PUBLIC TRANSPORT AS AN OPPORTUNITY TO PROMOTE TOURIST HOMES IN URBAN PERIPHERIES: THE CASE OF MADRID, SPAIN

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ABSTRACT
The implementation of the collaborative economy in the tourist sector has led to a partial relocation of the accommodation (traditionally concentrated on hotels and resorts) through tourist homes scattered all over the city. Although some aspects of this new phenomenon (such as its impact on hotel occupation, the housing and long-time rental price) have been already analysed, socioeconomic and urban factors influencing tourists' accommodation choice need to be explored. This research aims to analyse and quantify the role of the urban public transport network on the occupation and promotion of tourist homes in contrast to other urban factors. The research is based in Madrid, a first-class urban tourist destination with a dense and efficient public transport system which may be an opportunity for peripheral accommodation locations compared to homes located in the city centre (usually at higher fares). Based on information of tourist homes in the city of Madrid provided by AirDNA for the period 2022–2023 (number of housings, fares, occupation rates, type of home, etc.), this research develops a methodology that relates the role of the urban public transport network and the occupation of tourist homes. To achieve this, linear regression models have been applied to two groups of accommodations separately: those located in the city centre and those located in the periphery. Results show that, for all accommodations, occupancy is strongly dependent on the average daily rate and the rating. However, for the group of accommodations located in the periphery, the distance to the nearest bus station also exhibits significant importance, highlighting the role of public transportation in decentralising the concentration of tourist accommodations and promoting greater sustainability in tourism within our cities.
Keywords: tourist homes, collaborative economy, urban mobility, social cohesion, public transport.

1 INTRODUCTION

City tourism, or urban tourism [1], [2], is a growing sector, and one of the fundamental causes of this expansion, especially in European capitals, is attributed to the emergence of new types of accommodation compared to the traditional hotel and catering industry. The rise of the collaborative economy, called the 'platform economy', has brought with it a relocation of traditional hotel accommodation, previously concentrated in fixed points of the city, and thus, tourist apartments, tourist homes and even shared rooms have emerged scattered around the city, most of them managed by large digital platforms 'of minimums' (lean platforms), with minimal costs, as they only manage the matching of hosts and guests, without owning any real estate assets. One of the main attractions [1] of this type of accommodation, apart from the cost and the ease of digital booking, lies in the tourist's desire to break away from traditional tourist circuits *(*off the beaten track) and identify with the local residents (live like a local). In the context of the growing urban tourism due to the proliferation of tourist accommodations, the leading international platform managing a significant portion of real estate assets is Airbnb, founded in 2018. It stands as the largest operator of tourist accommodations, with its success attributed to the seamless digital connection between hosts

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and guests. Any study analysing the supply and demand of tourist accommodations relies on the Airbnb database.

The rental of tourist housing scattered throughout the urban fabric places a ‘floating tourist’ in the city who moves, generating impacts on the centres of activity (restaurants, shops, museums, etc.), on public space and on mobility. To date, some aspects of this new tourism model have been analysed, such as the competitive advantages offered by this type of accommodation compared to pre-existing hotels for certain tourist profiles [3], its impact on hotel occupancy [4], sustainability [5] and house prices [6]. However, there are still unexplored lines of research around these new tourism models that examine the nature of the relationships between the mobility of this guest profile and the territory. The new tourist will trace new routes around the city, access public transport in a more delocalised way and likely visit activity centres different from those they would have explored if accommodated in a traditional hotel establishment.

While most major European tourist capitals boast dense and efficient public transportation systems, the concentration of tourist accommodations in the urban centre, often coinciding with the historic district, is a reality. This concentration is, in many cases, exerting pressure on the local population, leading to civic resistance from the inhabitants of these urban centres [7], phenomena associated with the concepts of ‘gentrification’ and ‘touristification’ [8]. Additionally, the clustering of tourist accommodations in the city centre implies a concentration of income (for hosts and local businesses) in this area, so a decentralisation of accommodations would bring about a redistribution of tourism-derived income to other areas, fostering greater social and territorial cohesion in the pursuit of a more sustainable form of tourism.

