Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

From Pressure to Saturation: A Multilevel Analysis of Short-Term Rental Density and Long-Term Rents in Colombia

Sergio A. Barona-Montoya
Pontificia Universidad Javeriana
Alexander Alegría Castellanos
aalegria@javerianacali.edu.co

Pontificia Universidad Javeriana
Alejandra Lozano Niño
Pontificia Universidad Javeriana

Article

Keywords:

Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11324911/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

From Pressure to Saturation: A Multilevel Analysis of Short-Term Rental Density and Long-Term Rents in Colombia

Sergio A. Barona-Montoya[1], Alexander Alegría Castellanos[1*], Alejandra Lozano Niño[2]

[1*]Department of Economics and Finance, Pontificia Universidad Javeriana Cali, Colombia.
[2*]Pontificia Universidad Javeriana Cali, Colombia.

*Corresponding author(s). E-mail(s): aalegria@javerianacali.edu.co (ORCID: 0000-0001-5091-1548);
Contributing authors: sergio.barona@javerianacali.edu.co (ORCID: 0000-0001-8390-6673); alejandralozano@javerianacali.edu.co (ORCID: 0009-0007-6286-5842);

Abstract

The rapid growth of short-term rental platforms such as Airbnb has transformed urban housing markets worldwide, yet empirical evidence from Latin American cities remains limited. This paper examines the association between short-term rental activity and long-term rental prices across 18 major Colombian cities. We estimate a two-level multilevel model accounting for both dwelling-level attributes and city-level characteristics, drawing on 6803 web-scraped rental listings nested within cities, combined with short-term rental market indicators and city-level census and household survey data. Roughly 17% of the variation in log rental prices is attributable to differences between cities, which indicates the presence of distinct urban housing submarkets. Short-term listing density, measured as active listings per 100 housing units, has a positive but nonlinear association with rental prices, which is consistent with market saturation. At average densities, more listings correspond to higher rents; however, this association diminishes and reverses beyond a threshold of three listings per 100 units above the mean. Cross-level interactions indicate that this pattern also varies with socioeconomic context and dwelling type. Higher-status neighborhoods reach peak prices at

lower listing densities, and the rent premium for houses over apartments declines as short-term rental activity intensifies. Furthermore, cities with more dynamic labor markets experience greater rental price pressures, particularly for houses. These findings show that platform-mediated short-term rentals are associated with substantial and uneven pressures on Colombian rental markets, with direct implications on housing affordability and regulation.

Keywords: Short-term rentals, Housing prices, Multilevel modelling, Airbnb, Colombia

JEL Classification: R31 , L83 , R14 , C31

1 Introduction

The expansion of digital short-term rental (STR) platforms, such as Airbnb and Vrbo, has reshaped urban housing market dynamics. Although these platforms emerged within the framework of the sharing economy (Crommelin, Troy, Martin, & Pettit, 2018; Schor, 2014), they have progressively evolved toward more commercialized and investment-oriented models, increasingly competing with long-term residential uses for the same housing stock. This transformation has contributed to broader processes of touristification, and urban spaces are progressively reorganized to accommodate preferences and consumption patterns of the visitors, often at the expense of residential stability (Cocola-Gant & Gago, 2021; Wachsmuth & Weisler, 2018). Touristification is frequently linked or even confused with gentrification. The latter generally involves the displacement of lower-income residents through reinvestment in the built environment and the arrival of higher-status populations (Jover & Díaz-Parra, 2020); the former, by contrast, operates through the conversion of residential space into short-term accommodation, replacing permanent inhabitants with transient visitors (Cocola-Gant, 2018). In the context of STR platforms, this dynamic does not strictly require the physical rehabilitation of deteriorated areas; it unfolds through the conversion of already attractive neighborhoods into short-term rental hotspots (Celata, Hendrickson, & Sanna, 2017).

Against this background, rent gap theory provides a useful framework for linking urban land markets to the dynamics of STR platforms. From this theoretical standpoint, when the potential value of land under alternative uses exceeds its current use value, incentives for reinvestment and displacement emerge (Smith, 1979). STR platforms activate precisely these gaps by the conversion of housing toward more profitable tourist uses, particularly in consolidated neighborhoods when the differential between long-term residential returns and short-term revenues is large (Grisdale, 2021; Yrigoy, 2019). More recent work shows that this process is driven less by occasional homesharing than by buy-to-let investment strategies that channel capital toward tourist accommodation, which facilitates the financialization of housing and intensifies displacement pressures (Cocola-Gant & Gago, 2021). Price consequences, however, are not uniform across cities and depend critically on the price elasticity of housing supply. In cities where supply is highly inelastic, a condition often determined by some

limitations, such as geographical constraints (e.g. coastlines, steep slopes, or mountainous terrain) that restrict the availability of developable land (Baum-Snow, 2023; Saiz, 2010), demand pressures translate into price increases rather than into an expansion of housing stock (Glaeser, Gyourko, & Saks, 2005).

A growing body of empirical research consistently finds that STR expansion is associated with increases in rents and housing prices, particularly in central areas with strong tourism demand. At the neighborhood level, evidence from Boston indicates that higher STR density is associated with rent increases (Horn & Merante, 2017). Studies of Barcelona estimate that Airbnb activity raised both rents and housing prices, with effects considerably larger in neighborhoods at the top decile of platform activity (García-López, Jofre-Monseny, Martínez-Mazza, & Seguí, 2020). At a broader scale, Barron, Kung, and Proserpio (2021) find that across US zip codes, increases in Airbnb listings lead to significant increases in both rents and house prices, with impacts amplified where investor-landlord activity is more prevalent. Similar positive associations have been documented for Portugal (Franco & Santos, 2021), as well as for several major French cities, particularly for professional entire-home listings (Ayouba, Breuillé, Grivault, & Le Gallo, 2020). At the same time, these impacts are not spatially uniform. Platform activity concentrates in a limited number of neighborhoods, which generates localized housing pressures that citywide averages may obscure (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019). Institutional context further conditions these dynamics, as regulatory capacity and local governance shape how tourism-related rent gaps translate into affordability pressures (Harvey, 1973; Logan & Molotch, 1987). Most of this evidence, however, is concentrated in North American and European cities. A recent systematic review confirms that research in Latin American cities remains at an early descriptive stage, focused more on characterization of the phenomenon than on the analysis of its housing market effects (Lerena Rongvaux & Rodríguez, 2024).

This gap is particularly relevant in Colombia, where housing markets are characterized by structural constraints such as high-income inequality, informality, and persistent affordability challenges. Since the pandemic, major Colombian cities, such as Medellín, have seen rapid growth in tourism and STR platform activity, positioning them as leading destinations for international visitors and remote workers (Aidi & Fabry, 2024), as well as for digital nomads (Bozzi, 2024). How the relationship between STR activity and prices varies across socioeconomic strata is also an empirical question that this study directly addresses[1].

Much of the empirical literature on the determinants of housing prices relies on hedonic specifications, which model housing as a differentiated good whose price reflects the implicit valuation of its attributes (Rosen, 1974), including structural characteristics such as floor area, number of rooms, and amenities, as well as locational and neighborhoods qualities (Chin & Chau, 2003; Sirmans, Macpherson, & Zietz, 2005).

[1]The Colombian residential system is further shaped by a socioeconomic stratification scheme that classifies the homes into six strata based on the characteristics of the housing unit and its surrounding area. This classification typically guides subsidy allocation and price discrimination in public utility services, though it has been criticized as an imprecise measure of household socioeconomic conditions (Chica-Olmo, Sánchez, & Sepúlveda-Murillo, 2020)

Nonetheless, most of these studies do not explicitly account for the hierarchical structure of housing markets. Dwellings within the same city share common contextual influences such as regulatory environments, tourism intensity, or labor market conditions, and failure to model this dependence, as noted by early studies (Brown & Uyar, 2004; Jones, 1991; Orford, 2000), may yield biased or inconsistent coefficient estimates. Research on housing submarkets documents that prices form within functionally distinct geographic segments rather than in fully integrated markets (Keskin, 2022; Watkins, 2001), and multilevel approaches have proved effective in capturing this nested structure (Brown & Uyar, 2004; Orford, 2000). Previous studies have examined the association between STR intensity and housing prices throughout multilevel frameworks (Deboosere et al., 2019). The present study extends this approach to a Latin American setting and incorporates cross-level interactions between city-level STR penetration and property-level attributes, a specification that permits the identification of differences in price associations across dwelling types and socioeconomic strata.

In this context, our paper analyzes the association between short-term rental activity and housing rental prices in 18 major Colombian cities. Housing prices are modeled using a cross-sectional multilevel model that incorporates both property-level attributes, including floor area, number of bathrooms, socioeconomic stratum, property age, and dwelling type, as well as city-level indicators of STR penetration and labor market conditions. This approach allows us to distinguish price patterns associated with dwelling attributes from those associated with city-level conditions, including platform-mediated tourism.

The remainder of this paper is structured as follows. Section 2 presents the geographical study area, the data sources at both the listing and city levels, the descriptive analysis strategy, and formalizes the two-level multilevel model that guides the empirical analysis. Section 3 presents the empirical results. Section 4 discusses the findings in relation to the theoretical framework and existing literature, concluding with a summary of the main contributions and acknowledging the study's limitations.

2 Data and Methods

2.1 Geographical study area

The sample consists of housing listings nested within 18 Colombian cities: Valledupar, Cúcuta, Villavicencio, Ibagué, Tunja, Neiva, Sincelejo, Manizales, Cali, Pasto, Armenia, Bucaramanga, Barranquilla, Santa Marta, Pereira, Bogotá, Cartagena, and Medellín. Figure 1 displays the geographical study area, locating each city within the national territory and mapping housing density, measured in units per square kilometer, to distinguish urban built-up areas from surrounding rural land. The proportion of land that is effectively urbanized varies substantially across study cities. This heterogeneity in urban built-up area carries direct implications for housing supply elasticity, which is a key determinant of how demand pressures translate into price outcomes, as noted in previous research (Glaeser et al., 2005). Cities with a more limited urban built-up area are therefore structurally less able to absorb demand pressures, making

upward price pressure more likely when demand intensifies. This dynamic is particularly salient in coastal tourism-oriented cities such as Santa Marta and Cartagena, where geographic containment coincides with rapidly growing STR activity and international visitor flows. This structural heterogeneity in urban form, and the resulting variation in how platform-mediated tourism is capitalized into rental prices, motivates the need to account for cross-city differences in the estimation of STR-associated price patterns.

