

Research Article

A Comparative Hedonic Analysis of Condominium Asking Rents in Bangkok, Phuket, and Pattaya

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Abstract

In Thailand, rent comparisons between cities are based on unadjusted averages of listings, which confuses the mix of units advertised with the price a city sets on property. I ask how much of the rent difference between Bangkok, Phuket, and Pattaya is composition and how much survives it. I use a cross-section of 14,849 active condominium rental listings from FazWaz in January 2026 to estimate nested hedonic models. The dependent variable is the natural log of monthly asking rent in Thai baht; all inference uses heteroskedasticity-robust (HC1) standard errors. Model 1 controls bedroom count, Model 2 adds $\ln(\text{size})$, Model 3 adds bathrooms and view type. The raw picture misleads: Model 1 places Phuket 22.8% above Bangkok (95% CI 20.3% to 25.4%) and Pattaya 11.5% below (95% CI -13.4% to -9.6%). Controlling size moves both, Phuket to 14.4% and Pattaya to 16.8% below, and lifts adjusted R-squared from 0.492 to 0.662; about a third of the apparent Phuket premium is size composition, not location. The central result is asymmetric. Adding bathrooms and view type leaves Phuket essentially unchanged, 0.130 to 0.134 log points, but widens the Pattaya discount from 15.6% to 22.4%: The listed stock in Pattaya leans toward sea-view and pool-view product and the city indicator had been absorbing that mix. City coefficients based on listing data are not location premiums or willingness to pay, but conditional associations. A third of the variation in rent is unexplained and the attributes that would close the gap are named.

Keywords: hedonic price model; condominium rental market; asking rents; online listings; Bangkok; Phuket; Pattaya

1. Introduction

Thailand's tourism cities let condominiums at scale, and the rents are compared constantly and badly. In Bangkok, Phuket and Pattaya, investors and developers let units that are hard to sell, drawn by the immediate income, and the resulting advertisements are the only rent series the market has. Comparisons built on them are usually unadjusted averages, or commentary that reports no method. Both confound two things: the price a city puts on housing, and the mix of units that city happens to advertise. Holding unit characteristics constant is what separates them. Hedonic pricing does this by construction, recovering the implicit price of each attribute. Its estimates nonetheless move with specification: an apparent location premium can be manufactured or erased by the choice of controls (Gröbel & Thomschke, 2018; Malpezzi, 2003; Mason & Quigley, 1996; Rosen, 1974; Sirmans et al., 2005).

Listings are not transactions. Instead of recording contracted rents, they record advertised rents. They are chosen based on what is promoted, by whom, and at what time. Additionally, posted rents move slowly; many units show no nominal change from one year to the next (Genesove, 2003). The cost gaps that separate one city from another reflect supply conditions as much as demand (Glaeser et al., 2008), and the local consumption amenities households pay for are capitalized into location itself (Anenberg et al., 2022). A hedonic specification recovers cross-city differentials from listing rents while holding measurable characteristics constant (Rosen, 1974; Sirmans et al., 2005).

Willingness to pay for building and environmental attributes systematically varies across high- and low-price settlements. Missing attributes in a specification distort estimated distance and spatial effects whenever they are correlated with the type of unit available (Tsai, 2025). Building age and structural condition move prices materially and belong in any specification aimed at spatial or submarket differences (Wang & Tsai, 2022). Thai applications have priced observable condominium attributes where transaction records are thin or unevenly distributed (Dendoung et al., 2020; Tochaiwat et al., 2023).

In addition to unit-level heterogeneity, housing markets have distinct types of heterogeneity, such as spatial interdependence and episodes of market overheating, where local market booms can spill over to adjacent neighborhoods and associated submarkets. Research related to the overheating of housing markets in London shows that such behaviors can travel and that the distribution of price and rent growth makes

spatial patterns critical. This is useful when setting benchmarks for submarkets, as opposed to simply using market averages (Tsai, 2023). Supply in housing micro-geographies further shows that local supply adjustments and constraints at the neighborhood level contribute to sustained cross-area variability in housing (Baum-Snow & Han, 2024). When considered collectively, this body of research suggests that adjusting for unit characteristics will still result in economically significant differences in rent between cities, albeit these differences should decrease if compositional factors are taken into consideration. In this case, unit size is significant. Phuket's listed stock is weighted toward larger resort-style product, whereas Bangkok and Pattaya differ in their share of smaller units marketed to different renter generations. Size is therefore included in the specification together with the other structural variables.

Neural-network models for Pattaya condominiums are among the machine-learning rent prediction systems that have made it to these markets (Buranasiri & Laokulrach, 2025). These techniques make better forecasts. This paper requires an interpretable city differential, which they do not provide. Using listing data and Bangkok as the reference market, I calculate hedonic models of monthly condominium rent for Phuket, Pattaya, and Bangkok. One baseline accounts for the number of bedrooms. A second adds $\ln(\text{size})$ and distinguishes the compositional component of the cross-city gap from the part that survives it. A third adds view type and the number of bathrooms. The design is consistent with contemporary research on structural premiums, depreciation, market dynamics, and supply restrictions (Buranasiri & Laokulrach, 2025; Tochaiwat et al., 2023; Tsai, 2023, 2025; Wang & Tsai, 2022) as well as conventional hedonic practice (Rosen, 1974; Sirmans et al., 2005).

There are three expectations that follow. Conditional differences against Bangkok should be non-zero once observable factors are controlled because the three locations have diverse labor markets, tourism intensity, and demand composition (H1). Since floor area is the dominant priced attribute and additional space is valued at a decreasing rate, the size elasticity should be positive and smaller than unity (H2). Because the composition of the listed stock varies throughout cities in terms of the mix of unit sizes and amenity attributes, the city coefficients should move materially when size is controlled and further when structural and locational qualities are incorporated (H3). According to Metzner and Kindt (2017), H3 is the compositional-bias mechanism, which explains why layered specifications rather than a single model are used in the analysis.

