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Crime and Perceived Insecurity as Determinants of Housing and Tourist Accommodation Prices: A Case Study of Barcelona

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Abstract

This study examines how crime rates and perceived insecurity influence the prices of Airbnb accommodations and the price per square meter of traditional housing in the city of Barcelona (Spain). We estimate two ordinary least squares (OLS) regression models and two geographically weighted regression models. All regression models include additional control variables grouped into three categories: insecurity, household or population structure, and the socio-spatial transformation of the neighborhood.

The results indicate that crime is not associated with housing prices, whereas perceived insecurity, national heterogeneity, and the arrival of residents from high-income countries play a key role in both tourist accommodation prices and price per square meter. The influence of these factors on housing prices varies substantially across neighborhoods. These findings suggest that the effect of crime on housing prices may be mediated by other structural neighborhood factors. This underscores the need for a neighborhood-centered approach, rather than analyzing the effect of each individual variable in isolation.

Keywords: *housing prices; crime; perceived insecurity; Barcelona; ArcGIS.*

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I. Introduction

The tourism sector has not been immune to the technological impact of the last decade. This has significantly altered its operational dynamics, primarily due to the development of peer-to-peer accommodation platforms that connect hosts renting out their homes or rooms with guests seeking lodging for their vacations (Brochado, 2017).

Undoubtedly, the most well-known and significant platform is Airbnb, with a market value that reached $100 billion in 2021. Since its founding in 2008, Airbnb has experienced rapid growth, boasting over 4 million hosts and 800 million guests worldwide, resulting in an offering of approximately 7 million unique accommodations (Airbnb Inc., 2021). Specifically for Spain, Airbnb launched in 2009, and between June and August 2018 it registered 3.6 million visitors who used the platform to search for lodging. This has made Spain one of the primary markets for Airbnb in Europe (Adamiak et al., 2019).

However, in line with international literature, research on the implications resulting from the proliferation of these accommodations in the Spanish context primarily focuses on gentrification and the housing market (Adamiak et al., 2019; Gil and Sequera, 2018). Additionally, studies have explored its impact on urban planning regulations (Gurran and Phibss, 2017) and various social issues and local effects (Cocola-Gant and López-Gay, 2020). Even scarcer are the analyses concerning the factors that explain the evolution and pricing of offerings on this platform (Adamiak et al., 2019).

Indeed, there are few studies that specifically focus on how crime and the fear of it influence the pricing of tourist accommodations offered on Airbnb, especially when security is a recurring concern among platform users (Norton and Herrera, 2020). Negative experiences related to criminal activities can directly impact the ratings of accommodations, leading other potential guests to decide against making a reservation despite the flexibility offered by Airbnb's platform. This is because guests expect accommodations to provide not only a high-quality stay but also a safe and tranquil environment. Consequently, they are generally willing to pay a higher price for lodgings located in safer areas.

However, the concentration of visitors in areas characterized by a high number of tourist accommodations indeed makes these locations particularly attractive to criminals. This is due to the availability of potential targets (Maldonado-Guzmán, 2020) concentrated in lodgings that typically lack the protective elements found in more traditional tourist accommodations, such as the presence of on-site staff or closed-circuit television surveillance (Xu et al., 2019)

This is because these accommodations hinder the establishment of social networks that play a crucial role as protective agents, a consequence of the high turnover brought about by tourism and, most notably, the displacement of local residents to other neighborhoods (Ke et al., 2021; Maldonado-Guzmán, 2023; Mawby, 2010).

There are studies on the relationship between crime and traditional hotel activity that determine an increase in crime leads to a decrease in hotel prices (Cró et al., 2019). However, for the case of Airbnb, only two studies have been found that analyze this issue. In the study by Yan and Mao (2020), they incorporate crime as an additional variable in their research on the factors determining the price of Airbnb accommodations. Surprisingly, they find no negative relationship between crime and pricing. The authors justify this finding by suggesting that individual hosts often lack the appropriate tools to timely identify the link between crime and guest demand, something that hotels can do more effectively through their marketing teams. In the second study (Herrera and Norton, 2020), a negative effect on the price of Airbnb tourist accommodations is found for the city of Buenos Aires (Argentina), with an elasticity of -0.074 (where 0.010 corresponds to spatial factors).

The scarcity of research on this issue is noteworthy given that security is a factor that influences the pricing of real estate per square meter in the housing market (Taltavull et al., 2022). Prices are negatively affected when the level of insecurity increases (Gibbons, 2004; Ihlanfeldt and Mayock, 2010; Margaretic and Bautista, 2025; Thaler, 1978, among others). This is because security is a fundamental element in individuals' decision-making when considering the possibility of accessing a residence in a specific neighborhood (Meehan and Benson, 2017). In this regard, the housing valuation approach posits that market participants determine the property's price based on the capitalization of the amenities and discomforts of the area where the housing they want to buy or rent is located (Wong et al., 2019).

Based on this approach, crime is identified as a "discomfort" that hinders the development of residents' lives, deteriorates the urban environment, and generates community instability (McIlhatton et al., 2016). Therefore, in neighborhoods considered safer there is higher demand, which puts upward pressure on prices, whereas the opposite occurs in insecure areas. In other words, there is lower demand along with an increase in supply, as homeowners in deteriorated locations would want to divest of these assets before their value further declines (Rukus and Warner, 2013).

Research analyzing this association generally stems from three points: the subjective interpretation of official crime statistics, geographical proximity to areas where recent crimes have occurred, and the perception of insecurity or fear of crime (Kim and Lee, 2018). For instance, Ceccato and Wilhelmsson (2011; 2012) find that both crime and fear of crime negatively impact apartment prices. Similarly, Buonanno et al. (2013) determine, in the case of a district in Barcelona, Spain, that the perception of security is a factor that positively affects the value of housing by up to 0.57%, while in insecure areas it may decrease by as much as 1.27%.

Indeed, all of this highlights the importance of providing empirical analysis to aid public administrations in managing this issue effectively. Furthermore, a comparative perspective between the pricing of Airbnb accommodations and the price per square meter of traditional housing will enable drawing conclusions regarding potential differences and similarities, which can inform the development of relevant public policies.

With this purpose in mind, this article examines the relationship between recorded crime and perceived insecurity with the pricing of Airbnb accommodations and owner-occupied housing in Barcelona. To achieve this, two global regression models and two local regression models are developed for 69 neighborhoods in the city of Barcelona. This approach enables revealing whether the relationships between the variables in the model differ in each studied neighborhood, avoiding assumptions that the results derived from an ordinary least squares estimated model are universally applicable.

The study conducted here is novel for the following reasons: (1) it represents one of the pioneering investigations at the national and European levels that examines how crime determines the prices of accommodations offered on Airbnb while controlling for other factors; (2) it compares the results obtained for Airbnb with associations established in traditional housing to identify potential differences; and (3) it employs local regression models to detect significant differences not revealed in the globally-used traditional models.

Subsequently, the methodology and data utilized are described. In Section III, the obtained results are elaborated upon, and finally, the conclusions and discussion of the research are presented.

