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Pre-Labeling Market Valuations in the U.S. Green Building Stock and the Causal Effect of Green Labels

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Pre-Labeling Market Valuations in the U.S. Green Building Stock and the Causal Effect of Green Labels*

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Abstract

While green-labeled buildings have been found to sell at a premium compared to nearby controls with similar observable characteristics, the voluntary nature of the labeling decision implies green-labeled buildings may have different unmeasured characteristics that may account for at least a portion of the premium. Therefore, it is unclear whether green-labeled building premiums are a causal effect of the labels. I use data on repeat sales transactions and detailed hedonic characteristics to test whether green-labeled office buildings were selling at a premium before they were labeled, and combine these results with post-labeling price premium estimates to identify realized cost-benefit ratios for green-labeling policies. The data suggest the causal net benefits of green labels range from \$11.50-\$19.95 per square foot. The estimated net benefits are smaller than previous estimates that have focused solely on the benefits and ignored the potential biases from nonrandom selection.

JEL classification: Q48, D61, R33
Keywords: Green Labels; Nonresidential Real Estate; Cost-Benefit Analysis

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1. Introduction

Environmentally sustainable building practices, as sanctioned by green-labeling programs developed by the Environmental Protection Agency and the United States Green Buildings Council, have been growing at near-exponential levels in recent years (Kok et al. (2011)), yet an unresolved question is whether value premiums accruing to green-labeled buildings are a causal effect of receiving a label. Green-labeled buildings differ significantly from the average office building on the basis of observable characteristics, and since participation in these programs is voluntary, nonrandom selection into the stock of green buildings may result in both observed and unobserved heterogeneity that may account for at least a portion of the premium. For example, buildings whose owners seek to undergo the third-party monitoring and verification required in the labeling process tend to be landmark structures with unique architectural characteristics, which reinforces the likelihood that unobservable characteristics differ among labeled and unlabeled buildings.

The Energy Star and LEED labeling programs have been credited with delivering both significant energy savings and value premiums in green-labeled buildings (Turner and Frankel (2008), EPA (2006)), Eichholtz et al. (2010), Eichholtz et al. (2013)). However, determining to what extent green building premiums arise from selection bias affects the realized net benefits of green labeling policies, and has broader implications for climate policy. Green labels can be an economically efficient response to informational market failures that dampen the returns to energy conservation investments (Jaffe and Stavins (1994)). They may improve market outcomes in cases when adverse selection makes property managers unable to persuasively communicate building characteristics to potential buyers and tenants (Milgrom (2008)). If green labels cause energy efficient buildings to obtain market premiums that they otherwise would not have received due to adverse selection, they can play a part in the optimal mix of policy responses to the climate change externality, to the extent that the benefits of green labels outweigh their costs. However, this latter point remains open to question (Fuerst and McAllister (2011a), Newsham et al. (2009), Navarro (2009)).

In this paper, I use repeat sales observations and detailed building hedonic characteristics

to estimate pre-labeling price premiums in buildings that subsequently received a green label, compared to similar buildings that never received a label. Since the green building sample is restricted to 206 buildings with data on sales transactions both before and after they received a label, I proceed to estimate post-labeling value premiums in green buildings and take the difference in the pre- and post-labeling price premiums, to obtain an estimate of the gain to labeling. Finally, I combine the gain to labeling estimate with data on the costs of obtaining a label, and calculate realized cost-benefit ratios for green labels.

The identification strategy uses the repeat sales data to difference out the effect of unobserved characteristics on building value. By differencing out potential sources of bias that remain constant before and after a building obtained a label, and incorporating the costs of green labels to obtain an estimate of the net benefits of a label, the approach improves upon previous work that has found large positive value premiums from green labels, such as Eichholtz et al. (2010).