2. Literature review

2.1 Hedonic pricing as the baseline framework for housing valuation

The hedonic approach views a home as a collection of characteristics, each of which has an implicit cost that is disclosed during transactions. Together with broader market conditions, rents break down into structural, neighborhood, and accessibility components. Each component is identified while keeping the others constant. Its prominence can be explained by two aspects: the decomposition is repeatable and compatible with appraisal practice, and it makes it possible to compare cities or submarkets by calculating location differences on a shared set of attributes. The weakness is specification dependence. Estimates vary based on how the market is defined and how the model is set. Three aspects of sensitivity are reported in literature reviews: the specification of spatial features, the variables included or excluded, and the functional form (Malpezzi, 2003; Sirmans et al., 2005). There are bounding techniques that reduce the degree to which location-dependent, omitted attributes can skew the outcome.

2.2 Automated valuation models and the centrality of disciplined feature selection

Hedonic regression is regarded as a fundamental technique in automated valuation work because of its interpretability and auditability. Metzner and Kindt (2017) make hedonic valuation central to automated valuation models and tie accuracy to three things: preprocessing, predictor selection, and the heterogeneity of micro- and macro-location variables. Their review identifies the relevant failure mode of listing data: imprecise measurement of attributes, uneven presence of attributes across units, and inconsistent definitions of attributes, all of which bias estimated location premia when the model does not control for unit size and quality.

Consistent records across observations are indicative of good predictors. The most informative and consistently present fields in housing datasets include size variables, floor area, bedroom count, and general qualitative and locational building descriptors. This approach minimizes compositional bias without tailoring the model to the peculiarities of specific ads by using a restricted collection of high-signal covariates. Web-scraped listings are a well-established foundation for large-scale rental analysis, with the standing caution that advertised rents carry selection and quality differences (Boeing & Waddell, 2017). Hedonic methods have been applied to web-sourced condominium rents (Miura & Asami, 2012) and extended with listing content such as floor plans (Solovev & Pröllochs, 2021).

2.3 Functional form, spatial structure, and heterogeneity across submarkets

Functional form is the persistent methodological problem. Metzner and Kindt (2017) review the debate over linear, semi-log and more flexible forms. Lisi (2013) demonstrates how the decision has a significant impact on both the reading of spatial price differentials and the size of the marginal effects. Rent modeling is dominated by semi-log since it makes coefficients percentage effects and stabilizes variance, but the literature makes it abundantly evident that the decision should be debated rather than taken for granted. Inference is further complicated by heterogeneity and spatial dependency. Price formation varies unevenly across space and is influenced by localized amenities, supply restrictions, and sorting. Helbich et al. (2013) document that heterogeneity and show pooled coefficients understate place-specific valuation regimes. Osland (2010) demonstrates that ignoring spatial structure understates the uncertainty and biases the estimates. When comparing cities, an estimated city effect could reflect omitted attributes rather than location, especially if such characteristics vary consistently between the cities under comparison.

Submarket definition is not a descriptive convenience. Day (2003) demonstrates the segmentation of property markets by identifying submarkets using a hedonic price model. A city-level premium is an average over whatever submarket composition the sample happens to contain because Bangkok, Phuket, and Pattaya each have multiple micro-markets influenced by accessibility, tourism intensity, and development type.

2.4 Location and accessibility as priced attributes

Location and accessibility price independently of structure. Ottensmann et al. (2008) compare alternative location measures within a hedonic house-price model and find accessibility to multiple employment centers outperforms simple distance to the center. Franklin and Waddell (2003) price activity-specific accessibility; Deboosere et al. (2019) find comparable effects in a multilevel hedonic of short-term rental listings; Lorenz et al. (2023) recover locational effects with interpretable machine learning. Measured coarsely or not at all, accessibility is absorbed into district or city indicators, which inflates apparent city differences.

Locational context is sharpened by GIS. Both Ismail (2005) on Glasgow and Bajat et al. (2017) employing auxiliary maps combine spatial statistics with GIS-assisted hedonic modeling, and both demonstrate that when covariates and diagnostics are spatially explicit, model performance and interpretability improve. Distance proxies serve as a backup when such measurements are not available.

2.5 Implications for the present study

A credible cross-city rent comparison has to be hedonic and has to confront three risks. Specification sensitivity, above all to functional form, is why the analysis runs nested specifications and reports robustness checks (Lisi, 2013; Metzner & Kindt, 2017). Spatial dependence and heterogeneity are why pooled estimates cannot be read as though the market were spatially homogeneous (Day, 2003; Helbich et al., 2013; Osland, 2010). Compositional bias is the third and, for listing data, the sharpest: left uncontrolled, differences in the mix of unit sizes, building quality and neighborhood type manufacture the appearance of a location premium (Metzner & Kindt, 2017).

This study applies hedonic methods to condominium rents in Bangkok, Phuket and Pattaya on a compact, consistently recorded set of controls, and reads the resulting city differentials as conditional on those controls. Consistent with submarket and accessibility theory, the gaps that survive combine location-specific willingness to pay with unobserved economic and qualitative attributes that differ systematically across listings (Franklin & Waddell, 2003; Ismail, 2005; Ottensmann et al., 2008).

3. Methodology

3.1 Study design and empirical framework

I estimate hedonic rent models on cross-sectional data for condominium units advertised for rent in Bangkok, Phuket and Pattaya. The dependent variable is monthly asking rent in Thai baht, logged, which stabilizes the variance of a strongly right-skewed distribution and lets coefficients be read as semi-elasticities and elasticities. Unit size in square meters, the number of bedrooms and bathrooms, the advertised view type, and the diminishing marginal rent of extra floor area are structural variables that are recorded in logs. The Phuket and Pattaya coefficients represent conditional rent disparities in comparison to the Bangkok market as the city enters as indicators with Bangkok as the reference. A baseline of city indicators and bedroom count, an extended specification that includes log unit size, and a full specification that includes bathrooms and view type are the three nested OLS requirements that follow. Since the data are listing-based and cross-sectional, heteroskedasticity-robust (HC1) standard errors are used in addition to traditional OLS errors for all inferences. Using continuous covariates kept at sample means and 95% confidence intervals, I also calculate adjusted expected rents by city using the size-adjusted specification.

