancy levels..

Specific to energy benchmarking and disclosure, Cluett and Amann (2013) summarized the current use of energy consumption disclosures in the U.S. and highlighted core considerations in implementing such policies. Dunsky and Hill (2013) discussed legal implications of such policies and provided recommendations for successful implementation of the policies.

C. *Impact of building energy efficiency policies on the real estate performance*

The U.S. Department of Energy (2017) suggests that measuring and revealing building energy use can drive owners to make improvements for lowering energy costs for both owners and 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 policy impacts, including their effectiveness in reducing energy use.

In terms of the real estate market, the impacts of building energy efficiency polices were also investigated by various researchers. Laposa and Villupuram (2010) examined the possible correlations between the Global Reporting Initiative (GRI)'s corporate sustainability reporting standards and corporate real estate disclosures. They 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) also examined quantitatively the effect of municipal policies on commercial green office building designations. The findings revealed that municipal regulatory policies are effective in promoting green office building designations, whereas incentive-based policies are not effective in general. Cox et al. (2013) indicated 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. They found that early engagement of people committed to energy efficiency is conducive to the adoption of such requirements in an economically driven environment.

D. *Summary*

In terms of buildings themselves, studies have demonstrated that buildings' energy efficiency level is a significant factor that positively influences the real estate performance. In other words, energy efficient buildings usually achieve better performance in real estate (e.g., higher occupancy and higher price) than less energy efficient buildings. However, previous studies also stated that the energy efficiency label has limited impact on the purchasing and renting decisions on a property. Such decisions largely rely on the availability (or disclosure) of energy consumption information, which implies the importance of energy disclosure policies.

Previous studies have also indicated positive impacts of energy policy implementations, such as lowering energy consumptions and costs, increasing the purchase of energy-efficient equipment, and so forth. Further, a number of recommendations regarding the implementation of such energy policies have also been proposed by previous studies. The literature review indicated that there is little to no study specifically aimed at investigating the impact of energy policies on the real estate market, and hence this study is expected to be 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. In particular, this interdisciplinary research is at the interface of building energy efficiency, policy planning, and real estate economics, making contributions in each field. The study findings will provide empirical measures to gauge the impact of a benchmarking policy on the real estate market.

3. BENCHMARKING AND DISCLOSURE POLICY IN CHICAGO

While Europe has mandated benchmarking and disclosure policies for many years, such policies are relatively new to the U.S. Specifically, the City of Chicago introduced the building energy benchmarking ordinance in 2013 with the objective of raising awareness of energy performance through transparent information sharing. This ordinance requires existing commercial, institutional, and residential buildings larger than 50,000 square feet to track whole-building energy use, report the data to the City annually, and verify the data accuracy every three years.

According to the Chicago Energy Benchmarking Report (City of Chicago 2016), nearly 2,700 properties tracked and reported their energy uses during 2013-2016. The report shows that the benchmarking and disclosure policy had a significant impact on supporting the City's sustainability efforts. For example, the buildings with three consecutive years of reporting since 2013 showed a reduction of 4% in energy cost, leading to an estimated savings of $11.6 million per year. These buildings also showed an improvement of 6.6% in their ENERGY STAR scores. The buildings with two consecutive years of reporting showed a reduction of 1.9% in energy cost, which equals to an estimated savings of $6.2 million per year, and with an improvement of 7.8% in their ENERGY STAR scores (City of Chicago 2016).

4. METHODOLOGY

This study applies interrupted time series (ITS) analysis to the time series data of real estate performance of office buildings, considering their energy efficiency as well as policy intervention. The objective is to investigate empirical relationships between energy, real estate, and the benchmarking and disclosure policy for office buildings in downtown Chicago.

A. Interrupted Time Series Analysis

ITS analysis is a quasi-experimental method that is widely used to assess if a time series of a specified outcome 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). This method is increasingly used in political science, which aims to assess 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). ITS analysis is based on a 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. While some methods such as regression discontinuity design (or segmented regression) share similar modeling assumptions, ITS was specifically selected in the present study because it has proven effective in dealing with longitudinal data.