The results indicate that the stock of green-labeled buildings that sold before they received a label did not sell at a premium compared to observationally similar control buildings. The estimated post-labeling premium is approximately 12%, which corresponds to a premium of $20 per square foot. Combining these results with cost estimates of obtaining a green label, which range from $0.05-$8.50 per square foot, suggests the net benefits of green labels vary from $11.50-$19.95 per square foot. The estimated net benefits suggest building owners obtain sizable returns from green labels, but they are smaller than previous estimates that have ignored the costs of green labeling strategies, which have found premiums of 13%-20%, corresponding to benefits in the range of $22-$42 per square foot (Eichholtz et al. (2010), Fuerst and McAllister (2011b), Eichholtz et al. (2013)). The statistically insignificant pre-labeling premiums suggest nonrandom selection is not a source of bias affecting the estimated benefits of labels.

The paper is organized as follows. Section 2 presents background information on green labels and reviews the existing evidence on their effectiveness. Section 3 describes the data set creation, Section 4 presents the empirical strategy, and Section 5 discusses the results. Section 6 briefly concludes.

2. Background

Green labels are awarded to buildings that demonstrate superior energy and environmental performance. In the U.S. buildings sector, two organizations are responsible for assigning the lion's share of these labels, the U.S. Green Buildings Council (USGBC) and the Environmental Protection Agency (EPA). The USGBC's Leadership in Energy and Environmental and Design (LEED) designation was introduced in 1993 to aid stakeholders involved in the building construction and operation trades to improve the environmental sustainability of the building stock (USGBC (2009a)). The EPA's Energy Star label was established in 1992 as a voluntary labeling program to promote energy efficient products. The Energy Star program was expanded to office buildings starting in 1999, and is awarded to buildings in the top quartile of energy performance (EPA (2012), EPA (2013)).

While the growth of certified commercial building space was slow to take off in the early years of these programs, the past five years have seen close to exponential growth in the fraction of certified space, with close to 20,000 certified commercial buildings in the U.S. as of the end of 2010 (Kok et al. (2011)). Several studies have been conducted on the market premiums resulting from green-labeled buildings, which have found benefits in the range of \$22-\$42 per square foot (Eichholtz et al. (2010), Fuerst and McAllister (2011b), Eichholtz et al. (2013)).

The Energy Star and LEED labels are widely touted by policymakers as bringing about improvements in the energy conservation characteristics of the building stock and increasing building values (EPA (2011), USGBC (2013), McGraw Hill Construction (2010)). However, though some studies have found that green-labeled buildings are associated with lower levels of energy use compared to an average building (Turner and Frankel (2008), EPA (2006)), others have found that ex-post evaluations of the energy performance of many labeled buildings is poorer than expected (ACEEE (2008), Newsham et al. (2009)).

Another consideration in the evaluation of green-labeled building performance is that participation in labeling programs is voluntary. The labeling procedure begins when a building owner or operator registers with either LEED or Energy Star for the purpose of obtaining

a label. This is followed by third-party building energy performance monitoring, typically for an 8-12 month period (USGBC (2009b)), and a building is certified as 'green' only after adequately demonstrating criteria for energy and environmental performance above a predetermined threshold. It is the voluntary participation decision at the outset of the process that creates a potential for selection bias in the estimation of the benefits of a label. Nonrandom selection into the pool of certified buildings is evidenced by the observable characteristics of green buildings in comparison to the average office building: the typical green building is 15 stories high and measures over 300,000 square feet, in contrast with the average office building, which is about two stories high and measures about 20,000 square feet (EIA (2003a)).

3. Data

Both of the major green labeling programs for the building sector, Energy Star and LEED, publish the addresses of labeled buildings on their website. I matched the addresses of labeled buildings to the CoStar Group's repeat sales database, a building-level archive of commercial building sales transactions with detailed hedonic characteristics on 2.4 million commercial properties. Each building-level observation is geocoded with a precise latitude and longitude coordinate. CoStar's transaction notes were used to discard sales observations that were made either under "distressed" conditions, deferred tax transactions (or 1031 exchanges), bulk or portfolio transactions (which results in a sale price per square foot representing an average over several disparate properties), or that were not arm's-length transactions. I also discarded building observations that underwent a renovation between the pre- and post-labeling sale transactions, in order to rule out price effects that arise from a change in building features that are not controlled for in both the pre- and post-labeling transactions.[1] This matching process culminated in 206 labeled buildings with recorded sale transactions both before and after a building was labeled.