II. Methodology

2.1. Study region

The region under study in this research is the city of Barcelona, Spain. Several interrelated reasons lead to choosing this city as the most suitable for this investigation. Firstly, it is one of the Spanish cities with the most significant housing affordability issues. The average price per square meter in Barcelona reached 4,306 euros in December 2022, placing the city 110% above the national average (Fotocasa, 2023). Reports from Idealista (www.idealista.com) - one of the most prominent real estate portals in Spain - indicate that a 40-square-meter dwelling in Barcelona had an average price of 165,240 euros in June 2023.

Furthermore, the rental price per square meter has also shown an upward trend, with an increase of 15.4% in June 2023 compared to June 2022. The issue becomes evident when considering that the average resident had to allocate up to 58% of their salary to rent an 80-square-meter dwelling in 2022 (Cotrina, 2023). This fact helps explain why the rising housing prices are the primary concern among residents in the majority of neighborhoods, according to the municipal services survey conducted by the city council.

Secondly, Barcelona constitutes a paradigmatic example of gentrification and touristic transformation due to its exposure to global demands in the local real estate market and its specialization in tourism (López Villanueva and Crespi-Vallbona, 2021). Data available from the National Statistics Institute (Instituto Nacional de Estadística, INE) reveals that in certain census tracts of Barcelona, especially those located in the historic center, the proportion of tourist accommodations compared to the total number of dwellings in the census tract reaches 31%. This touristic specialization has facilitated the widespread conversion of residential properties into tourist apartments, often at the expense of displacing local residents to other areas of the city (Zaar, 2019), thereby contributing to the upward surge in housing prices.

Lastly, in Barcelona, crime rates increased by more than 30% between 2015 and 2019 (Marteache and Trinidad, 2023). Authors such as Maldonado-Guzmán et al. (2023) have partially attributed this rise in criminal rates to the phenomenon of touristic transformation: the concentration of tourists leads to an increase in criminal opportunities and contributes to social disorganization in neighborhoods. Moreover, indicators of perceived insecurity also reach relatively high levels, and they are a concern for the residents according to municipal surveys.

In summary, Barcelona experiences a convergence of processes that are linked to an increase in the prices of both traditional and tourist housing, alongside other factors that may reduce these prices. This makes the city a suitable setting to explore how crime rates and feelings of insecurity can affect the pricing of both housing and tourist accommodations in a context where the local real estate market has become globalized, and neighborhoods have specialized in attracting visitors.

In this study, the neighborhood constitutes the spatial unit of analysis, and several reasons justify this choice. First, the indicators required to measure many of the variables included in the regression models are only available at this level of aggregation. Although an increasing amount of data is becoming available at finer spatial scales in Barcelona (see two notable examples in Sánchez-Delgado, 2024; 2025), several indicators necessary to construct the variables used here were not available at a smaller spatial scale, including housing prices.

Furthermore, factors such as ethnocultural diversity, gentrification, and other social processes exert their effects primarily at the neighborhood level. These factors may influence broader or narrower scales, but their origin lies within the neighborhood (Sampson, 2013), the environment where the most immediate and intimate social interactions take place and where the organizational foundation of the city is located (Park, 1952). In this regard, selecting the neighborhood as the spatial unit of analysis aligns with the criterion adopted by much of the specialized scientific literature on the spatial analysis of crime. Leading scholars in the field argue that the theoretical framework guiding the research should determine the appropriate size of the unit of analysis (Townsley, 2009).

2.2. Dependent and independent variables

Before describing the set of variables used in this study, it is necessary to explain why the dependent variables have been measured over a longer time interval compared to the independent variables related to crime and perceived insecurity. The use of different temporal windows reflects the distinct nature of the variables and the mechanisms through which they interact. Crime and perceived insecurity exhibit substantial short-term volatility and are therefore averaged over the 2015–2017 period to capture more stable, structural levels of neighbourhood exposure while reducing year-to-year noise (Barton et al., 2019). In contrast, housing prices reflect medium- to long-term capitalization processes, whereby market values gradually incorporate persistent neighbourhood characteristics. For this reason, housing prices are averaged over a longer period (2014–2021) to smooth real estate market cycles and better approximate long-run equilibrium values.

2.2.1. Dependent variables

The research focuses on two response variables: (1) the average price per square meter for the sale of residential properties and (2) the average price for the rental of Airbnb accommodations offered in the city. The first independent variable was calculated by taking the average price per square meter for the period 2014-2021 to account for potential fluctuations in the real estate market. Data was obtained from the open data portal of the Barcelona City Council, providing a reliable and comprehensive source for the study.

The average price for Airbnb rentals was estimated by georeferencing each of the accommodations advertised on the platform's website, thereby assigning them to their respective neighborhoods. Subsequently, the average price was calculated for all accommodations within each neighborhood, serving as the unit of analysis. During this estimation process, two types of accommodations were excluded: those with atypical prices within the context of the neighborhood and those with low rental frequency (less than 90 nights of bookings in a year). The exclusion of these accommodations was necessary as their limited activity could potentially distort the overall average prices for the respective neighborhoods. A threshold of 90 days was selected following the criterion established by the Inside Airbnb platform, which defines a listing as frequently booked when it is reserved for at least 90 nights per year.

2.2.2. Independent variables

In the current study, 11 variables have been constructed to potentially be included in the executed regression models. These variables can be categorized into three groups: those related to insecurity, those associated with household or population structure, and a set of variables linked to socio-spatial transformation processes within the neighborhood. The operationalization of each variable is described as follows.

A) Variables linked to insecurity

i) Density of crimes against property

This variable represents the average number of property crimes per square kilometer in the neighborhood during the period 2015-2017 (Maldonado-Guzmán, 2023). The decision not to use the per capita crime rate is based on the difficulty of estimating the true population at risk since, in many cases, neither the victims nor the perpetrators reside in the neighborhood where the crime occurs (Zhang et al., 2016). The use of the average crime density is a common practice to mitigate the random fluctuation of crime rates from year to year (Zhang et al., 2012). Additionally, the neighborhood's extent is measured by excluding forested or industrial areas to capture the actual space dedicated to residential and/or commercial uses, where the majority of people susceptible to victimization are concentrated.

The property crimes included in the database provided by the regional police of Catalonia are the number of petty thefts, thefts, petty thefts inside vehicles, thefts inside vehicles, robbery with force, burglaries inside vehicles, and motor vehicle thefts recorded in public areas by the aforementioned police force.

ii) Density of crimes against people

The variable for crimes against persons was calculated in the same way as the one capturing property crimes; that is, by computing the average of the following offenses for the period 2015–2017: homicides/murders, bodily injuries, sexual assaults, and robberies involving violence or intimidation against persons. The dominant legal doctrine (Mayoral Narros, 2017) holds that robbery with violence and/or intimidation is a multi-offensive crime, in the sense that, alongside the primary protected legal interest—property—other interests such as personal liberty and security are also affected. For this reason, in this study robberies involving violence or intimidation are treated criminologically as crimes against persons, given their violent and/or intimidating nature, insofar as the commission of physical acts upon the victim entails an attack on personal legal interests such as health or life.

iii) Perceived insecurity

Perceived insecurity among residents is measured using the annual victimization survey conducted by the Barcelona City Council. In one of the questions, respondents are asked to rate the level of safety in their neighborhood on a scale from 0 to 10, where 0 means "there is no safety at all" and 10 means "there is a great deal of safety." To calculate insecurity levels, responses to this question from the 2015, 2016, and 2017 editions of the survey were used, in order to also account for potential temporal fluctuations in perceived insecurity. Finally, the variable was constructed using the average of these responses within each neighborhood, and the scale was inverted so that a value of ten corresponds to "very unsafe" and a value of zero to "very safe" (Maldonado-Guzmán et al., 2021).

