Do Green Labels Signal Quality? Green Price Premiums and Market Dynamics in Taiwan's Housing Sector

Tsung-Yu Ho Yating Chuang

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Abstract

Despite the environmental and financial benefits of energy-efficient buildings, underinvestment in residential energy efficiency remains prevalent. This study examines the price premium effects associated with green building certifications under Taiwan's Green Building Labeling system. Using housing transaction data from New Taipei City spanning 2013–2023, we employ different matching methods and fixed-effects regression models to control for potential biases. Our results show an average green certification premium of approximately 3.8%. However, this premium exhibits a non-linear pattern: statistically significant premiums of 4.6% and 5.2% occur only at mid-tier certification levels (Bronze and Silver), while no significant premiums are observed at lower (Qualified) or higher (Gold and Diamond) certification levels. Additionally, the green building price premium increases with building age, suggesting stronger signaling effects in resale markets due to uncertainty regarding building quality and energy efficiency. We use a signaling model to explain these observed market dynamics. In contrast, presale market transactions show no significant premiums, possibly because of higher initial expectations and the limited informational value of certification for newly constructed buildings.

1 Introduction

As countries strive to achieve carbon neutrality, the building sector has emerged as a critical focus of climate action as they are responsible for nearly 30% of global energy consumption and a significant share of CO_2 emissions (International Energy Agency, 2024). Green buildings, which incorporate energy-efficient and environmentally sustainable design elements, are widely recognized as a promising strategy to meet net-zero goals. In this context, promoting green building adoption is a necessary policy tool to drive long-term sustainability in the residential housing sector.

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Despite the environmental and financial benefits of energy-efficient buildings, underinvestment in residential energy efficiency remains a persistent concern. As Allcott and Greenstone (2012) argue, energy efficiency may suffer from a classic "lemons" problem (Akerlof, 1970): buyers cannot easily observe or evaluate the quality of energy performance, especially in the residential sector where technical knowledge is limited. This information asymmetry is one reason why take-up of cost-effective energy retrofitting programs remains low, even when subsidies are available.[1] 2017). To close this efficiency gap, governments typically employ two complementary approaches: mandatory building codes and voluntary green certification schemes (Matisoff et al., 2016). Building codes ensure a minimum level of performance, while certification systems seek to reduce information asymmetry by providing standardized signals of environmental quality to prospective buyers. However, the effectiveness of these policy tools can vary across market contexts. If certification functions as a credible signal, it will be associated with a discernible price premium that reflects buyers' willingness to pay for quality. Estimating these premiums—especially under different certification levels—can offer insight into whether voluntary certification serves as a viable market-based complement to regulation. Our study contributes to the existing literature by examining Taiwan's green building label system and assessing how buyers respond to varying levels of green certification in the housing market.

In this paper, we study Taiwan's Ecology, Energy Saving, Waste Reduction, and Health (EEWH) certification system—a holistic, formula-based green building label—and estimate its effect on housing prices in New Taipei City. Developed by the Architecture and Building Research Institute under the Ministry of the Interior, EEWH is a government-directed program supported by professional organizations such as the Taiwan Green Building Council. We try to understand several questions: Does Taiwan's green building certification serve as a credible signal and reflect on housing prices? If so, how do the price effects vary across environmental and socio-economic factors? To answer these questions, we use more than 420,000 housing transactions between 2013 and 2023 in the Actual Price Registration of Real Estate Transactions for New Taipei City. We apply several matching methods and fixed-effects regression to quantify the average price premium and test for heterogeneity across certification levels and building types.

We find that EEWH-certified homes carry an average 3.8% price premium, but this premium is nonlinear. Only mid-tier certifications (Bronze and Silver) are associated with statistically significant price premiums, but the lower (Qualified) and upper-level (Gold and Diamond) ceritifications are not. Moreover, the average price premium is significantly larger for older buildings than for new or presale units. We interpret these findings through a simple signaling model, in which green labels convey more information when people hold

[1] Fowlie et al. (2018) find that even with substantial subsidies for whole-house retrofitting under the Weatherization Assistance Program and aggressive outreach effort, the take-up rate remains pretty low–only about 6 %. Without the encouragement intervention, participation is only less than 1% of the control group

lower prior belief about the energy efficiency of a randomly chosen house (in our case, older buildings in the resale market), and thus have a greater impact on valuations.

Our paper contributes to the literature in three ways. First, we add to the growing body of work on the price effects of green building certification, which has mostly focused on commercial and office buildings and housing markets in Europe and North America (Eichholtz et al., 2010; Fuerst and McAllister, 2011; Kok and Jennen, 2012).[2] By analyzing Taiwan's EEWH system–a formal, multi-tiered green certification program–we show that price premiums exist but are nonlinear, concentrated in the mid-tier Bronze and Silver levels. This pattern contrasts with earlier findings that suggest premiums increase monotonically with certification level(Brounen et al., 2013; Hyland et al., 2013; Fuerst et al., 2016).[3] It aligns more closely with recent evidence showing that price premium does not systematically increase with label class (Aydin et al., 2020).[4] Some other papers have examined price premium of green building labels in residential sectors, but only use one dimension without identifying the relationship between grade intensity and price premium (Deng and Wu, 2014; Walls et al., 2017; Kahn and Kok, 2014).

Second, we provide novel empirical evidence that green labels function as signals under different market conditions. The price premium is concentrated in the resale market, where building quality is less observable and certification offers stronger informational value. In contrast, the signaling value is weaker in the presale market, where homes are new and buyers rely more on developer-provided information. This finding supports a signaling interpretation of green labels and reveals a previously underexplored dynamics in residential real estate markets. Importantly, Taiwan's housing market—like those in some other Asian countries—features both an active presale market (based on floor plans) and a resale market with observable building characteristics. This dual structure uniquely allows us to examine how green labels signal quality at different transaction stages. To our knowledge, only one prior study has explored how certification effects vary across transaction stages. Zheng et al. (2012) highlight the signaling role of green labels in presale and resale markets in Beijing. However, since China did not have an established green certification system at the time, their analysis relies on a Google-based index of marketing language rather than a standardized certification verified by third-party institutions. As a result, their "green" label may reflect not only the presence of green features, but also consumer perceptions. In contrast, our

[2]In Shewmake and Viscusi (2015), one level–the second (2-star rating) level does not show significant price premium, but the magnitude roughly follows the monotone increasing pattern as certification grade increases.

[3]Zhang et al. (2018) provides a comprehensive review of green building price premiums across different certification levels, noting that nearly all the studies found that price premiums monotonically increase with the grade level. The studies are for example

[4]Notably, Aydin et al. (2020) use a continuous energy performance index and employ instrumental variable strategies to identify the causal impact of energy efficiency in the Dutch housing market. They find that the presence of a label does not independently affect prices once energy efficiency is controlled for, and they observe limited price variation across label classes.

study uses actual transaction data matched with a formal, government-backed certification system. This institutional setting offers a credible framework for empirically testing signaling predictions, as the certification is more plausibly exogenous to individual consumer preferences. This distinction is critical in signaling models, which rely on a separation between the cost or observability of the signal and the receiver's valuation of the underlying quality.

Third, this paper contributes theoretically by using a simplified signaling model combined with comparative statics to explain differing patterns in green-building price premiums observed in presale versus resale markets. In the resale market, green labels serve as strong signals effectively distinguishing high-quality, energy-efficient buildings, resulting in significant price premiums. In comparison, in presale markets, the signaling mechanism weakens because all properties are relatively new and inherently energy-efficient, thus failing to result in a clear separating equilibrium. This distinction helps clarify why observed premiums are more pronounced in resale transactions than in presales, and it also sheds light on the underlying market dynamics and signaling effectiveness. Finally, we also extend our model to show how the price premiums may exhibit an inverted U-shape–positive at the middle tier but not significant at the lowest and highest tiers–due to heterogeneity in consumer preferences and producers' costs for certification.

Finally, the observed nonlinearity in green building price premia we find has important implications for future policy design. In contexts where regulators can act as information designers to promote green building adoption, the high social costs of delaying progress toward net-zero carbon targets suggest that coarse certification schemes, like those used in Taiwan, may be more welfare-improving than fully continuous disclosure systems. Our results are consistent with a threshold-type behavioral response: once posterior beliefs about a building's green quality exceeds a threshold, buyers are willing to pay a price premium, and additional information above or below this threshold has limited marginal impact on behavior. Coarse certification can therefore shift more marginal buyers' posterior beliefs across the adoption threshold by providing a clearer, more decisive signal in some cases, without uniformly raising perceived quality across all buildings. In contrast, continuous rating schemes may add precision in regions that have limited behavioral bite. This may leave a large share of buyers near (but below) the threshold and yield weaker adoption responses. This threshold-based logic is precisely where coarse, partially revealing disclosure can be useful (e.g., Rayo and Segal (2010); Kamenica and Gentzkow (2011)). In this sense, when policymakers' welfare objective is to reduce false negatives and encourage green building adoption, coarse information disclosure may be more effective than fully continuous disclosure.[5]

[5]In this context, a false negative refers to a case in which a building with substantial environmental benefits fails to receive a price premium due to informational frictions. A false positive, in contrast, occurs when a building with relatively limited environmental benefits receives a price premium as a result of overly coarse or imperfect information. From a policy perspective, false negatives in this case are particularly costly because they delay climate mitigation by discouraging the adoption of environmentally beneficial buildings, whereas false positives primarily reflect the cost of greenwashing or misallocated rewards. Importantly,

The remainder of this paper is organized as follows. Section 2 introduces the EEWH green building certification system in Taiwan. Section 3 describes the data and presents summary statistics. Section 4 outlines our empirical methodology, including the matching strategy and regression models. Section 5 presents the main results and discusses heterogeneity in price premiums across certification levels and market dynamics, incorporating both a theoretical model and empirical analysis. Section 6 conducts robustness checks, and Section 7 concludes.

2 Green Building Certification in Taiwan

Taiwan's EEWH system–short for Ecology, Energy Saving, Waste Reduction, and Health–is the country's official green building certification framework. Introduced in 1999, EEWH was the first green building evaluation system globally to be specifically designed for subtropical climates, and remains one of the earliest national-level green building systems worldwide (Architecture and Building Research Institute (ABRI), 2023). Unlike standards developed in temperate regions, EEWH is tailored to Taiwan's unique environmental conditions, including high humidity, typhoons, intense heat, and dense urban landscapes.