The hedonic building characteristics included in the analysis are building size, number

[1]Therefore, the labeled sample includes office buildings with pre- and post-labeling sale prices that were either renovated before both transactions occurred or with no recorded renovations.

of stories, building age, year of sale, latitude, longitude, an indicator for high quality class A buildings and an indicator for building-level amenities.[2]

Figure 1 presents a map of the labeled building geographic distribution. The sample of green buildings spans eighteen states. At the state-level, California, Texas, Florida and Colorado have the largest concentration of green buildings in the sample, a pattern consistent with the population of green buildings in the U.S. (EPA (2011)).

A comparison group for the green buildings was created by matching each labeled building with two unlabeled buildings located in the same "market" as defined by CoStar, which approximately corresponds to the U.S. Census definition of a metropolitan statistical area. The labeled buildings were matched to their comparison buildings using the Mahalanobis metric, which selects matches by finding the smallest covariance-weighted Euclidean distance between the vectors of hedonic characteristics for a given labeled building and the unlabeled buildings in the same market. Since year of sale is one of the variables in the vector of hedonic characteristics, the matching process resulted in two separate comparison samples, one for the pre-labeling sales transactions and one for the post-labeling transactions. Figure 2 illustrates sets of pre- and post- labeling matches for green buildings in Boston, Massachussetts and Denver, Colorado.

Table 1 presents summary statistics for the pre-labeling sample, and Table 2 presents summary statistics for the post-labeling sample. The normalized difference for each covariate presented in the last column of each Table is a measure of overlap among the covariates in the green buildings and their control samples. A normalized difference less than 0.3 or so is typically considered good overlap (Imbens and Wooldridge (2009)).[3] Though the green buildings are slightly larger and taller than their controls on average, there is sufficient variability in these characteristics to maintain good overlap for all of the observable covariates.

[2]Amenities include: property manager on site, concierge, corner lot, courtyard or atrium, waterfront location, or the availability of nearby public transit, restaurants, day care, retail shops, or a fitness center.

[3]The normalized difference reports the difference in average covariate values by treatment status, scaled by the square root of the sum of a given covariate's variance.

4. Empirical Strategy

The outcome of interest is the sample average treatment effect on the treated (SATT), the average impact of green labels on selling values in labeled buildings. In contrast to previous work that has focused on estimating the SATT on building values exclusively in buildings that have already received a label, I estimate the SATT in two samples: selling prices in buildings that have received a green label and selling prices in the same set of buildings *before* they received a label.

Buildings are assigned to one of two states: labeled and unlabeled buildings. Using the potential outcomes framework, let D_i=1 if building i is green-labeled, and D_i=0 if building i has never received a label. Potential outcome $Y_i(1)$ denotes building values in building i contingent on having received a label (at the time of data collection), and potential outcome $Y_i(0)$ denotes building values in building i, contingent on never having received a label. The SATT can be expressed as

$$\alpha_{TT} = E\left[Y_i(1)|D_i = 1\right] - E\left[Y_i(0)|D_i = 1\right] = E\left[Y_i(1) - Y_i(0)|D_i = 1\right]. \tag{1}$$