The study of the current spatial distribution of tourist housing in a city, characterising the supply, is key to identifying the neighbourhoods with the highest concentration of tourist housing. On the other hand, the analysis of access to the public transport system of accommodation located in non-central geographical locations (usually with lower fares) is essential to promote a decentralisation of tourist housing in cities; even laying the foundations for a possible zoning regulation (as has already been done in Barcelona).

In this context, the aim of this paper is to analyse the conditioning factors of the choice of a tourist home using a weighted occupancy indicator and paying special attention to the accessibility of the homes to the public transport system. Madrid is a good case study, as it is representative of urban tourism in large cities in a country that is a world power in the tourism sector (more than 10% of GDP in 2019 came from this economic sector). In addition, the city offers a consolidated market for tourist housing (according to AirDNA data, 19,000 units in 2023), and has a dense and efficient public transport system. The methodology is based on an analysis of occupancy, with data provided by AirDNA of tourist homes in Madrid in the period 2022–2023, together with a study of the accessibility of tourist homes to the transport network.

This article is structured as follows: Section 1 includes the introduction; Section 2, the case study; Section 3, the methodology used; Section 4, the results of the analysis; and, finally, Section 5 includes the conclusions and future research lines.

2 MADRID CASE STUDY

Madrid is the capital of Spain, a country where tourism plays a crucial role in the economy. In 2019, tourism accounted for 12.4% of the total GDP and 13.5% of employment. However, the COVID-19 pandemic that began in 2020 led to a significant decline in the tourism GDP, reducing it to 5.5% of the total GDP, although it continued to represent 12% of Spanish employments [9]. Additionally, in recent years, tourism has been gaining importance in the

Community of Madrid, increasing from representing 6.0% of the GDP in 2015 to 7.1% in 2019 [10].

The selection of Madrid as a case study is, therefore, representative of urban tourism in major European capitals and additionally provides a dataset comprising nearly 20,000 tourist accommodations. With a population exceeding three million inhabitants, Madrid is part of one of the most segregated metropolitan areas in Europe [11]. Consequently, various distinct realities coexist within the city of Madrid, spatially configured into three major areas: the central core, or Central Almond, the north periphery, and the south periphery (Fig. 1). These zones exhibit differentiated characteristics in factors related to the existing residential stock, the resident population, prices, the real estate market, or the influence of new phenomena, such as the so-called ‘collaborative economy’, manifested in the emergence of tourist-use residences [12], which are analysed in this article.

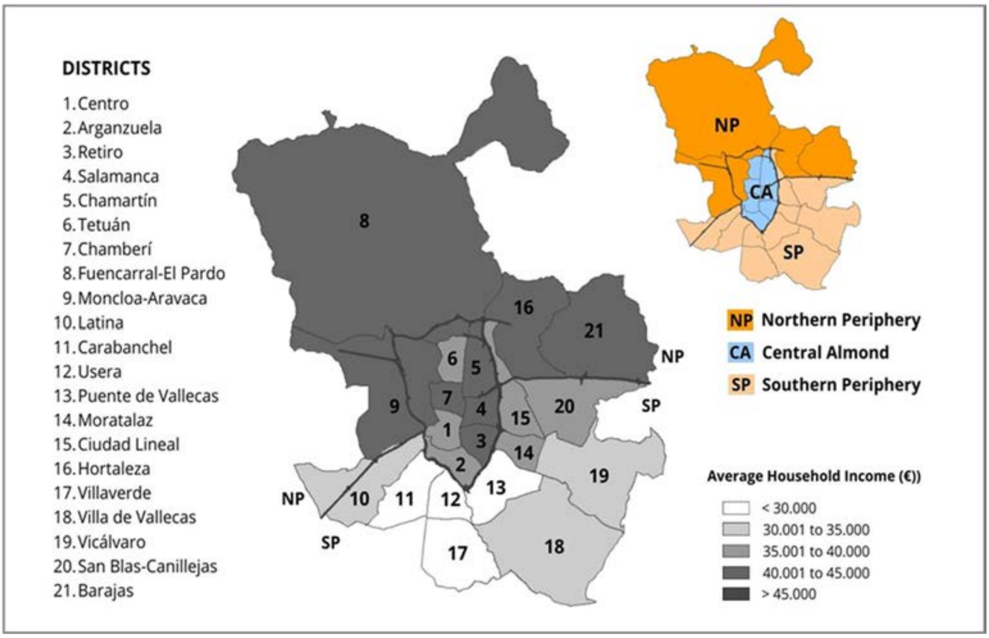

Figure 1: Distribution of the average annual income of households in each district of Madrid.