3.2 Data sources, unit of analysis, and sample construction

The unit of observation is the individual condominium rental listing. I retrieved the listings from FazWaz, a large commercial property portal covering the Thai market, as a single cross-sectional extract in January 2026 for the three cities studied. The extract is a snapshot of advertisements that were active at the point of retrieval. The portal retains listings that have not been withdrawn or refreshed, so the pool includes older advertisements still live from earlier years. It publishes no posting or last-updated date, so the vintage of an individual listing is not observable. The data are therefore treated throughout as a single cross-section rather than as a time series, and the consequences of this design are set out in Section 5.4.

The dependent variable is the advertised monthly rent in Thai baht (THB). Unit size in square meters was taken from the listing-reported room size field. Bedroom count was extracted from the listing title with a reproducible parsing rule in which studios are coded zero and '1 Bedroom', '2 Bedroom' and equivalent forms are parsed as integers. Bathroom count was taken from the bed and bath field, and view type from the listing attribute fields. No listing-level identifier is published by the portal, so records are identified by their content.

I clean in a fixed sequence, and Table 1 reports the number and percentage of observations removed at each step. I retain a listing only where advertised rent is present and positive and unit size is present and positive. The procedure originally specified for a missing unit size was reconstruction from the accounting relationship $\text{Size} = \text{Rent}/(\text{Rent per sqm})$. In the event this reconstruction was never applied: all twenty listings with a missing room-size field also lacked a price-per-square-meter field, and were therefore dropped rather than imputed. No observation in the analytic sample carries a unit size derived from rent, and the dependent variable consequently does not enter the construction of any regressor.

Two plausibility windows were then applied to remove mechanical data-entry errors. Unit size was required to lie between 15 and 1,000 square meters, a window that admits the smallest studio product marketed in these cities while excluding implausible entries, and monthly rent was required to lie between THB 3,000 and THB 2,000,000. Duplicate advertisements were removed last. A duplicate was defined as a record whose entire scraped content repeats, that is, identical building name, location, advertised rent, price per square meter, unit size, bed and bath counts, description title and body, and attribute fields. I evaluated and rejected a looser filter that matched just on building, rent, size, and number of bedrooms.

Table 1 | Sample Construction and Cleaning | N = 15,202 Retrieved.

Step	Removed	% of Retrieved	Remaining
Listings retrieved	-	-	15,202
Rent missing or non-positive	3	0.02%	15,199
Unit size missing and not reconstructable	20	0.13%	15,179
Bedroom count not parseable	0	0.00%	15,179
Unit size outside 15 to 1,000 sqm	7	0.05%	15,172
Monthly rent outside THB 3,000-2,000,000	0	0.00%	15,172
Exact duplicate listings (identical scraped content)	323	2.12%	14,849

Note. Observations removed at each cleaning step, in the order applied. Percentages are of the 15,202 listings retrieved. No observation required size imputation.

Only 531 of the 1,738 items in Bangkok that are flagged by this laxer criteria have the same description text. Condominium buildings routinely contain several genuinely distinct units of identical specification. The final analytical sample consists of 14,849 postings, of which 9,774 are in Bangkok, 2,835 are in Phuket, and 2,240 are in Pattaya.

3.3 Variable definitions and transformations Let i index listings.

The dependent variable is the natural log of monthly rent, $y_i = \ln(\text{Rent}_i)$. Important co-variables include:

- Bangkok serves as the reference category for a set of dummy variables called “City.” This is done while keeping observed unit attributes constant to isolate the average city-level rent premium/discount in comparison to Bangkok.
- Natural logarithms, or $\ln(\text{Size})$, are used to enter unit size. This captures the diminishing marginal rent effect of greater floor area, a common empirical regularity in rental pricing, and enables the size coefficient to be interpreted as an elasticity.
- To represent layout and utility differences that are not fully conveyed by floor area alone, bedrooms and bathrooms are added. To capture the outlook premium that is essential to pricing in the coastal markets, view type is added as a categorical attribute, with a city view serving as the reference category.

3.4 Model specifications

Model 1, the baseline market comparison, is given in Equation 1.

$$\ln(\text{Rent}_i) = \beta_0 + \beta_1 \text{Phuket}_i + \beta_2 \text{Pattaya}_i + \beta_3 \text{Bedrooms}_i + \varepsilon_i \quad (1)$$

Model 2, the primary hedonic specification, is given in Equation 2.

$$\ln(\text{Rent}_i) = \beta_0 + \beta_1 \text{Phuket}_i + \beta_2 \text{Pattaya}_i + \beta_3 \text{Bedrooms}_i + \beta_4 \ln(\text{Size}_i) + \varepsilon_i \quad (2)$$

Model 3, the fully specified hedonic model, is given in Equation 3.

$$\ln(\text{Rent}_i) = \beta_0 + \beta_1 \text{Phuket}_i + \beta_2 \text{Pattaya}_i + \beta_3 \text{Bedrooms}_i + \beta_4 \ln(\text{Size}_i) + \beta_5 \text{Bathrooms}_i + \sum_k \gamma_k \text{View}_{ki} + \varepsilon_i \quad (3)$$

where ε is the idiosyncratic error term and the index i denotes the listing. Coefficients on the city indicators represent conditional rent differences relative to Bangkok. The elasticity of rent in relation to floor space is represented by the coefficient on $\ln(\text{Size})$ in Models 2 and 3, whereas the coefficients on view type in Model 3 reflect conditional differences in relation to a city view. Equation 4 is used to convert indicator coefficients to approximate percentage effects because the dependent variable is logged.

$$\% \Delta = 100 \times (\exp(\beta) - 1) \quad (4)$$

Model summary statistics include R , R^2 , adjusted R^2 , and the standard error of the estimate.

Table 2 reports goodness of fit for the three nested specifications with $\ln(\text{rent})$ as the dependent variable: R, R squared, adjusted R squared and the standard error of the estimate. Model 1 contains city indicators and bedroom count, Model 2 adds $\ln(\text{size})$, Model 3 adds bathrooms and view type.

Table 3 gives the analysis-of-variance decomposition for the three models: regression and residual sums of squares and mean squares, with the omnibus F-test that the predictors jointly improve fit on an intercept-only model.

