Xymax Real Estate Institute

TOPIC REPORT

Analysis of the Economics of Green Buildings in Tokyo's Office Market

—The Effect of Office Lease Market Conditions and Green Labels on New Contract Rent—

November 20, 2019

"Do green labels have a positive economic effect on the real estate business?" This question is an important theme that should be examined in promoting green buildings.

However, the extreme complexity of Tokyo's office market, with its diverse mix of numerous buildings and companies, had made quantitative analysis difficult. Xymax Real Estate Institute ("Xymax REI") addressed this problem by combining the use of market division and quality adjustment to estimate the effect of green labels on new contract rent based on new contract rent data for offices in the 23 wards of Tokyo for 2013 and 2014. The result was a positive effect of +4.4% (95% confidence interval: +2.1–+6.7%).*

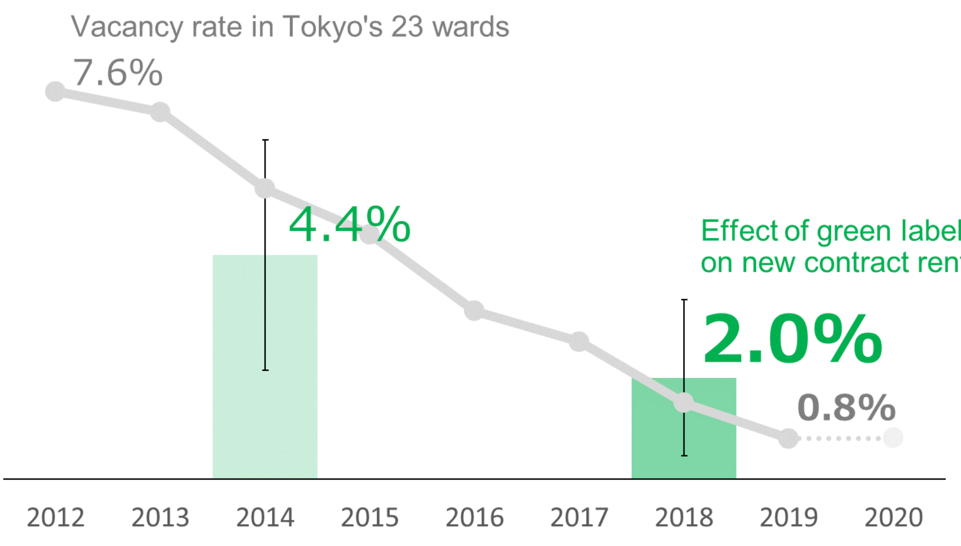
**The Importance of Environmental Management in the Future Real Estate Market* (in Japanese only), published June 1, 2015, ARES Real Estate Securitization Journal vol. 25
https://soken.xymax.co.jp/results/pdf/201506.pdf

This time we carried out the same analysis using data for 2017 and 2018. In this report, we analyzed the economic effects of green labels amid a volatile office market and compared the results with the previous results to examine the causes of the effects.

<Findings>

- The effect of green labels on new contract rent in the Tokyo office market for this analysis period (from January 2017 to December 2018) was +2.0% (95% confidence interval: +0.5–+3.5%), a positive effect even as the market shifts from a lessee's advantage to a lessor's advantage (**Figure 1**).
- A positive effect of +2.3% (95% confidence interval: +1.0–+3.7%) was observed among large and recently-built properties, which can obtain green labels more easily. No statistically significant effect was observed among medium-sized and old properties.

Figure 1: Effect of Green Labels on New Contract Rent (All Samples)



1. Social background: The connection between environmental issues and real estate

Today, environmental issues are recognized as the greatest uncertainty and risk factor against the sustainability of the development of humankind.

International measures for tackling environmental issues have been implemented in the past, such as emission control (direct measure) and environmental tax and emissions trading (economic measures) under the Kyoto Protocol and the Paris Agreement and. However, these international frameworks have a tendency to develop into political issues such as conflicts between developed and developing nations and the withdrawal of a major nation. Furthermore, environmental issues arise from the external diseconomy effect of free economic activities. Therefore, they seldom lead to voluntary suppression of economic activities by individuals and companies.

A new economic measure that is currently attracting attention is ESG investment. A consensus that ESG elements (environment, social, governance) are long-term risk factors has already been formed among investors. Huge pension funds in Japan and abroad, including Japan's Government Pension Investment Fund (GPIF), have signed the Principles for Responsible Investment (PRI), while 883 institutions from around the world support the report by the Task Force on Climate-related Financial Disclosures (TCFD), which was set up at the request of the G20. According to the Global Sustainable Investment Alliance (GSIA), the ESG investment market has reached 31 trillion dollars globally (a 34% growth between 2016 and 2018) and 2.2 trillion dollars in Japan (a 360% growth over the same period).

Amid such circumstances, countries around the world have established programs to assess and certify the environmental performance of real estate (green label programs), which are anticipated to serve as a tool that helps environmentally conscious investors and tenant firms in selecting properties to invest in or rent. They include LEED (established 1998) and BOMA360 (2009) of the United States, and BREEAM (1990) and GRESB (2009) of the United Kingdom. Japan uses the programs of other countries as well as its own programs such as CASBEE (2002), DBJ Green Building Certification (2011), and BELS (2014).

From the standpoint of real estate operators, a major concern was whether the advantage gained from obtaining a green label matched the cost of obtaining them. This is because obtaining a green label not only requires the gathering of data for green label acquisition and administrative procedures but also additional investment to conform with green labels. This led to a need for an examination of the economics of green labels, such as whether they "ensure higher rent," "stabilize occupancy rates," "reduce volatility of revenue," and "ensure higher evaluation or selling prices."

Pioneering studies such as those by Miller et al. (2008), Fuerst & McAllister (2011), and Reichardt (2012) have hitherto provided important insights into the economics of green buildings. Eichholtz, Kok & Quigley (2010) proved that green labels offer economic premiums after controlling for quality differences of properties. The economics of green labels have since been actively studied around the world. The existence of economic premiums to green buildings has been reported by Fuerst et al. (2015) in the United Kingdom, Kahn & Kok (2014) in California, Hyland, et al. (2013) in Ireland, Zheng et al. (2012) in China, and Deng et al. (2012) in Singapore. In Japan, Yoshida & Shimizu (2010) carried out an analysis of offer prices of condominiums in Tokyo, while Fuerst & Shimizu (2016) conducted an experimental study on green label premiums, taking into consideration the income of buyers.

The interest in studies on the economics of green labels is especially strong in the Tokyo office market. Tokyo remains one of the world's top-class economic cities with its concentration of companies and people, and its office market has one of the largest stocks in the global commercial real estate market. It also has a developed real estate investment infrastructure such as REITs and has an extensive accumulation of data. It has also experienced a range of socioeconomic events, including the post-war restoration, high economic growth, oil shock, and the birth and burst of the bubble economy, which have led to a wide variety of scale and performance of office buildings.