The Central Almond comprises primarily the districts of Centro, Arganzuela, Retiro, Salamanca, Chamartín, Tetuán, and Chamberí, although the City Council of Madrid also occasionally includes part of an eighth district, Moncloa-Aravaca (Fig. 1). This area is privileged, where individuals with medium and low incomes face diminishing prospects for housing access. It is subject to real estate dynamics, with recent years witnessing processes such as gentrification, touristification [13], and the channelling of international financial flows into real estate investments.

The north periphery encompasses the northern arc of the city limited by the A-2 and A-5 motorways and comprises the districts of Moncloa-Aravaca, Fuencarral-El Pardo, Hortaleza, Ciudad Lineal, and Barajas (Fig. 1). This area is characterised by a concentration of middle and high incomes. Lastly, the south periphery covers the southern arc of the city limited by the A-2 and A-5 access roads, including the districts of Latina, Carabanchel, Usera, Puente de Vallecas, Moratalaz, Villaverde, Villa de Vallecas, Vicálvaro, and San Blas Canillejas (Fig. 1). The latter area is home to almost half of the city's population (44.2%), households (42.5%) and homes (42.1%). Most of the popular classes are concentrated in it, with the lowest incomes and the lowest cost housing stock, and with the fewest contrasts between maximum and minimum, both in rent and prices [12].

Madrid's public transport network is characterised by its extension and the diversity of transport modes available, including the Madrid Metro, the city bus operated by the Municipal Transport Company (EMT), the intercity buses, the commuter rail service (*Cercanías*) and the light rail. In 2022, a total of 1,362.7 million journeys were recorded. Of the modes present in the city, the Madrid Metro and urban buses stand out, representing 42.0% and 27.4% of total trips, respectively [14]. In addition, the Metro network and urban buses are the main means of intra-municipal travel [14], so the accessibility of tourist homes to the transport system will be analysed in terms of the proximity of tourist homes to stations of these two modes of transport.

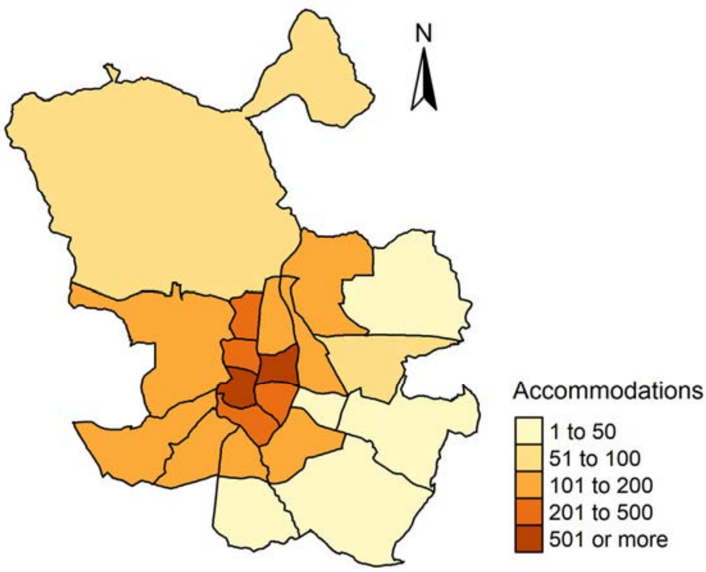

Figure 2: Spatial distribution of Madrid tourism homes (number of tourism accommodations per district).