B) Variables linked to the structure of the household and the population

iv) Average number of people per household and single-parent households

The average household size has been measured using data available on the *OpenData* Barcelona portal. The same data source has been used to calculate the proportion of households consisting of a single adult responsible for one or more minors.

v) Population density and distance to the city center

Population density captures the number of inhabitants per square kilometer in the neighborhood. The distance to the city center has been calculated by estimating the Euclidean distance (in square kilometers) between the centroid of each polygon (neighborhood) and the centroid of the Gothic Quarter polygon.

vi) Socioeconomic status

Socioeconomic status is determined by combining the Z-scores of the following three indicators: (i) average taxable income per person, (ii) proportion of the population with higher education standardized by the age structure of the neighborhood, and (iii) the percentage of economically active individuals. The standardization of individuals with higher education by the age structure of the neighborhood has been carried out to account for the expected variation in the proportion of people with higher education in communities where the population is younger (López-Gay et al., 2022).

vii) National heterogeneity

Heterogeneity in nationality is calculated using the Herfindahl index, which is commonly used to measure national heterogeneity in spatial studies of the relationships between insecurity (objective and/or subjective) and crime (Bruinsma et al., 2013; Hipp et al., 2009; Markowitz et al., 2001). This index assesses the probability that two randomly selected individuals have the same nationality, with values close to one indicating greater homogeneity and values closer to zero indicating the opposite. However, the value of the index (1-H) has been inverted so that higher observed values indicate a higher level of national heterogeneity (Cahill and Mulligan, 2007).

viii) Habitants from countries with a high Human Development Index (HDI)

The data required to calculate this variable were obtained from the 2017 municipal population register (padrón continuo) of the city. Its construction is based on the Human Development Index (HDI) classification established by the United Nations (UN). We then compute, out of the total number of foreign residents in each neighborhood, the proportion of those whose countries of origin have an HDI above 0.825 (López-Gay et al., 2021b). This entails a two-step calculation. First, the proportion of foreign residents in the neighborhood is calculated relative to the total population living there. Second, we determine how many of these foreign residents come from countries that, according to the UN, have an HDI greater than 0.825. This threshold is used because it is the criterion commonly employed by researchers using this indicator to capture the nature of gentrification processes (López-Gay et al., 2021b; Rodríguez & López-Gay, 2024), as values above this threshold allow for the inclusion exclusively of countries with very high HDI levels.

The presence of a significant population of highly skilled migrants can influence related urban processes. The arrival of these professionals—commonly referred to in the literature as *expats* (from expatriates) (see Gatti, 2009)—is often associated with increased demand for higher-quality housing and specialized services, which can lead to rising living costs in certain areas of the city.

C) Variables linked to the processes of socio-spatial transformation of the neighborhood

ix) Tourism intensity

Tourist intensity was measured using an adaptation of the tourism indicator proposed by Maldonado-Guzmán (2023). The author suggests combining the following variables to assess levels of tourism: (i) the number of accommodation listings on the Airbnb platform, (ii) the density of bar terraces weighted by the area (in square meters) occupied by each terrace, (iii) the density of bars, nightclubs, cocktail venues, and flamenco performance venues in the neighborhood, (iv) the density of photos uploaded to the social network Flickr with tourism-related tags, and (v) the presence of businesses substantially linked to the tourism industry (including, among others, fast-food restaurants and souvenir shops). This indicator has been shown to capture an adequate proportion of tourism intensity levels in the city of Barcelona, but we consider it necessary to incorporate a subjective dimension that reflects residents' perceptions of tourism. To this end, we include an indicator measuring residents' perception of the level of tourism in their neighborhood. This new factor is derived from the annual tourism survey conducted by the Barcelona City Council, which includes questions regarding the amount of tourism in the neighborhood, whether respondents consider their neighborhood to be highly touristic, and whether their building contains any tourist accommodations. All indicators were measured for the years 2015, 2016, and 2017, and the average of each indicator was calculated. Finally, the composite variable results from a combination of the Z-scores of each indicator to ensure that all are expressed on the same measurement scale.

x) Gentrification

To measure neighborhood gentrification, secondary data available from the research conducted by López-Gay et al. (2019) are utilized. The authors develop an indicator considering a wide range of neighborhood transformations and processes associated with gentrification dynamics. Examples of these dimensions include population rejuvenation, attraction of more qualified residents, and the substitution of the neighborhood's population.

xi) Physical disorder

The physical disorder variable is the result of calculating the average of the Z-scores of each of the following factors: (i) number of abandoned vehicles in public spaces, (ii) density of vandalism-related crimes registered by the Regional Police of Catalonia in the neighborhood, (iii) proportion of buildings in poor condition, (iv) number of incidents related to waste in public spaces managed by the Urban Guard, and (v) number of incidents related to disruptive activities in public spaces managed by the Urban Guard.

2.3. Analytical strategy

To achieve the objectives set in this research, four regression models are executed: two global models and two local models. The global models estimate those variables that are significant and related to the prices of Airbnb accommodations (for tourism purposes) and the price of housing (for residential use). Meanwhile, the local models explore to what extent the relationships found in the global models vary significantly across the study region, that is, if there are non-stationary spatial processes.

Global regression models

The method of estimation for global models is Ordinary Least Squares (OLS), which assumes the presence of normality, independence, and homoscedasticity. As the two dependent variables do not follow a normal distribution, both have been transformed using the natural logarithm to enforce the normality of the residuals (Hipp et al., 2009; Lagonigro et al., 2020).

The strategy used to ensure that the data meets the assumptions of the OLS regression models involved conducting exploratory regressions to find the most suitable combination of independent variables for building a robust model. This was achieved using a tool available within the Geographic Information System (GIS), ArcGIS, which executes as many combinations of models as the number of explanatory variables that have been incorporated.

The objective of this strategy is to find the combination that best meets a set of pre-established criteria: (i) the model explains at least 50% of the variance in prices (an R^2 greater than 0.5); (ii) the Variance Inflation Factor (VIF) is less than 7.5 to avoid multicollinearity problems; (iii) the p-value associated with the Jarque-Bera test is greater than 0.1 to ensure a normal distribution of residuals; and (iv) the p-value associated with the Moran's Index is greater than 0.1 to avoid spatial autocorrelation.

Once the tool is executed in ArcGIS, it is possible to observe if any of the combinations of independent variables meet one or more of the criteria mentioned. Additionally, the tool returns the value of the Corrected Akaike Information Criterion (AICc) for each regression model, allowing for comparison and selection of the most optimal one.

Local regression models

The local analysis is estimated using a Geographically Weighted Regression (GWR) model employing the MGWR software. This type of regression is considered one of the best alternatives to address spatial heterogeneity (Cardozo et al., 2012; Chu et al., 2018; Lagonigro et al., 2020; Sousa-Guedes, 2021), as it yields a distinct model for each observation, thus addressing the needs mentioned by Gonzalez-Alonso (2015, p. 33) to have a model that allows for flexible functions and parameters in space. Additionally, the GWR regression calculates the coefficient of determination for each unit of analysis. This allows us to know the percentage of variance in the dependent variable explained by the model for each neighborhood in Barcelona.