Table 4 reports B coefficients, standard errors, t statistics, p values and 95% confidence intervals for Models 1 and 2 under conventional OLS standard errors. Coefficients are read as semi-elasticities or elasticities according to the transformation applied, and indicator coefficients convert to conditional percentage differences through Equation 4. Rent is plotted versus unit size by city on log-log axes with fitted lines in Figure 1. The log-log hedonic structure of Models 2 and 3 is represented by a steep and positive gradient, which explains why $\ln(\text{size})$ significantly improves fit. The regression differentials detailed below are differences in those lines' city-specific intercepts.

Adjusted predicted rents from the size-adjusted specification, Model 2, are shown in Figure 2. This model uses $\ln(\text{rent})$ as the dependent variable and $\ln(\text{size})$, bedroom count, and city indicators as the variables. The 95% confidence interval for each expected mean is shown by the error bars. The continuous factors are retained at their sample means for calculating predicted rents, so the only difference between the shown values is city membership. In Figure 3, total rent is substituted with rent per square meter. Density plots show systematic cross-city differences in rent intensity; they are less mechanically influenced by unit size than headline rent and directly capture the cost of space. Figure 4 breaks down rent per square meter by the number of bedrooms in each city, ranging from studios to four-

Table 2 | Model Summary for Hedonic Rent Regressions | N = 14,849.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.702	.492	.492	.489
2	.814	.662	.662	.399
3	.817	.668	.668	.393

Note. Models 1 and 2 are estimated on the full analytic sample (N = 14,849). Model 3 is estimated on the subsample for which bathroom count and view type are both reported (N = 13,224).

Table 3 | ANOVA for Hedonic Rent Regressions | N = 14,849.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3448.373	3	1149.458	4802.734	.000
	Residual	3552.914	14,845	.239		
	Total	7001.287	14,848			
2	Regression	4633.466	4	1158.366	7261.862	.000
	Residual	2367.821	14,844	.160		
	Total	7001.287	14,848			
3	Regression	4106.201	13	315.862	2044.707	.000
	Residual	2040.651	13,210	.154		
	Total	6146.852	13,223			

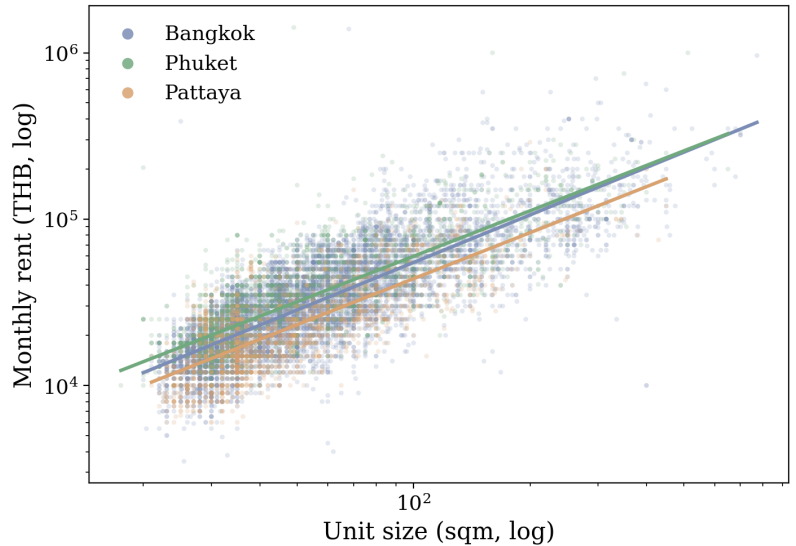


Figure 1. Rent vs size by city, log-log

bedroom units. It helps to understand why the incremental effect of an extra bedroom is small once unit size is controlled and illustrates how pricing intensity differs across product kinds.

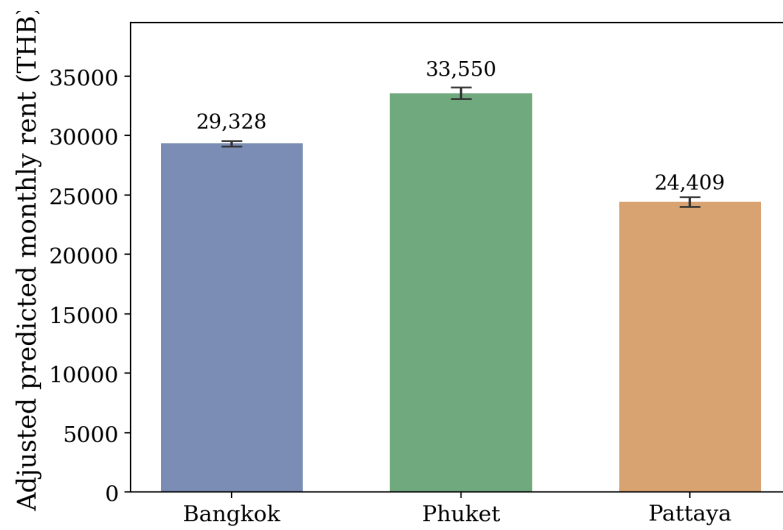


Figure 2. Adjusted predicted monthly rent by city

Table 4 | Coefficients, Conventional OLS Standard Errors | N = 14,849.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Intercept)	9.491	.009		1091.265	.000	9.474	9.508
	Phuket	.205	.011	.117	19.473	.000	.185	.226
	Pattaya	-.122	.012	-.064	-10.560	.000	-.145	-.100
	Bedrooms	.589	.005	.693	116.656	.000	.579	.599
2	(Intercept)	6.902	.031		223.657	.000	6.842	6.962
	Phuket	.135	.009	.077	15.558	.000	.118	.151
	Pattaya	-.184	.009	-.096	-19.381	.000	-.202	-.165
	Bedrooms	.104	.007	.122	14.866	.000	.090	.117
	ln(size)	.822	.010	.699	86.194	.000	.803	.841

Note. Estimated coefficients for Models 1 and 2 with conventional OLS standard errors and 95% confidence intervals. The dependent variable is $\ln(\text{rent})$ and Bangkok is the reference city category. N = 14,849.