Against this background, Sumitomo Mitsui Trust Bank (2015), Xymax REI (2015), and the Development Bank of Japan & Japan Real Estate Institute (2015–2019) have each conducted an empirical analysis of how much rent is higher at office buildings with a green label than those without. Many of these analyses indicate that green labels have a positive effect on rent and prices.

However, with the progress of the analysis of the environmental economic value in the Tokyo office market, several complicated problems have been revealed.

2. Identifying the problem: A complex market structure

As mentioned earlier, the Tokyo office market is a concentration of a diverse range of office buildings and companies. The structure (pricing of rent) of such a market is not always singular. Rather, it is closer to reality to think of the market as a mixture of multiple markets. The business environment, personnel market, and customers significantly differ between small and medium-sized companies that pay a rent of around 10,000 yen per tsubo for the building they rent and listed companies that pay a rent of more than 40,000 yen per tsubo. The priorities of the elements the companies require in an office building differ as well, with the former preferring small and medium-sized office buildings that are flexible even if they are old, and the latter favoring relatively new and large office buildings that serve as a landmark of the area.

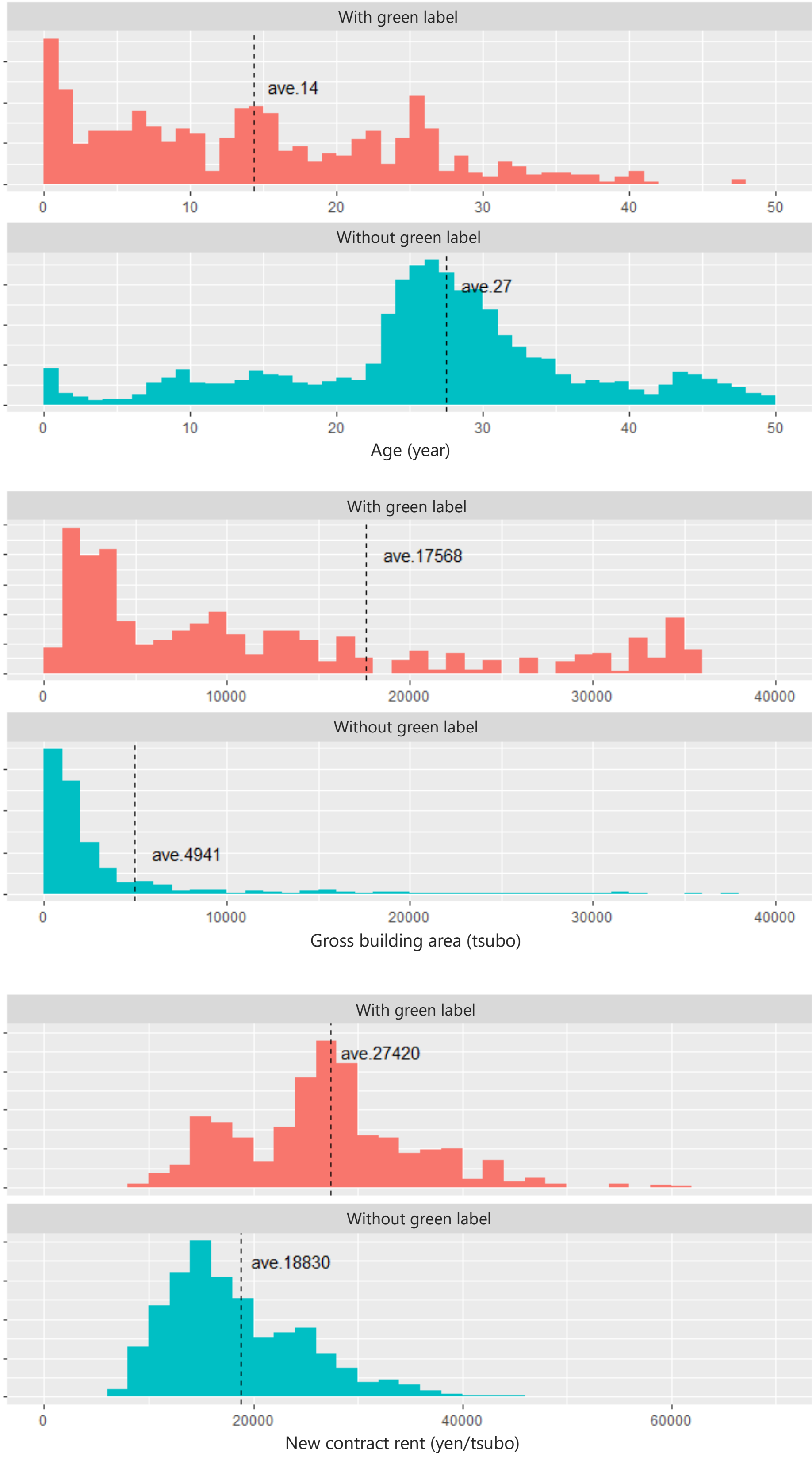
In such a complex market with a mixture of multiple market structures, two problems arise in terms of quantitative analysis (i.e. quality adjustment and sample selection bias).

The first problem is “**quality adjustment**.” **Figure 2** is the distribution of buildings’ age, gross building area, and new contract rent of the study data for the analysis. The red bars represent office buildings with a green label and the blue bars represent those without. Office buildings with a green label tend to be younger (toward the left of the chart) and larger in gross building area (toward the right of the chart). In such cases, it is not appropriate to compare the average new contract rent (the position of the vertical dotted line in **Figure 2**) between office buildings with a green label and those without and deem the difference as the economic effect of green labels.

The second problem is “**sample selection bias**.” Properties with enough performance to qualify for a green label and rented by environmentally conscious tenants have high rent even if they do not have a green label. It cannot be distinguished whether the rent is high since the property has a green label, or since it has high specifications, or because it has good tenants.

In order to measure the economic effect of green labels in a market with a complex structure such as Tokyo’s office market, it is necessary to address these two problems.

Figure 2: Distribution of Age (Top), Gross Building Area (Middle), New Contract Rent (Bottom) (Office Buildings in the 23 Wards of Tokyo)



3. Analysis process: Propensity score and hedonic approach

These problems arise from analyzing data with different market structures together. Therefore, one solution would be to divide the samples into groups with a similar market structure. In our analysis, it would be effective to divide the samples into a group of high-spec properties that attract environmentally conscious tenant companies and a group of properties with not such high specifications that attract tenants that are not so environmentally conscious.