The number of time series data points and the number of observations constituting each data point (e.g., mean of the observations) are particularly important in ITS analysis (Jandoc 2015). A larger number of data points and observations provide more stable estimates of trends and thus ensure a more reliable analysis. A minimum of 9 data points pre-intervention and post-intervention and at least 100 observations within each data point are recommended (Briescaher et al. 2013; Wagner et al 2002; and Zhang et al 2011). The data should be collected over equally spaced time intervals before and after an intervention.

B. Data Collection

The study involved aggregating building and performance data from downtown Chicago. In accordance with the research objective, data collection consisted of two parts. First, the real estate information (i.e., building features, vacancy, rent, and sale prices) was collected from a real estate database (CoStar). The only criterion used for building selection was the building size. All buildings larger than 100,000 sf were included in this research. In parallel, the building-level energy performance information was collected from the U.S. Green Building Council (USGBC), ENERGY STAR from EPA, and the City of Chicago Benchmarking reports. These datasets were aggregated and merged into a single database based on office building addresses to contrast meaningful patterns in energy efficiency improvements and real estate performance before-and-after the implementation of the benchmarking and disclosure policy by using ITS analyses.

C. **Data Description**

The present study is based on the premise that energy efficiency improvements are evident from the increasing number of energy-efficient (ENERGY STAR-labeled) buildings. The database contained a total of 292 office buildings in downtown Chicago, out of which 145 have or had the ENERGY STAR label and 147 buildings have never had the label. Figure 1 shows the increasing number of ENERGY STAR-labeled buildings for each year from 1999 to 2016. It shows a growing trend, with a significant upward trend commencing in 2007.

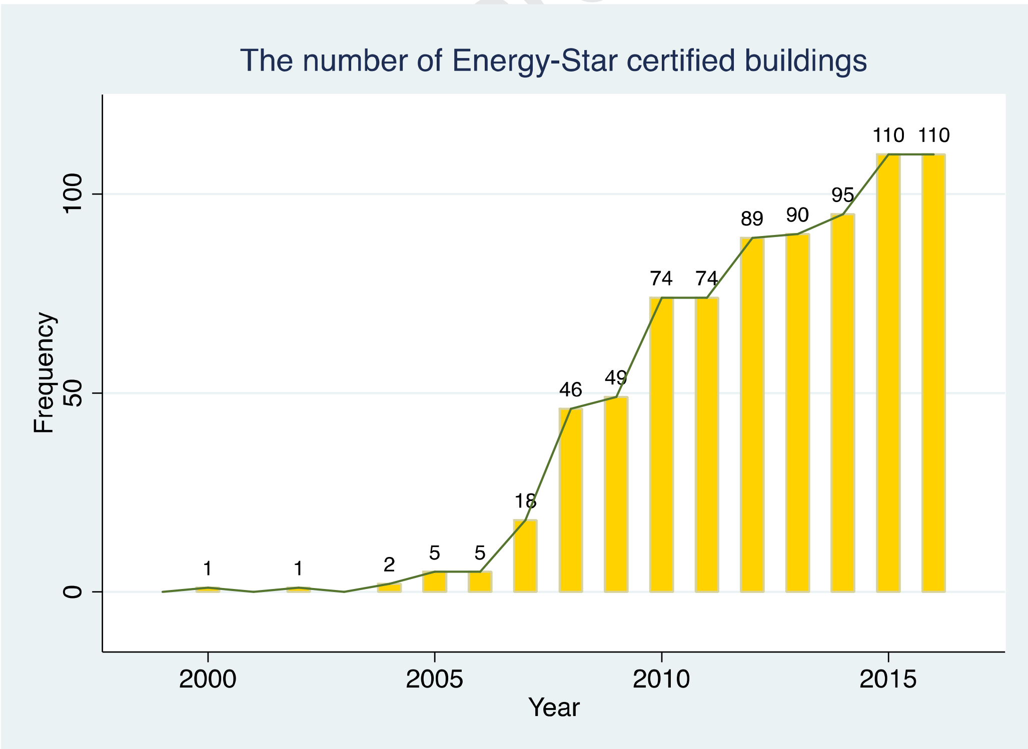

Figure 1. Annual trend of ENERGY STAR-labeled buildings in the database for downtown Chicago

A variety of variables can be used to assess the real estate performance of office buildings. The vacancy rate was chosen because it is more reliable than other variables in the database and it reflects tenant demand for properties that have or have not embraced sustainability. Figure 2 shows annual vacancy rates for ENERGY STAR certified buildings (a) and for non-ENERGY STAR certified buildings (b), respectively.