2.2 Data

Data on individual rental listings were obtained through a web-scraping procedure implemented in R statistical software (R Core Team, 2025) from a publicly accessible online real state platform. The resulting web-scraped dataset contains detailed listing-level information, including rental price (COP/month), total floor area (in square meters), number of bedrooms and bathrooms, property type (distinguishing between apartments and houses), property age, and socioeconomic strata (SES). Prior to analysis, listings with rental prices of 15 million COP/month or more were excluded, insofar as these observations correspond to a high-end market segment whose price dynamics fall outside the scope of this study, as they are more closely linked to wealth preservation and investment strategies than to pressures arising from local residential housing markets.

To account for local economic and housing market conditions, several city-level contextual variables were compiled from multiple sources. Total housing units were obtained from the 2018 National Population and Housing Census (Departamento Administrativo Nacional de Estadística (DANE), 2018), and the Labor Force Participation (LFP) rate, defined as the percentage of the working-age population in the labor force, was obtained from the fourth quarter of 2025 of the Great Integrated Household Survey (Departamento Administrativo Nacional de Estadística (DANE), 2025). STR market conditions were characterized using AirDNA data: the number of active STR listings in each city (Airbnb and Vrbo platforms); the average daily rate (ADR), defined as the average revenue earned per booked night (USD/night); annual revenue, which is equivalent to the number of booked nights multiplied by the ADR; the occupancy rate, which measures the proportion of reserved nights relative to the number of nights available for booking; and revenue per available rental (RevPAR), which combines ADR and occupancy rate and captures the average revenue generated per available rental night. We also construct a listing density measure, defined as the number of active STR listings per 100 housing units, to approximate the relative intensity of STR activity within each city.

2.3 Descriptive Analysis

Descriptive statistics are reported at the national and city levels. Univariate normality of continuous variables is assessed using the Jarque-Bera test. Normally distribute variables are summarized using the mean and standard deviation; for non-normal variables, the median and interquartile range (IQR) are reported. Categorical variables are presented as counts and percentages. Bivariate comparisons across cities use the

Chi-Square test for independence or Fisher's exact test for categorical variables and the Kruskal-Wallis test for continuous variables. The latter documents systematic differences in the distribution of rental prices across cities, which provides descriptive evidence of cross-city heterogeneity in the dependent variable.

2.4 Multilevel modeling framework

Multilevel regression models provide a framework for analyzing hierarchical data structures in which lower-level observations are nested within higher-level units (Hox, Moerbeek, & Van de Schoot, 2018). In this framework, the response variable is measured at the lowest-level of analysis, and explanatory variables may be defined at multiple levels of the hierarchy. Early studies have shown that ignoring the hierarchical structure of the data set and estimating a single-level regression can yield biased inference, most notably through underestimated sampling variance and inflated Type I error rates (Maas & Hox, 2005), whereas multilevel modeling explicitly accounts for the partitioning of residual variance across levels of the hierarchy. This framework also reflects the idea that individual outcomes interact with the social contexts to which they belong, which has led to its widespread use in social science research, including studies of housing market dynamics (Orford, 2000). Accordingly, this study adopts a two-level multilevel model with housing units at Level 1 nested within cities at Level 2, following a sequence of specifications that proceeds from an intercept-only model (M1), to a random intercept model with listing- and city-level covariates (M2), and finally to an extension with random slopes and cross-level interactions (M3).

Formally, the dataset consists of rental housing listings observed across J cities, with the number of listings n_j varying by city $j \in \{1, ..., J\}$. Let p_{ij} denote the dependent variable, defined as the grand-mean-centered logarithm of the monthly rental price for housing unit i in city j. All continuous covariates are grand-mean-centered as well. The first specification (M1) is the following null (intercept-only) model:

$$p_{ij} = \gamma_{00} + \mu_{0j} + \varepsilon_{ij} \tag{M1}$$

Where γ_{00} denotes the average of the dependent variable, ε_{ij} is the usual residual error term assumed to be independently and normally distributed with mean zero and variance σ^2_ε, and μ_{0j} is a city-level random residual error term with mean zero and variance τ^2_0. The two error terms are assumed to be independent. Based on (M1), the intraclass correlation coefficient (ρ) is computed as:

$$\rho = \frac{\tau^2_0}{\tau^2_0 + \sigma^2_\varepsilon} \tag{1}$$

Following standard interpretation (Snijders & Bosker, 2012), ρ is most directly interpreted as an estimate of the proportion of city-level variance in the population relative to total variance and can also be interpreted as the expected correlation in rental prices between two housing units randomly selected within the same city.

Let $X_{ij} \in \mathbb{R}^K$ denote the K-dimensional vector of listing-level covariates, and let $\beta \in \mathbb{R}^K$ denote the corresponding vector of fixed slopes. The Level-1 equation is specified as:

$$p_{ij} = \beta_{0j} + \beta_j^\top X_{ij} + \varepsilon_{ij} \tag{2}$$

Let $Z_j \in \mathbb{R}^L$ denote the L-dimensional vector of city-level contextual variables. The second specification (M2) introduces a random-intercept structure by modelling the intercept as:

$$\beta_{0j} = \gamma_{00} + \gamma_0^\top Z_j + \mu_{0j}, \tag{3}$$

where $\gamma_0 \in \mathbb{R}^L$ is the vector of fixed effects associated with Z_j. Substitution of (3) into (2) yields:

$$p_{ij} = \gamma_{00} + \gamma_0^\top Z_j + \beta^\top X_{ij} + \mu_{0j} + \varepsilon_{ij} \tag{M2}$$

The third specification (M3) extends M2 by allowing the effects of listing-level covariates to vary across cities and by admitting cross-level interactions. Specifically, the city-specific slope vector $\beta_j \in \mathbb{R}^K$ is modeled as:

$$\beta_j = \beta + \Gamma Z_j + \mu_j, \tag{4}$$

where $\Gamma \in \mathbb{R}^{K \times L}$ is the matrix of cross-level interaction parameters, which may be written as $\Gamma = (\gamma_1^\top, ..., \gamma_K^\top)^\top$ with $\gamma_k \in \mathbb{R}^L$ for $k = 1, \ldots, K$, and $\mu_j \in \mathbb{R}^K$ is a vector of random terms, $\mu_j = (\mu_{1j}, \ldots, \mu_{Kj})^\top$, with zero means and variances τ_k^2. Substituting (M2) and (4) into (2) produces the full cross-level specification:

$$p_{ij} = \gamma_{00} + \gamma_0^\top Z_j + \beta^\top X_{ij} + X_{ij}^\top \Gamma Z_j + \mu_{0j} + X_{ij}^\top \mu_j + \varepsilon_{ij} \tag{M3}$$

Models M1 to M3 were compared using the deviance for nested specifications. The deviance is defined as -2ℓ, where ℓ denotes the maximized log likelihood function evaluated at convergence. All models were estimated by maximum likelihood, so that deviance, AIC and BIC are comparable across specifications with different fixed effects.

3 Results

3.1 Descriptive Results

Table 1 reports descriptive statistics for listing- and city-level variables included in the analysis, along with variable descriptions. The results of the Jarque-Bera test reject the null hypothesis of normal distribution for all continuous variables; therefore, descriptive statistics are reported using medians and interquartile ranges. At the listing-level, a typical listing is a medium-sized dwelling of 87 m^2, featuring three bedrooms and two bathrooms. The median rental price is 2800 thousand COP (IQR: 1600 – 4700), approximately USD 757 (at an exchange rate of 3700 COP per USD). Apartments account for 79.7% of listings, and more than half of properties are located in high SES areas, which suggests that formally advertised rental supply is disproportionately concentrated in high-SES neighborhoods. The housing stock is largely composed of units built within the last three decades.

Table 2 presents property characteristics by city and reveals substantial cross-city heterogeneity. Although apartments constitute the predominant property type across all cities, their distribution differs across urban markets (Chi-2 test, $p < 0.001$). Listings are primarily concentrated in medium- and high-SES areas; however, the

socioeconomic composition of listings varies significantly across cities (Chi-2 test, $p < 0.001$), with coastal and tourism-oriented markets, such as Cartagena and Santa Marta, concentrating a large share of properties in high-SES areas. Rental prices, dwelling size, and housing amenities also differ across cities, as the Kruskal-Wallis test suggests ($p < 0.001$). Median prices and unit sizes are higher in Medellín, Cartagena, and Bogotá, whereas lower values characterize cities such as Villavicencio, Cucuta, and Valledupar, which reflect more localized housing markets. Within cities, houses command higher rental prices than apartments, as shown in Figure 2.

At the city-level, STR intensity differs markedly across the 18 urban markets, with the highest listing densities observed in Santa Marta (7.5%), Cartagena (5.97%), and Medellín (2.82%). Figure 3 illustrates the relationship between listing density and STR market performance. Panel A shows a positive association between listing density and ADR, with tourism-oriented markets such as Cartagena and Santa Marta combining higher platform penetration with higher price levels. Occupancy rates do not increase proportionally with listing density, as cities with comparable penetration display substantial variation in utilization, particularly in lower levels of listing density (Panel B). Panel C reveals that higher listing density generally corresponds to greater annual revenues, though cities such as Medellín generate markedly higher revenue than others with similar densities, which reflects differences in booking intensity.