4. Results

4.1 Overview of analytic sample

The analytical sample consists of 14,849 condominium listings: 9,774 in Bangkok, 2,835 in Phuket, and 2,240 in Pattaya. Bedroom counts are derived from the title-based extraction rule in Section 3.2, which reduces missingness and enhances comparability between cities by classifying studios as zero and parsing stated counts as integers. Table 5 lists the number of bedrooms, unit size, and monthly asking rent by city. The log-linear specification is motivated by the widely dispersed and strongly right-skewed nature of both rent and size.

4.2 Distributional diagnostics

All three cities’ asking rents have a long upper tail and a significant right skew. The rent distributions are plotted on a logarithmic horizontal axis in Figure 5, which allows the cross-city differences to be seen without distorting the majority of the observations. Because the log transformation stabilizes the variance and enables the coefficients to be interpreted as semi-elasticities and elasticities, the pattern supports modeling the dependent variable as $\ln(\text{rent})$.

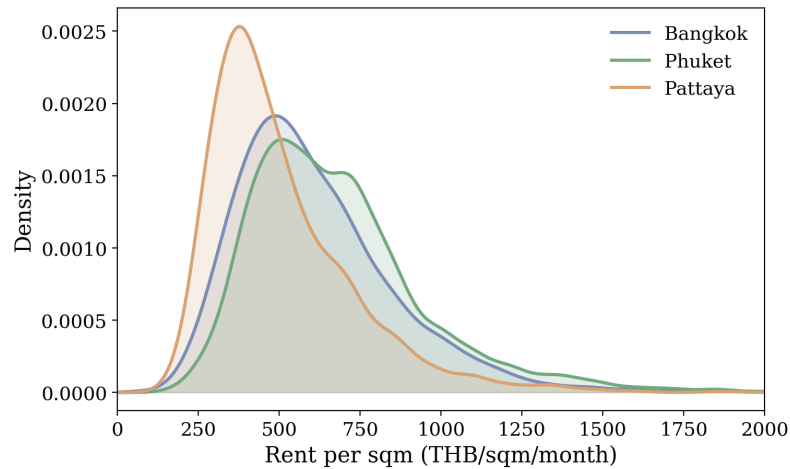


Figure 3. Rent per sqm density by city

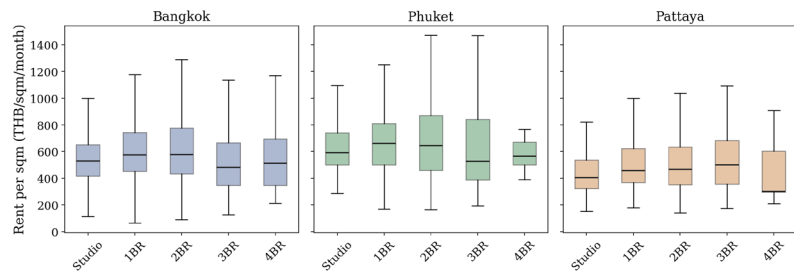


Figure 4. Rent per sqm by bedrooms, faceted by city

Table 5 | Descriptive Statistics by City | N = 14,849.

City		N	Minimum	Maximum	Mean	Std. Deviation
Bangkok	Monthly rent (THB)	9,774	3,500	1,390,000	40,403	44,184
	Unit size (sqm)	9,774	20.00	772.49	66.82	59.46
	Bedrooms	9,774	0.00	6.00	1.42	0.79
Phuket	Monthly rent (THB)	2,835	10,000	1,420,000	41,444	52,192
	Unit size (sqm)	2,835	17.50	650.00	61.20	53.55
	Bedrooms	2,835	0.00	5.00	1.12	0.80
Pattaya	Monthly rent (THB)	2,240	6,000	290,000	27,633	22,032
	Unit size (sqm)	2,240	21.00	450.00	56.25	40.74
	Bedrooms	2,240	0.00	5.00	1.10	0.80

Note. Summary statistics for the analytic sample (N = 14,849) reporting monthly asking rent (THB), unit size (sqm) and bedroom count by city.

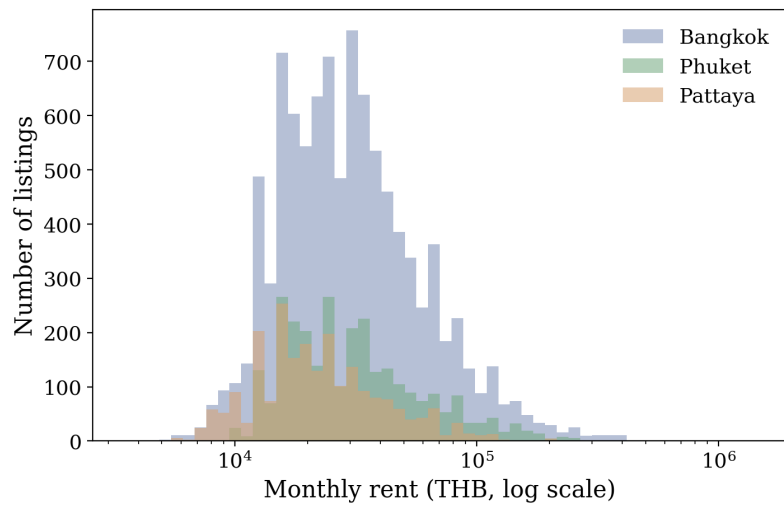


Figure 5. Rent distributions by city, log scale

Table 6 | Coefficients, Heteroskedasticity-Robust (HC1) Standard Errors | N = 14,849.