Observed prices in green-labeled buildings can be used to identify $E\left[Y_i(1)|D_i = 1\right]$, average building values in labeled buildings. However, the counterfactual $E\left[Y_i(0)|D_i = 1\right]$, average building values in labeled buildings *had they never received a label*, is unobserved. If the set of green-labeled buildings had been randomly selected to receive a label, it would be the case that, on average, values in labeled buildings had they not received a label would be the same as values in buildings that never obtained a label:

$$E\left[Y_i(0)|D_i = 1\right] = E\left[Y_i(0)|D_i = 0\right], \tag{2}$$

and the set of buildings that have never received a label could be used as a control group to estimate the unobserved counterfactual. However, the voluntary nature of the green-labeling decision creates nonrandom selection into treatment, such that

$$E\left[Y_i(0)|D_i=1\right]=E\left[Y_i(0)|D_i=0\right]+\eta, \tag{3}$$

where η represents a systematic variation in the value of the set labeled of buildings, before they receive a label, from the set of buildings that have never been labeled, which may result from nonrandom selection. My identification strategy generates a credible estimand of the causal effect of the label (denoted α^*_{TT}) by pointing out that if the unobservable characteristics in green buildings that generate η remain constant before and after a building receives a label, the following two SATT estimands can be used to identify α^*_{TT}:

$$\alpha_{prl}=E\left[Y_{i,prl}(1)|D_i=1\right]-E\left[Y_{i,prl}(0)|D_i=0\right]+\eta, \tag{4}$$

where α_{prl} measures the average difference in green-labeled buildings and nearby control buildings before they received a label (*prl* refers to this pre-labeled status), and

$$\alpha_{pol}=E\left[Y_{i,pol}(1)|D_i=1\right]-E\left[Y_{i,pol}(0)|D_i=0\right]+\eta, \tag{5}$$

where α_{pol} measures the average difference in green-labeled buildings and nearby control buildings after they received a label (*pol* refers to this post-labeled status).

α^*_{TT} is generated by taking the difference between (5) and (4):

$$\begin{aligned}\alpha^*_{TT}&=\alpha_{pol}-\alpha_{prl}\\&=E\left[Y_{i,pol}(1)|D_i=1\right]-E\left[Y_{i,pol}(0)|D_i=0\right]+\eta\\&-E\left[Y_{i,prl}(1)|D_i=1\right]-E\left[Y_{i,prl}(0)|D_i=0\right]+\eta\\&=E\left[Y_{i,pol}(1)|D_i=1\right]-E\left[Y_{i,pol}(0)|D_i=0\right]\\&-E\left[Y_{i,prl}(1)|D_i=1\right]-E\left[Y_{i,prl}(0)|D_i=0\right].\end{aligned} \tag{6}$$

Repeat sales data on pre- and post-labeling green building valuations can be used to difference out the η in the last two lines of equation (6). This generates the causal effect of green labels on values under the assumption that the unobservable characteristics determining selection into treatment remain constant before and after a building receives a label.

4.1 Spatial semi-parametric matching

To estimate α^*_{TT}, defined above, I implement a spatial matching estimator combined with regression-based bias adjustment (Abadie and Imbens (2006) and Abadie and Imbens (2011)). The average treatment effect on the treated in the pre-labeling is estimated by:

$$\tau_{prl} = \frac{1}{N_1} \sum_{j \in I_1} \left[Y_j - \sum_{k \in I_0} \frac{1}{m_{jk}} \left(Y_k + \hat{\mu}_0(\mathbf{X}_j) - \hat{\mu}_0(\mathbf{X}_k) \right) \right], \tag{7}$$

where N_1 is the number of green-labeled buildings (hereafter referred to as green buildings), I_1 is the set of green buildings, I_0 is the set of control buildings, and j and k index green and control buildings, respectively. Y_j and Y_k denote building values (log selling price) in the pre-labeled green buildings and the control buildings; $\mathbf{X}_j$ and $\mathbf{X}_k$ denote covariate vectors for the green and control units. The term $(\hat{\mu}_0(\mathbf{X}_j) - \hat{\mu}_0(\mathbf{X}_k))$ implements a bias adjustment that modifies the control outcome Y_k for the difference in covariate values between the green and control units, $\mathbf{X}_j$ and $\mathbf{X}_k$. Since the outcome of interest is the SATT, the estimate for $\hat{\mu}(\cdot)$ is obtained by regressing the control outcomes on their covariates (see Abadie and Imbens (2011) for further details).

