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Eco-Labeling, Rents, Sales Prices and Occupancy Rates: Do LEED and Energy Star Labeled Offices Obtain Multiple Premiums?

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Abstract

Drawing upon an updated and expanded dataset of Energy Star and LEED labeled commercial offices, this paper investigates the effect of eco-labeling on rental rates, sale prices and occupancy rates. Using OLS and robust regression procedures, hedonic modeling is used to test whether the presence of an eco-label has a significant positive effect on rental rates, sale prices and occupancy rates. The study suggests that estimated coefficients can be sensitive to outlier treatment. For sale prices and occupancy rates, there are notable differences between estimated coefficients for OLS and robust regressions. The results suggest that both Energy Star and LEED offices obtain rental premiums of approximately 3%. A 17% sale price premium is estimated for Energy Star labeled offices but no significant sale price premium is estimated for LEED labeled offices. Surprisingly, no significant occupancy premium is estimated for Energy Star labeled offices and a negative occupancy premium is estimated for LEED labeled offices.

Introduction

Over the last decade, the commercial real estate sector has seen the introduction of a wide range of, what can be loosely termed, environmental labels. Environmental labels are one of a number of alternative and complementary policy or market-based instruments that aim to alter patterns of demand for products in order to reduce their environmental impact. Within commercial real estate markets, a blend of compulsory and voluntary environmental labels is still evolving. Indeed, as more and more local regulatory bodies make the attainment of a voluntary environmental label a requirement for regulatory approval, labels such as LEED are becoming quasi-compulsory in some jurisdictions.

Given that they constitute the terms on which products are exchanged, prices are the fundamental instrument of markets. It is well-established that costly information concerning prices and quality can affect allocational efficiency. The central objective of environmental labels is to change supply and demand through the pricing mechanism. For producers (in this context - real estate developers), prices act as an “invisible hand” steering production. When the market price of a product is higher than its cost of production, increasing production is profitable, new producers have incentives to enter the market and resources are allocated to sectors where there is the highest willingness-to-pay.

This paper investigates the extent to which the growth of environmental labelling in US office markets is having expected price effects in occupier and investment markets. Building upon previous studies, this paper draws upon the growing sample of LEED and Energy Star labelled offices. Further, the sharp deterioration in market conditions since 2007, the effects of the market downturn can be evaluated. Further, this study applies robust regression techniques to control for potential problems created by outliers. For sale prices and occupancy rates, there are notable differences between estimated coefficients for OLS and robust regressions. The results suggest that both Energy Star and LEED offices obtain rental premiums of approximately 3%. A 17% sale price premium is estimated for Energy Star labeled offices but no significant sale price premium is estimated for LEED labeled offices. Surprisingly, no significant occupancy premium is estimated for Energy Star labeled offices and a negative occupancy premium is estimated for LEED labeled offices.

Environmental Labelling in Context

The direct aim of environmental labels is to provide information to consumers or users about the environmental performance of a product with the indirect aim of influencing their consumption choices, suppliers' production outputs and, as a result, the level of environmentally harmful emissions. While the presence of an environmental label and superior environmental performance are not necessarily synonymous, environmental labels can be particularly important for credence products, where the costs to the consumer of monitoring (environmental in this instance) performance can be prohibitive both before and after procurement. Due to high monitoring costs, it is common for third parties to emerge in order to provide independent verification. As such, the growth of environmental labels can be interpreted as a method of reducing the negative externality produced by Akerlofian information asymmetry. The adverse selection problem associated with information asymmetry can result in products with desirable credence attributes failing to be priced efficiently and lead to sub-optimal consumption and production. In order to remedy potential market failure, environmental labels must then provide a credible signal of the attribute of superior environmental performance.

As discussed above, the mechanism by which environmental labels can produce a net environmental improvement is by changes to the relative demand and supply of labelled and non-labelled goods. Assuming that environmental performance is a salient attribute for consumers, environmental labelling enables consumers to discriminate between products according to their environmental impact resulting in increased demand for products with reduced environmental impact and in price differentials for labelled products. Price premiums, in turn, provide an economic incentive for producers to innovate and incur any additional production costs associated with obtaining the environmental label.

However, it has been argued that the introduction of environmental labels can, in certain plausible circumstances, produce a net increase in environmental harm. Dosi and Moretto (2001) analyse this point in terms of whether environmentally labelled products act as a substitute or complement to conventional products. Where there is a complementary relationship, the introduction of an environmental label can create image spillovers for all products made by a company increasing the return on capital from all products and producing a net increase in environmentally harmful emissions. In contrast, where the labelled product acts as a substitute for conventional products, the return on conventional products remains stable or falls after the introduction of an environmental label with less investment in conventional products and improved environmental outcomes. Dosi and Moretto (2001) also point to other circumstances in which the introduction of an environmental level can cause an increase in aggregate emissions. This is produced by an increase in aggregate consumption due to changing behaviour as a result of the 'halo' effect of the environmental label. Essentially, although environmentally harmful emissions *per unit* decrease, this may be outweighed by the consumption of more units. For instance, office occupiers may use space less intensively in a LEED labelled building.

The interaction of demand, supply and pricing is central to Mattoo and Singh's (1994) analysis of the effect of the introduction of environmental labels on level of aggregate production. They identify certain conditions in which the introduction of an environmental label can result in an increase in aggregate output compared to the undifferentiated market. They demonstrate that the introduction of the environmental label can, in some circumstances, result in price premiums (relative to undifferentiated price) for labelled *and* non-labelled market segments leading to an increase in overall supply. However, relevant to the real estate context, such an outcome is more likely to occur where environmentally responsible production has a relatively large market share prior to the introduction of environmental labelling.