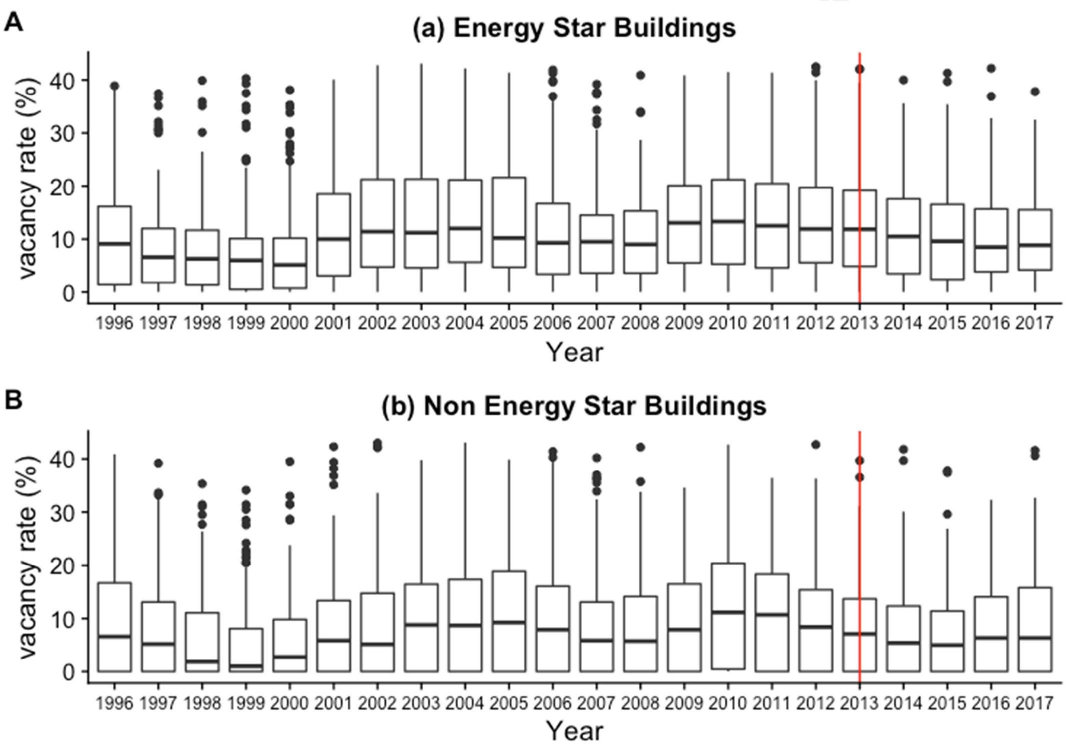

Figure 2. Boxplot of the vacancy rate for each year from 1996 to 2017 with the policy implemented in 2013

Once the outcome variable such as the vacancy rate was selected, the next step was to set up the hypotheses about how the policy would impact the variable, including if the impact was significant and if it had an immediate change in the level, a change in the gradient of the trend, or both. Based on the assumption of ITS mentioned previously, this study made the general hypothesis that the implementation of the policy would have no impact on office buildings from the real estate perspective.

When studying the impact of a large-scale intervention (e.g., a policy affecting all buildings in a city, as in this study), researchers often have an effective sample size of N = 1 (with no control group) or N = 2 (with one control group) (Linden 2015). In the present study, the sample (as the treatment group) consists of all of ENERGY STAR-label buildings. It is common to use an aggregated value (e.g., median, mean) to represent a sample in an ITS analysis. However, the distribution of vacancy rates for each group in each year is right skewed as most buildings have a vacancy rate close to zero. As a result, log transformation is used to reduce the skewness. For example, Figure 3 shows the distribution of log-transformed vacancy rates in 2015, which is nearly normal-distributed. Thus, the mean of log-transformed vacancy rates is used as the aggregated outcome variable for the ITS analysis.