Each green building j is matched with the two 'nearest' control buildings located in the same real estate market, where nearness is defined using the Mahalanobis distance, as described in the previous Section. The control observations are indexed by k, and m_{jk} is the number of matches for observation j. In this case, m_{jk}=2. The Mahalonobis metric used for matching incorporates the following covariates: building size, number of stories, building age, year of sale, latitude, longitude, an indicator for class A buildings and an indicator for building-level amenities.[4] The bias-adjustment covariates included in the regression to obtain $\hat{\mu}$ includes the same covariates. The average distance between the buildings in this approach is about 4 miles. The importance of controlling for locational characteristics at a fine geographic scale is well-established in the real estate literature (Bollinger et al. (1998)), and from an econometric standpoint avoiding 'geographic mismatch' is important in order

[4] Amenities include: property manager on site, concierge, corner lot, courtyard or atrium, waterfront location, or the availability of nearby public transit, restaurants, day care, retail shops, or a fitness center.

to achieve balance among the unobservables in the treated and control samples (Heckman et al. (1997), Duranton and Overman (2005)). However, since green building tend to be 'trophy' or landmark buildings with unique characteristics (for example, they are taller and larger than nearby buildings), few buildings with similar observable characteristics appear in the immediate vicinity of a green building. For this reason, the matching region was set to buildings in the same metropolitan area.

The matching estimator from equation (7) is also implemented to estimate post-labeling valuations:

$$\tau_{pol} = \frac{1}{N_1} \sum_{j \in I_1} \left[Y_j - \sum_{l \in I_0} \frac{1}{m_{jl}} \left(Y_l + \hat{\mu}_0(\mathbf{X}_j) - \hat{\mu}_0(\mathbf{X}_l) \right) \right], \tag{8}$$

where the same set of green buildings Y_j is used, but since the year of sale differs from the pre-labeling sample, the set of control buildings l is also different.[5]

4.2 Realized benefit-cost ratios

Having obtained estimates for both $\hat{\tau}_{prl}$ and $\hat{\tau}_{pol}$, which are both asymptotically normally distributed (Abadie and Imbens (2006)), the following test is applied to assess whether the two estimates are statistically different:

$$\text{DIFF} = \frac{\hat{\tau}_{pol} - \hat{\tau}_{prl}}{\sqrt{se(\hat{\tau}_{pol})^2 + se(\hat{\tau}_{prl})^2}}. \tag{9}$$

If DIFF is greater than the critical value for a two-tailed Z-test at the 5% significance level (1.96), I will take this as evidence that we cannot reject the hypothesis that the pre- and post-labeling premiums differ from each other. Either way, the term $\hat{\alpha}^* = \hat{\tau}_{pol} - \hat{\tau}_{prl}$ is an estimate of the causal effect of a green label, and represents the average benefits a building owner can expect from obtaining a label. It is also measures the market valuation of the expected stream of benefits accruing from a green label.

[5] However, close to 50% of the control buildings appear in both samples.

From a policy evaluation perspective, a more relevant calculation is the benefit cost ratio of a green-labeling policy, which requires considering the present value of the net benefits (i.e. the benefits net of the costs) of a label. To calculate the average net benefit, I will combine $\hat{\alpha}^*$ with information on the costs of obtaining a green label, discussed below in Section 5.2.

5 Results

5.1 Matching

The first row of Table 3 presents the results of estimating equation 7, and the second row presents results for equation 8. For purposes of comparison, columns (1) and (2) show results when only geographic distance is used as a criterion to match green buildings with the two control nearest buildings. Columns (3) and (4) show results from using the Mahalanobis metric and all observable covariates to match green buildings with the nearest two control buildings located in the same real estate market. Columns (1) and (3) present results of applying a simple matching estimator without applying the bias adjustment function $\hat{\mu}_0$. Columns (2) and (4) show the results of implementing the bias-adjustment.