Environmental Labelling in Commercial Office Markets: Expectations and Evidence

There is a considerable body of commentary suggesting that buildings with superior environmental performance deliver a bundle of benefits to occupiers and investors. A range of benefits has been attributed to buildings with superior environmental performance or associated with features common in buildings with superior environmental performance. Owners, developers and occupiers may benefit from the diverse range of incentives (subsidies, tax reliefs and reduced regulatory barriers) that have emerged in some markets. Widely cited benefits to occupiers include reduced utility costs, improved productivity (lower staff turnover, absenteeism, higher outputs *inter alia*) and reputational benefits. Investors may benefit from higher occupancy rates, lower utility costs (especially in gross leases), decreased rates of depreciation and reduced regulatory obsolescence. As a result of the latter in particular, it is also expected that buildings with superior environmental performance should attract a lower risk premium.

The analysis above suggests that there are a number of channels through which environmental labels may influence the capital values of commercial offices. In real estate pricing models for income generating assets, asset value represents the discounted sum all future net incomes. Assuming constant growth, the value (V) can be expressed as

$$V = \sum_{t=0}^{T} \frac{(R_t - C_t)(1+g)^t}{(1+i)^t} \quad (1)$$

where V is the current capital value, R_t is rental income, C_t is the periodic costs of owning the asset (management, vacancy, refurbishment etc - so that R_t – C_t = Net Operating Income), g is a constant growth rate, i is the target rate of return (composed of the risk-free rate of return plus a risk premium), and t is the life of the asset. Since freehold ownership is unlimited, this can be taken as a perpetuity and approximates to

$$V = \frac{NOI}{i - g} \quad (2)$$

where i – g is a capitalization rate. So

$$V = \frac{NOI}{CAPRATE} \quad (3)$$

As indicated above, the attributes of buildings with superior environmental performance have the potential to affect many of the variables in the pricing model.

R_t Assuming a well-functioning market and that the positive attributes outweigh negative attributes associated with environmental labeled buildings, occupiers should be willing to pay higher rents due to expected lower total occupancy costs and the benefits to occupiers of improved image and business performance.

C_t It is also expected that the increased attractiveness to occupiers should reduce the costs of ownership due to reduced vacancies and potentially reduced capital expenditure.

g Due to changes in relative demand, rental growth rates may be higher for assets with environmental labels. In addition, depreciation rates may be lower where buildings have incorporated latest technologies.

i The risk premium (and, therefore, capitalization rate) may also be lower due to expected reduced volatility in income and decreased risk of obsolescence due to regulatory changes or ‘future proofing’.

This analysis suggests that any sale price premium that investors in offices with buildings with environmental labels may be caused by number of factors; higher rents, higher occupancy rates, lower operational costs and a lower risk premium. Given the centrality of the pricing mechanism to supply shifts, a key research question has been whether these potential benefits actually produce an increased willingness-to-pay from occupiers and investors.

From both academic and corporate/professional bodies, there have been a large number of stated preference studies of occupiers' willingness-to-pay for buildings with superior environmental performance. From the sustainability perspective, the findings have been almost overwhelmingly positive. However, there have been only a small number of studies based on revealed preferences. Due to data availability, a group of studies have drawn upon the CoStar database to estimate the effect of environmental labelling on sale and rental rates. It is notable that all studies focus on the office sector due to the much higher market penetration of environmental labels in this sector relative to retail and industrial properties. Before going on to review these studies, it is important to point out that environmental labeling of offices has been a relatively recent phenomenon. Whilst growth rates have been rapid, they have been from a negligible base. Fuerst (2009) points out that in the first half of the decade the largest producers of environmental labeled buildings were government and corporate organizations. However, in the last few years, commercial developers have accounted for a greater proportion of schemes. Although researchers can only analyze the data that is available to them, existing studies have been based on small samples drawn from a relatively short timeframe.

Whilst econometric procedures are used by all studies to estimate the price effect of LEED and Energy Star labels, all studies vary in terms of their model specification, choice of explanatory variables, sample and, not surprisingly, results. To control for differences between their sample of environmental labeled buildings (927 buildings) and a much larger sample of non-labeled buildings, Miller, Spivey and Florance (2008) included a number of control variables such as size, location and age in their hedonic regression framework. They found that no statistically significant rent premium for Energy Star and LEED labeled offices. Using the same data source, Miller *et al* (2008) reported respective sale price premiums of approximately 6% and 11% for Energy Star and LEED labeled offices.

Wiley, Benefield and Johnson (WBJ) (forthcoming) focused on the effect of LEED and Energy Star labelling on rent, occupancy rate and sale price for Class A buildings in 46 office markets across the USA. Using an hedonic procedure, they estimated asking rental premia ranging from approximately 15-18% for LEED labeled offices and 7-9% for Energy Star labelled buildings. In terms of sales transactions, they estimated premia of $130 per sq ft for LEED labelled buildings and $30 for Energy Star. In addition, they estimated occupancy rate premia of 16-18% for LEED offices and 10-11% for Energy Star offices. However, these findings of large premia need to be treated with some caution. A key issue is in the WBJ paper is the control for location. In essence, they identify rental, sale and occupancy premia for environmental labelled offices relative to non-labeled offices *in the same metropolitan area*. However, if environmental labelled offices tend to be in better quality locations within a metropolitan area, observed premia may include a location as well as a environmental labelling premium. In terms of the sample, WBJ (forthcoming) do not state explicitly the period of the sample nor the numbers of Energy Star and LEED labelled buildings included in the study. From their summary statistics, it is possible to infer that the sample for LEED was extremely small - for LEED and Energy Star we estimate that the respective sample sizes were approximately 30 and 440 (rents) and 12 and 70 (sales).