WR considers the possibility of local variations in relationships by considering the spatial location from which each observation is derived in the dataset. Therefore, assuming a number n of observations, for observation$i \in [1, 2, \ldots, n]$ at location (u_i, v_i), the formula for GWR is expressed by the following equation (Oshan et al., 2019, p. 10):

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (1)$$

β_0(ui, vi) represents the intercept term, where (ui, vi) denotes the coordinates of the i-th point in space, and β_k(ui, vi) are the coefficients β of the continuous function k (u, v) for a number k of independent variables at point i. In other words, it becomes possible for β to form a continuous surface of parameter values, and measurements of this surface are taken at certain points to denote the spatial variability of the surface (Fotheringham et al., 2003, p. 52).

To estimate the regression parameters for each observation point, a bi-square weighting function is used, which is considered one of the most useful alternatives (Fotheringham et al., 2003). An adaptive kernel function is chosen due to the varying distances between the centroids of each polygon (Maldonado-Guzmán, 2022).

Furthermore, considering that GWR results are highly sensitive to the selected bandwidth, the Akaike Information Criterion corrected (AICc) is used to find the most appropriate bandwidth. It is one of the most common criteria in the search for the appropriate bandwidth (Fuentes and Sánchez, 2015), and the smaller its value, the better the model fit (Hilbe, 2017).

To test the statistical significance of any variations in the relationships between variables identified by the GWR model, a Monte Carlo non-stationarity test is conducted (Fotheringham et al., 1998). If the p-value associated with this test is less than 0.05, the null hypothesis of parametric stability can be rejected, and it can be assumed that the spatial differences shown by the regression parameters are statistically significant.

III. Results

3.1. Results of global models

Price of Airbnb tourist accommodation

The model in Table 1 is the one that best meets the established criteria. According to the exploratory regression, the five variables suggested to be included in the model explain 73.66% of the variance in the prices of Airbnb accommodations. This model has one of the lowest AICc values (77.48), the errors follow a normal distribution (Jarque-Bera test p-value = 0.061), and neither heteroscedasticity (Breusch-Pagan test p-value = 0.84) nor spatial autocorrelation (Moran Index p-value = 0.13) is present. Multicollinearity also does not reach problematic values (VIF = 4.77).

Table 1. Results of the global OLS model for the price of Airbnb accommodations

Variable	Beta	Std. Dev.	p-value	VIF
Constante	4.15	0.72	0.00	
Ln Single-Parent Households	1.01	0.06	0.00	1.92
Ln National Heterogeneity	-0.26	0.43	0.08	2.83
Ln Gentrification	0.65	0.45	0.10	4.77
Ln Distance to the City Center	- 0.43	0.00	0.00	3.57
Ln Perceived Insecurity	-0.18	0.05	0.00	1.63

In this model, gentrification is presented as a factor that positively influences the price of Airbnb accommodations with an elasticity of 0.65. A 10% increase in gentrification would result in a 6.5% increase in Airbnb prices. The variable representing housing demand - single-parent households - also shows a positive relationship with the dependent variable (1.01).

On the other hand, national heterogeneity in the neighborhood reduces the price of Airbnb accommodations (-0.26). It is also found that a 10% increase in perceived insecurity by residents reduces the price of Airbnb by up to 1.8%. The distance to the city center variable shows the expected relationship as well: as the Airbnb accommodation moves away from the center, its price is reduced (-0.43).

Table 2 presents the variables potentially introduced in the models, ordered according to the percentage of significance and the sign of the relationship with the price of Airbnb accommodations. This allows us to observe in what percentage of cases each variable establishes a positive or negative relationship.

Table 2. Variables and their significance frequency in the exploratory regression for the price of Airbnb accommodations

Variable	% significance	% negative relationship	% positive relationship
Distance to downtown	100%	100%	0%
Single-Parents Households	71.44%	0.13%	99.87%
Gentrification	45.42%	1.28%	98.72%
Perceived Insecurity	39.46%	100%	0%
National Heterogeneity	32.84%	91.04%	8.96%
Socioeconomic Status	29.69%	11.76%	88.24%
HDI	25.31%	29.85%	70.15%
Violent Crimes	23.10%	96.47%	3.53%
Person per Household	21.83%	25.90%	74.10%
Property Crimes	5.98%	55%	45%
Physical Disorder	3.68%	3.84%	96.16%
Total Crimes	3.09%	98.04%	1.96%
Population Density	2.52%	54.02%	45.98%
Tourism Intensity	0.09%	53.81%	46.19%

The distance to the city center is the only variable that consistently shows significance in 100% of the cases, with a negative relationship in all 39 exploratory models executed. This indicates that as the accommodation gets farther from the city center, the price decreases. Among all the variables related to insecurity (objective or subjective), perceived insecurity is the only one that demonstrates a higher percentage of significance (39.6%), suggesting that an increase in perceived insecurity would lower the price of Airbnb accommodations

Other variables related to the population structure, which might influence residents' feelings of insecurity in an area, also follow the expected pattern. For instance, national heterogeneity and HDI have an impact on the prices of Airbnb accommodations: a higher presence of immigrants in an area reduces the price of Airbnb accommodations in 91% of the cases, while the arrival of immigrants from countries with a high HDI increases the value of the area in which the tourist accommodations are located in 70.15% of the models.

The rest of the variables (crime rate and physical disorder) are significant in less than 6% of the cases, with the exception of violent crimes (23%). An increase in total crime, violent crime, and disorder generally decreases the price of Airbnb accommodations, but the relationship is not as clear for property crimes (Table 2).

The price of housing for sale per square meter of constructed

The model that best adheres to the principles assumed by the OLS models is presented in Table 3. This model explains 82% of the variance in the price per square meter of constructed area, has one of the lowest AICc values (-68.72), follows a normal distribution (J-B test p-value = 0.45), and shows no heteroscedasticity (B-P test p-value = 0.55), spatial autocorrelation (Moran Index p-value = 0.53), or multicollinearity (VIF = 4.20).

Initially, this model included the distance to the city center as one of the independent variables. However, a bivariate correlation analysis revealed that it is highly correlated with two other predictors: the proportion of residents with a high HDI (r = -0.742**) and national heterogeneity (r = -0.479**). Consequently, the decision was made to remove the distance to the center variable from the model.

The results of the final model (Table 3) indicate that the average household size has a positive and significant relationship with the price of the property, with an elasticity of 1.348. Another variable that is associated with an increase in price is the proportion of residents from countries with a high HDI, as a 10% increase in this proportion is linked to a 5.87% increase in property prices.