The EEWH system, administered by ABRI in collaboration with local construction authorities, evaluates projects across four major green categories and nine assessment indicators: biodiversity, greenery, on-site water retention, energy savings, CO_2 reduction, construction waste reduction, indoor environmental quality, water resources, and sewage and garbage management. Among these, energy savings and water resources are mandatory indicators; projects must meet minimum thresholds for both to be eligible for certification.

Certification is awarded across five levels—Qualified, Bronze, Silver, Gold, and Diamond—based on a building's weighted overall score. Unlike common international green building evaluation systems such as LEED, which adopt a menu-based, checklist-style approach—awarding points separately for each sustainability feature with independent credits and discrete scoring—Taiwan's EEWH system fundamentally differs in its evaluation philosophy. EEWH employs a holistic, formula-driven scoring framework that explicitly accounts for the interdependencies among sustainability dimensions. Specifically, each indicator is assigned both a baseline value and a design value under varying conditions. The normalized difference between these two values is then substituted into a formal scoring formula (such as RS_i) to derive a continuous performance score for each category. Rather than rewarding isolated green design choices, EEWH systematically evaluates a building's integrated environmental performance, emphasizing synergies, trade-offs, and cumulative impacts across categories. This structure encourages more flexible, innovative, and cost-effective combinations of sustainable design elements while reducing the risk of overinvestment in any single domain. Each indicator is assigned a corresponding weight, and the building's final total

however, a coarser disclosure scheme may reduce false negatives precisely by tolerating more false positives, so the welfare ranking depends on the relative social costs of false negatives versus false positives.

score determines its certification level (see Table 1 and Table 2 for detailed scoring categories and fomulas).

Since its introduction, EEWH certification has been widely adopted. As of October 20, 2024, a total of 4,476 development projects in Taiwan had received EEWH certification. According to the 2023 Green Building Evaluation Manual, certified buildings demonstrate approximately 20% improvements in both building envelope performance and air conditioning and lighting energy efficiency relative to the 2000 market baseline. Over the past two decades, EEWH-certified projects have collectively achieved annual savings of approximately NT11.7 billion dollars and reduced 1.63 billion kilograms of CO_2 emissions.

In response to global trends toward carbon neutrality, particularly after the 2015 Paris Agreement, Taiwan has progressively updated EEWH standards to incorporate near-zero-carbon building targets under the guidance of ABRI. A complementary system, EEWH-BERS (Building Energy Efficiency Rating System), was introduced to evaluate operational energy performance more explicitly. Under the current EEWH framework, residential buildings achieving a 30% or greater reduction in operational carbon emissions relative to the 2000 baseline are eligible for NZCB (Nearly Zero Carbon Building) designation.

Compared to international programs, EEWH reflects a distinct philosophy. LEED emphasizes modular credit accumulation across various sustainability categories, Energy Star focuses narrowly on energy efficiency benchmarks, and Energy Performance Certificates (EPCs) provide simple energy grading (A–G) mainly for residential transactions in Europe. In contrast, EEWH's integrated, formula-based structure offers a comprehensive evaluation of overall environmental performance, balancing energy conservation, ecological impact, waste reduction, and health considerations. This institutional design makes EEWH valuable for studying the role of certification signals in real estate markets, particularly in subtropical climates and highly urbanized contexts.

Table 1: Scoring Categories of EEWH System.

Category	Indicator			Design value	Baseline value	Normalized difference	Score		
							Scoring formula RSi = a * Ri + c	Maximum points	Total points
Ecology	Biodiversity			BD	BDc	R1 = (BD - BDc) / BDc	RS1 = 18.75 * R1 + 1.5	9	27
	Greenery			TCO2	TCO2c	R2 = (TCO2 - TCO2c) / TCO2	RS2 = 6.81 * R2 + 1.5	9	
	On-site water retention			λ	λ_c	R3 = (λ - λ_c) / λ	RS3 = 4.0 * R3 + 1.5	9	
Energy	Energy savings	House	Building envelope design	EEV	Table lookup	$RS4_1$ = 20.0 * EEV		10	33
			Air conditioning	EAC	0.9	$RS4_2$ = 17.2 * (0.9 - EAC)		5	
			Indoor lighting	EL	0.9	$RS4_3$ = 12.0 * (0.9 - EL)		6	
			Water heater	Energy Efficiency Labeling		$RS4_4$ = Table lookup of energy efficiency for water heater		6	
			Stove	Energy Efficiency Labeling		$RS4_5$ = Table lookup of energy efficiency for stove		6	
		Apartment building	Building envelope design	EEV	Table lookup	$RS4_1$ = 10.0 * EEV		5	33
			Air conditioning	EAC	0.9	$RS4_2$ = 13.8 * (0.9 - EAC)		4	
			Indoor lighting	EL	0.9	$RS4_3$ = 8.0 * (0.9 - EL)		4	
			Water heater	Energy Efficiency Labeling		$RS4_4$ = Table lookup of energy efficiency for water heater		6	
			Stove	Energy Efficiency Labeling		$RS4_5$ = Table lookup of energy efficiency for stove		6	
			Parking garage ventilation	Based on the adopted system		System score of parking garage ventilation		4	
			Elevator	Based on the adopted system		System score of elevator		4	
Waste Reduction	CO2 emission			CCO2	0.82	R5 = (0.82 - CCO2) / 0.82	RS5 = 19.4 * R5 + 1.5	8	15
	Construction waste reduction			PI	3.3	R6 = (3.3 - PI) / 3.3	RS6 = 13.13 * R6 + 1.5	7	
Health	Indoor environment			IE	60	R7 = (IE - 60) / 60	RS7 = 18.67 * R7 + 1.5	12	25
	Water resources			WI	2	R8 = (WI - 2.0) / 2.0	RS8 = 2.50 * R8 + 1.5	8	
	Sewage and garbage improvements			GI	10	R9 = (GI - 10) / 10	RS9 = 5.15 * R9 + 1.5	5	

Note: Since the data consist of residential buildings and apartments, the green building label used in our sample follows the guidelines in the manual titled "Green Building Evaluation Manual–Residential Building."

Table 2: Scoring Range for Each Level of the EEWH System.

EEWH Certification Level	Total Score	Total Score (exclude biodiversity indicator)
Qualified	$20 \leq RS < 37$	$18 \leq RS < 34$
Bronze	$37 \leq RS < 45$	$34 \leq RS < 41$
Silver	$45 \leq RS < 53$	$41 \leq RS < 48$
Gold	$53 \leq RS < 64$	$48 \leq RS < 58$
Diamond	$64 \leq RS$	$58 \leq RS$

Note: Buildings occupying less than 1 hectare are not evaluated on the biodiversity indicator.

3 Data and summary statistics

This paper utilizes all residential data from Actual Price Registration of Real Estate Transactions in New Taipei City. Surrounding Taiwan's capital, Taipei, New Taipei City has a moderate average population density of approximately 1,947 people per km^2, though some districts, such as Luzhou, are significantly denser with over 26,600 people per km^2. This higher density in certain districts is comparable to densities found in highly urbanized areas such as Tokyo (average density 6,158 people per km^2) and Manhattan in New York City, where population densities regularly surpass 20,000 people per km^2. The platform aims to address irrational housing prices and market failures by providing transparent real estate transaction information to the public, which is also highly useful for hedonic analysis.

We focus on home sales over the 2013 to 2023 period in New Taipei City, and whether a house has obtained a green building label is based on the Taiwan Architecture and Building Center. We focus on New Taipei City because it has the largest number of green-certified residential projects and exhibits neighborhood diversity that provides sufficient variation for our econometric estimation. In addition, New Taipei City is a densely populated metropolitan area characterized by high-rise apartment living, and thus shares many similarities with urban residential environments in other Asian countries, enhancing the external relevance of our findings.

Despite the temporal variation in our data, we analyze them as repeated cross-sections due to the limited occurrence of multiple sales for the same unit. As all green buildings in New Taipei City are part of apartment complexes, we focus our analysis on this type of data. In metropolitan Taiwan, apartment complexes are the standard form of residential housing, particularly for newly constructed buildings. To deal with the impact of outliers, we eliminate unreasonable observations as well as those below the 1st percentile and above the 99th percentile from our data.[6] In addition, we impute certain missing values to retain as

[6]To better focus on the price premium of green buildings, we also excluded data that included multiple floors or additional features, such as balconies, mezzanines, and terraces.

many observations as possible because many variables from the Actual Price Registration of Real Estate Transactions are not mandatory reporting fields. For building age, we estimate the values for green buildings by calculating backward from their completion dates, whereas for non green buildings, the variable is left unreported. For the number of bedrooms, living rooms, and bathrooms, we impute them by substituting the respective group means.

Table 3 presents summary statistics for green and non-green buildings. The table includes three categories of variables: dwelling, locational, and green label characteristics. Green buildings have a higher average price, larger size, newer and greater price volatility compared to non-green buildings. The interior space layout, including the number of bedrooms, living rooms, and bathrooms, is similar between green and non-green buildings. In terms of locational characteristics, green buildings are usually located in areas with better transportation accessibility. These differences highlight the importance of using matching method to account for factors that are related to both certification and home prices.

Table 3: Comparison of green-labeled dwellings and other homes. (standard deviations in parentheses)

	Non-green buildings		Green buildings		
Observations	379,524		42,658		
Dwelling characteristics					
Sales price(ten thousands of NT dollars)	1405.62	(716.99)	1935.56	(908.72)	-
Sales price per ping(NT dollars)	36.61	(13.42)	42.74	(13.11)	-
Building age(years)	8.96	(9.72)	1.37	(2.55)	-
Dwelling size(ping)	41.58	(16.55)	50.61	(22.24)	-
Number of bedrooms(number)	2.64	(0.81)	2.64	(0.83)	-
Number of living rooms(number)	1.80	(0.42)	1.83	(0.38)	-
Number of bathrooms(number)	1.63	(0.57)	1.70	(0.63)	-
Parking space	0.72	(0.45)	0.79	(0.41)	-
Locational characteristics					
Transportation accessibility	0.18	(0.39)	0.30	(0.46)	-
Cooling degree days per year(thousands)	3.59	(0.32)	3.61	(0.25)	-
Electric motorcycles share(percent×100)	0.030	(0.012)	0.026	(0.011)	-
Median income tax(thousands / per village)	615.48	(116.74)	619.10	(100.68)	-
Green building certification level	Observations	Percentage	Observations	Percentage	Average Number of Obtained Indicators
Diamond	-	-	3,678	8.62%	7.75
Gold	-	-	7,846	18.39%	7.07
Silver	-	-	25,199	59.07%	6.71
Bronze	-	-	1,002	2.35%	5.10
Qualified	-	-	4,590	10.76%	4.29
Earlier assessment	-	-	343	0.80%	-

Notes: These summary statistics are based on the sample after excluding the top and bottom 1% of the data. One ping is equal to 35.58 square feet.