Both the geographic matching and Mahalanobis matching estimates indicate a statistically insignificant pre-labeling premium, as shown in the first row, columns (2) and (4). In contrast, the post-labeling premium is statistically significantly positive using both geographic and Mahalanobis matching, shown in columns (2) and (4) of the second row. The premium is approximately 9% using the bias-adjusted geographic matching estimator, in column (2), and approximately 12% using the bias-adjusted Mahalanobis matching estimator, in column (4). Plugging the bias-adjusted estimates from column (4) into equation 9 results in a test statistic value of 2.45, which provides evidence to reject the null hypothesis that the pre- and post-labeling premiums are equal, at the 1% level.

To address concerns regarding whether premiums in the pool of buildings with sales observations both before and after a building sold may differ from those in which only one post-labeling transaction is observed, the third row of Table 3 presents results of applying equation 8 to estimate post-labeling premiums in the set of buildings that sold after being

labeled. As shown, 206 buildings were observed to be sold both before and after they were labeled, whereas 966 building sale transactions were observed in the full post-labeled sample. The bias-adjusted Mahalanobis matching premium in the full post-labeled sample is approximately 10%, which is not statistically different from the estimate of 12% in the restricted sample. These results suggest that, on the basis of post-labeling premiums in the two samples, there is no evidence of selection into the pool of buildings that sold twice, before and after they were labeled, compared to buildings that are only observed to have sold after they were labeled.

5.2 Net benefits

Given that the pre-labeling premium is statistically zero, the estimated premium for a green building, as discussed in the previous section, is approximately 12%. Since the average building selling price prior to receiving a label is $171 per square foot, the average premium is approximately $20 per square foot. This figure reflects the market's valuation of the net present value of the benefits of owning and operating a green building.

Costs incurred in the green-labeling process include capital costs of building upgrades, process modifications, labeling fees, as well as consulting and contractor fees. The number of studies that have assessed the financial costs of green labels is smaller than the work that focus solely on their benefits by an order of magnitude, and the former tend to be based on small sample sizes. Studies that do assess the financial costs of green buildings suggest the additional outlays, for buildings of approximately the same size and height as those in the sample, range from about $0.35-$8.50 per square foot (Kats (2003a), Kats (2003b) and Yudelson (2007)). The labeling fees alone come to about $0.05-$0.07 per square foot.

These benefit and cost values lead to a range of net benefit estimates. On the high end, a building owner that purchases an unlabeled building that is already energy efficient, without any need for capital upgrades or process changes, and does not pay a premium for the energy efficiency characteristics (a likely outcome based on the pre-labeled building results in Table 3) can expect to pay only about $0.05 per square foot to obtain a label. This reduces the benefit estimate of $20 per square foot by a negligible amount, to $19.95 per square foot. On

the lower end, a building owner who must first invest in building upgrades and all the other associated costs before receiving a label can expect a net benefit between $11.50-$19.50 per square foot.

6. Conclusion

This paper has proposed a simple approach to identify the causal net benefits of green labels. Most of the popular discussion on the benefits of green labels has both ignored the potential bias that may arise from nonrandom selection and neglected to consider the costs incurred in the labeling process. I have implemented a matching estimator that makes use of green building sales transactions before they received a label to identify the causal value premium of a green label, of approximately 12%, or $20 per square foot. This estimate represents the real estate markets's assessment of the net present value of the benefits of owning and operating a green building. Combining these results with estimates of the costs associated with obtaining a green label suggests the causal net benefits of obtaining a green label range from $11.50-$19.95 per square foot.

These estimated net benefits suggest building owners obtain returns from green labels that are smaller than previous estimates that have focused solely on the benefits, which have found premiums of 13%-20%, corresponding to benefits in the range of $22-$42 per square foot (Eichholtz et al. (2010), Fuerst and McAllister (2011b), Eichholtz et al. (2013)). This implies that while the lower bound of previous estimates of the benefits of green labels are quite similar to the estimated premiums in this study, incorporating the costs of green labels can reduce the estimated net benefits by up to 50%.