3.2 Multilevel regression analysis

3.2.1 Null model and intraclass correlation

The null model constitutes an intercept-only two-level specification without independent variables (Table 3). Based on the estimated between-city variance component ($\tau_0^2 = 0.09$ [0.05, 0.19]) and within-city variance component ($\sigma_\varepsilon^2 = 0.46$ [0.44, 0.47]), the intraclass correlation coefficient (ICC) is computed as $\rho = 0.1734$. This indicates that roughly 17.34% of the total variation in log rental prices is attributable to the city in which a housing unit is located, rather than heterogeneity across individual housing units. This magnitude is consistent with values that applied multilevel studies treat as non-negligible between-group variance (Gulliford, Ukoumunne, & Chinn, 1999), thereby motivating the use of multilevel modeling to account for the clustered nature of the data.

3.2.2 Random intercept and slope model: listing- and city-level effects

Model 2.1 introduces listing- and city-level covariates as fixed effects. At the city-level, STR listing density exhibits a positive but nonlinear association with rental prices (Table 4). The positive coefficient on listing density, together with the negative quadratic term, indicates that rental prices increase with STR intensity at lower levels of listing density but at a diminishing rate. The implied turning point occurs at a listing density of approximately 3 ($\times$ 100 housing units) above the sample mean, indicating diminishing marginal price effects as the STR markets become more saturated.

At low levels of STR activity, platform-mediated tourism appears to be linked to additional local demand pressure, consistent with higher long-term rents. However, beyond a certain threshold, an increasing share of housing units shifts from long-term to STR use, gradually withdrawing supply from the long-term market and offsetting further price growth. This mechanism is consistent with the diminishing and eventually negative marginal effects observed at higher listing densities, and may be reinforced by a parallel decline in residential demand, as areas with high STR concentration have been associated with resident depopulation in other urban contexts (Celata et al., 2017). In addition to STR-specific dynamics, city-level economic conditions also play a role in rental prices. The LFP rate is positively associated with rental prices, capturing stronger local economic conditions in more active urban labor markets.

At the listing level, larger floor areas and the presence of an additional bathroom are positively associated with higher log rental prices. Socioeconomic status is strongly related to rental values: properties located in low- and medium-SES areas are rented for substantially less than comparable units in high-SES neighborhoods. Relative to high-SES properties, units in low-SES areas rent for approximately 55.9% less, and those in medium-SES areas for approximately 36% less. Housing age is also negatively associated with rental prices, as older dwellings command lower rents relative to newer units. Houses rent for approximately 5.1% more than comparable apartments, though this estimate partly reflects the baseline premium prior to accounting for STR market conditions.

Model 2.2 extends Model 2.1 by allowing the effect of log floor area to vary across cities through a random slope. The STR listing density effects retain their sign, magnitude, and statistical significance relative to Model 2.1 (Table 4). The estimated slope variance for log floor area is $\tau_1^2 = 0.01(0.005, 0.024)$. This estimate indicates meaningful cross-city heterogeneity in the association between floor area and rental prices. Figure 4 displays the city-specific regression lines for log floor area and includes the fixed-effect slope, shown by the dashed line, which equals the mean of the city-specific slopes under the random-slope parameterization. The association between floor area and rental prices is positive in all cities, and approximately 95% of the regression coefficients for log floor area in the cities are predicted to lie between 0.21 and 0.60, which reflects substantial between-city heterogeneity in this relationship.

Model 3 extends Model 2.2 and incorporates cross-level interaction terms between city-level predictors and property-level attributes. Four alternative specifications were estimated, reported in Table 5. Model 3.1 includes the interaction between dwelling type and STR listing density; Model 3.2, the interaction between SES and STR listing density; Model 3.3 specifies the interaction between dwelling type and the labor force participation rate; and Model 3.4 incorporates all interaction terms jointly. The central finding from Model 3.4 is that the association between STR listing density and long-term rental prices is heterogeneous across socioeconomic contexts and dwelling types.

The association between STR listing density and long-term rental prices is not only non-linear but varies by SES group, as shown in Panel A of Figure 5. In high-SES neighborhoods, predicted rents reach their maximum at a listing density of approximately 2.85 listings per 100 housing units above the mean, which corresponds to a

predicted price of approximately 4813 thousand COP. Medium-SES neighborhoods peak at 3.10 (approximately 3200 thousand COP), and low-SES neighborhoods at 3.20 (approximately 2264 thousand COP). These findings suggest that higher-SES neighborhoods achieve higher peak prices at lower listing densities. Beyond the respective turning points, further increases in listing density are associated with diminishing or even modestly negative effects on long-term rents, consistent with market saturation dynamics.

The interaction between dwelling type and STR listing density indicates that the rent premium associated with houses relative to apartments diminishes as STR intensity increases. At low listing densities, houses command higher rents than apartments, which corresponds to their baseline market premium. However, as shown in Panel B of Figure 5, this advantage erodes as listing density rises. Notably, houses reach their peak predicted price at lower listing densities compared to apartments, which is also related to the relative scarcity of suitable houses for STR use. Finally, as shown in Panel C of Figure 5, the positive association between LFP and rental prices is stronger for houses than for apartments, such that the rent premium of houses widens with more active labor markets. This result is consistent with the relatively inelastic supply of houses that amplifies rent responses to income-driven demand pressures.

3.3 Model comparisons

The null model (M1) serves as the baseline. The introduction of listing- and city-level covariates in Model 2.1 produces a substantial reduction in deviance (14092.8 vs. 6443.4). Allowing the effect of log floor area to vary across cities in Model 2.2 yields further gains, with both AIC and BIC favoring Model 2.2 over Model 2.1 (AIC: 6383.7 vs. 6473.4; BIC: 6499.7 vs. 6575.8). Among the cross-level interaction specifications, Model 3.1 provides a modest improvement over Model 2.2 (deviance: 6303.3 vs. 6349.7), and Model 3.4, which incorporates all interaction terms jointly, achieves the largest reduction in deviance and the lowest AIC. Although Model 3.4 is penalized for its additional parameters, BIC still favors it over Model 2.2 Therefore, Model 3.4 is selected as the preferred specification, as it captures the heterogeneous effects of STR activity across dwelling types and socioeconomic contexts.

4 Discussion and conclusion

Our study contributes to the discussion about urban planning by estimating the association between STR activity and long-term rental prices across 18 Colombian cities within a multilevel (hierarchical) framework that explicitly accounts for the hierarchical structure of housing data. This methodological approach allows us to separate contextual variables such as the influence of STR density at the city scale and the LFP, from variables related to the characteristics of the dwelling place such as number of bathrooms, floor area and property type and age, instead of combining them into a single undifferentiated effect. In doing so, the multilevel framework reveals the uneven geography of STR-associated price patterns and shows that cities with more dynamic labor markets display stronger price pressure. From a spatial justice perspective, in

cities where STR activity is associated with higher rents, residents with limited economic opportunities may face a heightened likelihood of being priced out. Therefore, our analysis not only contributes methodologically but provides evidence directly relevant to planning debates on regulating tourism-driven housing transformations and protecting long-term residents.

Our analysis yields three main findings. First, our results show that a substantial share of the variation in rental prices is attributable to between-city differences in Colombia, with approximately 17% of total variation in log rental prices explained by city-level factors. This finding is consistent with the existence of housing submarkets, whereby housing markets are more appropriately understood as functionally distinct geographic segments rather than fully integrated units (Keskin, 2022). Although early work highlights difficulties in defining housing submarkets (Watkins, 2001), subsequent studies document segmentation into nested spatial units (e.g. administrative neighborhoods, street-based areas, census tracts or blocks, and cities) within which prices reflect both dwelling-level attributes and higher-level contextual factors (Alas, 2020; Chasco & Le Gallo, 2012; Keskin, 2022).

The second main finding highlights an important advantage of multilevel models emphasized in prior research: they allow the simultaneous estimation of the effects of unit-level structural attributes and higher-level contextual characteristics (Liu & Roberts, 2012). In the hedonic pricing framework, housing is treated as a differentiated good whose market price reflects the implicit price of its constituent attributes (Rosen, 1974). Accordingly, rental values capitalize structural characteristics such as floor area, number of bathrooms, bedrooms, and related amenities that differentiate units within a market (Sirmans et al., 2005). Our estimates indicate positive capitalization effects for key structural attributes, particularly floor area and the number of bathrooms. Consistent with the hedonic pricing literature, we find a positive association between floor area and rental prices, reflecting the capitalization of desirable structural attributes into market prices. A critical review identifies floor area as the single most important structural attribute in housing price determination and documents a consistently positive relationship between dwelling size and market prices across studies (Chin & Chau, 2003).

Third, our analysis reveals that STR listing density is associated with a positive but nonlinear association on long-term rental prices. At the mean level of listing density, a one-unit increase is associated with an approximate 15% increase in rental prices; nonetheless, this marginal effect diminishes as listing density rises and turns negative beyond a threshold of approximately 3 listings per 100 housing units above the mean, consistent with market saturation dynamics. A positive association between STR activity and rental prices has been consistently documented in prior research (Franco & Santos, 2021). At a wider geographic scale, Barron et al. (2021) find that, across US zip codes, a 1% increase in Airbnb listings leads to a 0.02% increase in rents and a 0.03% increase in house prices, with impacts larger where investor-landlord activity is more prevalent. At neighborhood levels, a greater effect has been found. Similar positive effects are documented for several major French cities, particularly when focusing on professional entire-home listings (Ayouba et al., 2020). For Barcelona,

García-López et al. (2020) estimate that Airbnb activity increased neighborhood rents and housing prices; specifically, they found that rents increase on the order of 1.9% at average exposure and roughly 7% in neighborhoods at the top decile of Airbnb activity. However, the nonlinear pattern documented in our paper extends this literature by identifying a saturation threshold beyond which additional STR listings are associated with diminishing and eventually negative effects on long-term rents, a dynamic that has received limited attention in prior works.