4 Empirical methodology

4.1 Matching

The observational data present challenges in identifying the causal effect of the green building label on housing prices, as buildings that receive green building labels may be highly selected. Because of this concern, we implement three widely used matching techniques: Coarsened Exact Matching (CEM)(Iacus et al., 2012), Propensity Score Matching (PSM)(Rosenbaum and Rubin, 1983), and Nearest-Neighbor Matching (NNM)(Rubin, 1973; Abadie and Imbens, 2006)[7]. Each of them offers a different way of addressing the selection problem. Specifically, CEM achieves balance by temporarily coarsening the covariates into discrete strata and then performing exact matching within these strata. PSM relies on estimating the probability of being a green building conditional on observable covariates, and then matches treated and untreated units with similar propensity scores. NNM directly compares observations based on the multidimensional covariate space and identifies the nearest control neighbors for each treated unit. We adopt one-to-one matching across all methods.

We follow the commonly used covariates in the hedonic pricing and real estate literature for the matching procedures (Kahn and Kok, 2014; Walls et al., 2017; Aydin et al., 2020). The set of covariates includes: building age, dwelling size, number of bedrooms, number of living rooms, number of bathrooms, transportation accessibility, and the availability of parking space. In addition, we further incorporate latitude and longitude in the NNM and PSM model since spatial proximity plays a crucial role in shaping property values.[8]

To assess the quality of the matching process, we rely on standardized bias measures, which quantify the extent to which the mean values of covariates differ between green and non-green buildings in standardized units (Rosenbaum and Rubin, 1985; Caliendo and Kopeinig, 2008; Imbens, 2015). A lower standardized bias indicates a higher degree of balance and hence greater comparability between the treatment and control groups. We also examine the p-values from two-sample t-tests of mean differences. Using the samples derived from these matching methods, we estimate a hedonic pricing model to evaluate the price premium associated with green buildings.

4.2 Hedonic model

Using the matched sample, we estimate a log-linear hedonic price model as follows:

$$\ln(P_{ijt}) = \alpha_0 + \beta_1 GB_i + X\beta + \gamma_t + \eta_j + \varepsilon_{ijt} \tag{1}$$

[7]The NNM estimator is implemented using Mahalanobis distance, which matches treated and control units based on a covariance-adjusted metric that accounts for variable scale and correlation.

[8]We do not include latitude and longitude in the CEM model, as it often results in overly fine spatial bins that lead to substantial sample loss

where P_{ijt} is the sale price per ping (35.58 square feet) of observation i in village j in year t.[9] The primary variable of interest is GB_i, a dummy variable indicating whether the building is certified as a green building. The coefficient β_1 captures the effect of certification on housing price. The regression includes a vector of house characteristics, X, village fixed effects (η_j), and year fixed effects (γ_t). All the standard errors are clustered at the village level.

In the second set of estimates, we include additional interaction terms in (Eq.2), interacting "GB_i" with vector Z of various characteristics (Eq.1):

$$\ln(P_{ijt}) = \alpha_0 + \beta_1 GB_i + \beta_2 GB_i Z + X\beta + \gamma_t + \eta_j + \varepsilon_{ijt} \tag{2}$$

We estimate Eq. (2) to examine whether the price premium effect varies with key factors such as green certification level,[10] climatic conditions, environmental consciousness, median income tax across districts, and building age.

We expect that green buildings are more valuable at higher certification levels, in areas that experience more hot days, and in villages where more green products are sold. In addition, consumers with higher environmental consciousness may place greater emphasis on sustainable development and healthy living, leading to a higher price premium in areas with greater environmental awareness. Because we do not have direct survey measures of individual environmental consciousness, we proxy for it using the share of electric motorcycles among all motorcycles in each district. As of 2023, Taiwan had 13.7 million motorcycles for 9.2 million households—approximately 1.48 motorcycles per household—making motorcycle usage a representative indicator of community-level environmental awareness across income groups. Green buildings may also offer long-term savings in energy expenditures, which could help maintain value as buildings age. We therefore use the interaction between building age and GB_i to analyze whether green buildings maintain their price competitiveness better than non-green buildings as they age.Finally, households in higher-income areas may have a greater willingness to pay a higher premium for green buildings. We use the interaction between the median income tax in each village and GB_i to verify this hypothesis.[11] Finally, We use the interaction between building age and GB_i to analyze whether green buildings maintain their price competitiveness better than non-green buildings as they age.

[9] In Taiwan, the village is the forth-level administrative division, under districts, townships, towns or cities.

[10] The specification for testing the price effects of different green certification levels is:
$\ln(P_{ijt}) = \alpha_0 + \beta_1 GB\_qualified_i + \beta_2 GB\_bronze_i + \beta_3 GB\_silver_i + \beta_4 GB\_gold_i + \beta_5 GB\_diamond_i + \beta_6 GB\_earlier\ assessment_i + X\beta + \gamma_t + \eta_j + \varepsilon_{ijt}$

[11] The most recent income tax data available in our dataset are from 2021, which limits the computation of village-level averages to that year.

5 Results

5.1 Basic Results: Green Building Premiums

Among the three matching methods, the NNM approach achieves the best covariate balance. As Table 4 shows, all the covariates are balanced between treated and control groups except that building age appears to be slightly different, and even this difference is small in economic terms. Thus, our preferred model is the NNM approach. We present all matching results in the main regression but keep only NNM for the later subgroup analysis. For brevity, we present the balance tables for the coarsened exact matching (CEM) and propensity score matching (PSM) samples in the Table A-2 and Table A-3.

Table 5 presents the results of the baseline ordinary least squares (OLS) regression model. Columns (1) through (4) report the estimates based on the full unmatched sample, the Coarsened Exact Matching (CEM) sample, the Propensity Score Matching (PSM) sample, and the Nearest-Neighbor Matching (NNM) sample, respectively. To account for temporal trends and spatial heterogeneity in local public goods, all models incorporate neighborhood and year fixed effects. Standard errors are clustered at the village level to control for intragroup correlation.

Based on the matched sample, where we have dealt with potential selection issues, the green price premium is between 3.8% and 5% (See column (2) to (4)). This magnitude is smaller than the unmatched OLS estimation (6.8%). Our preferable model is the NNM model in column 4, which shows 3.8%, as this model gives the best covariate balance.

When we compare the results with the most relevant related literature in Taiwan, we find that most papers using Taiwan data report a much larger price premium than ours (ranging from 4.5 % to even 17.7%). However, all these papers do not take into account the endogeneity, so all of them use only OLS regression estimation. The most relevant comparison is Chen and Liang (2018), which uses the New Taipei City data from 2012-2014. They find that price premium for green buildings is around 7.5%, which is much higher than ours. However, since they do not use any matching and use a much shorter time frame than we do, we restrict our sample into similar time frame to re-run our NNM estimation. The result in Table 5, column (5), shows that the price premium is around 5.2 % using earlier years of data–still below the unmatched estimate in their paper. We suspect that this likely reflects unobserved characteristics correlated with both green construction and housing prices. Our more conservative result may better represent the true premium.

To place our findings in the context of prior literature that more carefully addresses endogeneity, we note that our results are consistent with Brounen and Kok (2011) in the Netherlands, Deng et al. (2012) in Singapore, Walls et al. (2017) in three U.S. cities, and Kahn and Kok (2014) in California. All of them find that buildings with energy efficiency or green certifications yield modest price premiums (all less than 5 %).

Table 4: Balance of NNM matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.589	1.360	0.229	12.8961	0.0000	-0.08830
	(0.013)	(0.012)	(0.018)			
Dwelling size	50.387	50.612	-0.225	-1.4897	0.1363	0.01020
	(0.106)	(0.108)	(0.151)			
Number of bedrooms	2.642	2.643	-0.001	-0.0433	0.9655	0.00030
	(0.004)	(0.004)	(0.006)			
Number of living rooms	1.826	1.827	-0.001	-0.4204	0.6742	0.00288
	(0.002)	(0.002)	(0.003)			
Number of bathrooms	1.701	1.704	-0.003	-0.7591	0.4478	0.00520
	(0.003)	(0.003)	(0.004)			
Transportation accessibility	0.295	0.295	0	0.0000	1.0000	0
	(0.002)	(0.002)	(0.003)			
Parking space	0.790	0.790	0	0.0000	1.0000	0
	(0.002)	(0.002)	(0.003)			
Observations	42,658	42,658				

Notes: The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses. One-to-one Nearest-Neighbor Matching is employed, requiring exact matching for dummy variables (transportation accessibility and parking spaces), while other matching variables are continuous (building age, dwelling size, number of bedrooms, living rooms, and bathrooms, and geographical coordinates).

5.2 Heterogeneity in Green Building Premium Effects

To examine the heterogeneity of the green building premium effects, we consider the matched sample and the following covariates: green certification level, climatic conditions, a proxy for environmental consciousness, average median income tax across districts, and building age. The corresponding regression results are presented in Table 6. Since the Nearest-Neighbor matched (NNM) sample provides the best covariate balance and yields the most conservative estimate of the green building premium, all the analyses are based on this matched sample.

The results in column (1) show that the price premium of green buildings occurs only at the bronze and silver levels, at 4.6% and 5.2%, respectively. This result suggests that consumers recognize the value of green buildings only when they achieve at least the bronze level as public awareness increases over time. But once the basic requirement is met, consumers may no longer value the additional "green premium," leading to the insignificant result at the gold and diamond levels. This may be due to the law of diminishing marginal utility, insufficient public awareness, or other housing purchase priorities. Consequently, the preference for green buildings has shifted from a previously polarized pattern toward a greater concentration at the bronze and silver levels.

These findings contrast with those of Brounen and Kok (2011) and Hyland et al. (2013), which find that the price premium effect tend to increase with higher Energy Performance Certificate (EPC) ratings or Building Energy Rating (BER). For instance, Brounen and Kok (2011) finds a price premium of 2.2% for EPC grade C, increasing to 5.6% for grade B and 10.2% for grade A. Hyland et al. (2013) reports a price premium of 1.7% at lower energy ratings (BER C), rising to approximately 5.2% for BER B and 9.3% for BER A. These

Table 5: Hedonic regression results.

