**Inside Airbnb's performance and adaptive strategies in global destinations using deep learning and artificial neural networks: A longitudinal, spatial, and multi-host perspective.**

## Abstract

This research explores the Airbnb platform's performance and adaptive strategies by analyzing its spatial, temporal, and multi-host patterns. A three-layer model based on deep learning and neural networks is used to conduct a longitudinal analysis of three representative tourist seasons from 2016 to 2022. The study reveals the importance of longer stays and placing accommodations in the medium- and long-term residential markets, coupled with active price management and professionalization, to maintaining the platform's adaptive strategies. The findings also suggest a shift toward more professional host profiles and the emergence of new tourist hubs in the city. The study contributes to the understanding of Airbnb's performance and impact on global urban dynamics and demonstrates an application of deep learning to tourism and hospitality research. Theoretical and practical implications are discussed.

**Keywords:** platform economy, deep learning, artificial neural networks, resilience, tourism season performance, Airbnb.

## 1. Introduction

The significant growth of tourism in the last decade, excepting the pandemic parenthesis, has been predominantly based on the increased supply of short-term tourism rental platforms

(STRP) led by one company, Airbnb. This platform has been pivotal in the construction of urban space in the last decade, affecting the internal balance between the composite elements of cities' rental property (Cocola-Gant & Lopez-Gay, 2020). Its growth in cities has been exponential and extensive due to structural changes in tourism demand (low cost, geared toward millennials), the characteristics of this STRP supply (attractiveness to investors, central locations, home-away-from-home vibe), and institutional aspects (urban rental legislation) (Guttentag, 2019). Nevertheless, this development can also be linked to conjuncture, particularly to the consequences of the 2008 financial crisis. The collapse of housing prices, artificially inflated after decades of speculation, attracted new players, basically investment funds, which replaced banks in the provision of capital to the sector but renewed speculation in these markets (Lima, 2020). Moreover, the bankruptcy of numerous companies and increased unemployment favored the emergence of large population segments in need of the kind of supplementary incomes that STRP could provide.

In this context, tourism again represented an opportunity for capitalist recovery, and the moment for STRP to take off in cities, especially as businesses that did not require large physical infrastructure and structures to achieve greater shares of power in the strategic control of the accommodation supply. Furthermore, Airbnb's model quickly transitioned from its original ideal of a *sharing economy* champion to a clearly performance-based model in which the multi-hosting option took most of the supply, while the shared-rooms proposal was marginalized, if not outright banned (Morales et al., 2022). Importantly, this growth was fueled by some local governments that, citing the need to recover from the crisis, promoted *laissez-faire*. However, this fast growth soon had tangible negative impacts on urban destinations, including increased occupation of public and private spaces, deterioration of the local business fabric, and, most notably, the effects on the housing market itself. As has been showed (Lladós-

Masllorens & Meseguer-Artola, 2020; Wachsmuth & Weisler, 2018) the Airbnb supply's development had a direct impact in the increase of housing rental prices in several cities and was responsible for various "touristification" processes leading to the displacement of locals (Morales-Pérez et al., 2020).

Definitely, the expansion of Airbnb's profit-driven model has been a threat to affordable housing and an arena for the proliferation of venture capitalism (Wachsmuth & Weisler, 2018), due to the large difference in profitability between long-term rentals to residents and short-term rentals to tourists in central districts (García-López et al., 2020). Crucially, in many cities, the aforementioned *laissez-faire* allowed hosts to act in a flexible manner, quickly adjusting prices and diversifying their marketing channels with a growing ability to transfer STRP supply to housing markets. Hence, the greater survival rates of listings belonging to such professionalized multi-hosts, especially thanks to the proliferation of housing management software (Cocola-Gant & Gago, 2021). However, an unexpected "black swan," the COVID-19 crisis, suddenly changed the context. The plummeting demand for Airbnb reservations, which fell by more than 80% in many destinations, suggested that Airbnb's development had peaked. But these assumptions soon proved not entirely correct. In the wake of the lockdowns in the first waves of the pandemic, the company embarked on a clear recovery (Miguel et al., 2022) and finally began to show important growth figures again.

In any case, beyond looking at the pre- and post-pandemic periods separately, no longitudinal study has yet shed light on the strategies used by those listings that have managed to survive the different conjunctures experienced in these urban destinations in recent years. There thus remains a gap in the knowledge about the adaptive strategies adopted by Airbnb suppliers to cope with an increasingly uncertain and changing context. The present research aims to address this gap, identifying the performance and adaptive strategies of the Airbnb supply, specifically, the population of accommodations to survive from 2016 to 2022 using such strategies. To this end, it will consider its spatial and temporal patterns and unevenness while continuing to observe its impact on the housing market. The analysis focuses on the key period (2016-2022), spanning from the platform's moments of greatest growth in the rebound from the Great Recession to its recovery in the wake of the Pandemic, in Barcelona, an especially representative global urban destination. Specifically, three main hypotheses are tested:

H1: Despite the pandemic's impact, the Airbnb platform's performance remains multi-host and demand (tourist season) dependent.