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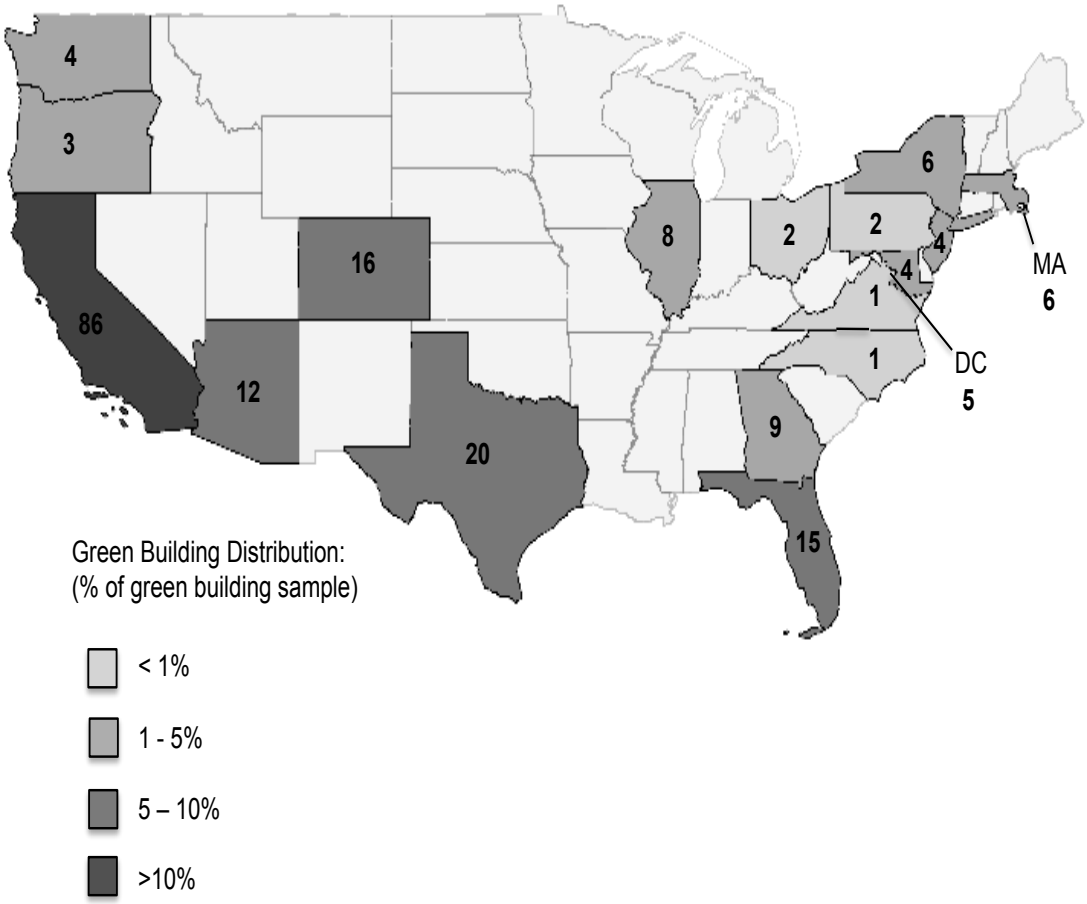
Figure 1: Sample Green Building Distribution



Note: The number of green office building observations in each state is also listed above.

Figure 2: Building Match Examples

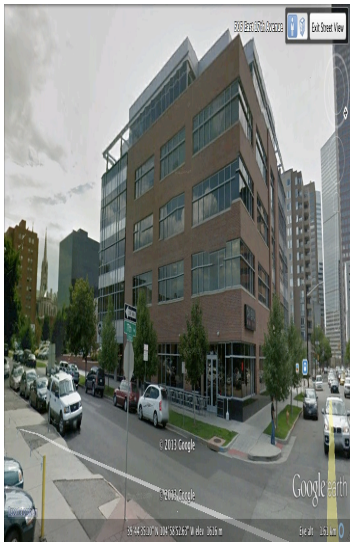
(a) Green building, MA

(b) Control, pre-label, MA

(c) Control, post-label, MA

(d) Green building, CO

(e) Control, pre-label, CO



(f) Control, post-label, CO

Notes: Each row shows a green building and its associated pre- and post-labeling matches. The top row buildings are located in Boston, Massachusetts. The bottom row buildings are located in Denver, Colorado.