	(1)	(2)	(3)	(4)	(5)
	Unmatched Sample	Coarsened Exact Matching	Propensity Score Matching	Nearest-Neighbor Matching	After applying NNM, the sample was restricted to 2013–2014
GB	0.068***	0.047***	0.050***	0.038***	0.052**
	(0.013)	(0.013)	(0.010)	(0.008)	(0.024)
Dwelling size	-0.001***	0.001**	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Building age	-0.014***	-0.016***	-0.017***	-0.017***	-0.028***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.006)
Number of bedrooms	-0.013***	-0.015***	-0.019***	-0.014**	-0.009
	(0.002)	(0.004)	(0.004)	(0.006)	(0.008)
Number of living rooms	0.012***	0.002	0.006	0.014	0.049*
	(0.004)	(0.008)	(0.007)	(0.014)	(0.028)
Number of bathrooms	0.008**	0.000	0.004	0.003	0.007
	(0.003)	(0.007)	(0.008)	(0.010)	(0.013)
Transportation accessibility	0.032***	0.006	-0.010	-0.023	-0.060*
	(0.011)	(0.016)	(0.016)	(0.026)	(0.036)
Parking space	-0.075***	-0.041***	-0.038***	-0.037***	-0.074***
	(0.005)	(0.006)	(0.006)	(0.009)	(0.020)
Constant	3.442***	3.031***	3.028***	2.969***	3.350***
	(0.016)	(0.028)	(0.024)	(0.045)	(0.097)
Observations	333,674	81,616	85,314	85,316	23,155
R-squared	0.825	0.856	0.834	0.840	0.845
Neighborhood fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES

Notes: This table presents the estimation results of Eq. 1 across different matching samples. The dependent variable in all specifications is the logarithm of transaction price per ping. All regressions include neighborhood and year fixed effects. Column (2) reports estimates based on the Coarsened Exact Matching (CEM) sample. Because strata that lack comparable counterparts are discarded in CEM, the number of observations in the matched sample is smaller than 85,316. Column (3) reports estimates based on the Propensity Score Matching (PSM) sample. In the PSM procedure, one green-building observation with a propensity score exceeding 0.99999 is excluded, leading to a reduction of two observations in the matched sample. Column (4) reports estimates based on the Nearest Neighbor Matching (NNM) sample, where matching is implemented using the Mahalanobis distance. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

patterns suggest that clearer and higher ratings are associated with larger price premiums. In contrast, our results align more closely with the findings of Aydin et al. (2020), which do not observe a systematic increase in price premium with higher green building certification grades.

The divergence between our findings and prior studies may come from in differences in consumer awareness, information transparency, and the nature of certification systems. EPC and BER programs explicitly disclose energy efficiency in standardized, easily interpretable formats, allowing consumers to directly assess and value building performance. This transparency strengthens the relationship between certification grades and housing prices, supporting monotonic premium patterns. In contrast, Taiwan's green building certification consider a broader set of environmental attributes beyond energy efficiency. These multidimensional features vary in salience across consumers and are often more difficult to evaluate, making it harder for buyers to directly perceive the incremental value of higher certification levels. Furthermore, while EPC and BER ratings are mandatory disclosures in housing transactions, Taiwan's transaction records do not systematically include green certification status, reducing the visibility and salience of these signals. Beyond differences in consumer awareness, the structure of the certification system itself may play a critical role. Certification levels are discrete rather than continuous, and developers face heterogeneous costs in achieving higher certification tiers. Combined with buyers' heterogeneous valuations of building attributes, these market frictions can result in strategic certification choices by developers, leading to pooling equilibria or bunching at intermediate certification levels. To formalize these ideas, in the next section we extend a signaling framework for illustration.

In column (2), we introduce an interaction term between climatic conditions and green buildings. Contrary to our hypothesis, the results suggest that green buildings in hotter climates do not yield a higher price premium compared to those in more moderate climates. However, Kahn and Kok (2014) finds the opposite results in California. This discrepancy may be due to the narrow latitude range of New Taipei City, which limits the variation in cooling degree days and makes spatial differences less pronounced.

Column (3) employs the share of electric motorcycles among all motorcycles in each village as a proxy for environmental consciousness. However, the results show no significant relationship between this proxy and the price premium of green buildings. This finding contrasts with the empirical study by Dastrup et al. (2012), which found that homes with solar panels exhibit a more pronounced price premium in communities with higher Prius hybrid vehicle registration rates. Similarly, Kahn and Kok (2014) analyzed the interaction between environmental awareness and green building certification and found that the green premium is significant in areas with greater environmental consciousness.[12] One possible explanation for our differing results is that the variation in electric motorcycle adoption

[12] Kahn and Kok (2014) use the share of Prius registrations within each zip code as a proxy for environmental consciousness.

across villages may not be large enough to capture differences in environmental awareness at the geographic level. Alternatively, environmental awareness itself may not be a strong determinant in our context.

The results in Column (4) demonstrate no significant relationship between income level and the price premium of green buildings. Higher-income individuals do not appear to pay higher prices for green-certified properties, suggesting that income may not be a decisive factor influencing consumers' willingness to pay for green features.

In column (5), we examine how the price premium of green buildings changes as they age. The estimated coefficient of the interaction term is statistically significant. A one-year increase in building age corresponds to an approximate 1.0% increase in the price premium of green buildings relative to non-green buildings, holding other factors constant. Our results indicate that green-certified buildings retain their value better over time due to their energy efficiency and sustainable features. For older buildings, a green certification may serve as an important signal of quality and durability, reassuring consumers about the long-term benefits of the property. To further explore the relationship between green building premiums and age, we estimate Equation 1 across different building age sub-groups (0 years, 1–5 years, 6–10 years, 11–15 years, and 16–22 years). Results in Table 7 show a consistent upward trend in the green building price premium across age groups, although the green premium in the last group is not statistically significant due to the limited sample size.

Some may be concerned that our result for building age is driven by its correlation with income. To ensure that our earlier results are not driven by this confounding factor, we estimate our regression including both interaction terms. The result in column (6) of Table 6 further validates our findings.

5.3 Information Asymmetry and Certification Premiums: Theory and Evidence

Understanding the structural differences between presale and resale housing markets is essential for analyzing when and how green labels function as effective signals of energy efficiency. These two markets operate under distinct pricing mechanisms and market dynamics, leading to significant differences in how housing prices are determined. Our data, along with the structure of the Taiwanese housing market, allows us to analyze how presale and resale transactions capture different aspects of pricing. In particular, we focus on how consumer demand shapes the hedonic pricing of green labels, a distinction that has not been thoroughly explored in past literature.

The core issue centers on information asymmetry. In the resale market, buyers often begin with a low prior belief that a given home is truly energy efficient, due to its age and outdated construction standards. While some green features may be observable through physical inspection, many important aspects of energy performance—such as insulation qual-

Table 6: Heterogeneity model results

	(1)	(2)	(3)	(4)	(5)	(6)
Qualified	0.007					
	(0.023)					
Bronze	0.046***					
	(0.017)					
Silver	0.052***					
	(0.010)					
Gold	0.025					
	(0.018)					
Diamond	0.017					
	(0.020)					
Earlier assessment	0.066					
	(0.049)					
GB		-0.037	0.033	0.031	0.021*	0.032
		(0.104)	(0.039)	(0.039)	(0.011)	(0.040)
GB×Cooling degree days		0.023				
		(0.029)				
GB×Electric motorcycles share			-0.091			
			(1.226)			
GB×Median income tax				0.000		-0.000
				(0.000)		(0.000)
GB×Building Age					0.010**	0.010***
					(0.004)	(0.004)
Constant	2.966***	2.971***	3.419***	3.007***	2.978***	3.025***
	(0.045)	(0.046)	(0.042)	(0.041)	(0.044)	(0.041)
Observations	85,316	78,439	46,499	83,820	85,316	83,820
R-squared	0.841	0.841	0.645	0.839	0.841	0.840
Neighborhood fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

Notes: This table reports the estimation results of Eq.2 using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. The dependent variable in all specifications is the logarithm of transaction price per ping. All regressions control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Due to data constraints, the standard errors in column (3) are clustered at the district level. Neighborhood and year fixed effects are included in all models. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Green Building Price Premiums Across Building Age Groups

	(1)	(2)	(3)	(4)	(5)
Age group (years)	0	1 - 5	6 - 10	11 - 15	16 - 22
GB	0.004	0.045***	0.060**	0.073***	0.158
	(0.015)	(0.017)	(0.024)	(0.028)	(0.118)
Dwelling size	0.000	0.001*	-0.001	0.001	-0.008
	(0.001)	(0.000)	(0.001)	(0.001)	(0.006)
Number of bedrooms	-0.008	-0.012	-0.007	-0.026**	0.012
	(0.005)	(0.008)	(0.007)	(0.011)	(0.036)
Number of living rooms	-0.006	0.005	0.035**	0.053***	0.124
	(0.008)	(0.019)	(0.014)	(0.015)	(0.100)
Number of bathrooms	0.015	-0.011	-0.009	-0.040	0.179
	(0.010)	(0.013)	(0.017)	(0.027)	(0.129)
Transportation accessibility	-0.007	-0.030	0.032	0.133	
	(0.026)	(0.025)	(0.042)	(0.118)	
Parking space	-0.015*	-0.058***	-0.104***	-0.124***	-0.052
	(0.008)	(0.015)	(0.016)	(0.019)	(0.066)
Constant	3.117***	2.969***	3.259***	3.098***	2.712***
	(0.023)	(0.060)	(0.047)	(0.072)	(0.163)
Observations	45,354	33,243	5,079	1,524	116
R-squared	0.912	0.814	0.857	0.878	0.927
Neighborhood fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES

Notes: This table reports the estimation results using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. The dependent variable in all specifications is the logarithm of transaction price per ping. The coefficient for transportation accessibility is not reported in column (5) due to collinearity with the neighborhood fixed effects. All regressions include neighborhood and year fixed effects. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ity, building envelope tightness, or long-term utility savings—remain difficult to assess. As a result, green labels serve as valuable signals that help reduce information asymmetry. Additionally, the cost of obtaining a green label is more differentiated across seller types: truly efficient homes may already qualify with minimal upgrades, while inefficient homes would face significant retrofit costs. The utility gap between efficient and inefficient homes is also more pronounced in older buildings, where energy savings, comfort, and performance can vary substantially. These conditions make green labels both more credible and more valuable in the resale market, leading to stronger belief updating and larger price premiums—consistent with the separating equilibrium in our signaling model.

In contrast, the presale market is characterized by higher buyer expectations and less variation in perceived energy performance across units. Since construction is not yet complete, buyers must rely entirely on promotional materials, sample homes, or digital renderings. However, because new buildings are often assumed to meet modern efficiency standards by default, the prior belief that a unit is energy efficient is relatively high. The cost of qualifying for a green label is also less differentiated, as green features can be built in at similar marginal cost across projects. Finally, the utility gap between efficient and inefficient new homes is smaller, as all units typically meet a relatively high baseline. These conditions reduce the informational value of green labels and weaken their signaling power, leading to smaller price premiums in the presale context.