H2: Airbnb's hosts have pursued different multi-host and spatially uneven strategies to adapt to the pandemic context, fundamentally based on a shift toward longer-term rentals and the adjustment of supply prices to changes in demand.

H3: The evolution of this performance and the adaptation strategies has created and reinforced new tourist hubs in the city and impacted its long-term rentals.

## 2. Literature review

### Airbnb's markets and performance

Although Airbnb's exponential growth began to slow down in 2015 for several reasons (particularly first regulations of the company's development), it did not decline until the outbreak of COVID-19. This outbreak led to widespread lockdowns until early summer, and mobility collapsed in the subsequent months, causing a dramatic drop in demand in many destinations. Soon, authoritative voices (Dolnicar and Zare, 2020) predicted that, although Airbnb demand would begin to rebound with the first signs of recovery, it would not return to pre-pandemic levels. Indeed, they argued that the pandemic would have a long-lasting impact on Airbnb's growth, pushing much of its supply to long-term residential uses. In contrast, Bugalski (2020) argued that this transformation would not be so easy due to the required investments and dependence of the international funds managing them; indeed, early on, STRP were evaluating the potential risks and returns of any radical transformation. Meanwhile, Boros and Kovalcsik (2021) found that the effects of the initial waves of the pandemic on price categories varied from one location to another, which they related to the characteristics of local tourism markets.

In any case, the pandemic dramatically reshaped the tourism images of many cities, with booking rates declining in all markets and the tourist demand composition beginning to change. The spatial distribution of the demand for Airbnb listings, measured by reviews, showed a trend toward suburbanization, while tourists displayed less interest in tourism-related activities (Liang et al., 2021). For Sainaghi and Chica-Olmo (2022) the pandemic reduced the importance of well-known variables (e.g., size) for explaining the variance in listing performance, while increasing the importance of other aspects, such as host characteristics (superhost badge) or the presence of commercial and transportation facilities. Likewise, Liang et al. (2021) found that the evolution of Airbnb markets in this period was particularly dependent on the measures taken by the platform particularly by governments, highlighting lockdowns. For Kourtit et al. (2022), the restricted access to tourist amenities decreased the attractiveness of dense downtown locations, a finding corroborated by Sainaghi and Chica-Olmo (2022).

Nevertheless, at the outbreak of the crisis, not all actors in the STRP business were equally affected by the market changes. During Airbnb's expansion, global destinations witnessed win-win situations, whereby the company made substantial profits even as many hosts earned considerable incomes. The situation changed fast after the first wave of the pandemic. The financial losses experienced by hosts have been estimated to be 6.5 times greater than those incurred by Airbnb (Chen et al., 2020), indicating that the impact of the crisis was being clearly transferred. This can be interpreted as related to the asymmetry of power and control between the platform and its participants (Calo & Rosenblat, 2017). Moreover, given the increasing importance of health-and-safety standards for accommodation-sharing properties, the platform was expected to exercise tighter control over its participants on both the supplier and consumer sides (Gerwe, 2021). Nadal (2021) emphasized this idea, confirming that the pandemic outbreak entailed a new phase in Airbnb's increasing control over its hosts.

In this context, tourists were more inclined to book entire homes than shared options (Bresciani et al., 2021). Gossen and Reck (2021) corroborated this for the supply side, showing that renting out whole homes, and renting long-term, increased the likelihood of a listing remaining on the market. Lockdowns also had a significant influence on listings' survival, decreasing the probability of an active listing. Finally, survival patterns varied between shared and non-shared listings, with hosts with shared listings showing the least dependence on the negative evolution of market variations, a fact that may have helped them survive (Fan et al., 2023). Indeed, shared listings had a higher expected survival rate than non-shared ones, confirming the idea that professional and non-shared listings have been more likely to leave the Airbnb market when there have been problems with demand, particularly at the start of the pandemic (Fan et al., 2023). Nevertheless, this was not the case in some cities, such as Barcelona, where the shared-rooms options failed to survive due not to the pandemic but a ban by the local council.

**Adaptation strategies of Airbnb professional multi-hosts and their impact on destinations**

The rise of STRP professional management in recent years has facilitated investment by second-home owners and mobile middle classes in Airbnb (Cocola-Gant & Gago, 2021). Together with buy-to-let investment, new actors (middle- and high-income classes, financial institutions) pursue buy-to-leave strategies attracted by rising property values (Gotham, 2005). Therefore, multi-hosting has no longer been the exclusive province of large holders, but has also been embraced by owners with fewer homes, professionalized by the easy and cheap access to management systems. These new performances were crucial at the outbreak of the pandemic, allowing hosts to act with great flexibility, quickly adjusting prices and transferring listings from the short-term tourist rental market to other medium- and even long-term ones. For professional multi-hosts, the initial effects of the crisis were felt in their inability to assume the costs of salaried staff and other business-related expenses. Though some of these multi-hosts profiles combined their supply between the STRP and long-term rental markets, others sought to exit STRP markets, by either ceasing all activity or transferring it entirely to long-term residential rentals (Farmaki et al., 2020). The increasing use of management systems allowed hosts, particularly small owners, to advertise their apartments on different platforms, including medium- and long-term rental portals, simultaneously. This became exceptionally important in the pandemic, as it permitted hosts to speculate on assets for a few months while waiting for the tourism markets to rebound, transferring their supply to long-term rental markets (Buckle et al., 2020) changing vacancy rates and causing rents to fall.