An analysis technique used for collecting samples with a similar market structure as in this case is "**propensity score**." Propensity scores are used in academic papers on such wide-ranging areas as medicine, economy, and psychology. The score was also used in the field of online surveys (refer to the appendices at the end of this report on the theoretical background of propensity scores and sample adjustment using analysis data).

Even within a group with a similar market structure, the location, age, and size of buildings differ slightly. Therefore, it is necessary to measure the effect of green labels on new contract rent after adjusting for such attributes (qualities). This problem can be dealt with by measuring the quality-adjusted effect of green labels for each group using the **hedonic approach**. The hedonic approach is an analysis method that employs a regression analysis technique and is widely used for measuring the economic effects of policies and infrastructure construction. Specifically, the effect of green labels is measured by building the following hedonic model and estimating the partial regression coefficient of a green label dummy (a variable of "1" if the building has a green label and "0" if not).

$$\ln R_i = \alpha + green_i{}' \cdot \beta + x_i{}' \cdot \gamma + \varepsilon_i$$

The symbols represent the following:

R_i	:	New contract rent
i	:	Subscript indicating each sample
α	:	Constant term
$green_i$	:	Green label dummy
β	:	Effect of existence of green label on new contract rent
x_i	:	Independent variable other than green label dummy [Size] Gross building area, number of stories above ground, standard story area [Newness] Age, renovation dummy [Performance, equipment] Raised floor dummy, individual air conditioning dummy, automated security dummy [Location] Time to nearest station, five central Tokyo wards dummy [Contract period] Quarterly dummy
γ	:	Effect of independent variable x on new contract rent
ε_i	:	Error term

As shown above, quality adjustment is carried out for each group after the samples are classified into groups with a similar market structure. The effect of green labels on new contract rent is thus estimated while taking into consideration the complex structure of the Tokyo office market.

4. Analysis targets: Changes in market structure due to market conditions

In this analysis, we estimated the economic effect of green labels using the method described in the previous chapter over a period between January 2017 and December 2018. The analysis data was compiled from new contract rent and property attributes of new tenancy cases in office buildings located in the 23 wards of Tokyo. The attribute concerning green labels is "1" if the building has obtained any of the following comprehensive ratings by a third party: CASBEE, CASBEE for real estate, and DBJ Green Building Certification, and "0" if it has not.

Market conditions can also be cited as a factor that changes market structures. The economic effect of green labels may differ between a period when vacancies are difficult to fill and a period when vacancies are scarce due to strong demand from tenants. The effect may also change depending on how much green labels have penetrated the market.

Figure 3 shows that while there is no significant change in the property attributes of the samples such as location, size, and age, the percentage of green label acquisition rose from the previous 5.3% (Period 1: January 2013 to December 2014) to 10.0% (Period 2: January 2017 to December 2018) in this analysis. As the previous analysis was conducted during the dawn of the green label program for real estate, this result reflects the fact that the program has begun to spread in the market over the four years from the previous analysis. The office lease market conditions have also changed significantly. According to data by Xymax REI, the vacancy rate of Tokyo's entire office market was relatively high at 5–7% during the previous period but has dropped to the 1% level during the period for this report due to tenants' strong demand for offices.

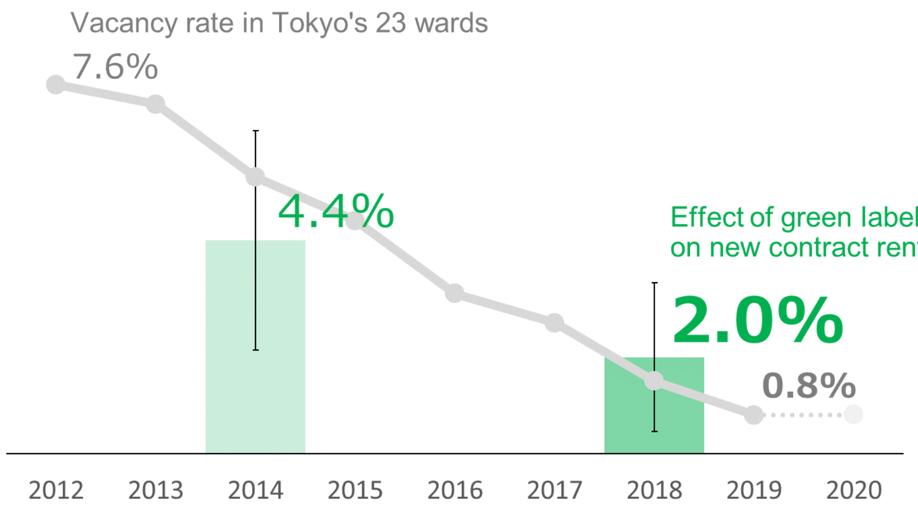
Figure 3: Summary Statistics of Analysis Data

	Name of variable	Unit	Period 1: Jan. 2013–Dec. 2014					Period 2: Jan. 2017–Dec. 2018				
			No. of samples	Avg.	Standard deviation	Minimum	Maximum	No. of samples	Avg.	Standard deviation	Minimum	Maximum
Dependent variable	New contract rent	Yen/ tsubo	6,758	17,090	6,155	6,100	55,040	7,129	19,723	7,431	7,000	60,975
Independent variable	Green label dummy	(0, 1)	6,758	0.053	0.225	0.000	1.000	7,129	0.100	0.310	0.000	1.000
	Gross building area	Tsubo	6,758	5,726	11,327	300	114,783	7,129	6,253	12,083	300	114,783
	Age	Year	6,758	23.730	11.826	0.000	59.910	7,129	26.120	11.860	0.000	60.320
	No. of stories above ground	Story	6,758	11.690	7.698	3.000	60.000	7,129	12.250	8.500	3.000	60.000
	Standard story area	Tsubo	6,758	236	241	30	2,975	7,129	238	257	30	2,975
	5 central Tokyo wards dummy	(0, 1)	6,758	0.769	0.422	0.000	1.000	7,129	0.770	0.420	0.000	1.000
	Time to nearest station	Minute	6,758	3.358	2.313	0.000	15.000	7,129	3.300	2.240	0.000	19.000
	Raised floor dummy	(0, 1)	6,758	0.685	0.465	0.000	1.000	7,129	0.830	0.380	0.000	1.000
	Individual air con dummy	(0, 1)	6,758	0.800	0.400	0.000	1.000	7,129	0.820	0.390	0.000	1.000
	Automated security dummy	(0, 1)	6,758	0.833	0.373	0.000	1.000	7,129	0.950	0.210	0.000	1.000
	Renovation dummy	(0, 1)	6,758	0.131	0.337	0.000	1.000	7,129	0.260	0.440	0.000	1.000

5. Analysis result: The effect remains positive in the overall market

We will first present the results of the analysis of all samples. The new contract rent for buildings with a green label was higher than that for buildings without a green label by 4.4% in Period 1 (from January 2013 to December 2014) and 2.0% in Period 2 (from January 2017 to December 2018) (**Figure 1**). The figures are statistically significant for both periods, implying that green labels have a positive effect on new contract rent even when the market shifts to the advantage of lessors.