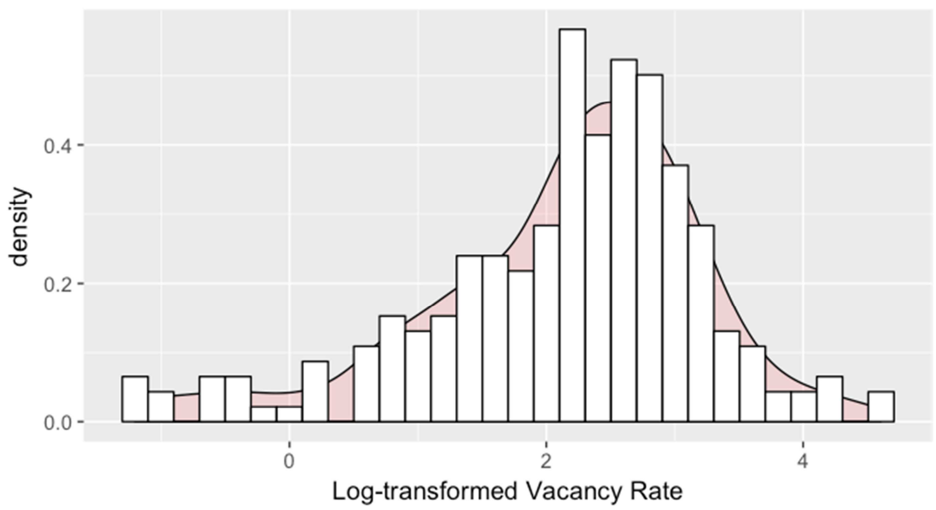

Figure 3. Distribution of the log-transformed vacancy rates in 2015

D. Regression Analysis

A key assumption of standard regression models is that observations are independent, but it is commonly violated in time series data due to the autocorrelation. Thus, the autocorrelation must be considered in an ITS analysis. There are commonly two methods used to correct for autocorrelations, including autoregressive integrated moving-average (ARIMA) and ordinary least-squares (OLS) regression-based model. Some shortcomings of our dataset prevented us from using the ARIMA-based model (such as that it generally requires at least 50 data points, and it is limited to a single series). Instead, we used the OLS regression-based model as it is appropriate for our dataset and requires a smaller number of data points (6 or more) (Ramsay et al. 2003).

To achieve the research objective, two ITS analyses were conducted based on two outcome variables, respectively: (1) the number of ENERGY STAR-label buildings for each year and (2) the mean of log-transformed vacancy rates for each year. The first analysis used a single-group ITS analysis to assess the impact of the benchmarking policy on energy-efficiency improvements, while the second analysis used a multiple-group ITS to examine if the policy led to any changes in the real estate performance represented by vacancy rates.

(1) Single-Group Analysis

The first analysis aims to examine if the number of ENERGY STAR-label buildings (a single group) changes significantly after the introduction of the policy in 2013. This single-group ITS analysis is based on the following model (Huitema and Mckean 2000a; Linden and Adams 2011):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 T_t X_t + \varepsilon_t, \qquad (1)$$

where Y_t = the number of ENERGY STAR-label buildings at year t; T_t = the time since the starting year of the data, 1999; X_t = the dummy variable to indicate the pre- or post-intervention period (0 = pre-intervention period and 1 = post-intervention period); 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 ε_t = the random error term.

At the time of the study, the data for 2017 was incomplete and thus excluded from this analysis. There were 15 pre-intervention data points (from 1999 to 2013) and 3 post-intervention data points (2014 to 2016). The p-value for β_2 is used to determine if an immediate level change occurs after the intervention, and the p-value for β_3 can show if a continuous change of the trend occurs after the intervention (Linden and Adams 2011).