To examine these intuitions empirically, we first construct a basic signaling framework drawn from the literature. This allows us to theoretically and empirically compare certification premiums across presale and resale markets. We then extend this signaling model. To examine these intuitions empirically, we first construct a basic signaling framework borrowed from the literature. We then extend this framework to explicitly incorporate discrete certification levels, heterogeneity in costs, and varying degrees of information asymmetry interact to generate these observed market differences.

5.3.1 Conceptual Motivation

We use a simple signaling theoretical framework to illustrate the intuition behind our context. We draw on a signaling model with asymmetric information, following the framework of Dewatripont and Bolton (2005).

Model Setup

Consider sellers who are of two types:

$$\theta \in \{H, L\}$$

where H denotes a high energy-efficiency (truly green) home, and L denotes a low-efficiency home.

Sellers observe their type, but buyers do not. Sellers can choose whether to obtain a green label $s \in \{0, 1\}$, where:

- $s = 1$: seller chooses to obtain the green label,
- $s = 0$: seller does not obtain the label.

Obtaining the label incurs a type-dependent cost:

$$c(\theta), \quad with \quad c(H) < c(L)$$

This reflects the fact that green certification is less costly for truly efficient homes, especially in the resale market.

Buyers form beliefs about a seller's type conditional on the label:

$$\mu(1) = \Pr(\theta = H \mid s = 1), \quad \mu(0) = \Pr(\theta = H \mid s = 0)$$

Buyers are risk neutral and pay the expected value of the home based on their beliefs $\mu(s)$. The buyer's willingness to pay is:

$$p(1) = \mu(1)v(H) + (1 - \mu(1))v(L), \quad p(0) = \mu(0)v(H) + (1 - \mu(0))v(L)$$

where $v(H)$ and $v(L)$ are the buyer's utilities from high- and low-efficiency homes, respectively, with $v(H) > v(L)$.

A seller of type θ earns the following payoff:

- If the seller chooses $s = 1$ (labeled): payoff $= p(1) - c(\theta)$
- If the seller chooses $s = 0$ (not labeled): payoff $= p(0)$

Equilibrium Conditions

We focus on a separating equilibrium where only type-H sellers choose to obtain the label. The incentive compatibility conditions are:

$$TypeH: \quad p(1) - c(H) \geq p(0)$$

$$TypeL: \quad p(1) - c(L) \leq p(0)$$

Combining both:

$$c(H) \leq p(1) - p(0) \leq c(L)$$

Thus, a separating equilibrium exists only if the price premium lies in this interval—high enough to incentivize type-H to label, but not so high that type-L would mimic.

Comparative Statics

This framework yields the following comparative statics relevant to our setting:

1. **Cost differential** $(c(L) - c(H))$:

$$\frac{\partial(p(1) - p(0))}{\partial(c(L) - c(H))} > 0$$

   A larger cost gap between types increases the feasibility of separation. In the resale market, $c(L) \gg c(H)$ due to high retrofitting costs for inefficient homes, while in the presale market, $c(L) \approx c(H)$ due to standardized new construction. This suggests a higher label premium in the resale market.

2. **Buyer prior belief** $(\pi = \Pr(H))$: Let $\pi = \Pr(\theta = H)$ denote the buyer's prior belief that a randomly chosen home is energy-efficient. This belief affects the buyer's valuation when no label is provided:

   - If no label is shown $(s = 0)$, buyers rely on the prior:

$$p(0) = \pi v(H) + (1 - \pi)v(L)$$

   - If a green label is shown $(s = 1)$, and the equilibrium is separating, then:

$$p(1) = v(H)$$

   The price premium is:

$$p(1) - p(0) = (1 - \pi)(v(H) - v(L))$$

   and the comparative static is:

$$\frac{\partial(p(1) - p(0))}{\partial \pi} = -(v(H) - v(L)) < 0$$

   Interpretation: When buyers are already confident that homes are efficient (high π), the label adds little information. In contrast, with low prior beliefs (e.g., in the resale market), the label is more informative and has a stronger price effect.

3. **Regulation level**: In regulated presale markets, energy performance is standardized, reducing variation and the informational content of labels. In our setting, where regu-

lation is limited, this mechanism is neutralized. Therefore, we predict no contradiction with the observed premium pattern.[13]

4. **Utility gap** $(v(H) - v(L))$:

$$\frac{\partial(p(1) - p(0))}{\partial(v(H) - v(L))} = \mu(1) - \mu(0) > 0$$

So long as the label is at least partially informative—meaning high types are more likely to label—then $\mu(1) > \mu(0)$ and the price premium increases with the utility gap. A larger gap between efficient and inefficient homes increases the value of the label. In resale markets, this variation tends to be larger; in presale markets, especially regulated ones, the gap shrinks. Our prediction is thus a higher label premium in the resale market.

In summary, the signaling framework naturally and consistently predicts the empirical result that green labels command higher price premiums in older housing markets than in the presale market when: (1) the cost of labeling is more differentiated in the resale market; (2) buyers are more uncertain about energy performance in resale; (3) regulatory floors do not flatten energy performance in presale; and (4) utility differences between types are larger in resale than in presale.

5.3.2 Empirical Evidence: Presale vs. Resale Markets

To empirically test the signaling value across housing market. We first categorize the observations into presale and resale groups and then apply 1:1 Nearest-Neighbor Matching to mitigate potential biases arising from differences in housing characteristics and locational attributes. We then estimate Equation 1 using ordinary least squares (OLS) on the matched sample. [14]

The estimated coefficient from the matched sample is 0.046, which is close to the 0.038 obtained in subsection 5.1. The minimal discrepancy between these two estimates indicates that the application of this matching method does not introduce significant bias or fundamentally alter the estimated price premium effect.

Focusing on the next two columns, the price premium effects differ significantly between the resale and presale groups. The results indicate that in the resale market exhibit a 5.8%

[13] In markets with strong energy efficiency regulations for new construction—such as mandatory insulation standards, appliance efficiency requirements, or green building codes—the variation in energy performance across new homes tends to be compressed. As a result, the green label provides less additional information to buyers, diminishing its signaling value and price impact. In contrast, our setting features minimal regulation, allowing greater heterogeneity in energy performance among new homes and preserving the potential for labels to be informative—though still subject to limited cost differentiation in labeling across types.

[14] The balance statistics for the matched samples are reported in the Appendix (see Table A-4).

green premium, supporting the signaling hypothesis that green certification conveys more credible information in market with greater asymmetry, where people hold lower prior belief about a randomly chosen house is energy-efficient. This finding is also consistent with the comparative static prediction that a larger utility gap between efficient and inefficient homes amplifies the informational value of green certification. In the resale market, where variation in energy performance tends to be greater, buyers place greater emphasis on long-term operating costs, which in turn results in a stronger observed price premium.

However, there is no statistically significant price premium in the presale group. This outcome can be explained by the characteristics of the presale market, where newly constructed buildings are typically subject to stricter building regulations and more likely to meet the high energy-efficiency standards. As a result, the buyers' prior beliefs that new units are energy efficient are relatively high in the context of a smaller utility gap between efficient and inefficient homes. These conditions weaken the signaling role of green certification. Unlike buyers in the resale market, who can physically inspect properties and directly assess their attributes, presale buyers are limited to viewing sample units or digital renderings. Consequently, they face greater uncertainty regarding the final delivery of the property—such as potential deviations from the original design or even the risk of project incompletion—which may further obscure the signaling effect of green certification and lead to an insignificant price premium.

5.3.3 Signaling and Non-Monotonic Certification Premiums

Our previous results (Section 5.2) on price premiums across different certification levels reveal two puzzles that are not immediately explained by the baseline signaling framework. We further provide some discussions here. More formalized model framework is provided in Appendix B.

Puzzle 1: Lack of Premium for Gold and Diamond Certifications

While Bronze and Silver certifications are associated with significant price premiums, we find no statistically significant premium for Gold and Diamond certifications. This pattern is somewhat counterintuitive under standard signaling models, which typically predict larger premiums for higher signals. One possible explanation relates to pooling equilibria in settings with discrete signals and heterogeneous signaling costs (Cho and Kreps, 1987). When the marginal cost of achieving higher certifications diminishes for lower-quality developers, or when buyers' willingness-to-pay for higher certifications increases only modestly, high- and low-quality developers may both select the same high-level certifications. As a result, the informational value of Gold and Diamond labels is diluted, leading to no additional price premium.

Puzzle 2: Similar Premiums for Bronze and Silver Certifications

Additionally, we observe that Bronze and Silver certifications command similar price

Table 8: Results of Green Building Price Premiums Across Presale and Resale Markets.

	(1)	(2)	(3)
Group	Full Matched Sample	Resale	Presale
GB	0.046***	0.058***	0.019
	(0.009)	(0.012)	(0.016)
Constant	3.006***	3.014***	3.206***
	(0.033)	(0.046)	(0.020)
Observations	85,316	45,442	39,874
R-squared	0.834	0.825	0.892
Neighborhood fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES

Notes: This table reports the estimation results using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. Prior to matching, the dataset is partitioned into presale and resale transactions, and NNM is performed separately within each group. The dependent variable in all specifications is the logarithm of transaction price per ping. All models control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Neighborhood and year fixed effects are included in all regressions. Column (1) reports estimates based on the combined matched samples from both the presale and resale groups, referred to as the "Full Matched Sample." Standard errors are clustered at the village level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

premiums, despite the expectation that achieving Silver would involve higher certification costs. Several factors may contribute to this pattern. First, the incremental cost of moving from Bronze to Silver may be relatively small once basic green design investments are made, particularly if the certification system exhibits threshold effects. Second, buyers may not sharply differentiate between Bronze and Silver, resulting in compressed willingness-to-pay across these two levels. Third, developers may pursue higher certifications like Silver for non-price benefits, such as enhanced marketing value or reputation gains, even if the transaction price premium is not substantially higher.

These puzzles suggest that certification levels may not operate as perfectly separating signals, especially when marginal costs and marginal buyer valuations flatten across certification tiers. An additional explanation focuses on heterogeneity among developers' costs of obtaining certifications. Some firms may find it substantially easier to achieve higher certifications due to firm size, experience, or access to resources, while others face steeper costs. Developers with greater resources may therefore be more likely to pursue Silver certifications even if the average price premium is similar to Bronze.