Apart from this market diversification, the other main crisis adaptation strategy undertaken by hosts bas based in adjusting prices to (expected and real) variations in demand. To date, many studies have focused on these prices' dependence on location. For example, Gyódi and Nawaro

(2021) showed that neighborhoods' attractiveness had a robust impact on listing prices. Nevertheless, in a study comparing prices before and during the pandemic, Bode et al. (2021) showed the influence of different categories of factors on Airbnb's prices. Specifically, guests' marginal willingness to pay for social distancing features changed dramatically, mainly for listings with kitchen amenities, which saw a year-on-year price increase of more than 15% in summer 2020 versus a year-on-year decrease of nearly 3% in the marginal willingness to pay for size-related features. Comparing the adaptation strategies of hotels and Airbnb, Gyódi (2021) revealed the initial impact of the pandemic in both markets. While hotels aggressively cut prices in 2020, Airbnb listing numbers and prices trended downward, especially in summer. Unlike hotels, Airbnb hosts were not forced to respond to the pandemic immediately and waited for market developments. After several months, listings had fallen by around 20%, indicating that a large share had pivoted from STRP provision. Listing prices also fell early on in the pandemic. However, Airbnb hosts' price response was significantly smaller than that of hotels, supporting the idea that Airbnb hosts did not have to provide services at lower price points and could use their property for purposes other than the STRP supply. Llaneza and Raya (2021) found that prices in the STRP market effectively declined due to the pandemic, especially for entire-room listings and professionalized units (13.6%). Occupancy likewise declined (more than 30%) due to decreased demand, with the non-professionalized supply being hit hardest. These impacts on price and occupancy negatively impacted revenues, most notably for entire-room and professionalized accommodations. Finally, as advanced in Gyódi (2021), they also showed an increase in the minimum booking length for all listing segments.

New references offered greater insight into what had happened after the pandemic's initial outbreak. STRP and property management companies prioritized immediate response measures and ad-hoc actions such as declaring *force majeure* in order to generate communication and balance the interests of guests and hosts. Miguel et al. (2022) confirmed the two previously most commonly reported strategies, i.e., diversification of the listing supply to medium- and long-term residential rental markets and the initial drop in prices, while adding, in the specific case of big multi-host owners, the provision of new services and promotion of their own websites to obtain direct bookings and thus save money on platform commissions. These authors also confirmed that other platforms, such as HomeExchange or HomeAway, have not experienced a substantial reduction in the number of listings, which they attribute to the fact that their listings mostly consist of second homes, which owners are less likely to transfer to the long-term residential market.

**New tourist hubs and impacts on long-term rentals**

In the last years, other studies have renewed the analysis of the distribution of the Airbnb supply in cities and, especially, how developments in its prices have impacted other markets, mainly, housing. For example, new studies have presented evidence of the symmetrical nature of the "Airbnb effect" the impact of the company's development on rental markets, associating the impact of the company's declining activity with an initial reduction in long-term rental prices. For instance, in their study of Sidney, Thackway and Pettit (2021) corroborated the correlation between the decline in Airbnb activity and an increasing long-term rental market supply in 2020, mainly due to the greater stability of this market's revenue in the absence of tourism during the lockdowns. The authors also found a clear decline in long-term rents in the areas where Airbnb was most active. Long-term rental prices remained stable in this period for low-Airbnb-activity areas, which the authors attribute to the inverse relationship between rental supply and rental prices. Trojanek et al. (2021) reported similar findings for Warsaw, observing a substantial drop in long-term rents between March 2020 and December 2020, with the largest decline occurring in centrally located neighborhoods, which they largely attributed to the inflow of new housing supply from the STRP market.

Benítez-Aurioles (2021) also corroborated the hypothesis that Airbnb's contraction could lead to lower prices in long-term rentals and housing, finding that that the intensity of the contraction in the tourism demand was not offset by the reduction in the STRP supply, the prices for which generally fell. Finally, taking a broader view following the pandemic's initial impact, Jang and Kim (2022) again corroborated the importance of agglomeration effects in the impact of Airbnb development on destinations, predicted by various authors pre-pandemic (e.g., Lladós-Masllorens & Meseguer-Artola, 2020). For these authors, although social resilience negatively influenced Airbnb revenue, community capital resilience positively influenced Airbnb bookings, and social resilience attenuated the negative effect of hospitality clusters on both Airbnb revenue and bookings.

## 3. Data and Methods

### Data

To gather the empirical data, we used different information sources on Airbnb's performance and expansion in Barcelona, where it has played a prominent role in the STRP (Garay et al., 2022) and is particularly representative of the global urban destinations. Among the multiple references analyzing Airbnb's development in the city, several have focused on the "rent gap" to emerge in Barcelona (for example, Lladós-Masllorens et al., 2020). Nevertheless, as noted, no study has yet delved into the Airbnb hosts' performance and adaptive capacity in such urban destinations from a longitudinal perspective, observing the behavior of those to survive over an extended period of time and, especially, the pandemic crisis.