(Aforementioned) Figure 1: Effect of Green Labels on New Contract Rent (All Samples)



As mentioned earlier, a wide range of market structures coexist in the Tokyo office market, requiring appropriate market division when conducting quantitative analysis. In this analysis, we estimated the effect of green labels on new contract rent by dividing the market into five groups based on propensity of obtaining green labels using propensity scores and making quality adjustments to each group using the hedonic approach. The results of the estimate for each group are summarized in **Figure 4**. Groups 1 to 3 have been excluded from the examination due to the small number of samples with a green label and the lack of statistically significant results and implications due in part that their samples mainly consist of small and old buildings.

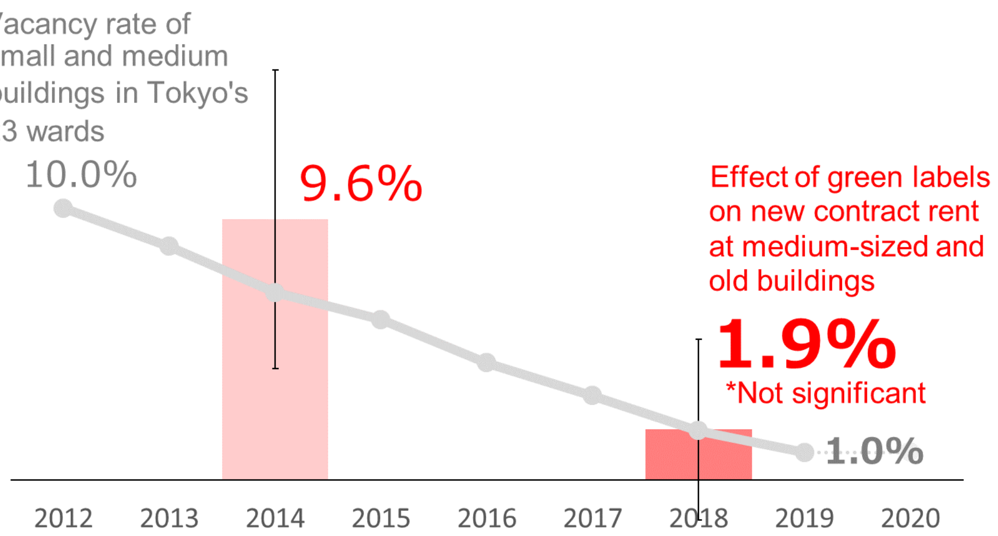
Figure 4: Effect of Green Labels on New Contract Rent in Each Group

	Group 1	Group 2	Group 3	Group 4	Group 5	Overall
This analysis Period 2: Jan. 2017–Dec. 2018	(Unable to calculate)	+17.2% -3.3% – +33.7%	+1.3% -5.1% – +7.8%	+1.9% -1.5% – +5.2%	+2.3% 1.0% – +3.7%	+2.0% 0.5% – +3.5%
Previous analysis Period 1: Jan. 2013–Dec. 2014	(Unable to calculate)	+12.8% -17.0% – -42.8%	+6.3% -14.8% – +27.5%	+9.6% +4.1% – +15.0%	-1.1% -3.2% – +1.0%	+4.4% 2.1% – +6.7%

*The upper row indicates estimates of partial regression coefficients of the green label dummy. The lower row is the 95% confidence interval range.
*Figures in red frames are statistically significant results.

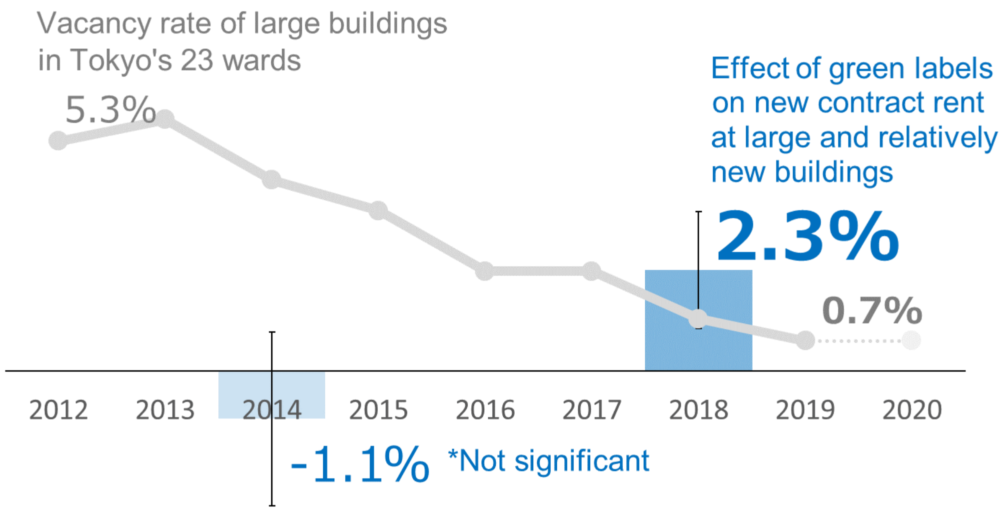
Group 4 mainly consists of samples that are relatively medium in size and old. The effect of green labels was +1.9% for the analysis period of this report (Period 2) but was not statistically significant. The effect in the previous analysis period (Period 1) was +9.6%, which was statistically significant (**Figure 5**). In this group of relatively medium-sized and old building samples, the effect of green labels was significantly positive during the period when lessees had an advantage in the market and vacancies were abundant but became almost nonexistent when lessors had an advantage in the market and vacancies were few.

Figure 5: Effect of Green Labels on New Contract Rent in Group 4 (Medium-sized, Old Buildings)



Group 5 mainly consists of samples that are large in size and relatively new. The effect of green labels during the period of this analysis (Period 2) was +2.3% and statistically significant (**Figure 6**). On the other hand, the effect during the previous period (Period 1) was -1.1% but was not statistically significant. In this group of large and relatively new building samples, the effect of green labels was not observed during the period when lessees had an advantage in the market, but a positive effect was seen during the period when it was a lessors' market. The results were different from Group 4.

Figure 6: Effect of Green Labels on New Contract Rent in Group 5 (Large, Relatively New Buildings)



6. Insight into the background: Social changes and market cycle

Based on the above analyses, we examine the background to the difference in the effect of green labels on new contract rent due to the different periods.