Model		Unstandardized Coefficients		Standardized Coefficients		t	Sig.	95% Confidence Interval for B	
		B	Robust Std. Error	Beta				Lower Bound	Upper Bound
1	(Intercept)	9.491	.008			1128.881	.000	9.474	9.507
	Phuket	.205	.011	.117		19.402	.000	.185	.226
	Pattaya	-.122	.011	-.064		-11.309	.000	-.143	-.101
	Bedrooms	.589	.005	.693		114.160	.000	.579	.599
2	(Intercept)	6.902	.038			181.536	.000	6.827	6.977
	Phuket	.135	.009	.077		15.625	.000	.118	.151
	Pattaya	-.184	.009	-.096		-19.629	.000	-.202	-.165
	Bedrooms	.104	.009	.122		12.202	.000	.087	.120
	ln(size)	.822	.012	.699		67.554	.000	.798	.846

Note. Estimated coefficients for Models 1 and 2 with heteroskedasticity-robust (HC1) standard errors and associated test statistics. Robust inference is emphasized given cross-sectional listing data and potentially heteroskedastic residuals. The dependent variable is $\ln(\text{rent})$ and Bangkok is the reference city category. N = 14,849

4.3 Model fit and incremental explanatory power

What each block of attributes adds is quantified by three hierarchical specifications. Model 1 achieves an adjusted R squared of 0.492 using only bedroom count and city indicators. Unit size is the most significant observable determinant of rent in these markets, and size composition accounts for a substantial part of the raw cross-city gap. Adding $\ln(\text{size})$ to Model 2 raises it to 0.662, a gain of 0.170. Model 3 adds bathrooms and view type and reaches 0.668 on its common sample, a further 0.013. The omnibus F-tests in Table 3 reject the intercept-only model in every specification.

Roughly one third of the variation in log rent remains unexplained even in the fullest specification, and the attributes recoverable from listing records close little of that gap. The residual is most plausibly attributable to attributes that listing records do not report consistently: building age and construction quality, developer and management reputation, micro-location within a district, furnishing tier, floor level in the Bangkok subsample, and contract terms such as lease length, deposit and included services. This is a limitation of listing-based hedonic analysis in general rather than of the present specification in particular, and it is the reason the city coefficients are interpreted throughout as conditional associations rather than as willingness-to-pay estimates.

4.4 Hedonic effects and economic interpretation

Table 4 reports conventional OLS estimates and Table 6 the same models with heteroskedasticity-robust (HC1) standard errors, which are preferred because cross-sectional listing data typically show heteroskedastic residuals. The two sets are numerically close and support identical conclusions.

In Model 2 the coefficient on $\ln(\text{size})$ is 0.822: an elasticity that is high but significantly below unity. Holding city and bedroom count constant, a 1% increase in

floor area is associated with 0.82% higher monthly rent. The anticipated trend in condominium rental markets is this near-proportionate but sub-unitary response, which validates H2. Space is the dominant priced attribute, with each additional square meter worth slightly less than the last.

The number of bedrooms keeps a lower association once size is under control. The Model 2 coefficient of 0.104 indicates that for two units in the same city and with the same floor space, an extra bedroom is associated with about 10.9% more rent. Since the number of bedrooms is effectively a proxy for the corresponding floor area in the baseline, the decrease from 0.589 in the baseline, the decrease from 0.589 in Model 1 to 0.104 in Model 2 is expected. The Model 2 city coefficients are conditional differentials against Bangkok when size and bedroom count remain constant. Phuket carries a significant premium, whereas Pattaya carries a significant discount. According to Equation 4, the Phuket coefficient of 0.135 is approximately 14.4% higher than Bangkok (95% CI 12.5% to 16.3%), whereas the Pattaya coefficient of -0.184 is approximately 16.8% lower (95% CI -18.3% to -15.2%). H1 is supported by the precise estimation of both. In Figure 6, the Model 2 coefficients are presented with robust standard errors and 95% confidence intervals, so that sign, scale and significance can be read at a glance.

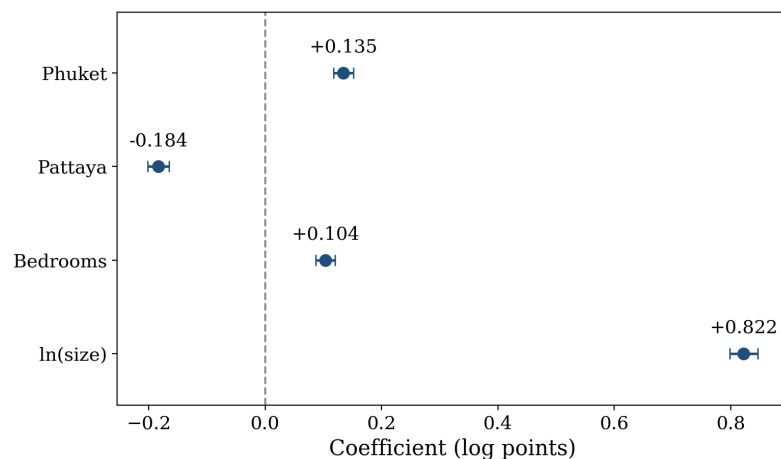


Figure 6. Model 2 coefficient plot, robust SE

4.5 Richer specification: bathrooms and view type

The city indicators in Models 1 and 2 may absorb unmeasured attributes that systematically differ between markets. As a result, Model 3 adds the two characteristics that the listing records report at high coverage: the number of bathrooms and the advertised view type. Figure 7 shows the city coefficients for each of the three nested specifications, and Table 7 presents the estimates with robust standard errors.

Both added attributes are priced as expected. Keeping size, number of bedrooms, and city constant, an extra bathroom is linked to an 8.0% increase in rent. View type is economically substantial. Sea views are about 17.2% and lake views are about 20.0% more expensive than city views, which are the reference category; pool, garden, mountain, and river views are between 7% and 15% less expensive. The latter should not be interpreted as distaste for those outlooks because the coefficient shows that these outlooks are more common in less expensive inland and secondary regions.

The main outcome of the extended specification is that the effect on the city coefficients is asymmetric. Since the Phuket premium, as estimated on the common sample, is essentially unchanged, changing from 0.130 to 0.134 log points, the conclusion that Phuket commands a genuine premium over Bangkok survives the addition of these variables. In contrast, the Pattaya discount increases from -0.170 to -0.254 log points, or around 15.6% to 22.4% less than Bangkok. Pattaya's listed stock is weighted toward sea-view and pool-view product, and once those attributes are priced individually the city's underlying position turns out to be weaker than the size-adjusted comparison suggests. This is direct evidence for H3, and evidence that city indicators in parsimonious hedonic specifications can absorb compositional differences in amenity mix as well as in unit size. It is the principal reason all city coefficients reported here are described as conditional associations rather than as location premiums.