6 Robustness check

We perform an additional robustness check using an alternative dependent variable—the logarithm of the total housing transaction price (without dividing by area, in ping)—as this specification is comparable to several prior studies (Hyland et al., 2013; Kahn and Kok, 2014; Walls et al., 2017; Dell'Anna and Bottero, 2021; Tsai, 2022; Huang, 2023). The basic model results are reported in Table 9. Our findings indicate a premium between 1.9% and 4.4% for green-certified buildings after matching. This result is slightly smaller than our main result, yet u remains consistent with Kahn and Kok (2014) in California and Deng et al. (2012) in Singapore, both of which show that buildings with green certification yield a modest price premium.

Table 10 shows the heterogeneity analysis. The result reinforces the consistency of our earlier findings: The price premium effect continues to be statistically significant only at the bronze and silver certification levels, and green buildings consistently exhibit greater price competitiveness compared to non-certified buildings as they age. We turn to the estimation of green building price premiums across presale and resale markets in Table 11. The results suggest that replacing the dependent variable with unit housing price does not materially alter the estimated results. Overall, the results are consistent with the signaling framework, indicating that the informational content of green certification is more evident in unit-level price variation, while total price captures broader valuation dimensions shaped.

We additionally perform robustness checks by implementing nearest neighbor matching with varying numbers of matches. Specifically, we replicate the analyses presented in Sections 5.1, 5.2, and 5.3 using 1:2 and 1:3 nearest neighbor matching. The estimated coefficient for

the green building variable remains stable across different matching specifications. The results using 1:2 and 1:3 nearest neighbor matching can be found in Appendix A(From Table A-7 to Table Table A-11).

Table 9: Robustness check: Hedonic regression results.

	(1) Unmatched Sample	(2) Coarsened Exact Matching	(3) Propensity Score Matching	(4) Nearest-Neighbor Matching
GB	0.044***	0.041***	0.042***	0.019**
	(0.014)	(0.013)	(0.011)	(0.008)
area_ping	0.018***	0.017***	0.015***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
age	-0.013***	-0.012***	-0.012***	-0.011***
	(0.000)	(0.002)	(0.002)	(0.003)
bedroom	0.044***	0.028***	0.033***	0.024***
	(0.004)	(0.005)	(0.005)	(0.006)
living_room	0.074***	0.058***	0.053***	0.067***
	(0.007)	(0.011)	(0.013)	(0.016)
bathroom	0.022***	0.045***	0.036***	0.051***
	(0.006)	(0.008)	(0.011)	(0.015)
mrt	0.032***	0.005	-0.008	-0.023
	(0.011)	(0.017)	(0.018)	(0.031)
park	0.018***	0.032***	0.041***	0.042***
	(0.007)	(0.009)	(0.011)	(0.012)
Constant	15.054***	14.884***	14.986***	14.925***
	(0.029)	(0.039)	(0.042)	(0.046)
Observations	333,679	81,616	85,314	85,316
R-squared	0.884	0.906	0.893	0.898
Neighborhood fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES

Notes: This table presents the estimation results of Eq. 1 across different matching samples. The dependent variable in all specifications is the logarithm of transaction price. All regressions include neighborhood and year fixed effects. Column (2) reports estimates based on the Coarsened Exact Matching (CEM) sample. Because strata that lack comparable counterparts are discarded in CEM, the number of observations in the matched sample is smaller than 85,316. Column (3) reports estimates based on the Propensity Score Matching (PSM) sample. In the PSM procedure, one green-building observation with a propensity score exceeding 0.99999 is excluded, leading to a reduction of two observations in the matched sample. Column (4) reports estimates based on the Nearest Neighbor Matching (NNM) sample, where matching is implemented using the Mahalanobis distance. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Robustness check: Heterogeneity model results.

	(1)	(2)	(3)	(4)	(5)	(6)
Qualified	-0.008					
	(0.018)					
Bronze	0.046**					
	(0.024)					
Silver	0.033***					
	(0.009)					
Gold	-0.008					
	(0.018)					
Diamond	0.030					
	(0.036)					
Earlier assessment	0.010					
	(0.037)					
GB		0.000	0.008	0.025	0.001	0.027
		(0.101)	(0.041)	(0.041)	(0.011)	(0.042)
GB×Cooling degree days		0.006				
		(0.028)				
GB×Electric motorcycles share			0.764			
			(1.341)			
GB×Median income tax				-0.000		-0.000
				(0.000)		(0.000)
GB×Building Age					0.010***	0.011***
					(0.004)	(0.004)
Constant	14.921***	14.932***	15.255***	14.924***	14.935***	14.944***
	(0.047)	(0.048)	(0.052)	(0.044)	(0.045)	(0.043)
Observations	85,316	78,439	46,499	83,820	85,316	83,820
R-squared	0.898	0.899	0.827	0.897	0.898	0.898
Neighborhood fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

Notes: This table reports the estimation results of Eq.2 using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. The dependent variable in all specifications is the logarithm of transaction price. All regressions control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Due to data constraints, the standard errors in column (3) are clustered at the district level. Neighborhood and year fixed effects are included in all models. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Robustness check: Estimation of Green Building Price Premiums Across Presale and Resale Markets.

	(1)	(2)	(3)
Group	Full Matched Sample	Resale	Presale
GB	0.025***	0.038***	0.003
	(0.008)	(0.010)	(0.018)
Constant	14.948***	14.918***	15.201***
	(0.041)	(0.055)	(0.031)
Observations	85,316	45,442	39,874
R-squared	0.895	0.888	0.928
Neighborhood fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES

Notes: This table reports the estimation results using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. Prior to matching, the dataset is partitioned into presale and resale transactions, and NNM is performed separately within each group. The dependent variable in all specifications is the logarithm of transaction price. All models control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Neighborhood and year fixed effects are included in all regressions. Column (1) reports estimates based on the combined matched samples from both the presale and resale groups, referred to as the "Full Matched Sample." Standard errors are clustered at the village level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Conclusion

This study examines the price premium effect of green building certification in New Taipei City using matching methods to mitigate selection bias and hedonic price models to analyze housing transaction data. Our findings reveal that green-certified buildings command an average price premium of 3.8% over non-certified buildings, indicating that consumers perceive green certification as a value-added feature. However, the premium effect is observed only at the bronze and silver levels, suggesting that while consumers recognize the value of certified buildings, higher certification levels do not necessarily translate into proportionally higher market premiums. This may reflect the diminishing informational value and marginal utility of higher certification levels. Consumers may find it difficult to differentiate among tiers, and other housing attributes may exert a stronger influence on their purchase decisions.

From a dynamic perspective, the long-term price performance of green buildings also demonstrates notable trends. Green-certified properties maintain greater price resilience compared to non-certified buildings, with their price premium increasing over time. By the tenth year after completion, the premium reaches approximately 10.0%, suggesting that energy savings and other benefits become more salient as buildings age. This finding implies that green buildings provide increasing long-term value to homeowners, possibly driven by rising energy costs, improved comfort, and the durability of sustainable construction materials, which in turn enhances the perceived quality signaled by certification. Nonetheless, no significant relationship is observed between the price premium and external factors such as climatic conditions, environmental consciousness, or income levels. This implies that the price advantage of green buildings is largely determined by intrinsic property characteristics rather than regional or socio-economic factors.

Furthermore, green certification conveys a stronger signaling effect in the resale market than in the presale market, which is consistent with both theoretical expectations and empirical evidence. This finding supports the notion that certification serves as a credible signal of building quality and energy performance in markets characterized by greater information asymmetry. In the resale housing market, where buyers often face uncertainty regarding the true condition and long-term performance of existing buildings, green labels help reduce informational gaps and enhance market transparency. In contrast, the signaling value of certification is weaker in the presale market, where new buildings are already subject to stringent energy-efficiency regulations and buyers hold relatively high prior beliefs about building performance.

Taken together, these findings demonstrate that green labels do signal quality, but their effectiveness depends on market context, certification tier, and information conditions. Green certification enhances both price competitiveness and long-term value, yet its signaling strength varies across market segments—being more pronounced in resale markets where information asymmetry is greater. This highlights that the informational and quality-

assurance functions of certification are most valuable when buyers face greater uncertainty about building performance.

At the same time, the results provide key insights into the broader economic value of green building certifications. While certification improves resale value and supports price resilience over time, its impact is contingent on consumer awareness and market structure. For policymakers, these findings underscore the importance of promoting clearer differentiation among certification levels, enhancing public understanding of certification benefits, and strengthening trust in the credibility of green labeling systems. Integrating sustainability more effectively into housing market mechanisms could further amplify the economic and environmental benefits of green building adoption.

References

Abadie, A. and Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267.

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic perspectives*, 26(1):3–28.

Architecture and Building Research Institute (ABRI) (2023). *Green Building Evaluation Manual*. Architecture and Building Research Institute, Ministry of the Interior, Taipei, Taiwan.

Aydin, E., Brounen, D., and Kok, N. (2020). The capitalization of energy efficiency: Evidence from the housing market. *Journal of Urban Economics*, 117:103243.

Brounen, D. and Kok, N. (2011). On the economics of energy labels in the housing market. *Journal of Environmental Economics and Management*, 62(2):166–179.

Brounen, D., Kok, N., and Quigley, J. M. (2013). Energy literacy, awareness, and conservation behavior of residential households. *Energy Economics*, 38:42–50.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1):31–72.

Chen, F.-Y. and Liang, J.-H. (2018). The price premium of green building certification - a case study of New Taipei City residential building. *Journal of Taiwan Land Research*, 21(1):61–85.

Cho, I.-K. and Kreps, D. M. (1987). Signaling games and stable equilibria. *The Quarterly Journal of Economics*, 102(2):179–221.

Dastrup, S. R., Zivin, J. G., Costa, D. L., and Kahn, M. E. (2012). Understanding the solar home price premium: Electricity generation and "green" social status. *European Economic Review*, 56(5):961–973.

Dell'Anna, F. and Bottero, M. (2021). Green premium in buildings: Evidence from the real estate market of Singapore. *Journal of Cleaner Production*, 286:125327.

Deng, Y., Li, Z., and Quigley, J. M. (2012). Economic returns to energy-efficient investments in the housing market: Evidence from Singapore. *Regional Science and Urban Economics*, 42(3):506–515.

Deng, Y. and Wu, J. (2014). Economic returns to residential green building investment: The developers' perspective. *Regional Science and Urban Economics*, 47:35–44.

Dewatripont, M. and Bolton, P. (2005). Contract theory. Technical report, ULB–Universite Libre de Bruxelles.

Eichholtz, P., Kok, N., and Quigley, J. M. (2010). Doing well by doing good? Green office buildings. *American Economic Review*, 100(5):2492–2509.