Fuerst and McAllister (forthcoming) estimated the hedonic rental regression for a sample of 197 LEED and 834 Energy Star as well as over 15,000 benchmark buildings. The results suggested that environmental labeled offices have an average asking rental premium of 4-5% with a LEED labeled offices having a slightly higher premium than Energy Star. Furthermore, based on a sample of sale prices for 559 Energy Star and 127 LEED labeled offices, they found substantial price premia of 26% and 25% respectively with higher ratings e.g. Silver, Gold, Platinum achieving higher premia. The same authors (2009), using OLS and quantile regression analyses, found a significant positive relationship between occupancy rate and the LEED and Energy Star eco-label. Controlling for differences in age, height, building class and quality, their results suggested that occupancy rates are approximately 8% higher in LEED labeled offices and 3% higher in Energy Star labeled offices. However, for Energy Star labeled offices effects were concentrated in certain market segments (see Fuerst and McAllister 2009).

The best-known empirical study of the price effects of environmental labeling is by Eichholtz, Kok and Quigley (EKQ) (forthcoming). They also use an hedonic procedure to investigate the effect of the LEED and Energy Star labels on the current asking rents of 694 and sale prices of 199 environmentally labeled office buildings sold in the period 2004 to 2007. Using GIS techniques, they control for location effects by identifying other office buildings in the CoStar database within a radius of 0.2 miles of each labeled building. The authors identify a statistically significant rent premium on the asking rents per square foot of 3.3% for Energy

Star labeled buildings. Surprisingly, they find no significant rent premium for LEED labeled buildings. They also report similar results for 199 sales that took place between 2004 and 2007. They find a substantial 19% sale price premium for Energy Star labeled buildings but no statistically significant sale price premium for LEED labeled buildings. However, EKQ (forthcoming) provide no breakdown of the numbers of LEED and Energy Star buildings included in their sample. Since previous studies suggest that the LEED labeled buildings are unlikely to account for more than 20% of all environmental labeled buildings, this suggests that the study is based upon approximately 150 LEED offices and 550 Energy Star offices (rents) and 40 LEED offices and 160 Energy Star offices (sales).

Two other papers have focused on different aspects of financial performance. Dermisi's (2009) study also examines the effect of differences within LEED rating on the appraised values of 351 LEED labeled office buildings in the US. More pertinent to this paper, drawing upon the NCREIF database, Pivo and Fisher (2009) include environmental labeled properties in a broader sample of "RPI properties" that use proximity to transit stations (669 properties), Energy Star (209 properties) and/or inclusion in a designated regeneration area as criteria (158 properties). Using hedonic procedures, they estimate a 12.5% premium on appraised capital value and a 3.3% Net Operating Income premium for Energy Star labeled buildings. They also estimated that utility costs were approximately 10% lower for Energy Star buildings. However, although statistically significant, they found a small occupancy rate premium of 1%.

Data

This study is also based upon the LEED and Energy Star environmental labels for commercial buildings in the US. The Energy Star program tends to be more commonly used for existing buildings and is an assessment of buildings' energy performance. Energy Star accreditation reflects relative energy efficiency and environmental performance since only buildings that are in the top quartile are eligible for Energy Star accreditation. LEED accreditation relies upon scores in a number of different categories focused on; location, water efficiency, energy and atmosphere, materials and resources, indoor environmental quality and innovation and design process. The LEED thresholds are primarily absolute. All buildings that reach the required levels can be certified. There are four levels of certification; certified, silver, gold and platinum. LEED certification is comparable to other real estate environmental labelling schemes in the UK, Germany and Australia and is likely to provide the framework for prospective harmonized global standards.

Exhibit 1 Summary Statistics

OVERALL	Age	**Age at sale**	**Rent $ psf**	**Size sq ft**	Stories	**Sale price psf**	**Occupancy rate (%)**
Mean	32	28	19.94	66511	4	181.65	71.35
Median	26	22	18.00	24000	2	150.51	82.64
Maximum	256	253	271.90	3781045	110	1384.19	100.00
Minimum	0	0	1.00	0	0	0.05	0.00
Std. Dev.	28	26	8.90	133681	6	135.14	31.49
Observations	39,391	19,498	40,492	44,489	44,151	14,048	44,484
Energy Star	Age	**Age at sale**	**Rent $ psf**	**Size sq ft**	Stories	**Sale price psf**	**Occupancy rate (%)**
Mean	25	20	26.10	289,989	13	273.53	86.9
Median	23	19	23.93	201,028	9	239.28	90.4
Maximum	135	125	271.90	2,650,000	82	859.78	100.0
Minimum	0	0	5.50	3,255	1	23.04	0.0
Std. Dev.	17	16	11.68	284,715	12	143.00	14.4
Observations	2,375	1,693	2,082	2,379	2,378	939	2,379
LEED	Age	**Age at sale**	**Rent $ psf**	**Size sq ft**	Stories	**Sale price psf**	**Occupancy rate (%)**
Mean	20	22	27.03	259,088	10	271.73	72.82
Median	8	17	24.49	156,040	5	237.21	88.45
Maximum	124	107	94.03	3,448,680	58	859.78	100.00
Minimum	0	0	8.00	1,775	1	32.07	0.00
Std. Dev.	26	25	10.95	345,671	12	157.68	33.60
Observations	387	209	317	397	397	147	397