In terms of mobility between the areas of the city, there is a great use of the public transport network, especially in the area known as Central Almond. In particular, 69% of mechanised journeys within this area are made by public transport. In addition, transport between the central area and the urban peripheries takes place 64% of the time using public transport. In contrast, private vehicles prevail in the peripheries, representing 54% of journeys, while public transportation accounts for 42% [15]. Regarding non-motorised journeys, they are more common for trips with both origin and destination within the same zone and much less common in journeys between the two zones, possibly due to the considerable distance separating them. Lastly, concerning mechanised modes, public transport constitutes more than half of the journeys with origin and/or destination in the central core. However, its usage decreases for journeys within the urban periphery, as the transportation network is heavily focused on centre-periphery movements and virtually neglects movements within the periphery [16].

3 METHODOLOGY

This study seeks which factors affect tourism homes occupation rates, or indirectly which factors make a tourist choose housing depending on the city zone, based on the reservation process. The reservation process for tourist accommodations typically involves three steps. Initially, a tourist chooses a city and a date range, and the reservation platform (e.g., Airbnb) displays available accommodations for the chosen city and timeframe. Note that, in this stage, tourists cannot view accommodations that are fully booked. Subsequently, the tourist narrows their search to a specific area within the city. In the final stage, the tourist selects an accommodation from those available in the chosen area that best meets their needs. If no suitable options are found, the tourist can either restart the entire process or return to the second stage to select a different city area.

The proposed methodology analyses housings of different zones of the city (centre and periphery) separately. First, dependent (tourist housing occupation) and independent variables for each tourist housing were collected, processed, and examined, leading to the creation of an ad hoc database. Secondly, this database was divided in two samples: centre and periphery housings. Finally, these samples were used in the modelling process, which included the application of the multiple linear regression.

3.1 Dependent variable

The dependent variable should reflect the answers to the question ‘Why do tourists prefer certain city areas for their stay?’. The proposed output variable is the occupation rate of each housing, calculated as total number of reservation days over total number of offered days (eqn (1)). Where OR_i is the occupation rate of the housing i, and R_i and O_i are the number of reserved and offered, respectively, for the tourist housing i.

$$OR_i = R_i / O_i \tag{1}$$

3.2 Independent variables

Once the possible housings are showed to the tourists, they should decide which one to choose. This election depends on a wide range of factors that could be grouped in house variables, house surrounding variables, and proximity to tourism attractions variables.

House variables included in the AirDNA database are average daily rate (ADR), number of bedrooms, number of bathrooms, maximum guests, number of amenities, and overall rating. In this study, the tourists are expected to seek for different housings depending on the number of guests in their group. Hence, some house factors were normalised considering that the maximum number of guests of a housing is equal to the number of people in the tourists’ groups. With this consideration, house factors are ADR per person, bedrooms per person, bathrooms per person and overall rating.

House surrounding variables include the economic status and the amenities of the area of the housings. The economic status is shown in the average income per person of the census tract where the house is located, being Madrid divided in more than 2,000 census zones. In addition, the amenities are the number of local commerce points of interest (POIs) within a 5-minute walk from the house (400 m). The number of tourist housings within 200 m from the house was also recorded, as a customer could perceive an area with many housings as more attractive or safer.

Proximity to tourism attractions variables reflects the proximity of tourism POIs from the housings. The proximity is calculated as the mean of the distances between the housing and 15 selected most-visited tourism POIs (Fig. 3).

Regarding **public transport network**, tourists are expected to find how near the housing is to access the network. In this sense, the number of transfers is not expected to matter to them. Instead, the Euclidean distances to the nearest bus stop and metro entrance were obtained for each housing.

Table 1: Definition of independent variables.