Beyond the aggregate effect, the cross-level interactions reveal that STR-associated price pressures operate differently across socioeconomic and dwelling types. Higher-SES neighborhoods reach their rent peak at lower listing densities, which is consistent with concentrated high-income demand coinciding with more rapid price appreciation even at relatively few platform listings. At low STR densities, houses command a rent premium over apartments, but apartments surpass houses in predicted rents at higher STR intensities. This pattern is consistent with evidence that suggests that investment-driven STR activity is predominantly concentrated in the apartment sector (Wachsmuth & Weisler, 2018), and with the relative scarcity of houses suitable for short-term rental conversion. These dynamics are consistent with the broader literature on tourism-driven housing transformations. For Barcelona, Garay Tamajón and Morales Pérez (2022) show that the concentration of Airbnb listings in "highly touristified" and "trendy" neighborhoods has been closely associated with rapid rent escalation, resident displacement toward peripheral areas, and subsequent price pressures in those receiving neighborhoods as well. A previous study in New York City also found that in professionalized, high-revenue hosts are disproportionately located in well-connected residential neighborhoods, where converting long-term rentals into "de facto hotels" yields a substantial premium relative to conventional renting and incentivizes the removal of units from the long-term stock (Deboosere et al., 2019). These findings are complemented with important qualitative work: a previous study in Lisboa finds that Airbnb primarily channels buy-to-let investment rather than "sharing" spare rooms, which facilitates the financialization of housing and tourism-driven displacement of tenants (Cocola-Gant & Gago, 2021). According to the rent gap theory, cases like Lisbon (Cocola-Gant & Gago, 2021) or Palma de Mallorca (Yrigoy, 2019) show how investors quickly took advantage of the rent gap between the actual and potential housing price, since the platform allows owners to capture a "tourist rent" that's higher than a normal residential rent, which drives them to shift toward short-term use. While our data do not allow direct observation of investor behavior or unit conversion, the nonlinear price effects and the differential impacts across dwelling types and SES groups are broadly consistent with these mechanisms operating in Colombian urban markets, particularly in cities with high tourist activity.

The emergence of platform-mediated STRs, as an important factor associated with rental prices, has important regulatory implications. Urban planning research in Sidney indicates that platform-mediated STR growth has raised acute concerns about the erosion of permanent rental stock and affordability. This has led planers to reconsider zoning and land-use controls (Gurran & Phibbs, 2017). Comparative work on European cities further shows that local governments have experimented with caps on entire-home listings, primary-residence rules, and cooperation agreements with

platforms, in order to achieve measurable reductions in professional STR supply but facing persistent enforcement and data-access challenges (Aguilera, Artioli, & Colomb, 2021; Bei & Celata, 2023). Our study of Colombian cities not only adds to international evidence but suggests that platform-mediate accommodation cannot be treated as purely marginal or benign tourism innovation; it must be integrated into housing policy debates, with particular attention to how different regulatory designs affect both the scale of STR activity and its distributional consequences for tenants across socioeconomic groups.

Three limitations of the study should be acknowledged when interpreting the results, each of which points toward productive directions for future research. First, the analysis relies on observational data drawn from online housing listings and short-term rental platforms, which capture only properties actively advertised on digital platforms. These findings characterize the segment of housing market most directly exposed to platform-mediated dynamics, rather than the full spectrum of residential market activity. Second, the empirical analysis draws on data observed in 2025, capturing consolidate phase of post-pandemic platform activity rather than the immediate recovery period following the pandemic. While this strengthens internal validity by reflecting stabilized market conditions, it limits the ability to trace dynamic adjustment processes or distinguish short-run from longer-term structural effects. Third, our analysis is conducted at the city level, with measures of STR activity and contextual socioeconomic conditions constructed at this scale of aggregation. In a previous study, Huang, Qiao, and Yeh (2024) show that housing price differences across cities persist even after controlling for city-wide socioeconomic and demographic conditions, which points to city-level heterogeneity as a substantive driver of housing market outcomes. This approach, nonetheless, comes with a clear limitation, as many affordability dynamics likely operate at finer spatial scales, such as the neighborhood level. Deboosere et al. (2019) nest Airbnb listings within census tracts and boroughs in New York City to capture neighborhood-level heterogeneity and microneighborhood effects that standard OLS models miss. In the same vein, Alas (2020) shows that, in Istanbul, multilevel models using smaller spatial units, including street-based submarkets, improve dwelling-price prediction relative to broader city-wide and administratively defined submarkets. This evidence indicates that both spatial scales carry an independent explanatory value and that a city-level approach may not fully capture localized effects within cities, a limitation that is especially relevant for spatially heterogeneous metropolitan areas such as Bogotá and Medellín. This constraint stems directly from data availability, and closing this gap by incorporating neighborhood-level STR intensity into our framework remains a priority for future research.

The evidence presented here underscores the importance of interpreting STR-associated housing pressures through a multilevel, spatially sensitive lens. By disentangling dwelling, and city-level factors, our approach shows that STR growth interacts with existing urban structures in ways that amplify affordability challenges in cities with strong economic dynamism and high tourist appeal. The differentiated effects across dwelling types, combined with the uneven geography of rental prices, highlight that STR expansion is not merely a housing-market phenomenon but appears closely linked to the socio-spatial foundations of some Colombian cities. As urban planners

and policymakers confront these multidimensional pressures, the evidence presented here provides a critical empirical basis to design regulatory frameworks that balance economic opportunities with the necessity to preserve equitable access to housing.

Figures

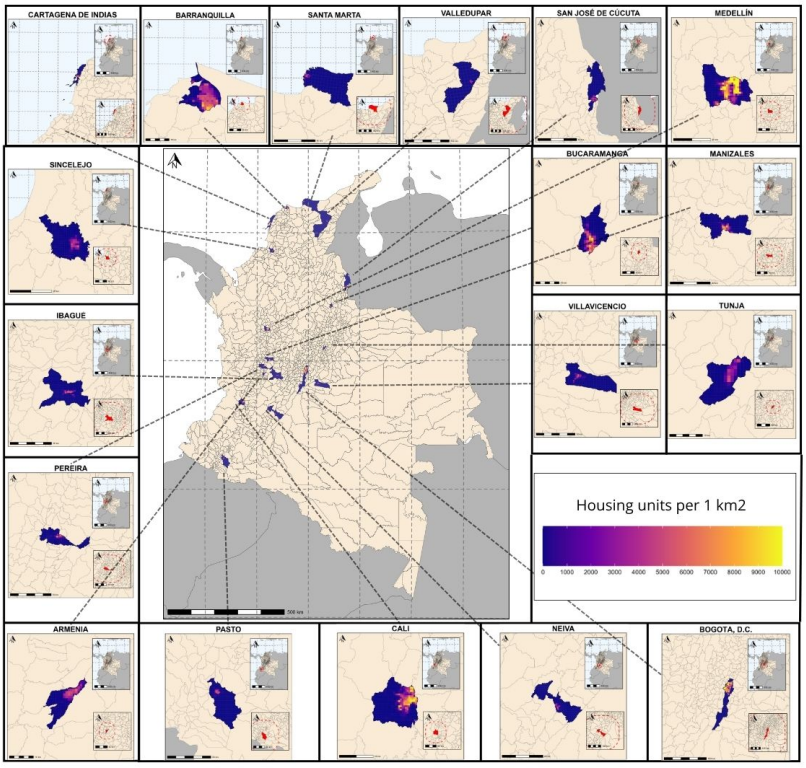


Fig. 1 Geographical distribution of the study area and housing density across 18 Colombian cities. Each inset displays the spatial distribution of housing density within the administrative boundary of the respective municipality, measured in housing units per square kilometer and computed from a 1 km2 grid. The color gradient ranges from deep blue (low density) to yellow (high density), distinguishing urban built-up areas from surrounding rural land. Municipal boundaries were obtained from the Geographic Institute Agustín Codazzi (IGAC). Housing density was derived from the 2018 National Population and Housing Census (DANE, 2018).

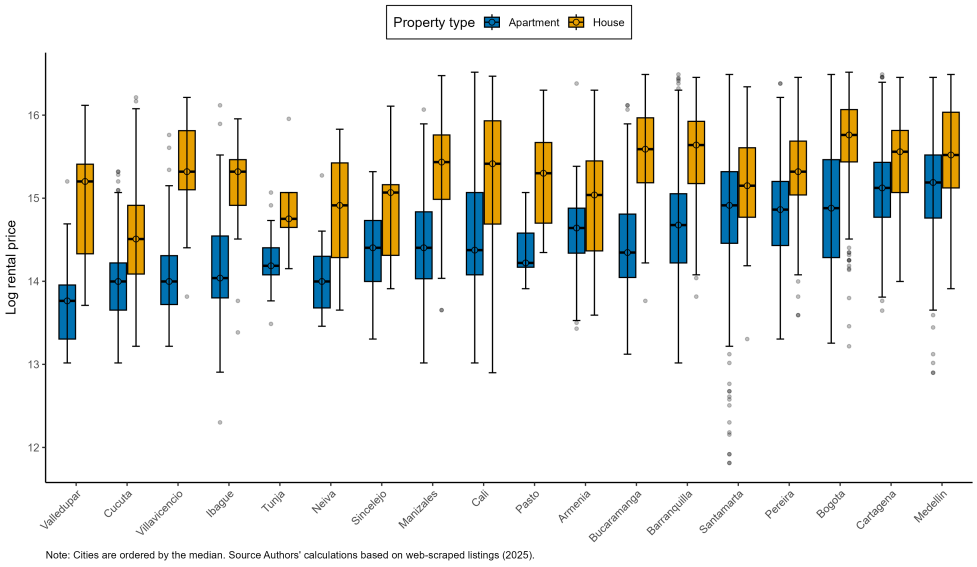


Fig. 2 Distribution of rental prices across cities by dwelling type. Cities are ordered by the median. Source: Author's calculations based on web-scraped listings (2025).