The study draws on CoStar's comprehensive national commercial real estate database which includes approximately 43 billion square feet of commercial space in two million properties making it the largest available real estate database in the United States. In the first step, we drew details of approximately 2776 environmentally labeled offices of which 397 were LEED labeled and 2,379 were Energy Star. Of the LEED buildings, In the second step, buildings were selected in the same metropolitan areas and submarket as the labeled sample. Sample selection was based on the criteria a) same submarket or market as labeled buildings and b) at least 10 comparable observations for each labeled building in the database. In total, we have used 14,048 observations of transaction prices and 40,492 rent observations. While transaction prices are considered over a period of 11 years from 1999 through end of 2009 to obtain a sufficiently large sample, all rent observations are as of Q4 2009.

The descriptive statistics are displayed in Exhibit 1. There are clearly some differences between environmental labeled and non-labeled office buildings. The former tend to be newer. In particular, the median age of LEED labeled offices is eight years. The comparable figure for the benchmark sample is 26. While there is relatively little difference between buildings with Energy Star label and the benchmark sample in terms of age, the former tend to be dominated by tall buildings suggesting that they are mainly located in CBD locations. This is supported by the fact that Energy Star buildings tend to be much larger than non-labeled buildings. Without controlling for the differences between the samples, median rental rates are approximately 35% higher in LEED and Energy Star labeled buildings. Environmental labeled offices buildings also tend to have lower vacancy rates than non-labeled buildings. However, compared to previous studies the gap between the control sample and the labeled buildings seems to have narrowed. For instance, Fuerst and McAllister (2009) found that the median occupancy rate for a multi-tenanted LEED labeled offices was 99%. In this sample, the comparable figure is 88%. A similar change is found for Energy Star labeled buildings. Indeed, there seems to have been a convergence between Energy Star and LEED buildings. Compared to previous research, in this sample LEED and Energy Star labeled buildings have notably similar rents and sale prices. Compared to the buildings in the control sample, they are much more similar in terms of size and height.

Since the results of regression procedures can be sensitive to outliers caused by faulty data, it is important to be transparent about the treatment of outliers or data errors in the study. Similar to EKQ (forthcoming), we also find that there were some discrepancies between the properties identified as certified by CoStar and details of the properties listed by US Green Building Council. When this occurred, corrections have been made. However, a number of additional problems emerged when analyzing the CoStar data. At the top end of the price distribution, due to their relatively small number it was relatively straightforward to identify data errors and remove them from the sample. These anomalies were typically due to portfolio sale prices used as the basis for calculating the price per square foot of an individual asset within that portfolio. However, apparent data anomalies at the lower end of the price scale were more numerous. Put simply, there was a large number of sales prices that seemed to be unrealistic. Preliminary investigation suggested that these data errors were due to sales of a part of a building being recorded as representing the sale of the whole building, non-arms length transactions and portfolio sales (price of building psf being calculated as price of building divided by size of *portfolio*).

The potential implications of such data errors are not trivial. Given samples of thousands of transactions, investigating the reliability and provenance of each individual transaction can be extremely time-consuming. Nevertheless, the outputs from our OLS models were extremely sensitive to the choice of trimming criteria used to try to exclude potential data errors. Furthermore, a clear relationship was found. The lower the 'cut-off' used to exclude potential data errors, the larger the premium estimated for environmental labeled buildings. For instance, when all sale prices below $30 psf. are trimmed, we estimate an 18% sale price premium for Energy Star labeled office buildings and no statistically significant sale price premium for LEED labeled office buildings. The corresponding figures when the cut-off is $5 psf. are 27% and 20% respectively. In order to control for potential bias due to outliers, robust regressions are also used to model the determinants of rental and sale prices and occupancy rates.

Robust regression as implemented in the STATA package uses Huber and Tukey biweights to mitigate the impact of outliers on regressions coefficients in the estimation (Huber, 1964 and Rousseeuw and Leroy, 1987). Outliers are identified using Cook's distance which measures the effect of deleting a given observation based on each observation's residual in the regression and its leverage in the estimation process. All observations with Cook's distances larger than 1, automatically obtain a zero weight in the estimation. Verardi and Croux (2009) describe the highly efficient M-estimator computed by robust regression, in particular the Tukey Biweight function as.

$$\rho(u) = \begin{cases} 1 - \left[1 - \left(\frac{u}{k}\right)^2\right]^3 & \text{if } |u| \leq k \\ 1 & \text{if } |u| > k \end{cases}$$

The iterative algorithm starts off with a Huber (p) function with the following specification:

$$\rho(u) = \begin{cases} \frac{1}{2}(u)^2 & \text{if } |u| \leq c \\ c\,|u| - \frac{1}{2}c^2 & \text{if } |u| > c \end{cases}$$

Although this method of estimating robust regressions has been criticized for not completely controlling all bad leverage observations and potential clusters of outliers (see for example Rousseeuw and Van Zomeren, 1990), it provides a sufficiently robust estimation in the framework of this analysis which is not plagued by extreme outliers which may occur in other types of analyses.