First of all, we believe the background to the difference in Group 5 (large-scale, relatively new buildings) to be structural changes in society. Following the spread of the recognition of SDGs and ESG investment markets, awareness toward environmental issues has been rising among large companies, especially those that operate on a global scale. These companies are large-scale and highly creditworthy, and have the ability to afford the rent of large and relatively new office buildings that would qualify for Group 5. With the progress of globalization and labor shortage, companies face an increasing need for competent personnel to improve their competitiveness. Companies that rent offices that belong to Group 5 are now required to provide a comfortable environment to attract competent talents. Indoor comfort, which is one of the assessment items of green labels, responds to such needs.

With a certain amount of time having passed since the start of the green label program, there has been a rise in the number of office buildings with a green label. In Group 5, in particular, the percentage of cases at office buildings with a green label has significantly increased from approximately 15% in Period 1 to approximately 42% in Period 2. Office buildings with a green label are now included in companies' search options when they look for offices. Following such social changes that have intensified in recent years, we believe that tenant companies have begun to appreciate green labels, resulting in their positive effect on new contract rent especially in Group 5, which includes buildings that respond to companies' appreciation of green labels.

Meanwhile, we believe the background to the difference in Group 4 (medium-sized, old buildings) to simply be a change in the power balance between lessors and lessees. During Period 1, the vacancy rate was high and lessees (tenants) had many vacancies to choose from. In such a market environment, green labels functioned as a differentiating factor. However, during Period 2 when the vacancy rate was low, lessors had the upper hand. Even vacancies in less competitive office buildings could be filled quickly if the owner put a call out for tenants. In this market environment, green labels no longer worked as a differentiator.

Additionally, social changes that we cited as a background to Group 5 are not believed to have been manifested as strongly in Group 4. At companies that take up tenancy in office buildings belonging to Group 4, there remains a gap (compared to companies that rent buildings in Group 5 above) between their awareness of environmental issues and the development of a comfortable office environment and their actual actions, due in part to their lack of financial capacity. Furthermore, although the percentage of office buildings with a green label has risen, it remains at around 7% in Period 2, which is not high enough to allow companies to encounter such buildings when they look for offices.

Thus, we believe that green labels have ceased to function as a differentiating factor in Group 4 where the impact of social changes has not been felt strongly, amid a shift of the market to the advantage of lessors.

7. Summary

In this analysis, we conducted an empirical quantitative analysis of the effect of green labels on new contract rent amid a shift of the market from the lessee's advantage to the lessor's advantage. Among large and relatively new buildings, the effect turned positive on the back of the spread of green buildings and a rise in environmental awareness mainly among large companies. On the contrary, the effect was no longer observed among medium-sized and old buildings, as buildings have been able to attract tenants even if they were less competitive, due to the tight supply-demand balance. In terms of the overall market, a positive effect can still be observed.

The future outlook of the Japanese economy is increasingly uncertain. When companies' demand for offices drop and vacancies increase, leading to a shift of the market to the lessee's advantage, green labels will once again attract attention as a differentiating factor in some markets. Meanwhile, various social changes are also ongoing, such as the progress of labor shortage, work style reforms, technology, and the aging of building stock. The penetration of initiatives in environmental issues that involve investors and companies, such as ESG investment and SDGs, is one of the major social changes.

Going forward, it will be important to determine both the cyclical changes of the market and the irreversible changes of society separately.

[Appendices] Technical paper: Sample adjustment by propensity score

Appendix 1. Background

In the appendices, we provide technical explanations on the quantitative analysis techniques used for the analysis. For the analysis data, we use Period 1 of the report (from January 2013 to December 2014).

As in this analysis, an incentive to accurately estimate the causal effect of intervention has long existed. Statistical causal inference deals with this matter. An important issue in statistical causal inference has been the removal of the effect of confounding factors. The design of experiments advocated by Fisher, the founder of modern inferential statistics, removed the effect of confounding factors by defining a control group with potentially equal attributes as the treatment group through a random allocation of treatments. However, since almost all data that social science handles is observation data, the effect of confounding factors cannot be removed with the design of experiments.

The hedonic approach advocated by Lancaster (1966) and Rosen (1974) has econometric consistency with economic theory backgrounds and has been used in a broad range of areas such as price indices of real estate as well as for measuring the effect of intervention in the social science field, such as in impact analyses of environmental policies and social capital policies. The hedonic approach considers a good as a bundle of various attributes and estimates a hedonic model that regresses a good to its various attributes. The marginal value of intervention can be estimated by using the partial regression coefficient of each attribute derived from the estimation of this hedonic model.

One of the problems that requires the most attention in using the hedonic approach is endogeneity. When there is a correlation between the independent variable and the error term in an econometric model, it is endogenous. In this case, the estimator derived by the hedonic approach has no consistency but is biased and therefore cannot accurately assess the effect of intervention. The mechanisms that produce endogeneity include observational error, omitted variable, simultaneity, and sample selection bias. While all of these are important issues that should be addressed, in these appendices we focus on sample selection bias, which is often encountered when using or appropriating an existing data set. A sample selection bias is a bias that emerges when attributes differ between the treatment group and the control group of the obtained samples due to constraints and problems when the data was collected. Countermeasures against sample selection bias include heckit, which was advocated by Heckman (1974), DID (difference in difference), known by the works by Besley and Case (2000), and propensity score.

In these appendices, we will explain about sample adjustment using propensity scores, with the analysis of this report as the subject. We will start off with an overview of the theoretical background of propensity scores in Appendix 2. We will then estimate the propensity score in Appendix 3 using data that was used in the main text of this report. In Appendix 4, we will explain about matching as the first example of sample adjustment using propensity score. In Appendix 5, we will explain about stratification using propensity scores as the second example of sample adjustment. Appendix 6 is a summary of what we explained in the appendices.

Appendix 2. Theory on propensity score

Analysis using propensity scores was advocated by Rosenbaum and Rubin (1983). It is used as a method to remove the effect of confounding factors by consolidating several covariates into one propensity score. Since biased samples can be adjusted under certain assumptions to become as close to random samples as possible by using propensity scores, propensity score has the potential to be applied as a technique for dealing with sample selection bias, which we mentioned in the previous section, and has attracted attention since the early

2000s. Its range of application is broad, and many studies have been reported in the fields of medicine, economics, and psychology. There was also a case where propensity score was used in adjustments for online surveys.

An analysis using propensity scores first sets a model that explains with covariates whether samples can be allocated to the group to which intervention is made (treatment group) and estimates the parameters of the model. Using the estimate of the estimated parameters, the predictive probability allocated to the treatment group for each sample is calculated, which is deemed the estimate of propensity score. Then, based on the estimated propensity score, two similar groups are created, with the only major difference between them being the allocation variable: either “1” or “0.” The effect is estimated subsequently. This is the process of the analysis.