Table 3. Results of the global OLS model for the price per square meter of built area

Variable	Beta	Std. Dev.	P-value	VIF
Ln Person per Household	1.348	0.372	0.001	1.623
Ln Crime against Persons	0.042	0.033	0.210	2.193
Ln National Heterogeneity	-0.367	0.087	0.001	3.030
Ln HDI	0.587	0.062	0.001	3.078
Ln Tourism intensity	-0.001	0.000	0.072	1.862
Ln Perceived insecurity	-0.146	0.031	0.001	1.910

The rest of the variables in the model are presented as factors that devalue the property. National heterogeneity again emerges as an element that reduces the price per square meter of the property, as indicated by the Herfindahl index with an elasticity of -0.367. Perceived insecurity also correlates negatively with the price per square meter, although the reduction it causes (-0.146) is smaller compared to the effect on Airbnb prices (-0.18). The density of crimes against persons is not statistically significant (p-value > .05), suggesting that violent crime is not related to the price per square meter.

Table 4 presents the frequency with which the variables have been significant in the regression models and the percentage of times they show a positive or negative relationship. Perceived insecurity by residents is the only variable that is significant in 100% of the cases to explain the price per square meter of the property. This means that it has been included in all 39 models and has shown significance with at least 90% confidence level in all of them, and also consistently showing a negative association in 100% of the cases.

Table 4. Variables according to the percentage of times they are significant in the exploratory regression for the price per square meter of the property

Variable	% Significance	% Negative relationship	% Positive relationship
Perceived insecurity	100%	100%	0%
Distance to downtown	99.98%	100%	0%
Socioeconomic Status	95.33%	0%	100%
HDI	88.25%	0.21%	99.79%
National Heterogeneity	44.47%	79.37%	20.63%
Person per household	42.00%	24.81%	75.19%
Gentrification	31.80%	22.76%	77.24%
Tourism intensity	40.65%	89.68%	10.32%
Single-Parents household	29.35%	7.19%	92.81%
Property Crime	27.69%	36.17%	63.83%
Violent Crime	23.70%	83.99%	16.01%
Population Density	13.05%	48.17%	51.83%
Total Crime	3.24%	40.66%	59.34%
Physical Disorder	2.51%	61.78%	38.22%

Other independent variables show a certain stability in terms of statistical significance. The distance to the center, like in the case of Airbnb prices, remains highly significant in 99.98% of the 39 executed models and consistently shows a negative relationship with the dependent variable. The socioeconomic status and the arrival of people from countries with high HDI have a very similar percentage of significance and are related to an increase in the price per square meter in almost all models.

On the other hand, the variables related to property crimes, crimes against individuals, total crime, and physical disorder in the neighborhood once again show reduced statistical significance, with variations ranging from 1 to 11 across the 39 models conducted in the exploration.

3.2. Results of local models

3.2.2. Results for Airbnb accommodation prices

The local regression model identifies spatial variations in the regression parameters, but none of these variations are statistically significant according to the results of the Monte Carlo test (Table 1a, in the appendices). This means that the results obtained for each predictor in the global regression model (see Table 1) can be assumed as valid. Consequently, there is no need to geographically represent the variability of the regression parameters.

3.2.1. Results for the price per square meter of residential properties

The results of the local regression model for the price per square meter of residential properties suggest that the relationships between the variables and the price vary across each neighborhood (Table 5). This implies that the regression parameters are spatially unstable, indicating the presence of non-stationary spatial processes. Therefore, it is necessary to cartographically represent the values of the different regression parameters to understand how they vary across space.

Figure 1 shows that the model for the price per square meter achieves its highest explanatory power in the northeast and east of the city (mainly in the districts of Nou Barris, Sant Andreu, and parts of Sant Martí), as well as in some neighborhoods in the central expansion area of the city and the Gràcia district. In this area of Barcelona, the model explains between 86.3% and 87.4% of the variance, while in the central and western parts of the city, the coefficient of determination has slightly lower values (74.9%-78.1%).

Table 5 indicates that the relationship between violent crime and property prices is contradictory. The increase in the density of crimes against individuals is associated with a reduction in the price per square meter in certain areas (-0.065), while in other locations, it leads to a moderate increase of 0.158.

This suggests the need for applying regression models that reveal hidden local processes.

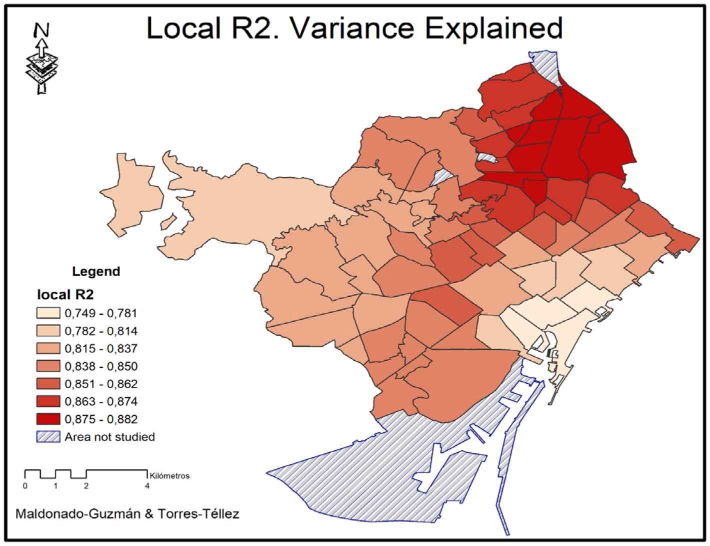

Figure 1. Local coefficient of determination for the model of the price per square meter

Table 5. Results of the local regression model (GWR) for the price per square meter

Variable	Mean	STD	Min	Median	Max	Monte Carlo p-value
Intercept	-0.003	0.088	-0.156	-0.020	0.164	0.002
Ln people per household	0.213	0.141	-0.051	0.134	0.556	0.000
Ln Violent Crimes	0.158	0.109	-0.065	0.163	0.438	0.005
Ln National Heterogeneity	-0.478	0.123	-0.714	-0.461	-0.316	0.001
Ln HDI	0.903	0.164	0.738	0.822	1.360	0.000
Tourism Intensity	-0.054	0.020	-0.090	-0.054	-0.009	0.604
Ln Perceived Insecurity	-0.318	0.091	-0.477	-0.308	-0.160	0.025

Figure 2 represents the spatial distribution of two parameters of the variable "crimes against people": the beta coefficient and the p-value. The map shows that in the southeastern neighborhoods of the city, an increase in violent crime is associated with a reduction in the price per square meter of property. However, this association is not statistically significant. On the other hand, in the northwestern neighborhoods (mainly Sarrià), a 10% increase in violent crime is associated with an increase in the price per square meter of property, ranging from 2.9% to 4.3%.