Hedonic regression modeling is the standard methodology for examining price determinants in real estate research. We use this method in our study primarily to isolate the effect of LEED and Energy Star certification. As described in the literature review section of this paper, higher mean rents or transaction prices may simply be due to the fact that certified buildings are newer, higher or located in more attractive locations or markets. The quintessential log-linear hedonic rent model takes the following form:

$$\ln R_i = \alpha_i + \beta x_i + \phi Z_i + \varepsilon_i \qquad (2)$$

Where R_i is the natural log of average rent per square foot in a given building, x_i is a vector of the natural log of several explanatory locational and physical characteristics, β and φ are the respective vectors of parameters to be estimated. Z_i is a vector of time-related variables and ε_i is a random error and stochastic disturbance term that is expected to take the form of a normal distribution with a mean of zero and a variance of σ_e^2. The hedonic weights assigned to each variable are equivalent to this characteristic's overall contribution to the rental price (Rosen 1974). For the purpose of this study, we specify two types of hedonic models. The first type explains rents, the second explains price per square foot in sales transactions and the third explains occupancy rates.

To capture the effects of environmental labels on rental and sale prices, we use dummy variables to indicate whether a building has an Energy Star or LEED label. A positive co-efficient is expected and would indicate that, on average, environmental labeled offices rent or sell for more than non-labelled offices. In addition to mitigating the effects of extreme values, the log-linear specification of the hedonic model allows us to interpret the coefficients in terms of average percentage premiums. The complete specification of the log –linear model is as follows

$$LNRENT_i = C_0 + \beta_1 ES + \beta_2 LEED + \beta_3 \sum_{n=1}^{N} AGEBANDS + \beta_4 OCCUPANCY + \beta_5 LNSTOREYS_i$$
$$+ \beta_6 LNSIZE + \beta_7 LNLAND + \beta_8 NET + \beta_9 GROSS + \beta_{10} CLASSA + \beta_{11} CLASSB + \beta_{12} SINGLETENANT$$
$$+ \beta_{13} AIRCON + \beta_{14} ATRIUM + \beta_{15} BANK + \beta_{16} COMRAIL + \beta_{17} CORNER + \beta_{18} DRYCLEAN +$$
$$\beta_{19} FITNESS + \beta_{20} ONSITEMAN + \beta_{21} RESTAURANT + \beta_{22} SIGNAGE + \beta_{23} PARKING$$
$$+ \beta_{24} SUBWAY + \beta_{25} \sum_{n=1}^{N} SUBMARKETS_i + \varepsilon_i$$

Where:

$LNRENT_i$	represents the natural log of asking rent per square foot.
C_0	is a constant term
ES	is a binary variable set to indicate one if the property has an Energy Star label.
LEED	is a binary variable set to indicate one if the property has a LEED label.
AGEBAND	represents the band (see Appendix 1) in which the property lies measured from the year of construction or the year of a major refurbishment (whichever occurred more recently). The omitted category is Band 1 – properties less than three years old.
OCCUPANCY	represents the percentage of building that is occupied.
LNSTOREYS	is the natural logarithm of number of stories of the property.
LNSIZE	represents the natural logarithm of rental building area.
LNLAND	represents the natural logarithm of the plot size.
NET	is a binary variable set to indicate one if the property is let on net lease.
GROSS	is a binary variable set to indicate one if the property is let on gross lease.
CLASSA	is a binary variable set to indicate one if the property is categorized as Class A.
CLASSB	is a binary variable set to indicate one if the property is categorized as Class B.
SINGLETENANT	is a binary variable set to indicate one if the property has a single tenant.
AIRCON	is a binary variable set to indicate one if the property has air-conditioning.
ATRIUM	is a binary variable set to indicate one if the property has an atrium.
BANK	is a binary variable set to indicate one if the property has a bank branch.
COMRAIL	is a binary variable set to indicate one if the property is within 800m of a rail terminus.
CORNER	is a binary variable set to indicate one if the property is located on a corner plot.
DRYCLEAN	is a binary variable set to indicate one if the property has a dry cleaning facility in the building.
FITNESS	is a binary variable set to indicate one if the property has a gym in the building
ONSITEMAN	is a binary variable set to indicate one if the property has an onsite manager.
RESTAURANT	is a binary variable set to indicate one if the property has a restaurant in the building.
SIGNAGE	is a binary variable set to indicate one if the property has a sign.
PARKING	is a binary variable set to indicate one if the property has parking.
SUBWAY	is a binary variable set to indicate one if the property is within 800m of a subway station.
$SUBMARKET_i$	a binary variable indicating in which of the T submarkets that the property is located in
ε_i	is the error term which is assumed to be independent across observations and normally distributed with constant variance and a mean of zero.

Similarly, the regression for estimating price per square foot in sales transactions is estimated in the same way with many common independent variables:

$$LNSALEPRICE_i = C_0 + \beta_1 ES + \beta_2 LEED + \beta_3 \sum_{n=1}^{N} AGEBANDS + \beta_4 OCCUPANCY + \beta_5 LNSTOREYS$$
$$+ \beta_6 LNSIZE + \beta_7 LNLAND + \beta_8 NET + \beta_9 GROSS + \beta_{10} CLASSA + \beta_{11} CLASSB + \beta_{12} SINGLETENANT$$
$$+ \beta_{13} AIRCON + \beta_{14} ATRIUM + \beta_{15} BANK + \beta_{16} COMRAIL + \beta_{17} CORNER + \beta_{18} DRYCLEAN +$$
$$\beta_{19} FITNESS + \beta_{20} ONSITEMAN + \beta_{21} RESTAURANT + \beta_{22} SIGNAGE + \beta_{23} PARKING$$
$$+ \beta_{24} SUBWAY + \beta_{25} \sum_{n=1}^{N} SUBMARKETS + \beta_{26} 3MTHTBILL + \beta_{27} YIELDCURVE + \beta_{28} DEFAULTRISK$$
$$+ \beta_{29} MITTBI + \varepsilon_i$$

A number of additional variables are used in the sale transaction model to control for time varying financial and macro-economic conditions:

$LNSALEPRICE_i$	represents the natural log of sale price per square foot in real terms.
3MTBILL	represents the three month Treasury bill rate.
YIELDCURVE	represents the difference between the 10 year and three month Treasury bill rate.
DEFAULTRISK	represents the Baa corporate bond yield less the AAA corporate bond yield.
MITTBI	represents the total return on office property for the MIT transaction-based real estate index.