(2) Multiple-Group Analysis

The second analysis aims to investigate the impact of the benchmarking policy on the real estate performance represented by vacancy rates. However, many unobserved factors could potentially affect vacancy rates. Therefore, by adding a control group, a multiple-group ITS analysis can help account for the other confounding factors (e.g., time-varying confounders) when an exogenous intervention affects all the groups (Linden 2015). The multiple-group ITS analysis hypothesizes that the level or trend of the outcome variable remains unchanged for all groups if no intervention occurs. In other words, it assumes that the unobserved factors affect the groups to the same extent. This study conducted a multiple-group ITS analysis on two comparable groups, including one control group consisting of the 147 buildings that have never had ENERGY STAR labels (i.e., 147 observations within each data point) and one treatment group consisting of the 145 buildings that have or had ENERGY STAR labels (i.e., 145 observations within each data point). By accounting for confounding factors, this grouping enables us to focus on investigating how the benchmarking policy affected vacancy rates differently between the energy-efficient buildings and their non-energy-efficient counterparts. The multiple-group ITS analysis with two groups is based on the following regression model that is expanded from Eq. 1 (Linden and Adams 2011; Simonton 1977):

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 T_t X_t + \beta_4 Z + \beta_5 Z T_t + \beta_6 Z X_t + \beta_7 Z T_t X_t + \varepsilon_t, \quad (2)$$

where Y_t = the aggregated outcome variable (mean of log-transformed vacancy rates) at each equally spaced (annual) time point *t*, and *Z* = the dummy variable to indicate the group (control or treatment). In Eq. 2, 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. In particular, 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.

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 for β_6 and β_7 then provide statistical evidence on whether the policy affects the treatment group differently from the control group.

(3) Autocorrelation Correction

When analyzing the two ITS models, we estimated the Newey-West standard errors to correct for autocorrelation. When selecting an ITS model, it is important to consider the number of lags in the time series data for which autocorrelation exists. This study started with fitting two initial OLS models (single-group and multiple-group) with no lags specified and then tested for autocorrelation in the error distributions. Table 1 and 2 present the results of Cumby-Huizinga test for autocorrelation (Cumby and Huizinga 1992) for the initial single-group ITS model and the initial multiple-group ITS model, respectively.

For the single-group analysis, as shown in Table 1, the autocorrelation for lags 1 and 2 exceed the significance bounds (p-value < 0.05) but not for any higher lag orders (up to the eight lags tested). Thus, a model specifying two lags should appropriately account for the autocorrelation. For the multiple-group analysis, the autocorrelation is present at lag 1, but not at any higher lag orders, as seen in Table 2, suggesting that a model with one lag can account for the autocorrelation structure. After correcting for autocorrelation, the OLS models are estimated for the two ITS analyses. The results are presented in Tables 3 and 4.

Table 1. Autocorrelation Test for the Initial Single-Group ITS Model with no lags

Cumby – Huizinga test for autocorrelation (Breusch-Godfrey)
H_0: variable is MA process up to order q (q = specified lag-1)
H_A: serial correlation present at specified lags > q

Lag	Chi square	Degree of freedom	P value
1	8.052	1	0.0045
2	4.558	1	0.0328
3	0.000	1	0.9832
4	2.055	1	0.1518
5	0.020	1	0.8877
6	0.861	1	0.3536
7	2.863	1	0.0906
8	1.554	1	0.2125

Table 2. Autocorrelation Test for the Initial Multiple-Group ITS Model with no lags

Cumby – Huizinga test for autocorrelation (Breusch-Godfrey)
H_0: variable is MA process up to order q (q = specified lag-1)
H_A: serial correlation present at specified lags > q

Lag	Chi square	Degree of freedom	P value
1	13.608	1	0.0002
2	0.017	1	0.8962
3	0.784	1	0.3761
4	0.079	1	0.7784
5	3.368	1	0.0665
6	0.192	1	0.6614
7	0.497	1	0.4810
8	1.591	1	0.2071

5. RESULTS

A. Impact of Benchmarking Policy on Energy-efficiency Improvements

As mentioned earlier, the single-group analysis tries to determine if the implementation of the policy resulted in a shift in the annual trend of the number of ENERGY STAR-label buildings. The result can be used to infer if the policy has an impact on energy-efficiency improvement decision-making. The office buildings in downtown Chicago were specified as the treatment group and 2013 was the year of the policy intervention. The regression model is estimated and presented in Table 3.