Table 7 | Model 3 with Heteroskedasticity-Robust (HC1) Standard Errors | N = 13,224.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B		%Δ
	B	Robust Std. Error				Lower Bound	Upper Bound	
(Intercept)	7.097	.046		152.770	.000	7.006	7.188	
Phuket	.134	.012	.077	10.974	.000	.110	.158	+14.4
Pattaya	-.254	.013	-.135	-20.278	.000	-.279	-.230	-22.4
View: Garden	-.074	.016	-.024	-4.728	.000	-.105	-.043	-7.1
View: Lake	.183	.033	.029	5.490	.000	.117	.248	+20.0
View: Mountain	-.079	.017	-.027	-4.519	.000	-.113	-.045	-7.6
View: Pool	-.136	.013	-.054	-10.314	.000	-.162	-.110	-12.7
View: River	-.158	.049	-.013	-3.205	.001	-.255	-.061	-14.6
View: Sea	.159	.015	.078	10.491	.000	.129	.188	+17.2
View: Skyline	.044	.014	.017	3.206	.001	.017	.071	+4.5
View: Unblocked Open	-.092	.015	-.031	-6.075	.000	-.121	-.062	-8.8
Bedrooms	.088	.009	.104	9.521	.000	.070	.107	+9.2
ln(size)	.755	.016	.633	47.358	.000	.723	.786	
Bathrooms	.077	.013	.075	5.997	.000	.052	.102	+8.0

Note. Model 3 adds bathroom count and view type to Model 2. The dependent variable is $\ln(\text{rent})$, Bangkok is the reference city category and a city view is the reference view category. N = 13,224. Adjusted R squared = 0.668. The %Δ column converts a coefficient to a percentage effect using Equation 4 and is reported only where a one-unit change in the regressor is meaningful, that is, for the indicator and count variables. It is left blank for $\ln(\text{size})$, whose coefficient is an elasticity and is read as the percentage change in rent associated with a one percent increase in floor area.

4.6 Robustness checks

Two further attributes are reported for only part of the sample, so I examine them in subsamples rather than in the pooled specification. Table 8 reports both. For Bangkok, the listing records report distance to the nearest BTS or MRT station for 83% of listings. Added to the Model 3 specification for Bangkok alone, it returns a coefficient of -0.082, so each additional kilometer from a station is associated with rent about 7.9% lower, holding unit attributes constant. This is the accessibility control that the pooled specification lacks, and its magnitude is consistent with the accessibility literature discussed in Section 2.4. The comparable field is absent for Phuket and Pattaya, where urban rail does not operate.

More than 95% of listings in Phuket and Pattaya provide the floor level, while only 4% of listings in Bangkok do so. I add floor level to the Model 3 specification for the two coastal cities and get a coefficient of 0.0017 per story that is not statistically significant (p = 0.18). Once view type is controlled, height per se does not command a measurable premium in these markets: it is the outlook that is priced, for which floor level is only a proxy. In this subsample a sea view is worth about 31.5% and the Pattaya discount relative to Phuket about 34.3%.

Additionally, I created and tested an index counting advertised amenities, covering furnishing, balcony, washing machine, wifi, pool access, gym, microwave, television and recent renovation, and excluded it from the reported specifications. It entered negative and significant, an implausible sign that diagnostic examination attributes to the source data’s structure rather than preferences. There are only a few attribute slots available in the listing design, which are filled with basic appliances in lower-priced ads and various descriptions in higher-priced ads. Mean amenity count accordingly falls from 2.35 in the smallest size quartile to 1.82 in the largest, and the individual indicators price a television at -5.0% and

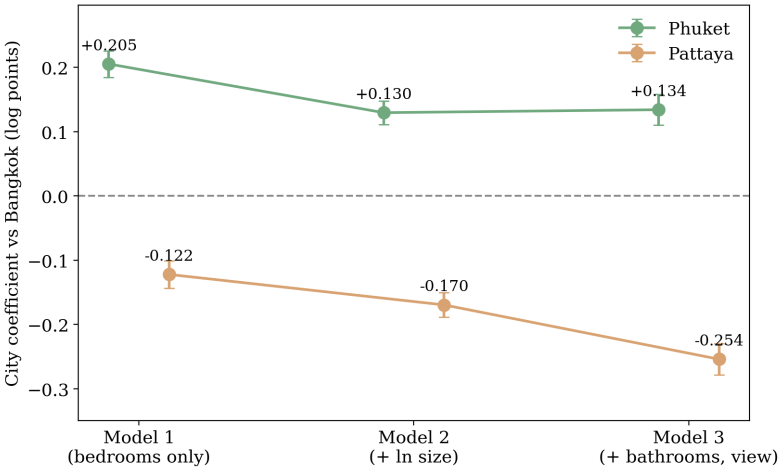


Figure 7. City coefficients relative to Bangkok across nested specifications

Table 8 | Subsample Robustness Checks | N = 7,195 and 4,422.

Specification		B	Robust Std. Error	Sig.	%Δ
Bangkok (+ transit distance)	Distance to BTS/ MRT (km)	-.082	.004	.000	-7.9
	ln(size)	.735	.024	.000	
	Bathrooms	.086	.015	.000	+9.0
	Bedrooms	.070	.014	.000	+7.2
Phuket & Pattaya (+ floor level)	Floor level	.002	.001	.183	+0.2
	ln(size)	.629	.021	.000	
	Bathrooms	.073	.026	.005	+7.6
	Bedrooms	.157	.014	.000	+17.0
	Pattaya	-.420	.016	.000	-34.3

Note. Both specifications add the stated attribute to the Model 3 covariate set. The Bangkok specification is estimated on 7,195 listings with adjusted R squared 0.674. The Phuket and Pattaya specification is estimated on 4,422 listings with adjusted R squared 0.703, with Phuket as the reference city. The dependent variable is ln(rent) in both cases. As in Table 7, the %Δ column is left blank for ln(size), whose coefficient is an elasticity.

a recent renovation at -10.4%. The index therefore measures advertising style rather than amenity provision, and including it would import that artefact into the city coefficients. It is documented here for transparency and excluded from the preferred specification.