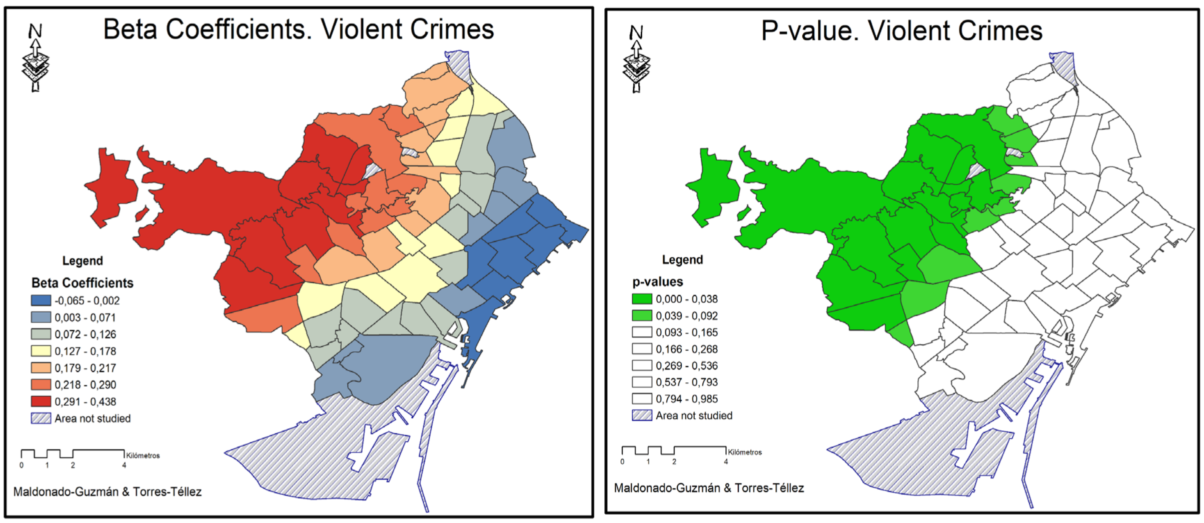

Figure 2. Spatial variability of regression coefficients (left map) and p-values (right map) for the variable "violent crimes" in relation to the price per square meter of housing.

Regarding perceived insecurity, it maintains a negative relationship with the price per square meter of housing across all neighborhoods (Figure 3). A 10% increase in the level of perceived insecurity results in an average decrease of 3.18% in property prices per square meter. This inverse relationship has a more pronounced impact in the northeastern part of the city (Nou Barris district), where the increase in insecurity is associated with a decrease ranging from 4.3% to 4.8% in property prices. Conversely, the devaluation of property prices due to perceived insecurity is less pronounced in the historical center of the city, where a 10% increase in perceived insecurity is related to a 1.6% decrease in property prices per square meter (Figure 3).

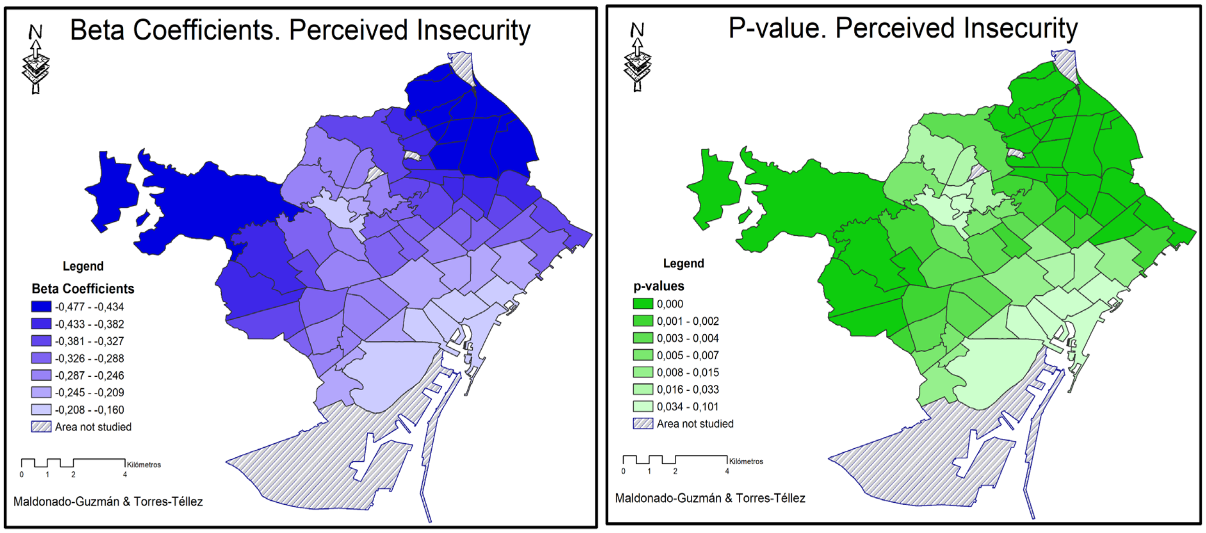

Figure 3. Spatial variability of regression coefficients (left map) and p-values (right map) for the variable "perceived insecurity" in relation to the price per square meter of housing.

In contrast, national heterogeneity also maintains a negative association with the price per square meter throughout the city of Barcelona, although the magnitude of this relationship varies depending on the neighborhood. A 10% increase in national heterogeneity reduces housing prices on average by 4.61%, but in other neighborhoods, the price decrease can reach up to 7.14%. Figure 4 shows that national heterogeneity is associated with a greater price drop per square meter in the neighborhoods of Horta, Sarrià, and Gràcia. On the other hand, in the neighborhoods of Diagonal Mar, Poblenou, and Villa Olímpica, national heterogeneity maintains an elasticity of -0.316 with the price per square meter.

The direction of the association between the heterogeneous presence of nationalities and the price per square meter changes when considering the proportion of foreigners in the neighborhood coming from countries with a high HDI. The higher this proportion, the higher the price per square meter of housing (Figure 5).

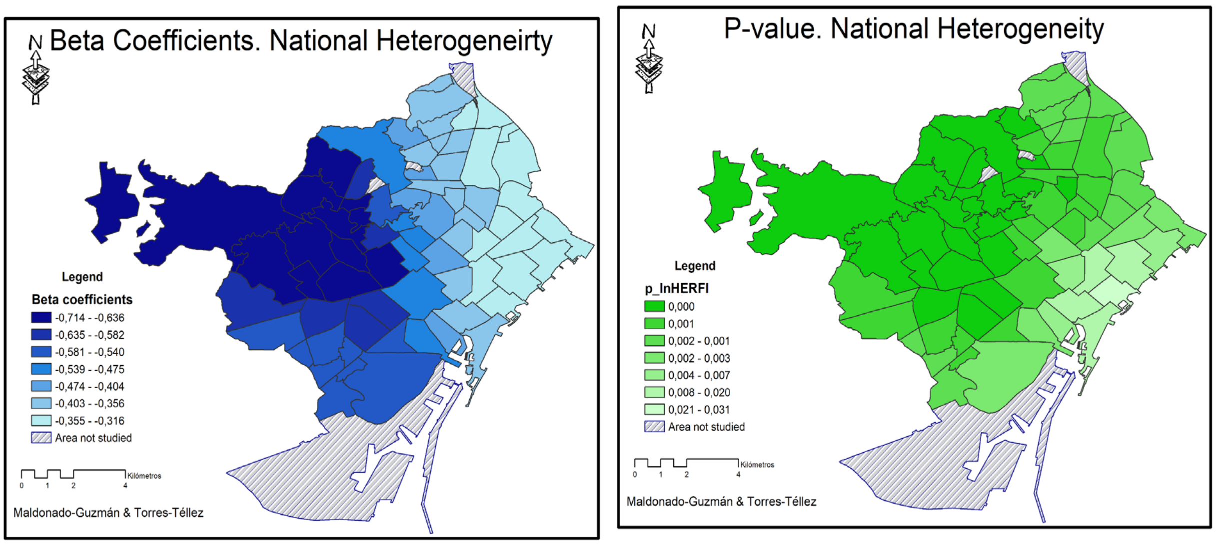

Figura 4. Spatial variability of regression coefficients (left map) and p-values (right map) for the variable "national heterogeneity" for the price per square meter.