Table 1: Summary Statistics, Pre-Label Sample

	GREEN				CONTROL				NORM. DIFF
	MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX	
Stories	14.7	11.5	2	62	11.1	9.4	1	52	0.24
Size (000s)	322.2	270.1	11.4	2,002	226.2	262.3	1.03	2,550	0.25
Year Sold	2001	3.5	1991	2013	2002	4.1	1991	2009	-0.19
Built	1982	16.9	1912	2004	1979	19.6	1900	2006	0.12
Class A (%)	82.0	38.4	0	100	74.0	43.9	0	100	0.14
Amenities (%)	97.1	16.8	0	100	97.3	16.1	0	100	-0.01
Observations:	206				412				

Notes: The table presents summary statistics for the sample of green buildings and nearby controls located within the same real estate market and matched using the Mahalanobis metric. The normalized difference presented in the last column measures the degree of overlap for each covariate across the treated and control samples. It is defined as $(\bar{X}_1 - \bar{X}_0)/(\sqrt{S_1^2 + S_0^2})$, where $\bar{X}_i$ denotes the mean of a given covariate for each treatment status $i = 0, 1$, and S_i^2 denotes the sample variance of X_i. A normalized difference of less than 0.3 is typically considered good overlap.

Table 2: Summary Statistics, Post-Label Sample

	GREEN				CONTROL				NORM. DIFF
	MEAN	SD	MIN	MAX	MEAN	SD	MIN	MAX	
Stories	14.7	11.5	2	62	11.1	9.1	1	49	0.25
Size (000s)	322.2	270.1	11.4	2,002	229.5	241.2	1.0	2,438	0.26
Year Sold	2007	2.2	2000	2013	2006	2.2	1997	2009	0.32
Built	1982	16.9	1912	2004	1980	20.2	1900	2009	0.08
Class A (%)	82.0	38.4	0	100	74.0	43.9	0	100	0.14
Amenities (%)	97.1	16.8	0	100	95.9	19.9	0	100	0.05
Observations:	206				412				

Notes: The table presents summary statistics for the sample of green buildings and nearby controls located within the same real estate market and matched using the Mahalanobis metric. The normalized difference presented in the last column measures the degree of overlap for each covariate across the treated and control samples. It is defined as $(\bar{X}_1 - \bar{X}_0)/(\sqrt{S_1^2 + S_0^2})$, where $\bar{X}_i$ denotes the mean of a given covariate for each treatment status $i = 0, 1$, and S_i^2 denotes the sample variance of X_i. A normalized difference of less than 0.3 is typically considered good overlap.

Table 3: Matching and Bias-Adjusted Matching Results

Nearest two control neighbors located near a green building

	(1)	(2)	(3)	(4)	Treated	Control
Dependent Variable:						
Log(price) pre-label	-0.006	0.040	-0.104**	-0.051	206	412
	(0.040)	(0.040)	(0.047)	(0.047)		
Log(price) post-label	0.507***	0.091**	0.141***	0.119**	206	412
	(0.039)	(0.039)	(0.050)	(0.050)		
Log(price) all sales, post-label			0.120***	0.102**	966	1932
			(0.044)	(0.044)		
Geographic Distance	YES	YES	NO	NO		
Mahalanobis Distance	NO	NO	YES	YES		
Bias-Adjusted	NO	YES	NO	YES		
Mean distance, geo. match:	0.4 mi					
Mean distance, maha. match:	4.2 mi					

Notes: Standard errors are in parentheses. * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level. Clustering is at the market level.