Treating data using propensity scores enables to achieve a certain degree of balance in the average covariate between the two groups, making it possible to address the problem of endogeneity. Furthermore, since multidimensional covariates are consolidated into one dimension, it can withstand detailed analysis using stratification.

We define the elements as follows:

Y_1: Dependent variable when intervened (D = 1)

Y_0: Dependent variable when not intervened (D = 0)

D: Allocation variable (1: When intervened; 0: When not intervened)

$\boldsymbol{x}$: Attribute observable as a covariate. However, $\boldsymbol{x}$ shall be a vector whose element is $(x_1, \ldots, x_i)$.

$\mathrm{P}(\boldsymbol{x}) = Pr(D = 1|\boldsymbol{x})$: Predictive probability of sample with attribute $\boldsymbol{x}$ being allocated to $D = 1$

If we deem that the effect of an intervention is the difference between the expected value of the dependent variable of samples allocated to “D=1” and that of samples allocated to “D=0,” the effect will be expressed by the following formula.

$$\mathrm{E}(Y_1|D = 1) - \mathrm{E}(Y_0|D = 0) \quad (1)$$

In this case, if the covariate affects the propensity of being allocated to “D=1,” the estimated result may be biased. Therefore, the effect of intervention is considered as the following formula:

$$\Delta_{D=1}(\boldsymbol{x}) = \mathrm{E}(Y_1 - Y_0|P(\boldsymbol{x}), D = 1) \quad (2)$$

This formula expresses the expected value of the difference in the dependent variable between when intervention was made and when supposing that intervention was not made for samples to which intervention was actually made. Thus, the pure effect of intervention can be derived if the dependent variable of when supposing that intervention was not made to samples to which intervention was actually made can be identified. However, since such data cannot usually be observed, we estimate a proxy for them from the dependent variable of samples to which intervention was not actually made, weighted by P(x). When matching this proxy value and the samples to which intervention was actually made, the estimate of the effect of intervention will be as follows:

$$\hat{\Delta}_{D=1}(x) = \frac{1}{n_1} \sum_{\substack{i=1 \\ \{D_i=1\}}}^{n_1} \left\{ Y_{1i}(\boldsymbol{x_i}) - \hat{E}(Y_{0i}|P(\boldsymbol{x_i}), D_i = 0) \right\} \quad (3)$$

Here, “n1” represents the number of samples to which intervention was actually made. The expected value of the dependent variable of the samples to which intervention was not made, which is used as a proxy, is expressed by the following formula:

$$\hat{E}(Y_{0i}|P(\boldsymbol{x_i}), D_i = 0) = \sum_{\substack{j=1 \\ \{D_j=0\}}}^{n_0} W_i\big(P(\boldsymbol{x_i})\big)Y_{0j} \tag{4}$$

Here, “n0” represents the number of samples to which intervention was not made and “W” represents the weight of when “P(x)” was given. Nearest neighbor matching is used for weighting when making a comparison. In nearest neighbor matching, samples to which intervention was made and samples to which intervention was not made, which have the nearest probability of intervention, are matched, and the dependent variable of the matched samples to which intervention was not made is used as a proxy for the dependent variable of when supposing that intervention was not made to samples to which intervention was actually made.

To estimate the probability of samples with attribute “x” to be allocated to the group to which intervention is made, a logistic regression or a probit regression, which is shown below, is often used. Here, “β” represents the vector that expresses the attribute of the property.

$$\mathrm{P}(\boldsymbol{x}) = \mathrm{Pr}(D = 1|\boldsymbol{x}) = \Phi(\boldsymbol{x\beta}) = \int_{-\infty}^{x\beta} \frac{1}{2\pi} exp\left(-\frac{z^2}{2}\right) dz \tag{5}$$

Appendix 3. Estimation of propensity score

As explained in the previous section, analysis using propensity scores adopts an approach of removing the effect of covariates on the independent and dependent variables by creating samples with similar covariates. There are several ways to create similar samples, and in this study we use the following two: propensity score matching (Appendix 3) and stratification using propensity score (Appendix 4).

In this study, the office new contract rent function is estimated by specifying the existence of green labels and other independent variables that affect new contract rent of office buildings. New contract rent of an office building is generally expressed as a hedonic price function as below, based on the attribute information and green label acquisition status of the office building.

$$\ln R_i = \alpha + green_i{}' \cdot \beta + x_i{}' \cdot \gamma + \varepsilon_i \tag{6}$$

Here, the left member is the dependent variable and a logarithm of the new contract rent of contract example “i.” The second term is the green label dummy, which is “1” if the building has a green label and “0” if not. “x” is a vector that expresses an attribute of type “n” in contract example “i.”

The result of an OLS estimate of the analysis data of this report using a hedonic model of formula (6) is indicated in (1) of **Appendix Figure 1**. Since the same data is used as in the main text of this report (Period 1), we will omit explanations on data such as summary statistics. The result of the estimate was positive and significant at +0.0439 (0.0115) (the figure in brackets is the standard error). This indicates that the new contract rent of buildings with a green label is around 4% higher than that of buildings without a green label. However, does this result justify an assertion that obtaining a green label is an economically rational action that can be expected to lead to greater revenue? We believe that the following points require attention.