We first considered information from Inside Airbnb (http://insideairbnb.com/), the most important information source for this paper.I It provided all the relevant data on Airbnb in Barcelona and for its ten districts, for different time periods. Table 1 shows the Inside Airbnb variables used in the analysis along with their description. We also obtained data on each district's demographics, tourist supply, and economy from the regional census.

**Insert Table 1 here**

Variables were selected according to previous research. For example, among the factors explaining Airbnb's situation and performance, recent studies (Lladós-Masllorens et al., 2020; Cai et al., 2019; Gibbs, et al., 2018; Perez-Sanchez et al., 2018) have highlighted home type, location, host profile, the relationship with users, and user opinions. Accordingly, in this paper, the variable "number of reviews" is interpreted as a proxy for the level of demand. These factors have also been found not to be uniformly influential everywhere (Chattopadhyay & Mitra, 2019).

The vast majority of studies on Airbnb are cross-sectional; few make longitudinal analyses. Those that do have only studied the evolution of the platform in aggregate, and do not track individual offers (Guttentag, 2019). To fill this gap, we gathered data from Inside Airbnb from 2016 to 2022 to perform a longitudinal analysis for three specific moments in each year, which, according to official data, represent three different tourist seasons in the city: December (off season), February (peak MICE tourism, e.g., the Mobile World Congress), and August (peak season). Due to the seasonal behavior of the study variables, we constructed three databases, one with data for all the months of December from 2016 to 2021, another for all the months of February from 2017 to 2022, and the last for all the months of August from 2017 to 2022. Each database thus contained information for 6 periods (P1 to P6) about those listings offered uninterruptedly each year for the month in question. These temporal and longitudinal analyses allowed us to identify the main characteristics of the platform's performance and also allowed us to characterize the adaptive strategies according to fluctuations in tourist demand and the different socioeconomic and political contexts across different host profiles.

As shown in Table 2, Airbnb accommodation supply differed by district and tourist season. The total accommodation supply during the peak tourist season was nearly 1,700 listings greater than in the off season for almost all districts. Although the survival rate was quite similar for all cases, the highest survival rate was found for February (20.57%), the biggest season for MICE tourism. According to the data, the Airbnb accommodation supply has uneven spatial patterns and is mainly concentrated in five city districts in all seasons. The Eixample district had the largest concentration of tourist accommodation marketed through Airbnb (ranging from 5,607 units in the off season to 6,464 in the peak season); it also had the highest survival rate in the city (over 20% for all seasons). The same stability of supply and (higher-than-average) survival rates were also found for the Sants-Montjuïc, Gràcia, and San Martí districts, bearing witness to the new tourist hubs produced by the Airbnb effect in the city (Morales et al., 2020). In contrast, despite the concentration of accommodations (nearly 4,000 in all seasons), the city center (Ciutat Vella) had the lowest survival rate for December and February (8.21% and 9.62%, respectively), and the second lowest for August (9.62%). This is relevant as it is the neighborhood with the largest illegal short-term rental offer in Barcelona (Arial & Quaglieri,

2016) and was also affected by the halt in the concession of new licenses for accommodation establishments of any kind approved by City Council in 2017 (Wilson et al., 2020).

**Insert Table 2 here**

One of this study's main objectives is to analyze hosts' behavior over the last 6 years in search of possible differences. Previous research has identified different behaviors by host type, especially between multi-host professionals and non-professionals (Boto-García, 2022; Nilsson, 2021).

**Insert Table 3 here**

In Table 3, it is shown that more that 60% of the hosts to survive the last 6 years had just one listing; about 20% had between 2 and 5. These results held across most districts and periods. The percentage of hosts with one listing was very high, while the percentage of hosts with 2 to 5 listings was around 10%. In most cases, the percentage of hosts with more than 10 listings was greater than that of hosts with 6 to 10. The multi-hosting analysis thus indicates that Airbnb's accommodation supply in Barcelona is commercial, professionalized, and controlled by a relatively small group of property owners. The results in Table 3 bear witness to the importance of medium and large property owners in listing management and the spatial and temporal unevenness of the phenomenon. As can be seen, large-scale multi-hosting practices are mostly concentrated in the districts with the highest listing concentrations, which can underpin socio-spatial transformations and influence the housing market.

## Methods

To explain hosts' performance and adaptive strategies in recent years by the number of listings, a model based on deep learning (artificial neural networks, ANN) was run with data from each of the three databases (see Figure 1). A three-layer model was used. The number of hosts' listings in the last period (P6, i.e., 2021 for December, and 2022 for February and August) defined the output layer. The input layer variables were price, minimum nights, number of reviews, year-round availability (all variables from 2016 to 2020 for December and from 2017 to 2021 for February and August), as well as city center and entire home. The third layer was the hidden layer. This methodology allowed us to detect possible non-linear relationships between variables and determine the relative importance of each explanatory factor (Ahani et al., 2017). The min-max scaling method was used to range all data between 0 and 1 and, thus, improve training performance (Negnevitsky, 2017).