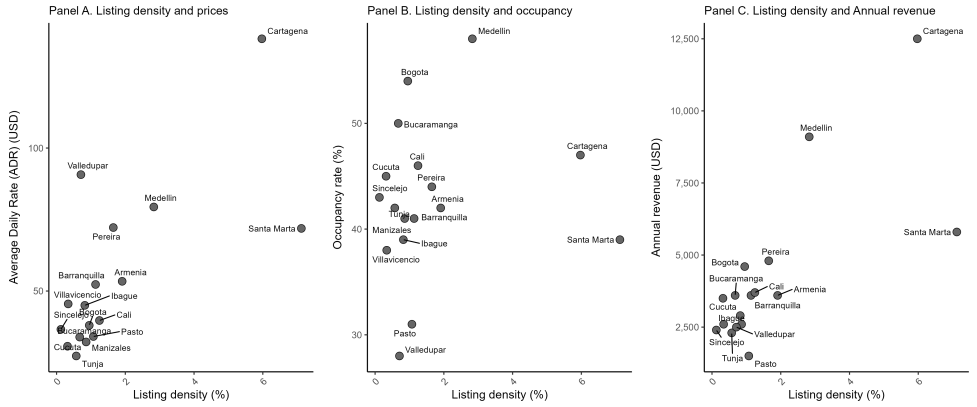


Fig. 3 Short-term rental market performance and listing density across 18 Colombian cities. Panel (A) shows the relationship between listing density, defined as the number of active STR listings per 100 housing units, and the Average Daily Rate (ADR), measured in USD per booked night. Panel (B) shows the relationship between listing density and the occupancy rate. Panel (C) shows the relationship between listing density and annual revenue. Each dot represents one of the 18 cities included in the analysis. STR data are drawn from AirDNA and cover both Airbnb and Vrbo platforms.

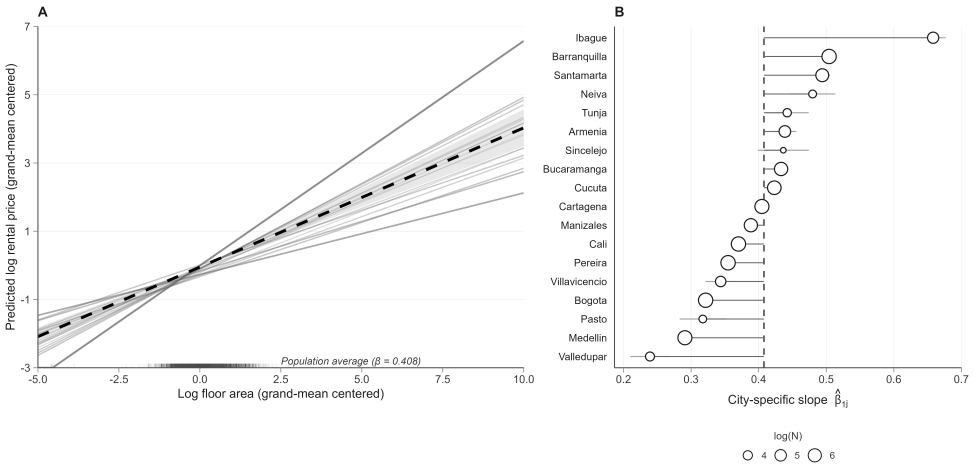


Fig. 4 : City-specific random slopes for log floor area across 18 Colombian cities (Model 2.2). Panel A displays the city-specific predicted relationships between log floor area (grand-mean centered) and log rental price (grand-mean centered). Each grey line represents one city, and the dashed black line represents the population-average slope. Rug marks on the horizontal axis show the distribution of log floor area values across listings. Panel B displays the city-specific slope estimates ordered from smallest to largest, with dot size proportional to the log of the city sample size. The dashed vertical line marks the population-average slope.

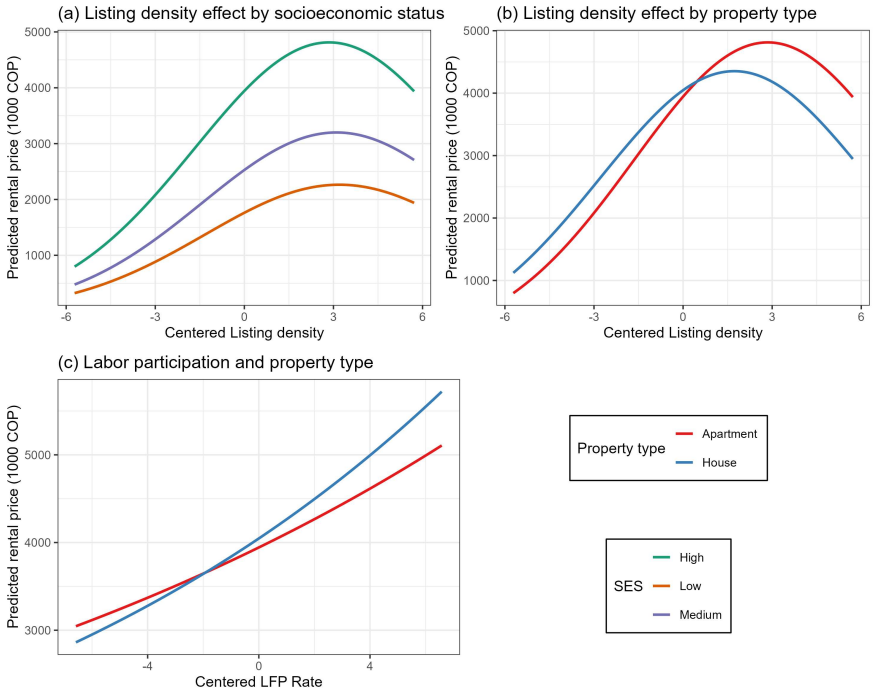


Fig. 5 Predicted Rental Prices: Interactions with Listing Density, Socioeconomic Status, Property Type, and Labor Market Conditions. Continuous variables are evaluated at their sample means, and categorical variables are set to reference categories. Listing density and labor force participation (LFP) rate are mean-centered.

Tables

Table 1 Characteristics of listing- and city-level variables (18 Colombian cities).

Variable	Category	Summary	Description
Listing-level			
Rental price (1000 COP)		2800 (1600, 4700)	Rental price of the property, expressed in Colombian pesos (COP).
Total floor area		87 (60, 140)	Total constructed area of the property, expressed in square meters.
Bedrooms		3 (2, 3)	Total number of bedrooms in the property.
Bathrooms		2 (2, 3)	Total number of bathrooms in the property.
Property type	Apartment	5421 (79.7)	Structural type of the property: house (1) or apartment (0).
	House	1382 (20.3)	
SES	Low	225 (3.3)	Socioeconomic stratum of the property according to Colombian classification, from the lowest (stratum 1) to the highest (stratum 6). Low: strata 1–2; Medium: strata 3–4; High: strata 5–6.
	Medium	3021 (44.4)	
	High	3557 (52.3)	
Property age	$<$ 1 year	639 (9.4)	Age of the property measured in years since construction.
	1 to 8 years	2261 (33.2)	
	9 to 15 years	1426 (21.0)	
	16 to 30 years	1630 (24.0)	
	$>$ 30 years	847 (12.5)	
City-level			
Total housing units		282344 (170177, 666526)	Total number of housing units (houses and apartments) in each city.
Active listings		3745 (2092, 16862)	Total number of active short-term rental listings in the city across Airbnb and Vrbo platforms.
Listing density		1.2 (1.0, 1.9)	Number of active short-term rental listings per 100 housing units in the city.
ADR		52.3 (38.0, 72.2)	Average rental revenue earned per booked night (USD/night).
Annual revenue		3700 (3600, 4800)	Average annual revenue per active short-term rental listing (USD), computed as booked nights multiplied by ADR
Occupancy rate		46 (41, 50)	Percentage of available nights that a short-term rental listing is booked.
RevPAR		20.4 (17.1, 25.2)	ADR multiplied by the occupancy rate.
LFP rate (%)		64.9 (62.2, 66.3)	Percentage of the working-age population that participates in the labor force.

Notes: Continuous variables are reported as median (Q1, Q3). Categorical variables are reported as n (%). COP = Colombian peso; SES = socioeconomic stratum; ADR = average daily rate; RevPAR = revenue per available rental; LFP = labor force participation. STR data are drawn from AirDNA; housing listing data were obtained through web scraping of a publicly accessible real estate platform; LFP rates are from DANE (2025)

Table 2 Listing-level characteristics by city (18 Colombian cities).