Group	**Variable**	**Definition**
House features	ADR per person	ADR per person (€)
	Bedrooms per person	Number of bedrooms per person
	Bathrooms per person	Number of bathrooms per persons
	Rating	Overall rating of the housing
House surrounding	Average income per person	The average income per person (€) of the census tract where the house is located
	Local commerce	The number of shopping and catering POIs within a 5 minute walk from the house (400 m)
	Competence	Number of tourist housings in 200 m
Proximity to tourism attractions	Proximity to tourist POIs	Mean distance to the top 15 tourist destinations from the housing
Public transport network	Bus	Distance to the nearest bus stop from the housing
	Metro	Distance to the nearest metro station from the housing

3.3 Data sources

The database was built with data obtained from different sources. Tourist housing data was extracted from the AirDNA database. AirDNA collects the most comprehensive database of tourist accommodations, as it includes information on tourist-use properties offered through the Airbnb and Vrbo platforms. Property owners often list their homes on more than one platform, but according to verified data, AirDNA accounts for 90% of the total supply [17], thus making AirDNA's supply and demand data for the city of Madrid considered representative. For each vacation rental and for every month, the data includes its location, property features (number of bedrooms, bathrooms, type of property, etc.), offer (ADR, number of available days) and demand (number of reserved days, occupation rate).

Regarding house surroundings, the average income per person was extracted for the last year available, 2021, from the Spanish National Statistics Institute (INE). The local commerce POIs were extracted from OpenStreetMap [18], considering only the catering and shopping points, through Geofabrik (download.geofabrik.de). Additionally, the list of the top-visited tourist attraction was extracted from TripAdvisor [19], which is based on the quality, quantity, recency, consistency of reviews, and the number of page views over time. These locations were geolocated in an ad hoc GIS file. Fig. 3 shows the names and locations of the chosen tourist attraction. Finally, bus stops and metro entrances were gathered from the Open Data Portal of the Consortium of Transportation for Madrid [20].

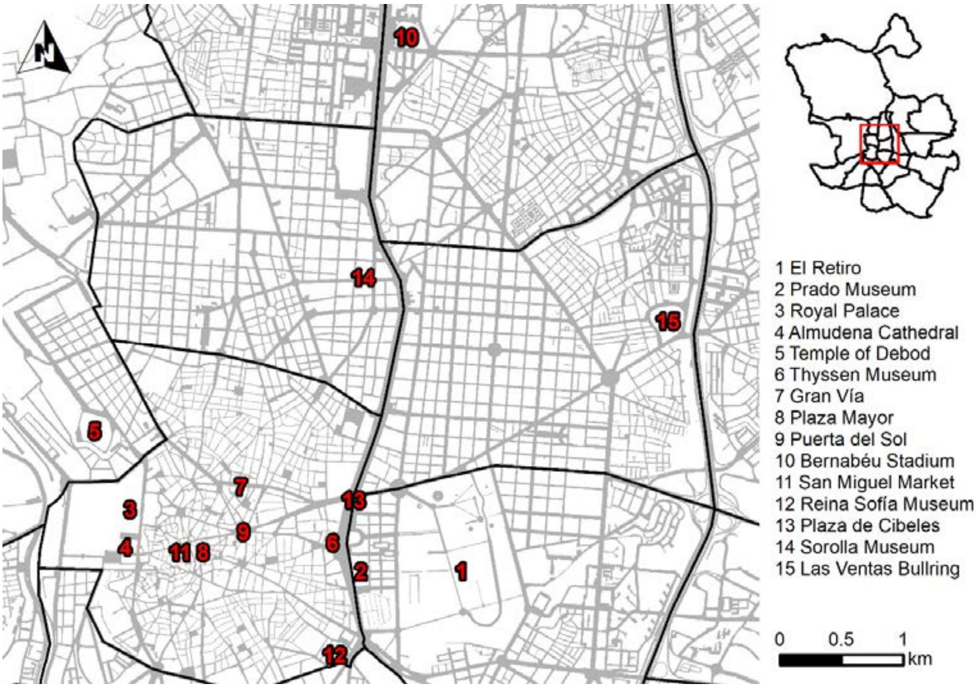

Figure 3: Madrid main 15 tourist POIs, provided by TripAdvisor [19].

3.4 Housing selection

Some housings were excluded from this study based on the following criteria. The month of the AirDNA data was October 2022, because it was the month with the highest occupation. Housings included in the analysis were those being entire homes or apartments, thus excluding rooms, those that were offered to the tourist at least one day of that month, and those with at least one bedroom. Also, only records with no missing data were studied. Finally, data from 7,888 tourist housings were suitable for this study.