We used the traditional backpropagation algorithm (Günther & Fritsch, 2012), with the logistic activation function to train each network, and the root-mean-square error (RMSE) to evaluate each model's accuracy. The number of nodes in the hidden layer of each model was determined based on two key restrictions (Negnevitsky, 2017; Liébana-Cabanillas et al., 2018). First, a small number of hidden nodes does not enable detection of complex patterns. Second, a high number of nodes can result in overfitting problems. Next, we considered Blum's proposal (Blum, 1992), whereby the optimal number of nodes is a value between the number of inputs and the number of outputs. Finally, we followed a trial-and-error procedure (Chong & Bai, 2014; Sharma et al., 2015), which determined that 20 nodes were the best choice for the December model, 17 for the February model, and 15 for the August model. Finally, to prevent overfitting issues in the training process, we conducted a 10-fold cross-validation for each of the three models, with a data set ratio of 90:10 for training and testing (Chan & Chong, 2012; Liébana-Cabanillas et al., 2017).

**Insert Figure 1 here**

**ANN results**

The RMSE values for both the training and testing data were acceptable in all three models (see Table 4). Therefore, we can safely establish that they are efficient and give good predictions for the output variable. Additionally, the estimations are reliable, and all input variables are suitable for predicting the host's listing counts.

**Insert Table 4 here**

We used Garson's (1991) algorithm to analyze the importance of each input factor. For each network, the relative importance of the explanatory variables was determined from the results of the 10 training processes as the proportion of their importance with respect to the factors' maximum importance (Leong et al., 2013; Sharma et al., 2015).

## 4. Results

The model's forecasting results are summarized in Table 5, which shows the relative importance of each variable for each period using the number of listings for a particular host as a dependent variable. In the model, the higher this variable is, the greater its importance for explaining performance on the platform from a multi-host perspective. The model identifies “minimum nights” as the most important variable explaining platform performance from a multi-hosts perspective for all periods under study, albeit with significant differences between them. Its importance is greater for December and, particularly, February (MICE tourist demand) and lower for August (peak tourist season), where multiple shorter stays ensure higher profits for hosts. From a vertical temporary analysis, this variable offers relevant information about multi-hosts’ adaptive strategies during the COVID-19 pandemic period. As Table 5 shows, this variable’s evolution for the peak tourist season – from an importance of 25% in 2019 to 32% in 2020 (hard lockdown period in Spain) to 100% in 2021, when tourist mobility restarted in Spain but still in a COVID-19 context – made it the key element for hosts’ adaptation to the limitation of demand and mobility restrictions implemented to manage and stanch the pandemic.

The model identifies “number of reviews” as the second most important variable explaining platform performance from a multi-host perspective. This variable is more important in times of lower tourist activity, especially in the MICE season, and has lost significance over time, falling to 57% in 2021.

The third most important variable, “price,” also behaved differently depending on the tourist season and temporal context. In both February and, especially, August, its importance has increased over time (from 15.4% to 23.2% in February and 7.9% to 10.0% in August). In contrast, it had been losing influence in the off-season, except for the most critical COVID-19 times when pricing has an increasing importance as an adaptation strategy pursued by hosts.

However, the model shows that distance from the city center was not an important variable in explaining performance, except in the off and MICE seasons, when its importance multiplied as did that of the accommodation type “entire home” (19.0% and 15.1%, respectively). Although the model identified the variable “availability_365” (number of days a particular host is available on the platform in a year) as an explanatory variable, it was of non-relevant importance. Nevertheless, its inclusion points to the connection of multi-host and platform performance with the housing market.

As shown, Airbnb multi-host performance and adaptive strategies were diverse and temporally uneven, making flexibility the key attribute of platform performance in terms of adapting to tourism seasonality and, thus, demand fluctuations. These elements elucidate flexibility as the core of the platform’s adaptive capacity, enabling rapid adaptation of the performance to both the volume and behavior of the demand. Finally, the scant importance of the “city center” and “availability_365” variables reflects and implies the spatial unevenness of the platform’s performance and its influence in urban dynamics, including on the housing market and via the creation and expansion of new tourist hubs in the city.