						SES, n (%)			Property age, n (%)					Property type, n (%)	
City	N	**Price**	**Floor area**	**Bed.**	**Bath.**	Low	Medium	High	<1 yr	1–8 yr	9–15 yr	16–30 yr	>30 yr	Apartment	House
Armenia	140	2400 (1687.5, 3200)	72.4 (59.5, 111.2)	3 (2, 3)	2 (2, 2)	1 (0.7)	41 (29.3)	98 (70.0)	14 (10.0)	67 (47.9)	27 (19.3)	24 (17.1)	8 (5.7)	112 (80.0)	28 (20.0)
Barranquilla	831	2500 (1600, 3900)	82.0 (62, 127)	3 (2, 3)	2 (2, 3)	27 (3.2)	410 (49.3)	394 (47.4)	60 (7.2)	331 (39.8)	223 (26.8)	155 (18.7)	62 (7.5)	732 (88.1)	99 (11.9)
Bogotá	823	3400 (1710, 6500)	76.0 (47.8, 157)	2 (2, 3)	2 (1, 3)	27 (3.3)	412 (50.1)	384 (46.7)	95 (11.5)	203 (24.7)	139 (16.9)	197 (23.9)	189 (23.0)	677 (82.3)	146 (17.7)
Bucaramanga	388	2469 (1500, 4500)	91.5 (65, 203)	3 (3, 4)	2 (2, 3)	16 (4.1)	252 (64.9)	120 (30.9)	75 (19.3)	58 (14.9)	103 (26.5)	115 (29.6)	37 (9.5)	264 (68.0)	124 (32.0)
Cali	829	2200 (1300, 4500)	85.0 (60, 154)	3 (2, 3)	2 (2, 3)	35 (4.2)	395 (47.6)	399 (48.1)	81 (9.8)	262 (31.6)	157 (18.9)	224 (27.0)	105 (12.7)	658 (79.4)	171 (20.6)
Cartagena	693	3800 (2700, 5542)	97.0 (65, 135)	2 (2, 3)	2 (2, 3)	4 (0.6)	222 (32.0)	467 (67.4)	61 (8.8)	299 (43.1)	102 (14.7)	147 (21.2)	84 (12.1)	614 (88.6)	79 (11.4)
Cúcuta	487	1300 (927.5, 1900)	72.0 (53, 120)	3 (2, 3)	2 (2, 3)	39 (8.0)	394 (80.9)	54 (11.1)	35 (7.2)	121 (24.8)	99 (20.3)	185 (38.0)	47 (9.7)	337 (69.2)	150 (30.8)
Ibagué	115	1366.1 (1000, 2500)	65.0 (56, 102)	3 (3, 3)	2 (2, 2)	15 (13.0)	90 (78.3)	10 (8.7)	11 (9.6)	57 (49.6)	20 (17.4)	16 (13.9)	11 (9.6)	98 (85.2)	17 (14.8)
Manizales	377	2166 (1391, 3800)	82.0 (52, 170)	3 (2, 4)	2 (1, 3)	12 (3.2)	151 (40.1)	214 (56.8)	21 (5.6)	70 (18.6)	67 (17.8)	136 (36.1)	83 (22.0)	279 (74.0)	98 (26.0)
Medellín	684	4050 (2700, 5900)	92.0 (68, 130)	3 (2, 3)	2 (2, 3)	13 (1.9)	233 (34.1)	438 (64.0)	54 (7.9)	234 (34.2)	176 (25.7)	178 (26.0)	42 (6.1)	579 (84.6)	105 (15.4)
Neiva	35	1600 (1047.5, 3250)	102.0 (69.5, 200)	3 (3, 4)	2 (2, 3)	6 (17.1)	21 (60.0)	8 (22.9)	2 (5.7)	7 (20.0)	5 (14.3)	10 (28.6)	11 (31.4)	18 (51.4)	17 (48.6)
Pasto	34	2200 (1500, 3800)	140.0 (85.8, 229.5)	3 (3, 4.8)	3 (2, 3.8)	4 (11.8)	20 (58.8)	10 (29.4)	2 (5.9)	8 (23.5)	12 (35.3)	1 (2.9)	11 (32.4)	18 (52.9)	16 (47.1)
Pereira	872	3250 (2187.5, 4557.5)	95.0 (70, 150.8)	3 (2, 3)	2 (2, 3)	6 (0.7)	166 (19.0)	700 (80.3)	98 (11.2)	347 (39.8)	170 (19.5)	152 (17.4)	105 (12.0)	637 (73.1)	235 (26.9)
Santa Marta	301	3000 (2000, 5000)	81.0 (56, 122)	2 (1, 3)	2 (2, 3)	4 (1.3)	82 (27.2)	215 (71.4)	13 (4.3)	114 (37.9)	78 (25.9)	63 (20.9)	33 (11.0)	260 (86.4)	41 (13.6)
Sincelejo	28	2050 (1237.5, 3500)	103.0 (84.5, 146.6)	3 (3, 4)	2 (2, 4)	3 (10.7)	22 (78.6)	3 (10.7)	1 (3.6)	11 (39.3)	10 (35.7)	4 (14.3)	2 (7.1)	17 (60.7)	11 (39.3)
Tunja	39	1500 (1365, 2250)	67.0 (56, 107)	3 (2, 3)	2 (2, 2)	1 (2.6)	27 (69.2)	11 (28.2)	5 (12.8)	13 (33.3)	6 (15.4)	8 (20.5)	7 (17.9)	30 (76.9)	9 (23.1)
Valledupar	47	1150 (850, 3100)	80.0 (60, 175)	3 (2, 3)	2 (2, 3)	5 (10.6)	24 (51.1)	18 (38.3)	0 (0.0)	16 (34.0)	19 (40.4)	7 (14.9)	5 (10.6)	29 (61.7)	18 (38.3)
Villavicencio	80	1325 (1000, 2775)	60.5 (54, 128.4)	3 (2, 3)	2 (1, 3)	7 (8.8)	59 (73.8)	14 (17.5)	11 (13.8)	43 (53.8)	13 (16.2)	8 (10.0)	5 (6.2)	62 (77.5)	18 (22.5)
Jarque–Bera		<0.001	<0.001	<0.001	<0.001										
Kruskal–Wallis		<0.001	<0.001	<0.001	<0.001										
Chi-square							<0.001				<0.001				<0.001

Note. Continuous variables are reported as median (Q1, Q3). Rental prices are expressed in thousands of COP. Categorical variables are reported as n (%). Jarque–Bera p-values refer to univariate normality tests for continuous variables; Kruskal–Wallis p-values test equality of distributions across cities for continuous variables. Chi-square p-values test independence between the respective categorical variable and city. Bed. = bedrooms; Bath. = bathrooms; SES = socioeconomic stratum.

Table 3 Null model estimates for log rental prices.

	Null model			
	b	SE	95% CI	p-value
Fixed effects				
Intercept	-0.142	0.073	$[-0.285,\ 0.002]$	0.053
Random effects				
τ_0^2	0.096	–	$[\ 0.049,\ 0.188]$	–
σ_ε^2	0.458	–	$[\ 0.443,\ 0.474]$	–
Log-likelihood				−7046.39
Deviance				14092.78
AIC				14098.78
BIC				14119.26
ICC				0.1734

Note. 95% confidence intervals are reported in brackets. ICC = intraclass correlation coefficient; τ_0^2 = variance of the random intercept; σ_ε^2 = residual variance; AIC = Akaike information criterion; BIC = Bayesian information criterion; Deviance = $-2\times$ Log-likelihood.

Table 4 Multilevel regression results for log rental prices: random-intercept and random-slope specifications.

	Model 2.1				Model 2.2			
	b	SE	95% CI	p-value	b	SE	95% CI	p-value
Fixed effects								
Intercept	-0.093	0.047	[−0.185, 0.000]	0.049	-0.049	0.046	[−0.139, 0.041]	0.284
log(Floor area)	0.366	0.010	[0.347, 0.385]	<0.001	0.408	0.028	[0.354, 0.462]	<0.001
Bathrooms	0.168	0.005	[0.158, 0.178]	<0.001	0.162	0.005	[0.152, 0.173]	<0.001
SES (ref.: High)								
Low	-0.819	0.028	[−0.874, −0.764]	<0.001	-0.813	0.028	[−0.867, −0.758]	<0.001
Medium	-0.446	0.011	[−0.468, −0.424]	<0.001	-0.446	0.011	[−0.468, −0.425]	<0.001
Property age (ref.: 1–8 years)								
< 1 year	0.030	0.018	[−0.005, 0.064]	0.092	0.027	0.017	[−0.007, 0.061]	0.120
9–15 years	-0.059	0.013	[−0.085, −0.033]	<0.001	-0.060	0.013	[−0.086, −0.034]	<0.001
16–30 years	-0.122	0.013	[−0.148, −0.096]	<0.001	-0.128	0.013	[−0.154, −0.103]	<0.001
> 30 years	-0.099	0.017	[−0.131, −0.066]	<0.001	-0.105	0.017	[−0.138, −0.073]	<0.001
Property type (ref.: Apartment)								
House	0.050	0.015	[0.021, 0.079]	<0.001	0.035	0.015	[0.005, 0.064]	0.021
Listing density	0.134	0.028	[0.075, 0.193]	<0.001	0.144	0.026	[0.088, 0.200]	<0.001
Listing density^2	-0.021	0.008	[−0.039, −0.004]	0.019	-0.025	0.008	[−0.041, −0.008]	0.006
LFP rate	0.037	0.007	[0.021, 0.052]	<0.001	0.040	0.007	[0.026, 0.054]	<0.001
Random effects								
τ_0^2	0.009	–	[0.004, 0.020]	–	0.010	–	[0.005, 0.022]	–
τ_1^2	–	–	–	–	0.010	–	[0.005, 0.024]	–
σ_ε^2	0.150	–	[0.145, 0.155]	–	0.147	–	[0.142, 0.152]	–
Log-likelihood				−3221.72				−3174.85
Deviance				6443.45				6349.70
AIC				6473.45				6383.70
BIC				6575.82				6499.73

Note. 95% confidence intervals are reported in brackets. log(Floor area), listing density, listing density^2, and the labor force participation (LFP) rate are mean-centered. SES = socioeconomic stratum; τ_0^2 = variance of the random intercept; τ_1^2 = variance of the random slope of log(Floor area) across cities; σ_ε^2 = residual variance; AIC = Akaike information criterion; BIC = Bayesian information criterion; Deviance = −2× Log-likelihood. Reference categories are indicated in parentheses.

Table 5 Multilevel regression results for log rental prices: cross-level interaction specifications.