Table 3. Single-Group ITS Regression Model for ENERGY STAR Buildings

Regression with Newey-West standard errors; Maximum lag: 2. Number of obs = 18; F (3, 14) = 85.62; Prob > F = 0.000

Number of buildings	**Coef.**	**Newey-West Std**	**t**	**P > |t|**	**[95% Conf. Interval]**	
β_1: t	7.1209	1.4181	5.02	0.000	4.0793	10.1625
β_2: x2013	10.5934	12.3529	0.86	0.406	-15.9009	37.0877
β_3: x_t2013	-.3791	1.5635	0.24	0.812	-2.9742	3.7325
β_0: cons	-20.285	11.3160	-1.79	0.095	-44.5560	3.9846

The starting level of the number of ENERGY STAR-label buildings (β_0: cons) was -20.285. The negative value is a model artifact due to the linear trend assumption of the OLS model. The number of ENERGY STAR-label buildings appears to increase significantly by seven buildings per year (β_1: t) on average before the intervention (P<0.0001; CI = [4.08, 10.16]). However, the level change immediately after the intervention in 2013 (β_2: x2013; P=0.406) and the continuous trend change (β_3: x_t2013; P=0.812) are not significant. Therefore, based on the single-group ITS model, there is no strong evidence that the benchmarking policy has any impact on the trend of ENERGY STAR-label buildings. Figure 4(a) presents the visualized result of the regression model.

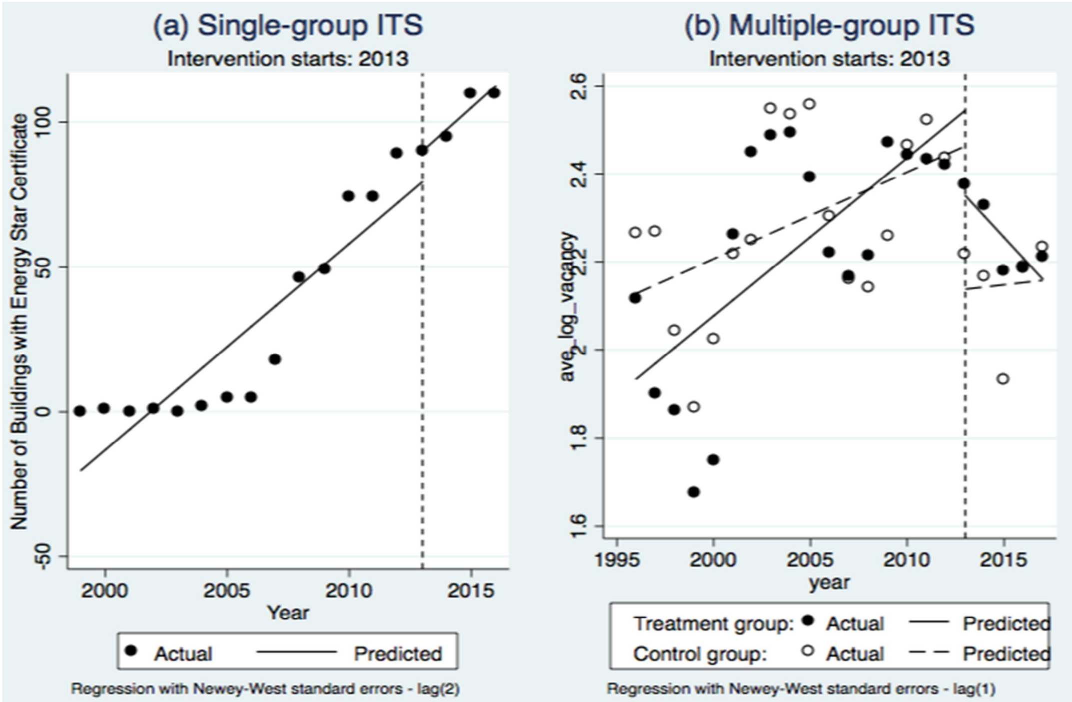

Figure 4. (a) Single-group ITS and (b) Multiple-group ITS

B. Impact of Benchmarking Policy on Real Estate Performance

The multiple-group ITS analysis aims to assess the impact of the benchmarking policy on the annual vacancy rates of the office buildings. The analysis was performed by specifying ENERGY STAR-label buildings as the treatment group and non-Energy Star label buildings as the control group. Table 4 summarizes the analysis result.