Appendix Figure 1: Probit Model that Estimates Propensity Scores and Hedonic Regression Model before and after Sample Adjustment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Base line model	Propensity score estimation model	Propensity score matching	Stratification by propensity score				
				Group 1	Group 2	Group 3	Group 4	Group 5
Intercept	7.8684***	-3.9439***	-74.6288	7.6919***	7.8393***	7.8943***	7.9906***	7.9708***
	(0.0318)	(0.5239)	(86.6478)	(0.0785)	(0.0781)	(0.0816)	(0.0791)	(0.0695)
Green label dummy	0.0439***		-1.6673		0.2453**	-0.0343	0.1378***	-0.0058
	(0.0115)		(1.8874)		(0.1231)	(0.0950)	(0.0328)	(0.0105)
Gross building area (log)	0.1074***	0.4199***	-6.0229	0.1556***	0.0961***	0.0801***	0.0967***	0.0767***
	(0.0090)	(0.1331)	(6.0873)	(0.0216)	(0.0273)	(0.0238)	(0.0220)	(0.0167)
Age	-0.0089***	-0.0727***	-0.0628	-0.0073***	-0.0023**	-0.0074***	-0.0111***	-0.0130***
	(0.0003)	(0.0045)	(0.0554)	(0.0007)	(0.0009)	(0.0022)	(0.0015)	(0.0008)
No. of stories above ground	0.0029***	-0.0146*	1.6052	-0.0004	0.0027	0.0078***	0.0043**	0.0034***
	(0.0007)	(0.0083)	(1.6120)	(0.0018)	(0.0027)	(0.0020)	(0.0019)	(0.0010)
Standard story area (log)	0.0027	-0.0492	17.2996	-0.0452*	-0.0139	0.0104	-0.0008	0.0382**
	(0.0103)	(0.1522)	(17.8718)	(0.0246)	(0.0309)	(0.0226)	(0.0230)	(0.0187)
Time to nearest station	-0.0238***	-0.0149	0.7583	-0.0240***	-0.0215***	-0.0247***	-0.0158***	-0.0218***
	(0.0011)	(0.0178)	(0.7291)	(0.0027)	(0.0032)	(0.0024)	(0.0023)	(0.0022)
Raised floor dummy	0.0040	0.0938	-2.9774	0.0271**	-0.0083	0.0147	-0.0256*	-0.0078
	(0.0058)	(0.1368)	(3.1113)	(0.0124)	(0.0134)	(0.0115)	(0.0133)	(0.0216)
Individual air con dummy	0.0051	0.1596*	-11.5097	0.0158	-0.0134	0.0116	-0.0172	-0.0099
	(0.0066)	(0.0970)	(11.7921)	(0.0167)	(0.0175)	(0.0164)	(0.0140)	(0.0119)
Automated security dummy	-0.0118*	0.1633	12.8193	-0.0495***	0.0078	0.0165	0.0025	0.0081
	(0.0067)	(0.1132)	(13.5811)	(0.0151)	(0.0145)	(0.0166)	(0.0164)	(0.0136)
Renovation dumy	0.0334***	1.0639***	-5.7735	0.0202	-0.0208	0.0946**	0.0553**	0.0397**
	(0.0079)	(0.1257)	(6.2213)	(0.0218)	(0.0233)	(0.0372)	(0.0239)	(0.0182)
Contract moment dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of samples	6,758	6,758	722	1,352	1,351	1,352	1,351	1,352
Percentage of "with green label"	0.0534		0.5000	0.0000	0.0022	0.0030	0.0222	0.2396
Determination coefficient adjusted for degrees of freedom	0.6770		0.9213	0.4669	0.5034	0.4852	0.6218	0.7684
Log likelihood		-831.1474						
AIC		1814.2950						

*Figures in brackets indicate standard error

First of all, buildings with a green label tend to be large and relatively new buildings that are developed and owned by a major developer or a REIT. Since such players have more financial resources than players of small and medium-sized building projects, they can afford to pay the necessary costs for obtaining a green label. In addition, the situation of obtaining a green label should be different depending on the construction period. The environmental performance of newly built office buildings is improving each year on the back of the progress of construction technologies such as the improvement of exterior thermal insulation and efficiency of equipment. For old office buildings with lower environmental performance to obtain a green label, it is necessary to spend costs for prior surveys and renovations. Meanwhile, newly built or recently built office buildings tend to have greater environmental performance in exterior and equipment and are able to obtain a green label more easily.

Appendix Figure 2 shows the aggregation of the analysis data for this study by existence of a green label. While the average values of gross building area and age of samples with a green label (green buildings) are 18,670 tsubo and 8.8 years, respectively, samples without a green label (non-green buildings) tend to be smaller and older at 4,995 tsubo and 24.6 years, respectively. In this study, the distinction between environmental performance and other building performances may also have been difficult. The estimated coefficient of the green label dummy— +4.4%— should be carefully analyzed about whether it is really due to the existence of a green label or whether it may have been affected size, newness, location, and contract timing.

Appendix Figure 2: Comparison of Major Covariates by Existence of Green Label (Sample Unadjusted)

	Green Buildings No. of samples: 361		Non-Green Buildings No. of samples: 6,397	
	Average	Standard deviation	Average	Standard deviation
New contract rent	25,251	7,122	5,030	1,743
Green label dummy	1.000	0.000	0.000	0.000
Gross building area	18,670	24,495	4,995	9,580
Age	8.777	9.775	24.574	11.359
No. of stories above ground	20.172	12.500	11.211	7.037
Standard story area	464	368	223	224
5 central Tokyo wards dummy	0.856	0.352	0.764	0.425
Time to nearest station	2.983	1.804	3.379	2.336
Raised floor dummy	0.956	0.206	0.669	0.471
Individual a/c dummy	0.812	0.392	0.800	0.400
Automated security dummy	0.873	0.334	0.831	0.375
Renovation dummy	0.125	0.331	0.131	0.338

This problem can be expressed as follows when examined from the perspective of an analysis technique called the hedonic approach. If the decision-making of obtaining a green label is influenced by the same variables as for the new contract rent of office buildings, such as size and newness, the method of estimation by distinguishing an office building's new contract rent function by the green label dummy may have generated a problem of endogeneity. Therefore, if we estimated the hedonic function as a simple linear model in the analysis data for this study, the effects related to size, age, and performance will be reflected in the difference between the existence of a green label, leading to a greater likelihood for the estimate to be biased.

Regarding how the effect of green labels influence new contract rent, we estimate the probability of office buildings with office building attribute "x" to obtain a green label by regressing the probit model expressed in formula (5).

The result of the estimate is shown in (2) of **Appendix Figure 1**. The coefficient of building age is estimated with significance as negative, reflecting the fact that relatively new buildings are more likely to be given a green label. Since the coefficients of the raised floor dummy, the individual air conditioning dummy, and the automated security dummy are positive at the 5% level, although not significant, office buildings with better equipment are thought to be more likely to be granted a green label. The estimated coefficient of gross building area is positive, reflecting the fact that larger buildings are more likely to be given a green label. The result for the time to the nearest station is not significant.

The above results indicate that large, relatively new, and high-quality office buildings with good equipment is more likely to have a green label. In order to meet the comprehensive environment performance requirements of green labels, it is necessary to establish good management of the property, such as energy-efficient exterior and air conditioning equipment, water-saving hygiene facilities, greening of the surroundings, appropriate maintenance, disaster prevention, and BCP. We believe that the background to the results was that only large office buildings could manage to acquire the site and ensure business profitability upon installing and maintaining such equipment.

Appendix 4. Propensity score matching

Appendix Figure 3 indicates, by existence of a green label, the descriptive statistics value of samples extracted by nearest neighbor matching using the estimated propensity score. Since office buildings with a green label and those without are matched at a 1:1 ratio, the number of samples will each be 361, totaling 722. When compared with the unadjusted samples of **Appendix Figure 2**, the average gross building area of non-green buildings after the matching has significantly closed in on that of the unadjusted samples, at 14,698 tsubo. The difference in the average age of non-green buildings has also been reduced at 8.4 years. The other variables have also been adjusted in general, with the difference between the two sample groups reduced due to the matching, creating similar samples.