Fowlie, M., Greenstone, M., and Wolfram, C. (2018). Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *The Quarterly Journal of Economics*, 133(3):1597–1644.

Fuerst, F. and McAllister, P. (2011). Green noise or green value? Measuring the effects of environmental certification on office values. *Real Estate Economics*, 39(1):45–69.

Fuerst, F., McAllister, P., Nanda, A., and Wyatt, P. (2016). Energy performance ratings and house prices in wales: An empirical study. *Energy Policy*, 92:20–33.

Huang, M.-Y. (2023). Analyzing the effects of green building on housing prices: Case study of Kaohsiung, Taiwan. *Environment, Development and Sustainability*, 25(2):1205–1235.

Hyland, M., Lyons, R. C., and Lyons, S. (2013). The value of domestic building energy efficiency—Evidence from Ireland. *Energy Economics*, 40:943–952.

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1):1–24.

Imbens, G. W. (2015). Matching methods in practice: Three examples. *Journal of Human Resources*, 50(2):373–419.

International Energy Agency (2024). Buildings – energy system. Accessed: 2025-04-21.

Kahn, M. E. and Kok, N. (2014). The capitalization of green labels in the California housing market. *Regional Science and Urban Economics*, 47:25–34.

Kamenica, E. and Gentzkow, M. (2011). Bayesian persuasion. *American Economic Review*, 101(6):2590–2615.

Kok, N. and Jennen, M. (2012). The impact of energy labels and accessibility on office rents. *Energy Policy*, 46:489–497.

Matisoff, D. C., Noonan, D. S., and Flowers, M. E. (2016). Policy monitor—Green buildings: Economics and policies. *Review of Environmental Economics and Policy*.

Rayo, L. and Segal, I. (2010). Optimal information disclosure. *Journal of political Economy*, 118(5):949–987.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

Rubin, D. B. (1973). The use of matched sampling and regression adjustment to remove bias in observational studies. *Biometrics*, pages 185–203.

Shewmake, S. and Viscusi, W. K. (2015). Producer and consumer responses to green housing labels. *Economic Inquiry*, 53(1):681–699.

Tsai, I.-C. (2022). Value capitalization effects of green buildings: A new insight through time trends and differences in various price levels. *Building and Environment*, 224:109577.

Walls, M., Gerarden, T., Palmer, K., and Bak, X. F. (2017). Is energy efficiency capitalized into home prices? Evidence from three us cities. *Journal of Environmental Economics and Management*, 82:104–124.

Zhang, L., Wu, J., and Liu, H. (2018). Turning green into gold: A review on the economics of green buildings. *Journal of Cleaner Production*, 172:2234–2245.

Zheng, S., Wu, J., Kahn, M. E., and Deng, Y. (2012). The nascent market for "green" real estate in Beijing. *European Economic Review*, 56(5):974–984.

A Tables and Figures

Table A-1: Variable descriptions

No.	Variable	Description	Years	Unit
Panel A: Dwelling characteristics				
1	Sales price	Transaction price of each housing unit	2013–2023	Daily
2	Building age	Difference between transaction date and construction completion year (rounded)	2013–2023	Daily
3	Dwelling size	Total floor area including main building, annexes, parking, and common areas	2013–2023	Daily
4	Bedrooms	Total number of bedrooms	2013–2023	Daily
5	Living rooms	Total number of living rooms	2013–2023	Daily
6	Bathrooms	Total number of bathrooms	2013–2023	Daily
7	Parking space	Binary variable indicating whether the unit includes a parking space	2013–2023	Daily
Panel B: Locational characteristics				
1	MRT accessibility	Binary variable: 1 if within 500 m of MRT entrance	2013–2023	Yearly
2	Cooling degree days (CDD)	Annual cooling degree days in the property's village	2013–2022	Yearly (village)
3	Electric motorcycles share	Share of electric motorcycles among all heavy motorcycles	2018–2023	Yearly (district)
4	Median income tax	Median household income tax in each district	2013–2021	Yearly (district)
Panel C: Green characteristics				
1	Green building certification	Binary variable: 1 if the property is certified as a green building	2013–2023	Yearly

Table A-2: Balance of CEM matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.488	1.367	0.121	6.6895	0.0000	0.04683
	(0.013)	(0.013)	(0.018)			
Dwelling size	48.143	48.961	-0.818	-5.6492	0.0000	-0.03955
	(0.103)	(0.102)	(0.145)			
Number of bedrooms	2.683	2.619	0.064	11.5785	0.0000	0.08106
	(0.004)	(0.004)	(0.006)			
Number of living rooms	1.819	1.823	-0.004	-1.6027	0.1090	-0.01122
	(0.002)	(0.002)	(0.003)			
Number of bathrooms	1.663	1.664	-0.001	-0.2141	0.8305	-0.00150
	(0.003)	(0.003)	(0.004)			
Transportation accessibility	0.286	0.286	0	0.0000	1.0000	0
	(0.002)	(0.002)	(0.003)			
Parking space	0.783	0.783	0	0.0000	1.0000	0
	(0.002)	(0.002)	(0.003)			
Observations	40,808	40,808				

Notes:
1. The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses.
2. One-to-one Nearest-Neighbor Matching is employed, requiring exact matching for dummy variables (transportation accessibility and parking spaces), while other matching variables are continuous (building age, dwelling size, number of bedrooms, living rooms, and bathrooms, and geographical coordinates).

Table A-3: Balance of PSM matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.753	1.360	0.393	21.7918	0.0000	0.14921
	(0.013)	(0.012)	(0.018)			
Dwelling size	53.301	50.612	2.689	17.0055	0.0000	0.11644
	(0.116)	(0.108)	(0.158)			
Number of bedrooms	2.700	2.643	0.057	10.2950	0.0000	0.07049
	(0.004)	(0.004)	(0.006)			
Number of living rooms	1.866	1.827	0.039	13.2110	0.0000	0.09046
	(0.002)	(0.002)	(0.003)			
Number of bathrooms	1.722	1.704	0.018	4.2761	0.0000	0.02928
	(0.003)	(0.003)	(0.004)			
Transportation accessibility	0.252	0.295	-0.043	-14.2056	0.0000	-0.09727
	(0.002)	(0.002)	(0.003)			
Parking space	0.774	0.790	-0.016	-5.6055	0.0000	-0.03838
	(0.002)	(0.002)	(0.003)			
Observations	42,657	42,657				

Notes:
1. The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses.

Table A-4: Balance of section 5.3.2 matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.655	1.360	.295	16.7020	0.0000	0.11436
	(0.013)	(0.012)	(0.018)			
Dwelling size	50.101	50.612	-0.511	-3.3943	0.0000	-0.02324
	(0.105)	(0.108)	(0.151)			
Number of bedrooms	2.642	2.643	-0.001	-0.0421	0.9664	-0.00029
	(0.004)	(0.004)	(0.006)			
Number of living rooms	1.827	1.827	0.000	-0.0637	0.9492	-0.00044
	(0.002)	(0.002)	(0.003)			
Number of bathrooms	1.700	1.704	-0.004	-0.9083	0.00000.3637	-0.00622
	(0.003)	(0.003)	(0.004)			
Transportation accessibility	0.295	0.295	0.000	0.0000	1.0000	0.00000
	(0.002)	(0.002)	(0.003)			
Parking space	0.790	0.790	0.000	0.0000	1.0000	0.00000
	(0.002)	(0.002)	(0.003)			
Observations	42,658	42,658				

Notes:

1. The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses.
2. One-to-one Nearest-Neighbor Matching is employed, requiring exact matching for dummy variables (transportation accessibility and parking spaces), while other matching variables are continuous (building age, dwelling size, number of bedrooms, living rooms, and bathrooms, and geographical coordinates).

Table A-5: Balance of 1:2 NNM matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.618	1.360	0.258	16.4294	0.0000	-0.09843
	(0.009)	(0.012)	(0.007)			
Dwelling size	50.322	50.612	-0.290	-2.2182	0.0265	0.01312
	(0.075)	(0.108)	(0.062)			
Number of bedrooms	2.643	2.643	0.000	0.0139	0.9889	-0.00008
	(0.003)	(0.004)	(0.002)			
Number of living rooms	1.826	1.827	-0.001	-0.3532	0.7239	0.00209
	(0.001)	(0.002)	(0.001)			
Number of bathrooms	1.701	1.704	-0.003	-0.8889	0.3740	0.00526
	(0.002)	(0.003)	(0.002)			
Transportation accessibility	0.295	0.295	0	0.0000	1.0000	0
	(0.002)	(0.002)	(0.001)			
Parking space	0.790	0.790	0	0.0000	1.0000	0
	(0.001)	(0.002)	(0.001)			
Observations	85,316	42,658				

Notes: The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses. One-to-one Nearest-Neighbor Matching is employed, requiring exact matching for dummy variables (transportation accessibility and parking spaces), while other matching variables are continuous (building age, dwelling size, number of bedrooms, living rooms, and bathrooms, and geographical coordinates).

Table A-6: Balance of 1:3 NNM matched samples

Variables	(1) Non-Green Buildings	(2) Green Buildings	(3) Difference (1)-(2)	(4) t-value	(5) $Pr(\|T\| > \|t\|)$	(6) Standardized Bias
Building age	1.623	1.360	0.263	17.5947	0.0000	-0.09996
	(0.008)	(0.012)	(0.006)			
Dwelling size	50.263	50.612	-0.349	-2.8449	0.0044	0.01584
	(0.061)	(0.108)	(0.053)			
Number of bedrooms	2.643	2.643	0.000	0.0574	0.9543	-0.00032
	(0.003)	(0.004)	(0.002)			
Number of living rooms	1.826	1.827	-0.001	-0.2617	0.7936	0.00146
	(0.001)	(0.002)	(0.001)			
Number of bathrooms	1.700	1.704	-0.004	-1.0114	0.3118	0.00564
	(0.002)	(0.003)	(0.001)			
Transportation accessibility	0.295	0.295	0	0.0000	1.0000	0
	(0.001)	(0.002)	(0.001)			
Parking space	0.790	0.790	0	0.0000	1.0000	0
	(0.001)	(0.002)	(0.001)			
Observations	127,974	42,658				

Notes: The numbers in columns (1) to (3) represent mean values, with standard errors in parentheses. One-to-one Nearest-Neighbor Matching is employed, requiring exact matching for dummy variables (transportation accessibility and parking spaces), while other matching variables are continuous (building age, dwelling size, number of bedrooms, living rooms, and bathrooms, and geographical coordinates).