**Insert Table 5 here**

*Spatial unevenness and multi-host adaptive strategies during and after Covid-19*

In addition to the model, a spatial and multi-host analysis of the “number of reviews” and “price” variables was performed to explore the connection between platform performance and urban dynamics. Figure 2 shows how the geographic distribution of demand has been spatially uneven over time, creating different tourist hubs, exposing its fluctuations and the negative impact on the sustained growth trend in occupancy due to the decreased demand of the pandemic years (2020 and 2021) for all tourist seasons. Demand was concentrated in those districts with the most listings, Eixample and Ciutat Vella, which were always above the city’s occupancy averages, especially for “entire home” accommodation. For instance, in the peak season, the “entire homes” supply in these neighborhoods withstood the COVID-19 crisis better than the rest (6.06 reviews for Ciutat Vella; 5.41 for Eixample). Nevertheless, Eixample has seen the greatest post-Covid recovery (28.5 reviews in 2022), followed by Sants-Montjuïc (26.9), Gràcia (25.6), and Ciutat Vella (24.8), indicating that the spatial pattern for listings has been strengthened in the post-Covid period. The demand for shared rooms disappeared completely in this period. The longitudinal multi-hosting analysis of the evolution of the number of reviews (Figure 3) shows how the demand for entire homes was concentrated mainly in listings from small and medium owners, especially those with 2 to 5 listings. However, global demand (including private rooms) increased business levels for large owners. Although this figure is considered a benchmark in the sharing business, our analysis shows that it is professionally managed. Consequently, as far as large holders are concerned, length of stay has become progressively more decisive for the supply on the platform than prices or evolving demand.

**Insert Figure 2 and 3 here**

As Table 6 shows, price management was very significant in the period under review, with marked differences between large and small owners, tourist seasons, and different accommodation types. The evolution of the price variable in all types of accommodation, but especially entire homes from August 2020 (when tourist mobility resumed in Spain following the first lockdowns), is a central finding of the research. Two different pricing strategies employed by hosts to adapt to the pandemic period were identified. In 2020, hosts lowered prices to attract the demand for domestic tourism mobilized after the hard lockdown by an average of 22.4 euros for entire homes in the city. In contrast, in 2021, increases in average accommodation prices (38.2 euros) far outstripped those of pre-pandemic periods, a trend that continued in 2022 (33.9 euros). The price fluctuations were motivated by the dramatic changes in the demand for short-term tourist accommodation rental in the city: a severe fall (80.6%) in 2020 followed by a strong recovery in 2021 (65.6%). This pricing strategy was more aggressive among large property owners (more than 11 properties under their control), whose price variation levels were almost three times greater than the city average. However, while the changes in pricing policies are more pronounced among large owners, small owners are progressively reproducing this behavior.

**Insert Table 6 here**

Professional hosts may benefit more easily from dynamic pricing (Eoni and Nilsson, 2021; Boto-García, 2022). They slashed their listings' prices significantly more than non-professionals (mostly individuals) during the pandemic, even though, on average, prices charged by professionals remain higher, probably because they are both more skilled in using intertemporal price discrimination when demand drops and less willing to have listings remain unoccupied, prompting them to lower prices to meet demand. Additionally, the business model of large property owners focuses on the highest-quality, higher-capacity housing (entire homes), in which they display a significant price premium.

Table 7 shows the evolution of rental prices before and during the pandemic by lodging location. The decline in rents is remarkable, and greater in the most central and touristified areas, such as Ciutat Vella, Eixample, or Sant Martí. The larger decrease in rents in those areas where Airbnb was more active was previously detected by Thackway and Pettit (2021) for Sydney and Trojanek et al. (2021) in Warsaw.

**Insert Table 7 here**

The steady rise in prices during the peak tourism seasons (for leisure or business) has also contributed to the accelerated rise of prices in the city's housing market, which have rebounded faster than expected, reaching levels similar to pre-pandemic ones, as shown in Tables 8 and 9.

**Insert Tables 8 and 9 here**

The recovery of the city's rental market has led to a growing presence of large owners in its medium-high and high-income districts (Sarrià-Sant Gervasi, Les Corts, Sant Martí, Gràcia, and Eixample), whereas their relative weight is no longer as strong in the downtown areas, where the residential housing has grown, as shown in Table 10.

**Insert Table 10 here**

## Discussion and concluding remarks

Barcelona has become a living example of Airbnb's effects in reshaping the urban fabric and associated place dynamics. This prominent position was severely impacted by COVID-19 and the mobility restrictions associated with its management.

This research has analyzed the evolution of the Airbnb supply in the city between 2016 and 2022, identifying the main factors explaining its performance and the adaptive strategies adopted by hosts during and after the COVID-19 period. Specifically, a longitudinal analysis was performed for each year for three highly representative tourist seasons in the city: December (off season), February (top event-related season), and August (peak season). For each season, we focused on those listings that were permanently offered. An innovative approach, based on deep learning and neural networks, was applied to explain the activity on the platform and discover the significance of each determining factor. This quantitative model was further combined with statistical and spatial analysis of the listings to analyze the differences between seasons in greater detail.

Our results reveal that changes in demand affected the evolution of prices and survival on the digital platform. The evolution of Airbnb markets in this period was particularly dependent on the measures taken by the platform and, even more so, those taken by governments, especially the lockdowns imposed at different times in 2020 and 2021 (Liang et al., 2021).