	Model 3.1				Model 3.2				Model 3.3				Model 3.4			
	b	SE	95% CI	*p*	*b*	SE	95% CI	*p*	*b*	SE	95% CI	*p*	*b*	SE	95% CI	*p*
Fixed effects																
Intercept	-0.055	0.046	[−0.145, 0.036]	0.240	-0.049	0.046	[−0.138, 0.041]	0.286	-0.045	0.046	[−0.135, 0.045]	0.328	-0.051	0.046	[−0.142, 0.040]	0.270
log(Floor area)	0.401	0.028	[0.345, 0.457]	<0.001	0.408	0.028	[0.353, 0.462]	<0.001	0.415	0.031	[0.355, 0.475]	<0.001	0.406	0.031	[0.345, 0.466]	<0.001
Bathrooms	0.163	0.005	[0.153, 0.173]	<0.001	0.162	0.005	[0.152, 0.172]	<0.001	0.162	0.005	[0.152, 0.173]	<0.001	0.162	0.005	[0.152, 0.173]	<0.001
SES (ref.: High)																
Low	-0.812	0.028	[−0.866, −0.758]	<0.001	-0.815	0.033	[−0.879, −0.750]	<0.001	-0.810	0.028	[−0.864, −0.755]	<0.001	-0.806	0.033	[−0.870, −0.742]	<0.001
Medium	-0.442	0.011	[−0.464, −0.421]	<0.001	-0.447	0.011	[−0.468, −0.425]	<0.001	-0.447	0.011	[−0.469, −0.426]	<0.001	-0.445	0.011	[−0.467, −0.423]	<0.001
Property age (ref.: 1–8 years)																
< 1 year	0.029	0.017	[−0.005, 0.062]	0.100	0.027	0.017	[−0.007, 0.061]	0.118	0.026	0.017	[−0.008, 0.060]	0.128	0.028	0.017	[−0.006, 0.062]	0.103
9–15 years	-0.061	0.013	[−0.087, −0.035]	<0.001	-0.059	0.013	[−0.085, −0.033]	<0.001	-0.058	0.013	[−0.084, −0.032]	<0.001	-0.059	0.013	[−0.085, −0.034]	<0.001
16–30 years	-0.128	0.013	[−0.154, −0.102]	<0.001	-0.128	0.013	[−0.154, −0.102]	<0.001	-0.127	0.013	[−0.153, −0.102]	<0.001	-0.127	0.013	[−0.152, −0.101]	<0.001
> 30 years	-0.105	0.017	[−0.137, −0.073]	<0.001	-0.105	0.017	[−0.138, −0.073]	<0.001	-0.109	0.017	[−0.142, −0.077]	<0.001	-0.108	0.017	[−0.140, −0.075]	<0.001
Property type (ref.: Apartment)																
House	0.025	0.015	[−0.005, 0.054]	0.102	0.035	0.015	[0.005, 0.064]	0.022	0.037	0.015	[0.007, 0.066]	0.015	0.026	0.015	[−0.004, 0.055]	0.089
Listing density	0.150	0.026	[0.093, 0.206]	<0.001	0.141	0.026	[0.084, 0.198]	<0.001	0.143	0.026	[0.087, 0.199]	<0.001	0.140	0.026	[0.083, 0.196]	<0.001
Listing density^2	-0.026	0.008	[−0.042, −0.009]	0.005	-0.024	0.008	[−0.041, −0.008]	0.006	-0.025	0.008	[−0.041, −0.009]	0.006	-0.024	0.008	[−0.041, −0.008]	0.006
LFP rate	0.040	0.007	[0.026, 0.055]	<0.001	0.040	0.007	[0.026, 0.054]	<0.001	0.038	0.007	[0.024, 0.052]	<0.001	0.039	0.007	[0.025, 0.054]	<0.001
Cross-level interactions																
House × Listing density	-0.055	0.008	[−0.070, −0.039]	<0.001	–	–	–	–	–	–	–	–	-0.055	0.008	[−0.071, −0.039]	<0.001
SES: Low × Listing density	–	–	–	–	0.001	0.022	[−0.042, 0.044]	0.967	–	–	–	–	0.017	0.022	[−0.026, 0.060]	0.437
SES: Medium × Listing density	–	–	–	–	0.004	0.006	[−0.007, 0.015]	0.477	–	–	–	–	0.012	0.006	[0.001, 0.023]	0.029
House × LFP rate	–	–	–	–	–	–	–	–	0.017	0.004	[0.009, 0.025]	<0.001	0.013	0.004	[0.005, 0.022]	0.001
Random effects																
τ_0^2	0.011	–	[0.005, 0.024]	–	0.010	–	[0.004, 0.022]	–	0.011	–	[0.005, 0.024]	–	0.011	–	[0.005, 0.025]	–
τ_1^2	0.011	–	[0.005, 0.025]	–	0.010	–	[0.004, 0.024]	–	0.013	–	[0.006, 0.030]	–	0.014	–	[0.006, 0.030]	–
σ_ε^2	0.146	–	[0.141, 0.151]	–	0.147	–	[0.142, 0.152]	–	0.147	–	[0.142, 0.152]	–	0.146	–	[0.141, 0.151]	–
Model fit																
Log-likelihood				−3151.65				−3174.60				−3166.65				−3144.21
Deviance				6303.30				6349.20				6333.30				6288.43
AIC				6339.30				6387.20				6369.30				6330.43
BIC				6462.15				6516.87				6492.15				6473.75

Note. 95% confidence intervals are reported in brackets; *p*-values below 0.001 are reported as <0.001. log(Floor area), listing density, listing density^2, and the labor force participation (LFP) rate are mean-centered. SES = socioeconomic stratum; τ_0^2 = variance of the random intercept; τ_1^2 = variance of the random slope of log(Floor area) across cities; σ_ε^2 = residual variance; AIC = Akaike information criterion; BIC = Bayesian information criterion; Deviance = −2× Log-likelihood. Model 3.1 includes only the dwelling type × listing density interaction; Model 3.2 includes SES × listing density interactions; Model 3.3 includes the dwelling type × LFP rate interaction; Model 3.4 includes all four cross-level interactions jointly.

Appendix A: Derivation of the Multilevel Specifications

This appendix presents the complete empirical content of each model estimated in the analysis. All continuous predictors are grand-mean centered prior to estimation. Note that the random-intercept model (M2.1) and the random-slope model (M2.2) share the general reduced form:

$$\begin{aligned} p_{ij} = \gamma_{00} + \gamma_0^\top Z_j + \beta^\top X_{ij} \\ + \mu_{0j} + \mu_{1j} \log(\text{Floor area}_{ij}) + \varepsilon_{ij} \end{aligned} \tag{1}$$

The listing-level predictor vector and its associated fixed coefficient vector are:

$$X_{ij} = \begin{pmatrix} \log(\text{Floor area}_{ij}) \\ \text{Bathrooms}_{ij} \\ \mathbb{1}[\text{SES}_{ij} = \text{Low}] \\ \mathbb{1}[\text{SES}_{ij} = \text{Medium}] \\ \mathbb{1}[\text{Property age}_{ij} < 1] \\ \mathbb{1}[\text{Property age}_{ij} \in [9, 15]] \\ \mathbb{1}[\text{Property age}_{ij} \in [16, 30]] \\ \mathbb{1}[\text{Property age}_{ij} > 30] \\ \mathbb{1}[\text{Type}_{ij} = \text{House}] \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \\ \beta_9 \end{pmatrix} \tag{2}$$

The city-level predictor vector and its associated coefficient vector are:

$$Z_j = \begin{pmatrix} \text{Listing density}_j \\ \text{Listing density}_j^2 \\ \text{LFP}_j \end{pmatrix}, \quad \gamma_0 = \begin{pmatrix} \gamma_{01} \\ \gamma_{02} \\ \gamma_{03} \end{pmatrix} \tag{3}$$

Note that, as seen in eq. 1, $\log(\text{Floor area}_{ij})$ is the only listing-level predictor assigned a random slope, as determined by the sequential random-slope selection procedure. The random effects satisfy $\mathbb{E}(\mu_{0j}) = \mathbb{E}(\mu_{1j}) = 0$, as well as $\text{Var}(\mu_{0j}) = \tau_0^2$ and $\text{Var}(\mu_{1j}) = \tau_1^2$.

The full cross-level interaction model (M3) is given by:

$$\begin{aligned} p_{ij} = \gamma_{00} + \gamma_0^\top Z_j + \beta^\top X_{ij} + X_{ij}^\top \Gamma Z_j \\ + \mu_{0j} + \mu_{1j} \log(\text{Floor area}_{ij}) + \varepsilon_{ij} \end{aligned} \tag{4}$$

By definition, Γ is the matrix of cross-level interaction parameters. In the empirical specification only four cross-level interactions are included, so Γ is sparse. The non-zero

entries correspond to the listing-level predictors that interact with city-level variables:

$$\Gamma = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ \gamma_{31} & 0 & 0 \\ \gamma_{41} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \gamma_{91} & 0 & \gamma_{93} \end{pmatrix} \tag{5}$$

where rows correspond to the elements of X_{ij} as ordered in eq. (2), and columns correspond to the elements of Z_j as ordered in eq. (3). Expanding the cross-level interaction term explicitly:

$$\begin{aligned} X_{ij}^{\top}\Gamma Z_j = {} & \gamma_{91}\, \mathbb{1}[\text{Type}_{ij} = \text{House}] \times \text{Listing density}_j \\ & + \gamma_{31}\, \mathbb{1}[\text{SES}_{ij} = \text{Low}] \times \text{Listing density}_j \\ & + \gamma_{41}\, \mathbb{1}[\text{SES}_{ij} = \text{Medium}] \times \text{Listing density}_j \\ & + \gamma_{93}\, \mathbb{1}[\text{Type}_{ij} = \text{House}] \times \text{LFP}_j \end{aligned} \tag{6}$$

The parameters γ_{91}, γ_{31}, γ_{41}, and γ_{93} are the cross-level interaction coefficients: γ_{91} captures the differential effect of STR listing density on rental prices between houses and apartments; γ_{31} and γ_{41} capture the differential sensitivity of low- and medium-SES properties to listing density relative to the high-SES reference group; and γ_{93} captures the differential effect of labor market conditions on rental prices between houses and apartments. The random effects structure is identical to that of M2.2.

Acknowledgments

An earlier version of this paper was presented at the Academic Seminars of the Department of Economics, Pontificia Universidad Javeriana Bogotá. The authors thank the seminar participants for their comments and suggestions, and any remaining errors are the sole responsibility of the authors.

Author Contributions

S.B.and A.A. contributed to conceptualization and methodology. S.B., A.A., and A.L. contributed to formal analysis, data curation, investigation, and writing of the original draft as well as its review and editing. S.B. and A.L. contributed to software. A.L. contributed to the literature review. All authors read and approved the final manuscript.

Declaration of Competing Interests

The authors declare that they have no competing interests.

Funding

No funding was received for this study.

Ethical considerations

Ethical approval was not required.

Data availability statement

The data used in this study are available in the following anonymized repository: https://github.com/str-density-colombia/str-density-colombia, which includes the listing-level data collected by web scraping a publicly accessible Colombian real estate platform, as well as the city-level source data together with its documentation.