Table 4. Multiple-Group ITS Regression Model for Vacancy Rate

Regression with Newey-West standard errors Maximum lag: 1				Number of obs = 44 F (3, 14) = 6.27 Prob > F = 0.001		
Mean vacancy (log transformed)	**Coef.**	**Newey-West Std**	**t**	**P > |t|**	**[95% Conf.**	**Interval]**
β_1: t	0.031	0.009	2.14	0.039	0.001	0.038
β_2: x2013	-.311	0.116	-2.80	0.008	-.561	-.090
β_3: x_t2013	-.023	0.028	-0.52	0.609	-.072	0.043
β_4: z	-.205	0.170	-1.15	0.260	-.538	0.159
β_5: z_t	0.011	0.014	1.18	0.245	-.012	0.044
β_6: z_x2013	0.135	0.141	0.93	0.357	-.154	0.418
β_7: z_x_t2013	-.058	0.032	-2.11	0.042	-.135	-.003
β_0 (cons)	2.111	0.105	20.26	0.000	1.915	2.341

Similar to Table 3, the starting level of difference between the treatment group and the control group (β_4: z) was not significant (P=0.260; CI = [-0.538, 0.159]), and the initial trend difference (β_5: z_t) was not significant either (P=0.245; CI = [-0.012, 0.044]). As mentioned earlier, in an ideal situation, the groups with *p*-values greater than a specified threshold (i.e., 0.05) for both β_4 and β_5 in Eq. 2 are preferred to ensure the comparability. Thus, the treatment and control groups in this study behave similarly before the intervention. After the intervention, while there is no statistically significant intervention effect on the treatment group during the first year of the policy introduction (β_6: z_x2013; P=0.357; CI=[-0.154, 0.418]), there is a statistically significant downward change in the trend compared with that of the control group (β_7: z_x_t2013; P<0.05; CI=[-0.135, -0.003]). This indicates that after the policy intervention, the mean of log-transformed vacancy rates of the ENERGY STAR-label buildings dropped significantly faster than that of non-Energy Star buildings (coefficient β_3 is larger and not significant). The results were verified upon the visual display of Figure 4(b).

Provided that when the outcome variable is log-transformed, the regression coefficient β_7 should be interpreted as the expected annual change in the log of the geometric mean of the original outcome variables (i.e., vacancy rates) for the treatment group compared to the control group. Thus, it is expected to see a 6.7% annual decrease in the geometric mean of vacancy rates for the treatment group (ENERGY STAR-label buildings) compared to the control group after the intervention in 2013, since exp(-.069) -1 = -0.06667.

6. DISCUSSION

As shown in Figure 1, the number of ENERGY STAR-label buildings has increased from 90 to 110 during 2013-2016. However, the single-group ITS analysis provides no statistical evidence that any level change or trend change has occurred after 2013. Thus, there is no strong evidence that the benchmarking policy implemented in 2013 led to an increase in the number of energy-efficient buildings. This result can be attributed to the already relatively high ratio of ENERGY STAR-label versus non- ENERGY STAR-label buildings in Chicago. Among the 292 studied buildings, 145 buildings (49.7%) have or have had an ENERGY STAR label. Although it has not yet reached the point of saturation, the building rating site (BuildingRating 2018), which tracks benchmarking adoption among U.S. cities, highlights that 85% of the overall Chicago building stock has embraced energy benchmarking. Therefore, a conjecture can be cautiously made that the impact of a benchmarking policy on the number of energy-efficient buildings can be limited for a city with a relatively high ratio of existing energy-efficient buildings.