As shown in Table 3, the Airbnb platform has remained strongly multi-host dependent. These operators' adaptive strategies on the platform has been significant; they account for more than a third of the tourist accommodation supply in the analyzed period. Their contribution is even larger in peak demand periods, such as August or February. In fact, one significant finding is the identification of two different host adaptive strategies during and after the pandemic and between seasons: first, the extension of the length of stay and tendency to place the accommodations (at least, temporarily) in the medium- and long-term residential markets; second, very active price management. In 2020, hosts focused on reducing prices to attract the demand for domestic tourism mobilized after the hard lockdown. These results are consistent with those of Llaneza and Raya (2021), who noted that the strategy for adapting supply to decreasing demand was to attract a more stable demand, coupled with lower prices and longer stays, especially for professionalized hosts. Attention has recently turned to international tourism, and the recovery of demand has propelled prices even beyond pre-pandemic levels. However, prices seem to be less decisive during the summer season, when demand rises significantly, making the requirement of longer stays more and more conclusive. Increasingly, the number of minimum nights is the critical factor for long-term permanence on Airbnb. As time goes by, those accommodation suppliers remaining on the platform require longer stays. Stay length is thus progressively more decisive for the supply on the platform than prices or evolving demand, with regard to large property owners. This verification of a behavior dependent on tourism demand and seasonality leads us to confirm hypothesis H1.

Both strategies point to the gradual shift among hosts (both large and small) toward more professional profiles. Contrary to the "return to the collaborative economy" predicted at the pandemic's start, patterns more closely linked to the business-oriented platform economy seem to be driving the achievement of greater resilience, in contrast to the assumption of Dolnicar and Zare (2020) that the pandemic would reduce Airbnb hosts' professionalization.

The research also verifies that the decrease in occupancy on the platform due to the fall in demand during the pandemic affected all accommodation types. However, entire homes have been more resilient than other types of accommodation, suggesting a wealth effect among the platform's users. The influence of location and accommodation type is higher during the business-tourism season, probably due to the greater guests' affluence. The outbreak of the pandemic impacted affected differently the various types of accommodation supplied on the platform differently, prompting different strategic price-based responses (Bresciani et al., 2021). Our findings confirm that in the pandemic context tourists were more inclined to book entire homes than shared options. This transfer of the STRP supply to the housing market in different places has been demonstrated (e.g., Kadi et al., 2020), although a drop in long-term rents was not observed because of this increase in supply. The absence of huge entry and fixed costs encouraged hosts to switch their supply to medium- and long-term residential markets, as suggested in Gyódi (2021). Thus, a potential relationship between the adaptation strategy of transfers between markets and that of price adjustments is observable. But the economic recovery in 2022 quickly drove rents and housing prices in the city higher. Although Benítez-Aurioles (2021) corroborated the hypothesis that Airbnb's contraction could lead to lower prices in long-term rentals and housing, this finding may not be sustainable when the demand for short-term accommodation is rebounding.

Homeowners also monetize the effects of reputation and evolving demand as, when tourist mobility restarted, the number of reviews encouraged a self-supporting process. Our findings reveal that hosts' price adaptation was asymmetrical and U-shaped. On the one hand, as stated in Gossen and Reck (2021), hosts renting entire apartments and long-term options were more likely to stay in the market during the spread of COVID-19. On the other, professional hosts followed a U-shaped process of price adaptation with a quick increase in rents as demand improved after the pandemic was brought under control. Although the professional players in the short-term rental market suffered the most from the economic consequences of COVID-19, they also made the most of the business generated by the recovery of tourism in the city.

The longer time perspective of this research made it possible to find support for the results reported by Boto-García (2022) demonstrating the heterogeneous price adjustments among Airbnb hosts during the pandemic. Our results indicate that professional multi-hosts lowered their listings' prices significantly more than non-professionals (mostly individuals) during the pandemic, even though the average prices charged by professionals remain higher. This suggests that professionals are more competent at practicing intertemporal price discrimination when demand drops, conditional on quality. Moreover, because these hosts are less willing to have vacant listings, they lower prices to meet demand. Significantly, the greater price drops among professional hosts began to vanish from February 2021 onwards, suggesting that the improved epidemiological conditions fostering demand prompted professional hosts to quickly adapt and raise their nightly rates again. This shift toward longer-term rentals and adjustment of supply prices reveal the interaction of both strategies on the digital platform, providing support for hypothesis H2.

These strategies also prompted significant changes in the city's housing market. The pandemic caused rents to fall throughout the city, but the impact on the most highly touristified neighborhoods was more severe. Restrictions on access to tourist amenities decreased the attractiveness and advantages of the densest areas (Kourtit et al., 2022; Sainaghi and Chica-Olmo, 2022). This fall in rents and increased availability of accommodations drove the demand for residential uses in the most central districts. Consequently, the lower prices in the places with the highest density of tourist amenities were coupled with a noticeable increase in rental contracts, indicating that factors other than demand, such as regulations, also influenced the decline in rents. It may also point to a change in housing uses, as the growth of the residential population in the downtown and peripheral areas was identified. The recovery of the city's rental market has led to a growing presence of large property owners in its medium-high or high-income districts, whereas their relative weight is no longer as great in the former central tourist areas, such as Ciutat Vella, where the survival rate seems lower and there is an increase in residential housing, causing new tourist hubs to progressively emerge in the city. Hypothesis H3 is corroborated. However, in the near future, the higher inflow of international tourism, one of the city’s main sources of income, will probably again determine the evolution of Barcelona’s rental market.