Code availability

The R code used for data collection (web scraping), processing and estimation are available in the same anonymized repository: https://github.com/str-density-colombia/str-density-colombia

References

Aguilera, T., Artioli, F., Colomb, C. (2021). Explaining the diversity of policy responses to platform-mediated short-term rentals in European cities: A comparison of Barcelona, Paris and Milan. *Environment and Planning A: Economy and Space*, *53*(7), 1689–1712, https://doi.org/10.1177/0308518X19862286

Aidi, N., & Fabry, N. (2024). Beyond the certification of smart tourism destination: insights from the city of medellín in colombia. *International Journal of Tourism Cities*, *10*(2), 577–603, https://doi.org/10.1108/IJTC-03-2022-0056

Alas, B. (2020). A multilevel analysis of housing submarkets defined by the municipal boundaries and by the street connections in the metropolitan area: Istanbul. *Journal of Housing and the Built Environment*, *35*(4), 1201–1217, https://doi.org/10.1007/s10901-020-09742-8

Ayouba, K., Breuillé, M.-L., Grivault, C., Le Gallo, J. (2020). Does Airbnb disrupt the private rental market? An empirical analysis for French cities. *International Regional Science Review*, *43*(1-2), 76–104, https://doi.org/10.1177/0160017618821428

Barron, K., Kung, E., Proserpio, D. (2021). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science*, *40*(1), 23–47, https://doi.org/10.1287/mksc.2020.1227

Baum-Snow, N. (2023). Constraints on city and neighborhood growth: The central role of housing supply. *Journal of Economic Perspectives*, *37*(2), 53–74, https://doi.org/10.1257/jep.37.2.53

Bei, G., & Celata, F. (2023). Challenges and effects of short-term rentals regulation: A counterfactual assessment of European cities. *Annals of Tourism Research*, *101*, 103605, https://doi.org/10.1016/j.annals.2023.103605

Bozzi, A. (2024). Digital nomadism from the perspective of places and mobilities: A literature review. *European Transport Research Review*, *16*, 47, https://doi.org/10.1186/s12544-024-00663-z

Brown, K.H., & Uyar, B. (2004). A hierarchical linear model approach for assessing the effects of house and neighborhood characteristics on housing prices. *Journal*

of Real Estate Practice and Education, *7*(1), 15–24,

Celata, F., Hendrickson, C.Y., Sanna, V.S. (2017). The sharing economy as community marketplace? Trust, reciprocity and belonging in peer-to-peer accommodation platforms. *Cambridge Journal of Regions, Economy and Society*, *10*(2), 349–363,

Chasco, C., & Le Gallo, J. (2012). Hierarchy and spatial autocorrelation effects in hedonic models. *Economics Bulletin*, *32*(2), 1474–1480,

Chica-Olmo, J., Sánchez, A., Sepúlveda-Murillo, F.H. (2020). Assessing Colombia's policy of socio-economic stratification: An intra-city study of self-reported quality of life. *Cities*, *97*, 102560, https://doi.org/10.1016/j.cities.2019.102560

Chin, T.L., & Chau, K.W. (2003). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications*, *27*(2), 145–165,

Cocola-Gant, A. (2018). Tourism gentrification. L. Lees & M. Phillips (Eds.), *Handbook of gentrification studies* (pp. 281–293). Cheltenham: Edward Elgar.

Cocola-Gant, A., & Gago, A. (2021). Airbnb, buy-to-let investment and tourism-driven displacement: A case study in Lisbon. *Environment and Planning A: Economy and Space*, *53*(7), 1671–1688, https://doi.org/10.1177/0308518X19869012

Crommelin, L., Troy, L., Martin, C., Pettit, C. (2018). Is Airbnb a sharing economy superstar? Evidence from five global cities. *Urban Policy and Research*, *36*(4), 429–444, https://doi.org/10.1080/08111146.2018.1460722

Deboosere, R., Kerrigan, D.J., Wachsmuth, D., El-Geneidy, A. (2019). Location, location and professionalization: A multilevel hedonic analysis of Airbnb listing prices and revenue. *Regional Studies, Regional Science*, *6*(1), 143–156, https://doi.org/10.1080/21681376.2019.1592699

Departamento Administrativo Nacional de Estadística (DANE) (2018). *Censo nacional de población y vivienda 2018* (Tech. Rep.). Bogotá, Colombia: DANE. Retrieved from https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018

Departamento Administrativo Nacional de Estadística (DANE) (2025). *Gran encuesta integrada de hogares (GEIH) 2025* (Tech. Rep.). Bogotá, Colombia: DANE. Retrieved from https://microdatos.dane.gov.co/index.php/catalog/853

Franco, S.F., & Santos, C.D. (2021). The impact of Airbnb on residential property values and rents: Evidence from Portugal. *Regional Science and Urban Economics*, *88*, 103667, https://doi.org/10.1016/j.regsciurbeco.2021.103667

Garay Tamajón, L.A., & Morales Pérez, S. (2022). Narrativas de seducción: Airbnb y la construcción de las imágenes de los destinos turísticos. *Cuadernos de Turismo*(49), 29–50, https://doi.org/10.6018/turismo.521781

García-López, M.-A., Jofre-Monseny, J., Martínez-Mazza, R., Seguí, M. (2020). Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona. *Journal of Urban Economics*, *119*, 103278, https://doi.org/10.1016/j.jue.2020.103278

Glaeser, E.L., Gyourko, J., Saks, R.E. (2005). Why have housing prices gone up? *American Economic Review*, *95*(2), 329–333, https://doi.org/10.1257/000282805774669961

Grisdale, S. (2021). Displacement by disruption: Short-term rentals and the political economy of "belonging anywhere" in Toronto. *Urban Geography*, *42*(5), 654–680, https://doi.org/10.1080/02723638.2019.1642714

Gulliford, M.C., Ukoumunne, O.C., Chinn, S. (1999). Components of variance and intraclass correlations for the design of community-based surveys and intervention studies. *American Journal of Epidemiology*, *149*(9), 876–883, https://doi.org/10.1093/oxfordjournals.aje.a009904

Gurran, N., & Phibbs, P. (2017). When tourists move in: How should urban planners respond to Airbnb? *Journal of the American Planning Association*, *83*(1), 80–92, https://doi.org/10.1080/01944363.2016.1249011

Harvey, D. (1973). *Social justice and the city.* Chapel Hill, NC: University of North Carolina Press.

Horn, K., & Merante, M. (2017). Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics*, *38*, 14–24, https://doi.org/10.1016/j.jhe.2017.08.002

Hox, J.J., Moerbeek, M., Van de Schoot, R. (2018). *Multilevel analysis: Techniques and applications* (3rd ed.). New York: Routledge.

Huang, G., Qiao, S., Yeh, A.G.-O. (2024). Multilevel effects of urban form and urban functional zones on housing prices: evidence from open-source big data. *Journal of Housing and the Built Environment*, *39*, 987–1011, https://doi.org/10.1007/s10901-023-10109-y

Jones, K. (1991). Specifying and estimating multi-level models for geographical research. *Transactions of the Institute of British Geographers*, *16*(2), 148–159, https://doi.org/10.2307/622610

Jover, J., & Díaz-Parra, I. (2020). Gentrification, transnational gentrification and touristification in Seville, Spain. *Urban Studies*, *57*(15), 3044–3059, https://doi.org/10.1177/0042098019857585

Keskin, B. (2022). Multilevel approach to the analysis of housing submarkets. *Regional Studies, Regional Science*, *9*(1), 264–279, https://doi.org/10.1080/21681376.2022.2067005

Lerena Rongvaux, N., & Rodríguez, L. (2024). Airbnb in Latin America: A literature review from an urban studies perspective. *Journal of Urban Affairs*, *46*(6), 1197–1218, https://doi.org/10.1080/07352166.2023.2168552

Liu, N., & Roberts, D. (2012). Do incomers pay more for rural housing? *Environment and Planning A: Economy and Space*, *44*(8), 1986–2005, https://doi.org/10.1068/a44527

Logan, J.R., & Molotch, H.L. (1987). *Urban fortunes: The political economy of place.* Berkeley, CA: University of California Press.

Maas, C.J.M., & Hox, J.J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology*, *1*(3), 86–92, https://doi.org/10.1027/1614-2241.1.3.86

Orford, S. (2000). Modelling spatial structures in local housing market dynamics: A multilevel perspective. *Urban Studies*, *37*(9), 1643–1671, https://doi.org/10.1080/00420980020080301

R Core Team (2025). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from https://www.r-project.org/

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55, https://doi.org/10.1086/260169

Saiz, A. (2010). The geographic determinants of housing supply. *Quarterly Journal of Economics*, *125*(3), 1253–1296, https://doi.org/10.1162/qjec.2010.125.3.1253

Schor, J. (2014, October). *Debating the sharing economy.* Great Transition Initiative.

Sirmans, G.S., Macpherson, D.A., Zietz, E.N. (2005). The composition of hedonic pricing models. *Journal of Real Estate Literature*, *13*(1), 3–43,

Smith, N. (1979). Toward a theory of gentrification: A back to the city movement by capital, not people. *Journal of the American Planning Association*, *45*(4), 538–548, https://doi.org/10.1080/01944367908977002

Snijders, T.A.B., & Bosker, R.J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). London: Sage.

Wachsmuth, D., & Weisler, A. (2018). Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A: Economy and Space*, *50*(6), 1147–1170, https://doi.org/10.1177/0308518X18778038

Watkins, C.A. (2001). The definition and identification of housing submarkets. *Environment and Planning A: Economy and Space*, *33*(12), 2235–2253, https://doi.org/10.1068/a34162

Yrigoy, I. (2019). Rent gap reloaded: Airbnb and the shift from residential to touristic rental housing in the Palma Old Quarter in Mallorca, Spain. *Urban Studies*, *56*(13), 2709 — 2726, https://doi.org/10.1177/0042098017726337