3.5 City zones

The relationships between dependent and independent variables are expected to differ across the geographical extension of the data. In addition, this study aims to analyse these differences. Madrid city was divided in two zones: Central Almond which correspond to district inside of the M-30 highway, and periphery, which are the rest of districts. Considering the location of each tourist housing inside of these two zones, the created dataset was divided in two samples. Central Almond includes most housings (6,629), and the periphery includes about 15% of them (1,259). The spatial distribution of these housings is shown in Fig. 2. Data modelling was applied to these two separate data samples separately. Table 2 shows the descriptive statistics of the collected variables considering the city zone.

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Table 2: Descriptive statistics of the collected variables considering the city zone.

Variable	Central Almond	Periphery	Total
	n = 6,629	n = 1,259	n = 7,888
	Mean (SD)	Mean (SD)	Mean (SD)
Occupation	0.841 (0.221)	0.786 (0.255)	0.832 (0.228)
ADR per person	46.3 (26.8)	32.6 (19.0)	44.1 (26.2)
Bedrooms per person	0.412 (0.155)	0.417 (0.143)	0.412 (0.153)
Bathrooms per person	0.358 (0.149)	0.334 (0.149)	0.354 (0.150)
Rating	91.9 (8.29)	91.8 (8.67)	91.9 (8.35)
Average income per person	20,100 (4,680)	15,700 (5,960)	19,400 (5,170)
Local commerce	304 (193)	39.1 (51.6)	262 (203)
Tourist distance	2,020 (804)	5,440 (2370)	2,570 (1730)
Competence	120 (85.1)	8.09 (12.0)	102 (88.3)
Distance to nearest bus stop	98.1 (55.3)	123 (94.6)	102 (63.9)
Distance to nearest metro station	192 (119)	486 (631)	239 (295)

3.6 Multiple linear regression

The multiple linear regression (eqn (2)) was applied to central and peripherical tourist housings separately. This model provides parameters and p-values, which can be interpreted to analyse how variables affect the dependent variable and if these effects are statistically significant. The linear regression relation is given by

$$y_i = \beta_0 + \sum_k^p \beta_k x_{ik} + \varepsilon_i \tag{2}$$

where y_i is the dependent variable at location i, β_0 and β_k are the intercept and parameters of the regression for the location i, respectively, x_{ik} are the independent variables in location i, p is the number of covariates, and ε_i is the error at location i.

3.7 Variable importance

The sign and significance level of the parameters of the covariates in the linear regression models give valuable insight in how independent variables affect the occupation of the housings of the two zones of the city. However, this approach is sensible to the variables included in the modelling process, as some could change the sign or significance level when the set of variables is modified. Furthermore, as independent variables present different units of measure, their effect should not be compared in terms of what variables are more important for occupation.

To solve these issues, an exhaustive model selection process was performed. This included computing all possible regression models with the list of independent variables (presented in Table 1) for the two samples. For each city zone, the number of models is 1,024 (2^{10}, being 10 the number of covariates). The intercept of the model was included all possible variable combinations. For each combination, parameters, p-values and, as a measures of the goodness-of-fit, the Akaike information criterion (AIC) were recorded. Later, for each possible combination of variables, the Akaike weight (w_i) was calculated as exposed in eqn (3). This Akaike weight is a normalised measure of each model being the best model, in terms of the AIC, inside a set of models. For a set of models, the sum of the weights is equal to 1 [21].

$$w_i = \frac{exp\left(-\frac{1}{2}\Delta(AIC)_i\right)}{\sum_{k=1}^{K} exp\left(-\frac{1}{2}\Delta(AIC)_k\right)} = \frac{exp\left(-\frac{1}{2}(AIC_i - min(AIC))\right)}{\sum_{k=1}^{K} exp\left(-\frac{1}{2}(AIC_k - min(AIC))\right)} \quad (3)$$

where w_i and AIC_i are the Akaike weight and the AIC of the model formed with the *i*th combination of independent variables, respectively, and K is the total number of combinations of independent variables.