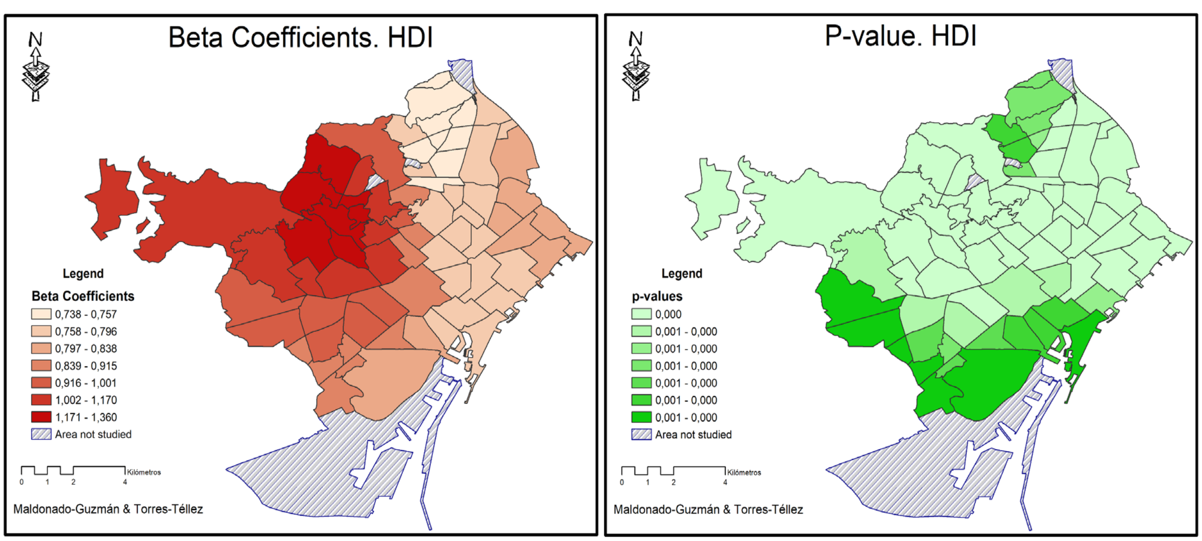

Figure 5. Spatial variability of regression coefficients (left map) and p-values (right map) for the variable "HDI" for the price per square meter.

However, the intensity of this relationship is not the same in all analyzed neighborhoods. An increase of 10% in the proportion of residents with a high Human Development Index (HDI) is, on average, associated with an 8.22% increase in the price per square meter. The neighborhoods where the increase in the price per square meter is more pronounced when the percentage of residents with a high HDI increases are concentrated in the districts of Gràcia, Horta, and some neighborhoods in Sarrià (Figure 5). Those neighborhoods where national heterogeneity was associated with a smaller decrease in the price per square meter (between -0.31 and -0.35) experience an increase in the price of between 7.3% and 8.4% when the incoming immigrant is from a country with a high HDI.

IV. Discussion and conclusions

This study aimed to analyze how crime and perceived insecurity influence the prices of Airbnb accommodations and the price per square meter of housing for sale while controlling for other factors related to land use, household structure, and population. Four regression models were estimated for the city of Barcelona: two global models and two local models.

From the results of this research, it can be inferred that the role of recorded crime on the price of traditional housing and Airbnb accommodations is not relevant for the case of Barcelona, although local regression models reveal contradictory processes. The results seem to indicate that in most neighborhoods, the fundamentals of real estate prices neutralize the effects of crime.

However, violent crime is significantly related ($p < 0.05$) to an increase in the price per square meter in 15 out of the 69 analyzed neighborhoods, especially in those neighborhoods with lower crime rates and higher levels of socioeconomic status. These results raise the need to explore other factors that contribute to understanding the positive relationship between violent crime and housing prices. Several hypotheses can be proposed and should be tested. For example, the issuance of visas to foreigners for the purchase of properties exceeding half a million euros may have outweighed the negative effect of violent crime during the analyzed period. Another hypothesis is that an increase in violence in neighborhoods with a high socioeconomic status stimulates the installation of private security in homes, which could contribute to an increase in housing prices.

While crime may not be a determining variable, the feeling of insecurity does act as a factor that reduces both the price of Airbnb accommodations (-0.18) and the price per square meter of homes (-0.146). This latter result is similar to the one obtained by Buonanno et al. (2013) for a district in Barcelona.

What stands out the most is the fact that perceived insecurity is revealed as a more determining factor in the case of traditional housing, although it also shows a more pronounced negative association with the price of Airbnb accommodation. This is evident as the variable of perceived insecurity is significant and negative for housing sales in 100% of cases (39 out of 39 models), while for Airbnb accommodations, it is significant in less than 40% of cases. Two possible explanations account for these results: (1) residents who are buying a housing have a more accurate perception of security and neighborhood circumstances in which they will reside, and (2) buying a house is a more important and complex decision compared to vacation rentals, making personal protection and family security fundamental aspects in decision-making.

The stability of perceived insecurity as a factor modulating the price of housing is also evident in the results of the local regression model. This variable is significant at a 95% confidence level in 62 out of the 69 analyzed neighborhoods. It is worth noting that the increase in perceived insecurity does not significantly affect the price per square meter in the neighborhoods that make up the historic center, with the exception of the Raval neighborhood. This result could be attributed to the revaluation of land in the city center, driven by pronounced gentrification and touristification processes in these areas (López-Gay et al., 2019). These two processes may mitigate the negative effect of insecurity on the price per square meter of housing in downtown Barcelona. On the other hand, in the peripheral neighborhoods of the northeast of the city, an increase in perceived insecurity is associated with a greater devaluation of the price per square meter. The concentration of disadvantages in the northeastern peripheral neighborhoods, the lack of community resources, and the settlement of a low-skilled migrant population may jointly contribute to the greater decline in prices associated with increased feelings of insecurity.

Regarding the greater impact of the feeling of insecurity on Airbnb accommodations, it can be explained by the flexibility of the supply on these platforms, which allows any event of significance to have an immediate response from both providers and demanders. A simple negative review highlighting security issues in an accommodation can negatively affect its demand and lead to a decrease in price. In contrast, the real estate market for home sales is less elastic and takes more time to respond to externalities (Ihlanfeldt & Mayock, 2010). On the other hand, Maldonado-Guzmán et al. (2021) find, for the city of Barcelona, that the feeling of insecurity in a given area is conditioned by the national heterogeneity of neighborhoods. This can be explained by prejudices and stereotypes associated with certain ethnic groups (García España, 2019), the higher crime rates found among some immigrant groups (Ferretti et al., 2018), or violence exercised according to cultural group affiliation (Soria-Verde et al., 2019).