5. Discussion

5.1 Principal findings

I set out to establish how much of the cross-city rent gap in Bangkok, Phuket and Pattaya is attributable to differences in what is being let, and how much survives those differences. Three findings organize the answer. Unit size is the dominant priced attribute: the elasticity is 0.82 in Model 2 and 0.75 in Model 3, positive and significantly below unity in both, which supports H2 and confirms the diminishing marginal valuation the log-log form assumes (Figure 1, Table 6). City differentials are large and they survive the controls, which supports H1: adjusted predicted rents at sample-mean characteristics differ materially across the three markets (Figure 2), and the city coefficients stay significant in every specification. According to H3 (Figure 7), these coefficients move differently for the two cities and vary dramatically as controls accumulate. When controls are put in place, the Pattaya discount moves in the opposite direction and widens; about one-third of the original Phuket premium is lost, with the remaining amount remaining consistent. Neither can be understood as a pure location premium.

5.2 Interpretation of the estimated differentials

The estimates describe markets with different supply and demand levels. Bangkok's listed stock is often larger and skewed toward multi-bedroom layouts, with an average of 66.8 square meters as opposed to 61.2 in Phuket and 56.3 in Pattaya. Part of what looks like a Bangkok premium in a raw comparison is actually a larger product being advertised because floor area is the key pricing consideration. Controlling size eliminates that component, leaving simply a difference in the price of similar space.

The rent-to-size relationship is reliable and consistent across all three markets (Figure 1). For real-world applications, that is more significant than level differences. A uniform rent-to-space gradient is necessary for rental underwriting and portfolio valuation, allowing comparable units to be benchmarked across cities. The elasticity is similar across three structurally different markets, which suggests the pricing of space itself is not strongly city-specific even where the price level clearly is.

Rent per square meter reveals what headline rents conceal (Figure 3). Two units advertised at similar rents can represent very different prices for space, and the cross-city distributions of rent intensity are systematically distinct. Disaggregating by bedroom count (Figure 4) shows further segmentation by product type within each city: studio and one-bedroom units price at consistently higher intensity than larger configurations. That is the expected consequence of a size elasticity below unity, and it indicates these markets are segmented by household and product type as well as by location.

5.3 A conjecture beyond the present evidence: the role of rental tenure

The findings concern the pricing of rents at a point in time. They do not speak to tenure choice, to mortgage credit, or to the long-run trajectory of the rental sector, none of which a cross-sectional design can test. What follows is a conjecture, not a result. Stable, precisely estimated attribute pricing combined with persistent city differentials is what one would expect of rental markets that are institutionally established rather than residual. Should affordability constraints tighten further in the major urban markets, rental tenure would plausibly take a growing share of housing access and the supply response would shift further toward income-producing product. Testing that requires evidence this study does not have: longitudinal rent series, household-level tenure transitions, and mortgage-credit conditions. It is a direction for future work, and no conclusion in Section 6 depends on it.

5.4 Limitations and future research

Several limitations bound the claims. The analysis uses advertised asking rents, not contracted rents. Thai residential leases are privately negotiated and no comprehensive public registry exists, so transaction-verified rents are not obtainable at this scale. The advertised cost varies depending on the length of the lease, furniture, deposit, and service fees, all of which may vary uniformly across the three cities. Asking rents also embed a negotiation margin.

The data are a single cross-sectional extract retrieved in January 2026. Because the portal does not publish posting or refresh dates, the vintage of an individual listing is unobservable, and the pool is known to retain older advertisements that have remained live. Two consequences follow. Advertised rents are not strictly contemporaneous with one another, which introduces measurement variability of unknown sign. And because the data contain no time dimension, year or quarter fixed

effects cannot be estimated and the stability of the city differentials over time cannot be assessed. Establishing whether these differentials are stable, and how they responded to the tourism disruption of the pandemic period, requires repeated extracts and is left to future work.

The specification also remains incomplete despite the additional controls introduced in Model 3. Coverage is the binding constraint. Building age and construction quality appear only in unstructured description text, at coverage too low to use; floor level is available for the coastal cities but not for Bangkok; accessibility is available for Bangkok but not for the coastal cities; and no measure of micro-location within a district is available for any city. About a third of rent variation remains unexplained, and the city coefficients should accordingly be read as conditional associations that may still absorb attributes correlated with city. Future work should link listing records to building registries and to spatially explicit accessibility measures, and should pursue partnerships with property managers in order to observe contracted rather than advertised rents.

6. Conclusion

I decompose condominium rents into the implicit prices of observable housing attributes (Rosen, 1974). Unit size accounts for the largest share of explained variation, while configuration, bathroom provision, outlook and city location account for further systematic differences (Sirmans et al., 2005). After controlling unit characteristics, economically significant city differences still exist, which is consistent with local amenities and demand circumstances being capitalized into rents (Anenberg & Kung, 2020; Roback, 1982).

When understanding such differentials, care must be taken, as the comparison of nested specifications shows. The Phuket premium remains unchanged when bathroom count and view type are included, but the Pattaya discount increases by more than eight log points: city indicators in parsimonious specifications absorb compositional variations in the listed stock's features. Comparative studies of this type should disclose the specification in addition to the estimate since city coefficients derived from listing data are conditional associations rather than indicators of willingness to pay. For three of Thailand's most important condominium rental markets, the contribution is comparative, listing-based, city-level evidence: how the main qualities are valued, how much of the apparent cross-city gap is compositional, and how much survives composition.

The process of cleaning and estimating is repeatable and applicable to other extracts.

To evaluate the stability of city differentials directly, future study should expand the attribute set to include building age, construction quality, and micro-location. Additionally, contracted rentals should be sought to quantify the difference between advertised and transacted values. Linking rental outcomes to macro-financial and credit conditions would let the tenure questions raised in Section 5.3 be examined with evidence capable of testing them.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author used Claude (Anthropic) and AI-assisted paraphrasing and language-editing tools to improve the language and readability of the manuscript. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article. All research design, data construction, analytical decisions, interpretations and conclusions are the author's own.

CRediT Authorship Contribution Statement

Than Dendoung: Conceptualization; Methodology/ Study design; Software; Formal Analysis; Investigation; Resources; data curation; visualization; Supervision; Project administration; Funding acquisition; Methodology/ Study design; Software; Validation; Formal analysis; Writing – original draft; Writing – review and editing; Supervision; Project administration; Funding acquisition.



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