From the result of the multiple-group ITS analysis, there is no statistical evidence for level changes in vacancy rates for either the ENERGY STAR group or non-ENERGY STAR group after the policy intervention in 2013. Therefore, it appears that the implementation of benchmarking policy will not have an immediate level change in office buildings' vacancy rates. However, the result of the multiple-group ITS analysis, as seen in Table 4 (the parameters β_2), indicates that after 2013, the vacancy rate started to drop gradually but significantly, which reflects an improvement in real estate performance since the policy implementation. Further, the parameter β_7 in Table 4 also indicates that the trends of annual vacancy rates are different between the two groups. The vacancy rate of the energy-efficient buildings drops faster than the less-energy-efficient buildings, which implies that the benchmarking policy will have more positive impact on energy-efficient buildings.

In addition, a post-intervention trend is further estimated by a post-estimation command "lincom" (the linear combinations of estimators in the ITS model) in STATA, and the result confirms the aforementioned findings. The result, presented in Table 5, reflects the difference in changes between the two groups after the intervention. Although the statistical significance is not within the threshold of 0.05, if the threshold is expanded to 0.10, the policy appears to have different levels of impacts on real estate performance between ENERGY STAR-label buildings and non- ENERGY STAR-label buildings.

The post-intervention decreasing trend in the vacancy rates of ENERGY STAR-label buildings seems to indicate that disclosure of energy efficiency leads more tenants to choose energy-efficient buildings. In turn, this would result in an increase in the vacancy rates of non-energy-efficient buildings when the market capacity is fixed. Based on the findings of this study, a preliminary conclusion can be drawn that the benchmarking policy can improve the real estate performance of energy-efficient buildings.

Table 5. Comparison of Linear Post-Intervention Trends

Treated: $\beta_1 T_t + \beta_3 T_t X_t + \beta_5 Z T_t + \beta_7 Z T_t X_t$
Controls: $\beta_1 T_t + \beta_3 T_t X_t$
Difference: _$\beta_5 Z T_t + \beta_7 Z T_t X_t$

Linear Trend	Coef.	Std. Err.	t	P > |t|	[95% Conf. Interval]	
Treated	-0.0475	0.012	-3.82	0.001	-0.072	-0.022
Controls	0.0050	0.027	0.19	0.854	-0.050	0.060
Difference	-0.0525	0.030	01.77	0.086	-0.112	0.008

As the first study to assess the impact of energy policies on real estate performance, this paper contributes to the existing literature in the following three aspects. Methodologically, this paper proposed a statistical approach to gauge the impact of a policy in the field of energy and real estate. Theoretically, the findings of this paper showed that energy benchmarking policies can positively impact the real estate performance of office buildings, and energy-efficient buildings will benefit more from such policies. Practically, the study results provided evidence to support the decision-making of property owners on building energy efficiency improvements.

7. CONCLUSION AND POLICY IMPLICATIONS

The energy benchmarking and disclosure policies raise awareness of energy-efficient properties among tenants and buyers. To contribute to the body of knowledge in sustainability, public policy, and real estate, this paper investigated the impact of the benchmarking policy on energy efficiency improvements and on real estate performances, by applying two ITS analyses to office buildings in downtown Chicago. The first analysis assessed if the policy affected the annual trend of the number of ENERGY STAR-label buildings, and the result provided no strong statistical evidence to support the hypothesis. The second analysis assessed the impact of the policy on real estate performances represented by vacancy rates. The result showed that

ENERGY STAR-label buildings experienced a decreasing trend of vacancy rates, indicating that the benchmarking policy can have a positive impact on improving the real estate performance of energy-efficient buildings (i.e., a 6.7% annual decrease in the vacancy rate).

This study, being the first of its kind, paves the way for some future research directions. First, more extensive ITS analyses can include other metropolitan areas with benchmarking policies in place. This would improve generalizability of findings. Second, future research can account for seasonality by including cyclic terms in ITS analyses. It should be noted that the authors have started expanding the present study by adding other major cities (such as San Francisco, CA and Washington, DC) and by using Fourier terms (Bhaskaran et al. 2013) to account for seasonality.

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