Our expectations are generally similar according to the whether rents or sale prices are being modeled. However, with age whilst we expect a negative relation for rents, a quadratic relationship has frequently been observed between price and age (Ling and Petrova, 2008). The estimated coefficients for the various amenities (parking, bank, gym etc), size and number of storeys are expected to be positive in both models. The variable Class A or B controls for building quality. We expect lower rents for offices let on leases on terms other than triple. Buildings that are unclassified are used as the control group. We also include a dummy variable to indicate whether a building is occupied by a single tenant. For the sale price model, we control for variations in market conditions at the time of sale by including a

Exhibit 2 Rental rates

OLS Regression	Coefficient		Robust Regression	Coefficient	
C_0	2.38	***	C_0	2.75	***
ES	0.03	***	*ES*	0.03	***
LEED	0.03		*LEED*	0.03	**
AGEBAND2	-0.14	***	*AGEBAND2*	-0.13	***
AGEBAND3	-0.17	***	*AGEBAND3*	-0.15	***
AGEBAND4	-0.22	***	*AGEBAND4*	-0.20	***
AGEBAND5	-0.24	***	*AGEBAND5*	-0.22	***
AGEBAND6	-0.25	***	*AGEBAND6*	-0.24	***
AGEBAND7	-0.26	***	*AGEBAND7*	-0.24	***
AGEBAND8	-0.25	***	*AGEBAND8*	-0.24	***
AGEBAND9	-0.24	***	*AGEBAND9*	-0.23	***
AGEBAND10	-0.23	***	*AGEBAND10*	-0.21	***

OCCUPANCY	0.00	***	*OCCUPANCY*	0.00	***
LNSTOREYS	0.06	***	*LNSTOREYS*	0.05	***
LNSIZE	0.00		*LNSIZE*	0.00	*
LNLAND	0.01	**	*LNLAND*	0.00	**
NET_i	-0.10	***	NET_i	-0.10	***
GROSS	0.04	***	*GROSS*	0.05	***
CLASSA	0.17	***	*CLASSA*	0.18	***
CLASSB	0.08	***	*CLASSB*	0.09	***
SINGLETENANT	0.01		*SINGLETENANT*	0.01	*
ATRIUM	0.02	**	*ATRIUM*	0.01	**
BANK	0.02	***	*BANK*	0.02	***
COMRAIL	0.05	**	*COMRAIL*	0.05	***
CORNER	0.00		*CORNER*	0.00	
DRYCLEAN	-0.01		*DRYCLEAN*	0.01	
FITNESS	0.02	**	*FITNESS*	0.01	**
FOODSERVICE	0.00		*FOODSERVICE*	0.00	
ONSITEMAN	0.00		*ONSITEMAN*	0.00	
RESTAURANT	0.00		*RESTAURANT*	0.00	
SIGNAGE	0.00		*SIGNAGE*	0.00	
PARKING	0.02		*PARKING*	0.02	
SUBWAY	0.02		*SUBWAY*	0.02	
SUBMARKET CONTROLS			*SUBMARKET CONTROLS*		
Adj R-squared	0.59		Adj R-squared	n/a	
F-test	71.98		F-test	105.24	
F-test prob	0.00		F-test prob	0.00	
N	22273		N	22273	

number of factors used to model real estate capitalization rates and capital values. Sub-market dummies are used to control for location effects.

Empirical Results

Rental rates

Exhibit 2 presents the empirical results for the OLS and robust regressions for the rental rates. The results reveal that the estimated coefficients on the variables are of the predicted sign in most cases. For example, the estimated coefficient on age is negative and statistically significant. Relative to office buildings less than three years old, rental rates tend to fall quickly in the following fifteen years and then stabilize for buildings over 20 years old. As expected, the estimated co-efficient on Class A is positive. Additionally, the estimated coefficient for leasing on net lease terms is also negative and the coefficient for a gross lease is significantly positive.

The estimated coefficients for the OLS and robust regressions are consistent. This suggests that outliers due to data errors are not as significant for rental rates. The most notable difference is that the estimated coefficient for a LEED label becomes significant at the 5% level in the robust regression. The estimated coefficients for rental rates for Energy Star and LEED labels are in line with previous studies. The estimated coefficients for the presence of amenities are variable. Not surprisingly, no amenities have a significantly negative effect on rental rates. Properties that have fitness centers and banking facilities tend to have higher rents. Various accessibility factors such as proximity to a rail terminus and a subway station or the presence of parking facilities also have a positive effect on rental rates.