Appendix Figure 3: Samples after Propensity Score Matching

	Green Buildings No. of samples: 361		Non-Green Buildings No. of samples: 361	
	Average	Standard deviation	Average	Standard deviation
New contract rent	25,251	7,122	25,207	7,548
Green label dummy	1.000	0.000	0.000	0.000
Gross building area	18,670	24,495	14,693	16,958
Age	8.780	9.770	8.360	8.030
No. of stories above ground	20.170	12.500	18.320	10.260
Standard story area	464	368	422	339
5 central Tokyo wards dummy	0.856	0.352	0.839	0.368
Time to nearest station	2.983	1.804	2.806	2.163
Raised floor dummy	0.956	0.206	0.928	0.259
Individual a/c dummy	0.812	0.392	0.820	0.385
Automated security dummy	0.873	0.334	0.892	0.311
Renovation dummy	0.125	0.331	0.086	0.281

The result of the estimate by the hedonic approach of samples extracted by the matching is indicated in (3) of **Appendix Figure 1**. The estimated coefficient of the green label dummy was -1.67 (1.88), which is not significant. When interpreted as is, this result indicates that green labels do not have an effect on new contract rent, a different result than the analysis in Appendix 3.

The point that requires attention here is the fact that the extracted 722 samples mainly consist of large and new office buildings, due to the method of matching 361 green building samples against non-green building samples with the nearest propensity score out of 6,397 samples of non-green buildings at a 1:1 ratio. This is also clear in the fact that non-green buildings in **Appendix Figure 3** are adjusted to large-scale and relatively new buildings. In other words, the data of the approximately 6,000 non-green buildings that were not matched has been discarded.

Therefore, it would be appropriate to interpret the analysis results in this section as meaning that the effect of green labels is almost nonexistent or marginally negative among relatively large and new office buildings but that the effect among other office buildings is unknown. In an analysis using propensity score matching, there is the problem of not being able to confirm the effect of green labels in old, small and medium-sized office buildings.

Appendix 5. Stratification using propensity score

In order to solve the problem of Appendix 4, we divided the samples into five groups based on the size of their propensity scores. Since buildings with a low propensity score tend to be small and old, analysis can be expected in groups with medium to low propensity scores. The calculation method of propensity scores is the same as in Appendix 3. The analysis data is divided into five groups using the estimated propensity scores. The number of samples of each group has been made roughly the same by using the quintile point as the segmentation boundary.

Appendix Figure 4 indicates the descriptive statistics value of the samples of Group 4 and Group 5 by existence of a green label. Even in Group 4, the average gross building area of green buildings is 6,018 tsubo while that of non-green buildings is 4,439 tsubo, showing a smaller difference between the two compared to **Appendix Figure 2**, which is before sample adjustment. The difference in average age is also smaller, with 19.3 years for green buildings and 22.2 years for non-green buildings.

In Group 5, the difference in average gross building area has been reduced, with 20,162 tsubo for green buildings and 13,560 tsubo for non-green buildings. The difference in average age has also been reduced, with 7.3 years for green buildings and 10.7 years for non-green buildings. The other variables have also been adjusted in general, with the difference between the two groups reduced due to stratification using propensity score as well, creating similar samples. Furthermore, unlike in matching, stratification enables to obtain samples for which the covariates have been adjusted in medium-sized and old buildings as in the buildings in Group 4.

Appendix Figure 4: Samples after Stratification using Propensity Score (Groups 4 and 5)

	Group 4				Group 5			
	Green Buildings		Non-Green Buildings		Green Buildings		Non-Green Buildings	
	No. of samples: 30		No. of samples: 1,321		No. of samples: 324		No. of samples: 1,028	
	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
New contract rent	18,950	5,611	17,196	4,695	25,985	6,922	23,131	6,737
Green label dummy	1.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
Gross building area	6,018	4,874	4,439	5,875	20,162	25,382	13,560	16,158
Age	19.327	8.356	22.194	7.882	7.261	8.444	10.682	8.131
No. of stories above ground	14.867	6.704	11.341	5.940	20.870	12.820	17.986	10.786
Standard story area	213	113	230	176	493	376	382	280
5 central Tokyo wards dummy	0.700	0.466	0.845	0.362	0.874	0.333	0.841	0.365
Time to nearest station	1.833	0.834	3.528	2.310	3.074	1.836	3.009	2.277
Raised floor dummy	0.733	0.450	0.810	0.393	0.982	0.135	0.941	0.236
Individual a/c dummy	0.567	0.504	0.799	0.401	0.830	0.376	0.793	0.406
Automated security dummy	0.967	0.183	0.894	0.308	0.861	0.346	0.890	0.313
Renovation dummy	0.000	0.000	0.207	0.406	0.133	0.340	0.119	0.324

(4)–(8) of **Appendix Figure 1** shows the estimates of the hedonic function of each group as in Appendix 3. In Group 5 (8), which has the highest propensity scores, the figure was a near-zero negative at -0.0058 (0.0105). The covariates of Group 5 mostly consist of large and relatively new building samples, and this result is consistent with the result of Appendix 4, which uses propensity score matching. In Group 4 (7), we found that there was a significantly positive effect at +0.1378 (0.0328). Compared to Group 5, Group 4 tends to have more medium-sized and old office buildings. The reason why the results were not significant for Groups 1–3 was probably due to the small percentage of green buildings and thus the lack of enough samples to measures the effect.

In view of the results of Appendix 4 as well, it is implied that the effect of green labels on new contract rent varies depending on the market segment. Tokyo's office building market, the target of this study, has one of the world's largest stocks. The age of office buildings is broadly distributed and thus their environmental performance varies due to the city's experience of high economic growth, the oil shock, and the birth and burst of the bubble economy. In terms of the companies, who are the users of office buildings, the 23 wards of Tokyo have a concentration of numerous companies diverse in scale. Furthermore, Tokyo is not dependent on certain industries, but all kinds of industries exist in it, such as manufacturing, telecommunications, finance, restaurant, and service. Due to these factors, the office market of the 23 wards of Tokyo is huge and diverse, and considered to consist of multiple segments with different pricing systems of rent. In other words, the effect that green labels has on new contract rent is not +4.4% generically for all office buildings but varies by the nature of the building. In particular, the effect is almost nonexistent among large buildings, which are likely to obtain a green label, while it is prominent at approximately +10% among medium-sized buildings.

Appendix 6. Summary

In these appendices, we used propensity scores to estimate the propensity of obtaining a green label and adjusted samples by matching and stratification. By doing so, we indicated that it was possible to collect only samples with a similar market structure. Using the techniques indicated in this analysis will enable us to estimate the effect of intervention more precisely in a market with a complex market structure as the Tokyo office market.

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