This value can be used to evaluate the models, as better adjusted models present higher weights. More interestingly, the Akaike weight can be used to detect which covariates are more important for the model adjustment, thus for defining the occupation of each housing. The idea is that more important variables appear in better adjusted models, so this importance is calculated as the sum of weights of the models where the variable appears. Note that each variable should appear in the same number of models for a fair comparison of the variable importance [21], [22]. In our case, each variable is used in half (512) of the regressions in each set of models. This process was carried out separately for both data samples. With this approach, we should inspect and compare the model with all variables, the best fitted model and the variables' importance for each sample. These are presented in the next section.

4 RESULTS

The results of this study are based on the parameters and *p*-values of the covariates in the multiple linear regression for both samples, and on the relative importance of these covariates in the accurate calculation of the dependent variable.

Regarding the regression models with all the independent variables, parameters and *p*-values are shown in Table 3. The same effects of the statistically significant variables on occupation are shown in both models. More bathrooms per person and more rating imply more occupation, while higher ADR per person and more distance to tourist destinations are related to lower occupation. The effect of ADR per person is higher in the periphery, and the

Table 3: Main statistics for the models (central almond and periphery) with all covariates.

Variable	**Central Almond**		**Periphery**	
	Estimate	***p*-value**	**Estimate**	***p*-value**
Intercept	3.70E-01	0.000***	4.53E-01	0.000***
ADR per person	−2.18E-03	0.000***	−3.25E-03	0.000***
Bedrooms per person	1.81E-02	0.355	−7.33E-02	0.192
Bathrooms per person	1.62E-01	0.000***	1.43E-01	0.012**
Rating	5.51E-03	0.000***	5.36E-03	0.000***
Average income per person	1.33E-06	0.055*	−1.44E-07	0.914
Local commerce	1.37E-05	0.581	8.09E-05	0.731
Tourist distance	−1.64E-05	0.001***	−9.22E-06	0.011**
Competence	4.67E-06	0.942	−9.34E-05	0.924
Distance to nearest bus stop	−3.83E-05	0.419	−1.14E-04	0.133
Distance to nearest metro station	2.98E-05	0.205	−1.08E-05	0.390
n	6,629		1,259	
AIC	−1855.85		45.06	

*** for 1%, ** for 5%, and * for 10%.

rest of variables affect more the occupation on central almond housings. The average income per person is statistically significant in the central almond model only, and higher values improve the occupation.

Turning to the regression models with the best goodness-of-fit considering the AIC (Table 4), these present a smaller and different set of independent variables for each sample. Note that AIC values are lower than those showed in Table 3. We find that some factors affect the occupation of all the housings regardless of the city zone, which are ADR per person, bathrooms per person, rating, and tourist distance. As in the models with all the variables, the effect of the ADR per person is higher in the periphery, while the rest of variables affect housings located inside the central almond more. Also, the effect of these variables is equal as in those models. Other variables are present in one of the models only. On the one hand, average income per person affects occupation only in central almond, and higher values are related with higher occupation. On the other hand, shorter distances to nearest bus stop are related with more occupation in the periphery, bus this effect is not significant at alpha 10%.

Table 4: Main statistics for the best-fitted models (central almond and periphery housings).

Variable	**Central Almond**		**Periphery**	
	Estimate	***p*-value**	**Estimate**	***p*-value**
Intercept	3.82E-01	0.000***	4.40E-01	0.000***
ADR per person	−2.17E-03	0.000***	−3.26E-03	0.000***
Bathrooms per person	1.70E-01	0.000***	1.04E-01	0.040**
Rating	5.54E-03	0.000***	5.36E-03	0.000***
Tourist distance	−1.75E-05	0.000***	−1.09E-05	0.000***
Average income per person	1.24E−06	0.029**	–	–
Distance to nearest bus stop	–	–	−1.20E-04	0.109
n	6,629		1,259	
AIC	−1862.741		37.92	