Table A-7: Robustness check: 1:2 and 1:3 Nearest-Neighbor Matching.

	(1) 1:2 Nearest-Neighbor Matching	(2) 1:3 Nearest-Neighbor Matching
GB	0.040***	0.041***
	(0.009)	(0.009)
Dwelling size	0.000	0.000
	(0.000)	(0.000)
Building age	-0.019***	-0.020***
	(0.002)	(0.002)
Number of bedrooms	-0.013**	-0.014**
	(0.006)	(0.006)
Number of living rooms	0.012	0.012
	(0.013)	(0.012)
Number of bathrooms	-0.000	-0.001
	(0.009)	(0.008)
Transportation accessibility	-0.016	-0.013
	(0.022)	(0.019)
Parking space	-0.033***	-0.033***
	(0.009)	(0.009)
Constant	2.966***	2.971***
	(0.045)	(0.041)
Observations	127,974	170,632
R-squared	0.833	0.832
Neighborhood fixed effects	YES	YES
Year fixed effects	YES	YES

Notes: This table presents the estimation results of Eq. 1 across different matching samples. The dependent variable in all specifications is the logarithm of transaction price per ping. All regressions include neighborhood and year fixed effects. Column (1) reports estimates based on the 1-2 Nearest Neighbor Matching (NNM) sample. Column (2) reports estimates based on the 1-3 Nearest Neighbor Matching (NNM) sample. Nearest Neighbor Matching (NNM) is implemented using the Mahalanobis distance. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-8: Robustness check: Heterogeneity model results(1:2 Nearest-Neighbor Matching).

	(1)	(2)	(3)	(4)	(5)	(6)
Qualified	0.014					
	(0.025)					
Bronze	0.055***					
	(0.015)					
Silver	0.053***					
	(0.011)					
Gold	0.023					
	(0.018)					
Diamond	0.024					
	(0.017)					
Earlier assessment	0.054					
	(0.048)					
GB		-0.055	0.022	0.025	0.026**	0.028
		(0.099)	(0.040)	(0.042)	(0.012)	(0.045)
GB×Cooling degree days		0.028				
		(0.027)				
GB×Electric motorcycles share			0.384			
			(1.251)			
GB×Median income tax				0.000		-0.000
				(0.000)		(0.000)
GB×Building Age					0.008**	0.008**
					(0.004)	(0.004)
Constant	2.963***	2.968***	3.427***	3.010***	2.971***	3.020***
	(0.045)	(0.046)	(0.033)	(0.038)	(0.044)	(0.038)
Observations	127,974	115,435	72,663	125,927	127,974	125,927
R-squared	0.834	0.830	0.664	0.832	0.834	0.832
Neighborhood fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

Notes: This table reports the estimation results of Eq.2 using the 1-2 Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. The dependent variable in all specifications is the logarithm of transaction price per ping. All regressions control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Due to data constraints, the standard errors in column (3) are clustered at the district level. Neighborhood and year fixed effects are included in all models. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-9: Robustness check: Heterogeneity model results(1:3 Nearest-Neighbor Matching).

	(1)	(2)	(3)	(4)	(5)	(6)
Qualified	0.019					
	(0.024)					
Bronze	0.056***					
	(0.013)					
Silver	0.054***					
	(0.012)					
Gold	0.021					
	(0.018)					
Diamond	0.026					
	(0.017)					
Earlier assessment	0.037					
	(0.050)					
GB		-0.041	0.022	0.023	0.028**	0.027
		(0.096)	(0.044)	(0.043)	(0.012)	(0.046)
GB×Cooling degree days		0.024				
		(0.026)				
GB×Electric motorcycles share			0.435			
			(1.369)			
GB×Median income tax				0.000		0.000
				(0.000)		(0.000)
GB×Building Age					0.008**	0.008**
					(0.004)	(0.004)
Constant	2.968***	2.972***	3.411***	3.011***	2.974***	3.018***
	(0.041)	(0.043)	(0.031)	(0.033)	(0.041)	(0.033)
Observations	170,632	153,035	98,824	168,160	170,632	168,160
R-squared	0.833	0.826	0.676	0.831	0.833	0.832
Neighborhood fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES

Notes: This table reports the estimation results of Eq.2 using the 1-2 Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. The dependent variable in all specifications is the logarithm of transaction price per ping. All regressions control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Due to data constraints, the standard errors in column (3) are clustered at the district level. Neighborhood and year fixed effects are included in all models. Standard errors clustered at the village level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-10: Robustness check: Estimation of Green Building Price Premiums Across Presale and Resale Markets(1:2 Nearest-Neighbor Matching).

	(1)	(2)	(3)
Group	Full Matched Sample	Resale	Presale
GB	0.048***	0.059***	0.023
	(0.008)	(0.012)	(0.017)
Constant	2.992***	3.010***	3.208***
	(0.030)	(0.037)	(0.024)
Observations	127,974	68,163	59,811
R-squared	0.825	0.813	0.884
Neighborhood fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES

Notes: This table reports the estimation results using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. Prior to matching, the dataset is partitioned into presale and resale transactions, and NNM is performed separately within each group. The dependent variable in all specifications is the logarithm of transaction price. All models control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Neighborhood and year fixed effects are included in all regressions. Column (1) reports estimates based on the combined matched samples from both the presale and resale groups, referred to as the "Full Matched Sample." Standard errors are clustered at the village level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A-11: Robustness check: Estimation of Green Building Price Premiums Across Presale and Resale Markets(1:3 Nearest-Neighbor Matching).

	(1)	(2)	(3)
Group	Full Matched Sample	Resale	Presale
GB	0.050***	0.059***	0.028
	(0.009)	(0.011)	(0.018)
Constant	2.985***	3.000***	3.198***
	(0.030)	(0.036)	(0.025)
Observations	170,632	90,884	79,748
R-squared	0.824	0.810	0.883
Neighborhood fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES

Notes: This table reports the estimation results using the Nearest Neighbor Matching (NNM) sample, where matching is implemented with the Mahalanobis distance. Prior to matching, the dataset is partitioned into presale and resale transactions, and NNM is performed separately within each group. The dependent variable in all specifications is the logarithm of transaction price. All models control for a comprehensive set of housing characteristics, including dwelling size, building age, numbers of bedrooms, living rooms, and bathrooms, transportation accessibility, and parking availability. Neighborhood and year fixed effects are included in all regressions. Column (1) reports estimates based on the combined matched samples from both the presale and resale groups, referred to as the "Full Matched Sample." Standard errors are clustered at the village level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Model Extension: Discrete Certification and Multiple Equilibria

B.1 Baseline Model: Discrete Certification Choices

Setup: Developers are heterogeneous in quality: $\theta \in \{H, L\}$ (High, Low). Each developer chooses a certification level $s \in \{None, Bronze, Silver, Gold, Diamond\}$. Certification incurs type-dependent cost $C_\theta(s)$, where $C_L(s) > C_H(s)$ for all s, but cost differentials diminish at higher certification levels.

Buyers observe certification s and form beliefs $\mu(s) = \Pr(\theta = H|s)$. Buyers' willingness-to-pay is:

$$V(s) = \mu(s)V_H + (1 - \mu(s))V_L$$

with $V_H > V_L > 0$.

Developer Problem: Each developer chooses s to maximize:

$$\max_s \{V(s) - C_\theta(s)\}$$

Equilibrium: An equilibrium consists of certification choices (s_H, s_L) and beliefs $\mu(s)$ such that: - Developers maximize profits given buyers' beliefs. - Buyers' beliefs are consistent with developers' strategies where possible (Bayes' Rule).

Multiple Equilibria and Bunching: Depending on the relative shapes of $C_\theta(s)$ and $V(s)$:

- *Separating equilibrium*: If cost differentials and buyer WTP gaps are large, high types select higher certifications (e.g., Silver or Gold), and low types select lower certifications (e.g., Bronze).
- *Pooling equilibrium*: If cost differentials shrink and buyer WTP differences narrow at higher certification levels, both types may select the same high certification (e.g., Gold), diluting the informational content and eliminating price premiums.
- *Bunching at mid-level certifications*: If marginal certification costs are small from Bronze to Silver, and buyer WTP differences are compressed, developers may cluster at these certification levels even if transaction price premiums are similar.

Interpretation: The observed lack of additional price premiums for Gold and Diamond certifications is consistent with a pooling equilibrium at high certification levels. The similar premiums between Bronze and Silver can be explained by relatively small incremental

certification costs, compressed buyer valuation differences, and additional non-transactional benefits (e.g., marketing advantages) associated with achieving higher certifications.

B.2 Extended Model: Developer and Consumer Heterogeneity

While our baseline model captures key dynamics through discrete certification choices and signaling costs varying by developer quality, additional heterogeneity among developers' certification costs and consumers' valuation gaps can further enrich the equilibrium predictions. We outline these extensions introducing heterogeneity both among developers and among consumers.

Developer-Side Heterogeneity: Each developer has a quality type $\theta \in \{H, L\}$ (High, Low) and an idiosyncratic cost parameter $\kappa \in R_+$. The cost of achieving certification level s is now given by:

$$C_\theta(s, \kappa)$$

where $C_\theta(s, \kappa)$ is increasing in s and κ. Developers with lower κ face lower marginal costs for obtaining higher certifications.

Consumer-Side Heterogeneity: Consumers are heterogeneous in how much they value certified quality. Each consumer has a valuation type $\eta \in R_+$, and the willingness-to-pay for a project with certification s is:

$$V^\eta(s) = \mu(s)V_H^\eta + (1 - \mu(s))V_L^\eta$$

where $V_H^\eta > V_L^\eta$, and the gap $V_H^\eta - V_L^\eta$ varies across consumers. Higher-η consumers place greater value on distinguishing high-quality developers.

Developer Problem: Each developer chooses certification s to maximize:

$$\max_s \{E_\eta[V^\eta(s)] - C_\theta(s, \kappa)\}$$

where $E_\eta[V^\eta(s)]$ represents the expected market valuation based on the distribution of consumer types.

Equilibrium: An equilibrium consists of certification strategies for developers and belief systems for buyers such that: 1. Developers maximize profits given buyers' beliefs and the consumer valuation distribution; 2. Buyers update beliefs based on observed certification levels and Bayes' Rule where possible.

Implications: Developers with lower κ are more likely to pursue higher certifications even when average market price premiums are relatively flat. Developers targeting high-η consumers (who require stronger quality signals) have stronger incentives to obtain higher certifications. Thus, the coexistence of substantial numbers of Bronze and Silver certifications with similar price premiums can be rationalized by the interaction of developer-side and consumer-side heterogeneity.