Sale prices

Exhibit 3 presents the empirical results for the OLS and robust regressions for the sale prices. It reveals that the estimated coefficients on the variables are of the predicted sign in most cases. However, for sale prices, the results indicate that data errors may be a significant problem. Crucially in the context of this paper, the results of both regressions are not consistent in terms of the estimated coefficients for LEED and Energy Star premiums. The OLS model (without trimming) estimates extremely large sale price premiums for both LEED (23%) and Energy Star (305). For the robust regression results, although positive, the estimated coefficient for the LEED dummy is not significant. However, although it is lower, the estimated sale price premium for the Energy Star label is 15% and is statistically

Exhibit 3 **Sale Prices**

OLS Regression	Coefficient		Robust Regression	Coefficient	
Constant	6.00	***	*Constant*	5.00	***
ES	0.30	***	*ES*	0.17	***
LEED	0.23	***	*LEED*	0.05	
AGEBAND2	0.25	***	*AGEBAND2*	0.11	***
AGEBAND3	0.27	***	*AGEBAND3*	0.03	
AGEBAND4	0.17	***	*AGEBAND4*	-0.07	***
AGEBAND5	0.11	***	*AGEBAND5*	-0.13	***
AGEBAND6	0.08	**	*AGEBAND6*	-0.18	***
AGEBAND7	0.09	***	*AGEBAND7*	-0.17	***
AGEBAND8	0.06	**	*AGEBAND8*	-0.19	***
AGEBAND9	0.03		*AGEBAND9*	-0.20	**
AGEBAND10	0.05		*AGEBAND10*	-0.19	***
OCCUPANCY	-0.001	*	*OCCUPANCY*	-0.001	
LNSTOREYS	0.08	***	*LNSTOREYS*	0.07	***
LNSIZE	0.27	***	*LNSIZE*	-0.20	***
LNLAND	0.13	***	*LNLAND*	0.13	***
NET	0.01		*NET*	0.03	*
GROSS	0.03		*GROSS*	-0.03	*
CLASSA	0.38	***	*CLASSA*	0.31	***
CLASSB	0.08	***	*CLASSB*	0.07	***
SINGLETENANT	0.15	***	*SINGLETENANT*	0.08	***
BANK[1]	0.07	**	*BANK*	0.07	***
FITNESS	0.12	***	*FITNESS*	0.08	***
FOODSERVICE	0.05	*	*FOODSERVICE*	0.02	
ONSITEMAN	0.11	***	*ONSITEMAN*	0.05	***
RESTAURANT	0.09	***	*RESTAURANT*	0.08	***
SUBWAY	0.14	**	*SUBWAY*	0.10	**
3MTBILL	0.02		*3MTBILL*	0.01	
10YRGBOND	0.01		*10YRGBOND*	0.01	
DEFAULTRISK	-0.11	***	*DEFAULTRISK*	0.00	
MITTBI	0.01	***	*MITTBI*	0.00	***
LNEMPGROWTH	-0.42	**	*LNEMPGROWTH*	-0.62	***
SOLD 2000	0.02		*SOLD 2000*	0.04	
SOLD 2001	0.08		*SOLD 2001*	0.10	***
SOLD 2002	0.18	***	*SOLD 2002*	0.13	***
SOLD 2003	0.13		*SOLD 2003*	0.14	***
SOLD 2004	0.14	*	*SOLD 2004*	0.19	***
SOLD 2005	0.15	*	*SOLD 2005*	0.27	***
SOLD 2006	0.00		*SOLD 2006*	0.24	***
SOLD 2007	-0.22		*SOLD 2007*	0.20	**
SOLD 2008	-0.28	*	*SOLD 2008*	0.17	*
SOLD 2009	-0.61	***	*SOLD 2009*	-0.02	
SUBMARKET CONTROLS			*SUBMARKET CONTROLS*		
Adj R-squared	0.37		Adj R-squared	N/A	
F-test	13.23		F-test	25.37	
F-test prob	0.00		F-test prob	0.00	
N	9672		N	9672	

[1] Estimated coefficients for signage, parking, atrium, drycleaner, corner site and commuter rail terminus were not significant. They are not reported here for the sake of brevity.

significant. This is consistent with our observation that, when using a simple trimming procedure, the estimated coefficients for LEED and Energy Star reduced substantially when (unrealistically) low value sales prices were trimmed.

The results for age and year dummies suggest that the robust regression provides more plausible and reliable estimates. For example, consistent with a quadratic relationship the estimated coefficients on age are initially positive, become negative as buildings age and stabilize after 220-25 years. In the OLS regression, less plausibly no negative capital depreciation relative to newer offices is ever estimated. Similarly, the effect of Year Sold also seems more plausible in the robust regression. For most of the other variables, the OLS and robust regression provide similar estimates. As expected, the estimated co-efficient on Class A is positive. Additionally, the estimated coefficient for leasing on net lease terms is positive with the coefficient for a gross lease being significantly negative at the 10% level. The estimated coefficients for the presence of amenities are variable. Not surprisingly, no amenities have a significantly negative effect on rental rates. Properties that have fitness centers and banking facilities tend to have higher rents. Various accessibility factors such as proximity to a rail terminus and a subway station or the presence of parking facilities also have a positive effect on sale prices.