*** for 1%, ** for 5%, and * for 10%.

About the variable importance, Fig. 4 shows the Akaike weight for the independent variables in the two studied samples. ADR per person and rating are the most important variables in both zones, presenting the maximum possible value of the Akaike weights. Distance to tourist destinations and bathrooms per persons are also important variables, having both higher Akaike weights in the central almond. Less important variables with similar Akaike weights for both city zones are distance to nearest metro station (0.42 and 0.39), local commerce (0.30 and 0.29) and competence (0.30 and 0.28). Average income per person is remarkably more important in the central almond (0.78) than in the periphery (0.27). Finally, more important variables in the peripherical housings are bedrooms per person (0.42 versus 0.35) and distance to nearest bus stop (0.55 versus 0.33).

5 CONCLUSIONS AND FUTURE RESEARCH LINES

This research highlights that in the selection of tourist accommodation within a city, two factors are particularly significant regardless of the location of the accommodation (city centre or periphery): the average price daily rate and the rating given by previously accommodated tourists. The third most important factor, the average distance to tourist points of interest, depends on the location of the accommodation and its connectivity with the transportation system. For the group of accommodations located in the periphery of the city,

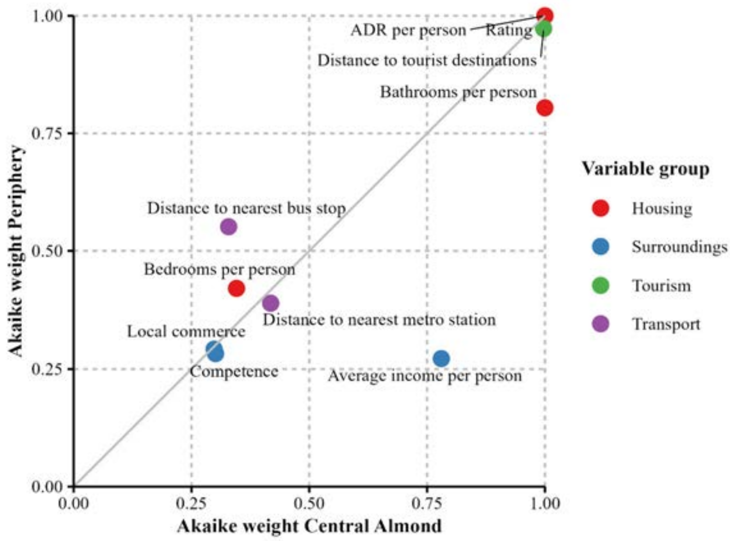

Figure 4: Akaike weight of the variables in the Central Almond and periphery housings samples.

occupancy levels are significantly more dependent on the distance from the accommodation to the nearest bus station than on the distance from the accommodation to the nearest metro station. In the selection of accommodations located in the city centre, the proximity of the accommodation to public transportation stations (neither metro nor bus) does not seem to have influenced the decision. This fact appears to be justified by the density of the public transportation network, which is higher in the city centre than in the periphery, and the proximity to touristic POIs. Accommodations in the city centre always have both bus and metro stops nearby. However, in accommodations in the periphery, metro stations are usually farther away, and the bus network serves as the first stage of the journey towards tourist points of interest.

In this context, if public administrations wish to promote tourist accommodations in the periphery, they should provide the bus public transportation network with greater reach and density of stations in these areas of the city. This would be a tool that could help to relocate the presence of tourist accommodations from the city centre, contributing to a greater sustainability of this new type of lodging. This result has a clear practical application in the regulation of tourist homes in city centres redistributing them throughout the city. In this sense, in some big cities, peripheral locations can let to the redistribution of the wealth generated by tourism around the city, favouring territorial and social cohesion.

With regard to future lines of research that may stem from this publication, concerning methodology, a new indicator of average accessibility to tourist points of interest could be studied. This time, it would not be based on the average Euclidean distance, but rather on travel times via public transportation from tourist accommodations to the 15 most significant points of interest. This indicator could weigh these access times based on the importance (tourist influx) of each tourist point of interest. This methodological improvement would serve to reassess the true role of public transportation in the choice of tourist accommodations located in the periphery.

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