Thus, native inhabitants may consider the possibility of moving to other urban centers due to the effect of immigration on their living conditions (Accetturo et al.,

2014) and the increase in feelings of insecurity (Renzulli & Evans, 2005). This study finds that national heterogeneity reduces both the price of Airbnb accommodations (-0.26) and the price per square meter of housing (-0.367). Again, the impact is greater on the sales price, possibly because tourists generally stay for a shorter period of time and are more concerned with other factors than the ethnic composition of the neighborhood. Meanwhile, regular residents interact with the local community every day, making this more relevant to them and influencing their consideration of the ethnic diversity of their neighborhoods.

Although national heterogeneity has a more negative impact on traditional housing prices than on tourist accommodation, this negative relationship does not have the same magnitude throughout Barcelona. The increase in levels of national heterogeneity is associated with a much smaller decrease in the price per square meter in the more touristic areas of the city (elasticity between -0.4 and -0.53) compared to other areas with greater population stability and socioeconomic status. In these latter areas, there is a negative correlation with the price per square meter with an elasticity of between -0.64 and -0.71. The real estate speculation linked to gentrification and touristification in central Barcelona (Caballero Rabanal, 2018; Zaar & Pontes de Fonseca, 2019) is likely dampening the effect of national heterogeneity on the price per square meter.

In contrast, immigration from countries with a high Human Development Index does increase the price of traditional housing (0.587). These foreigners are often associated with higher educational levels and higher economic capacity, making them potentially seen as a beneficial contribution. Additionally, it is possible that native inhabitants have fewer negative stereotypes or prejudices towards them compared to other immigrant groups. In other words, this result may reflect that potential homebuyers do not reject foreigners per se, but rather immigrants with lower socioeconomic status and stigmatized backgrounds, as hypothesized by Amuedo-Dorantes and Mundra (2013).

Furthermore, it is worth noting that gentrification processes are key to the revaluation of accommodation offered on Airbnb (0.65). This association is partly due to the revitalization and transformation of neighborhoods resulting from new investments, which encourage the opening of restaurants or improvements in communication infrastructure. Additionally, these accommodations are often located in areas close to the tourist center of Barcelona, as tourists seek quick access to the city's points of interest, with a wide range of entertainment and restaurants that are usually concentrated in the urban center. In fact, the results of this research show that the price of Airbnb tends to decrease (-0.43) as the accommodation is located in areas farther from the city center.

It should be noted that the findings of this study may have relevant implications for public policies implemented in the city of Barcelona. In this regard, the results indicate that perceived insecurity should not be relegated in decision-making processes, as it may exert an influence even greater than that of recorded crime on residents' living conditions, in this case through its impact on housing prices. This finding is particularly relevant in the current context, in which feelings of insecurity among the population have shown an increasing trend, despite the fact that recorded crime levels have not experienced a significant rise in recent years.

For this reason, public policies aimed at improving the sense of security among both residents and tourists appear to be necessary. In this respect, relatively simple urban interventions can be implemented to help reinforce perceptions of safety within a given area, such as improving street lighting, rehabilitating degraded spaces, or strengthening the maintenance and care of public space, in line with the principles of environmental criminology.

In this context, policing strategies oriented toward enhancing the sense of security may also play a relevant role. Potentially effective measures include the development of community-oriented policing models, increased police presence in neighborhoods where a greater rise in perceived insecurity is identified, and strategies that promote everyday interaction between police officers and local residents. However, policies focused solely on law enforcement risk overlooking the social and contextual dimensions through which insecurity is constructed. Moreover, in already disadvantaged neighbourhoods, an overreliance on punitive or surveillance-based strategies may reinforce territorial stigma and disproportionately affect vulnerable populations.

More effective policy responses should therefore combine security-related interventions with broader social, urban, and housing policies. Strengthening community networks, investing in local social infrastructure, promoting inclusive public spaces, and regulating tourism-related pressures may contribute to reducing perceived insecurity without exacerbating social exclusion. At the same time, improvements in neighbourhood conditions should be accompanied by housing affordability and anti-displacement measures to prevent the capitalization of these gains into higher prices and rents. Without such complementary policies, efforts to improve neighbourhood safety may unintentionally accelerate gentrification processes and further restrict access to housing.

Likewise, the differences observed in both the intensity and the direction of the effects of insecurity across neighborhoods highlight the need for interventions promoted by public institutions to be targeted and tailored to the specific characteristics of each neighborhood. In this way, the implementation of general and homogeneous interventions across all neighborhoods that fail to produce the desired outcomes can be avoided.

Finally, it is important to acknowledge that this article has a notable methodological limitation: its cross-sectional nature. To better understand the impact of crime and insecurity on the prices of tourist and traditional housing, longitudinal analyses are needed to capture changes in these prices as crime rates evolve. For example, the unexpected positive relationship found between violent crime and housing prices only in neighborhoods with higher socioeconomic status could be better understood with a longitudinal study that observes this relationship over a period of time.

Additionally, there is another limitation that, although not exclusive to this study, is essential to acknowledge: the modifiable areal unit problem (MAUP). The results presented here are derived from analyses conducted at the neighbourhood scale. Choosing a different spatial unit of analysis at a finer scale (for example, census tracts or street segments) may lead to results that differ from those observed in the present study. Changing the spatial unit of analysis could lead to differences in the statistical significance and stability of specific predictors (Fotheringham et al., 2003). Variables linked to recorded crime and tourism intensity, which already display limited or spatially heterogeneous significance at the neighbourhood level, would likely become more localized and unstable at finer spatial scales (Zhang et al., 2012), potentially yielding significant effects in specific micro-locations while losing global significance. In contrast, variables capturing broader social and perceptual processes, such as perceived insecurity, distance to the city centre, and indicators of socioeconomic composition, are expected to remain robust in terms of sign and general interpretation, although with reduced statistical power. Consequently, a finer spatial scale would likely shift the results from stable average effects toward fragmented and highly localized relationships (O'Sullivan & Unwin, 2010), rather than fundamentally altering the underlying mechanisms identified in this study. Future research should conduct the same analyses at different spatial scales to provide greater insight into the sensitivity of the results to changes in the scale of the unit of analysis.

Despite these limitations, this research yields consistent results with the literature in the field and highlights the need to reconsider the theoretical and methodological approach when analyzing the impact of crime and other structural factors on the prices of traditional and tourist housing. The local models have revealed that the devaluation of these prices due to crime, perceived insecurity, and national heterogeneity is lower in the historic center of the city. Therefore, it is necessary to analyze how different factors interact in each neighborhood to modulate housing prices, rather than analyzing the effect of each individual variable in isolation from the others. Future research should adopt a neighborhood-centered approach rather than a variable-centered one. This way, situations like those revealed in this study for Barcelona can be understood, including why the Ciutat Vella district (historic center) behaves notably differently from other areas of the city.

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Annex

Table 1a. The results of the Local Regression Model (LRM) for the price of Airbnb accommodations

Variable	Mean	STD	Min	Median	Max	Monte Carlo p-value
Intercept	0.071	0.102	-0.054	-0.063	0.250	0,153
Single-Parents Households	0.161	0.078	0.03	0.192	0.283	0,675
National Heterogeneity	-0.186	0.151	-0.405	-0.191	0.074	0,156
Gentrification	0.429	0.260	0.066	0.325	0.864	0,349
Distance to the downtown	-0.276	0.091	-0.537	-0.249	-0.173	0.766
Perceived Insecurity	-0.045	0.164	-0.236	-0.144	0.251	0.973