Occupancy Rates

Exhibit 4 presents the empirical results for the OLS and robust regressions for the sale prices. When controlling for the rent determinants such as building class, age, height, size and sub-market location, we do not find evidence that environmental labeled office buildings have higher occupancy rates. In the OLS model, there is a statistically significant positive coefficient for the Energy Star indicating an occupancy rate premium of approximately 2%. Surprisingly, the LEED dummy is significantly negative. The estimated coefficient from the OLS model suggests a 7% lower occupancy rate for LEED labeled offices. For Energy Star offices, this finding is consistent with previous research by Miller *et al* (2008), Pivo and Fisher (2009) and Fuerst and McAllister (2009). However, no other study has reported a significantly negative coefficient for LEED rating on occupancy rates. When, a robust regression procedure is used, the Energy Star premium disappears and the negative estimate for LEED is reduced but remains significant at the 5% level. This result is difficult to explain and requires further investigation. *Prima facie*, it suggests that LEED labeled offices have performed below average in terms of occupancy rates during the downturn.

Exhibit 4 Occupancy Rates

OLS Regression	Coefficient		Robust Regression	Coefficient	
Constant	-59.63	***	*Constant*	-26.36	***
ES	1.84	**	*ES*	0.52	
LEED	-6.95	***	*LEED*	-3.13	**
AGEBAND2	20.90	***	*AGEBAND2*	18.25	***
AGEBAND3	17.15	***	*AGEBAND3*	16.55	***
AGEBAND4	16.32	***	*AGEBAND4*	15.19	***
AGEBAND5	15.56	***	*AGEBAND5*	14.84	***
AGEBAND6	15.42	***	*AGEBAND6*	15.46	***
AGEBAND7	15.44	***	*AGEBAND7*	15.63	***
AGEBAND8	12.53	***	*AGEBAND8*	14.00	***
AGEBAND9	11.40	***	*AGEBAND9*	13.24	***
AGEBAND10	11.14	***	*AGEBAND10*	13.55	***
LNSTOREYS	0.00		*LNSTOREYS*	-1.65	***
LNSIZE	8.77	***	*LNSIZE*	7.01	***
LNLAND	-1.63	***	*LNLAND*	-1.19	***
NET	-10.21	***	*NET*	-7.89	***
GROSS	-3.08	***	*GROSS*	-4.26	***
CLASSA	-7.89	***	*CLASSA*	-5.03	***
CLASSB	-2.06	***	*CLASSB*	-2.42	***
LNRENT	6.54	***	*LNRENT*	6.75	***
ATRIUM	-0.59		*ATRIUM*	-1.07	*
BANK	0.44		*BANK*	0.03	
COMRAIL	-3.40	*	*COMRAIL*	0.91	*
CORNER	0.01		*CORNER*	-0.28	
DRYCLEAN	0.14		*DRYCLEAN*	-0.39	
FITNESS	-1.08		*FITNESS*	-1.08	
FOODSERVICE	-4.36	***	*FOODSERVICE*	-3.08	***
ONSITEMAN	0.87	*	*ONSITEMAN*	-0.18	
RESTAURANT	-0.24		*RESTAURANT*	-0.67	
SIGNAGE	1.56	***	*SIGNAGE*	0.23	
PARKING	-2.75		*PARKING*	0.90	
SUBWAY	-1.54		*SUBWAY*	1.44	
SUBMARKET CONTROLS			*SUBMARKET CONTROLS*		
Adj R-squared	0.25		Adj R-squared	n/a	
F-test	16.87		F-test	33.45	
F-test prob	0.00		F-test prob	0.00	
N	22273		N	22273	

The results for the other variables are in line with expectations. In line with previous research on price premiums in LEED and Energy Star offices and in other studies of office rental determination, occupancy levels (similar to rent levels) display a positive relationship with size. Compared to recently constructed offices (aged 0-3 years), occupancy rates of offices are higher for buildings all building types. This is presumably due to the numbers of relatively new buildings in the first age band which are still in the leasing up phase. However, the lack of a significantly different occupancy rate linked to building quality is notable and consistent with previous studies. The low explanatory power of the model is a concern and suggests that important variables may have been omitted.

Conclusion

The central aim of the policy of environmental or energy labelling real estate assets is to reduce their environmental impact by altering patterns of demand and supply. It is hoped that by providing independently verified information to investors and occupiers about the environmental/energy performance of buildings, their willingness-to-pay for buildings with superior environmental performance will increase. Consequently, this shift in demand from investors and occupiers will produce rental and sale price premiums and reduce operating costs and regulatory obsolescence. Suppliers of buildings (investors and developers) will have financial incentives to improve their environmental/energy performance. Pricing studies are central to evaluating the effectiveness of environmental labeling in real estate markets.

Drawing upon much larger samples of rental and sale prices compared to previous research, the contribution of this study has been twofold. Firstly, it indicates that, for sale prices in particular, outliers have the potential to produce overestimation of sale price premiums. In particular, the estimated coefficients for environmental labeled offices for sale prices are sensitive to choice of trimming parameters. Relative to OLS regression procedures, robust regression procedures estimate much lower sale price premiums for LEED and Energy Star environmental labels. Although a substantial sale price premium is found for Energy Star labeled buildings, in the robust regression model, no significant sales price premium is identified for the LEED label. Whilst these results are in line with Eichholtz *at al* (forthcoming), this finding seems surprising given the prominence of the LEED label. For rental rates, the results are consistent with previous studies that find a premium of 1%-3%. Most surprisingly, the estimated coefficients for occupancy rates indicate no significant occupancy rate premium for the Energy Star label and a negative effect on occupancy rates of the LEED label. This finding, in particular, needs further detailed checking.

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Appendix 1

Age Bands

Band	Age (years)
1	< 3
2	[3, 9)
3	[9, 15)
4	[15, 19)
5	[19, 22)
6	[22, 24)
7	[24, 29)
8	[29, 38)
9	[38, 71)
10	>= 71