**Limitations and future work**

This research is not without limitations. First, it is based on a single city, Barcelona. Although one of the world’s leading tourism destinations, Barcelona has its cultural and institutional specificities. To draw broader and more general conclusions, future studies could adopt a comparative perspective, using data from multiple cities. Second, even though our model has a longitudinal, spatial, and multi-host perspective, the number of variables used in it was limited to the data available from the main information source. According to the literature, other social, economic, or personal factors may be involved that are critical to understanding Airbnb’s performance and adaptive strategies. Therefore, future studies should take a qualitative perspective, employing interviews or even focus groups with different host profiles to gain a better understanding of hosts’ decision-making processes and adaptive capabilities in different contexts and conditions. Third, this study was conducted from the hosts’ perspective, utilizing a spatial and longitudinal approach. Future research should examine the influence of platform governance on the adaptive capability of both the platform and hosts, as well as how the COVID-19 pandemic impacted their relationships. Given the growing professionalization of hosts evidenced here and elsewhere, it is important to know the extent to which this is due to the platform’s influence and the extent to which it is the result of an adaptive strategy by hosts, and whether there are differences between profiles. Fourth, even though we have analyzed three periods separately over the different years due to the strong seasonality of the phenomenon under study, as the time series becomes longer, future research could consider other methodologies that make it possible to integrate all the periods in a single model. These methodologies should also incorporate the geospatial nature of the data. Finally, our analysis is based solely on the listings to survive throughout the three selected periods under study, which overlooks the complexity of the pandemic adaptive strategies applied by the surviving listings.

**Practical implications**

This research has various practical implications. From the user and industry perspectives, it enables better understanding of the matching mechanisms between demand and supply on digital tourism accommodation platforms in different economic and tourist seasonality contexts. It is an especially good guide to learn about these platforms' adaptive strategies in different contexts, including crises. For local governments, it offers a new approach to understand how certain host profiles act within the framework of these platforms and in these contexts, and how this influences the evolution of rental prices and determines the city's main tourism pressure points. Finally, in the context of increasingly saturated global urban destinations, it is especially relevant for governments to get to know these actors and processes better in order to act on their behalf, particularly in post-crisis situations, when more citizens find themselves in vulnerable circumstances.

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**Tables and Figures**

Table 1. Variables and information from Inside Airbnb used in the paper

| Variable | Description |
|---|---|
| Id | Listing ID in Airbnb |
| host_id | Host ID in Airbnb |
| neighborhood_group | Main area (BCN district) |
| neighborhood | Area (BCN neighborhood) |
| latitude | Geographical latitude of listing |
| longitude | Geographical longitude of listing |
| room_type | Type of listing: “Entire home/apt,” “Private room,” “Shared room,” or “Hotel room” |
| price | Price (in $US) per night |
| minimum_nights | Minimum stay length, as posted by the host |
| number_of_reviews | Number of reviews a listing has received |
| calculated_host_listings_count | Number of listings for a particular host |
| availability_365 | Number of days a particular host is available in a year |
| citycenter | Haversine distance to Plaça Catalunya |
| entirehome | 1=Entire home; 0=Other |
| multihost_type | 1=#1; 2=#2-5; 3=#6-10; 4=#11- |

Source: The authors.

Table 2. Number of listings in each database and survival rate across districts and periods

| | **December** | | | **February** | | | **August** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **2016** | **Until 2021** | **Survival rate (%)** | **2017** | **Until 2022** | **Survival rate (%)** | **2017** | **Until 2022** | **Survival rate (%)** |
| Ciutat Vella | 4078 | 335 | 8.21 | 3886 | 374 | 9.62 | 3993 | 384 | 9.62 |
| Eixample | 5607 | 1208 | 21.54 | 5653 | 1176 | 20.8 | 6464 | 1338 | 20.7 |
| Gràcia | 1776 | 330 | 18.58 | 1688 | 326 | 19.31 | 1794 | 382 | 21.29 |
| Horta-Guinardó | 550 | 70 | 12.73 | 576 | 78 | 13.54 | 626 | 83 | 13.26 |
| Les Corts | 330 | 76 | 23.03 | 355 | 70 | 19.72 | 438 | 86 | 19.63 |
| Nou Barris | 217 | 31 | 14.29 | 211 | 31 | 14.69 | 262 | 19 | 7.25 |
| Sant Andreu | 296 | 31 | 10.47 | 287 | 35 | 12.2 | 326 | 39 | 11.96 |
| Sant Martí | 1770 | 305 | 17.23 | 1795 | 313 | 17.44 | 2168 | 345 | 15.91 |
| Sants-Montjuïc | 2031 | 350 | 17.23 | 2153 | 378 | 17.56 | 2250 | 386 | 17.16 |
| Sarrià-Sant Gervasi | 714 | 122 | 17.09 | 719 | 114 | 15.86 | 739 | 129 | 17.46 |
| **Total** | **17369** | **2858** | **16.45** | **17323** | **3564** | **20.57** | **19060** | **3191** | **16.74** |

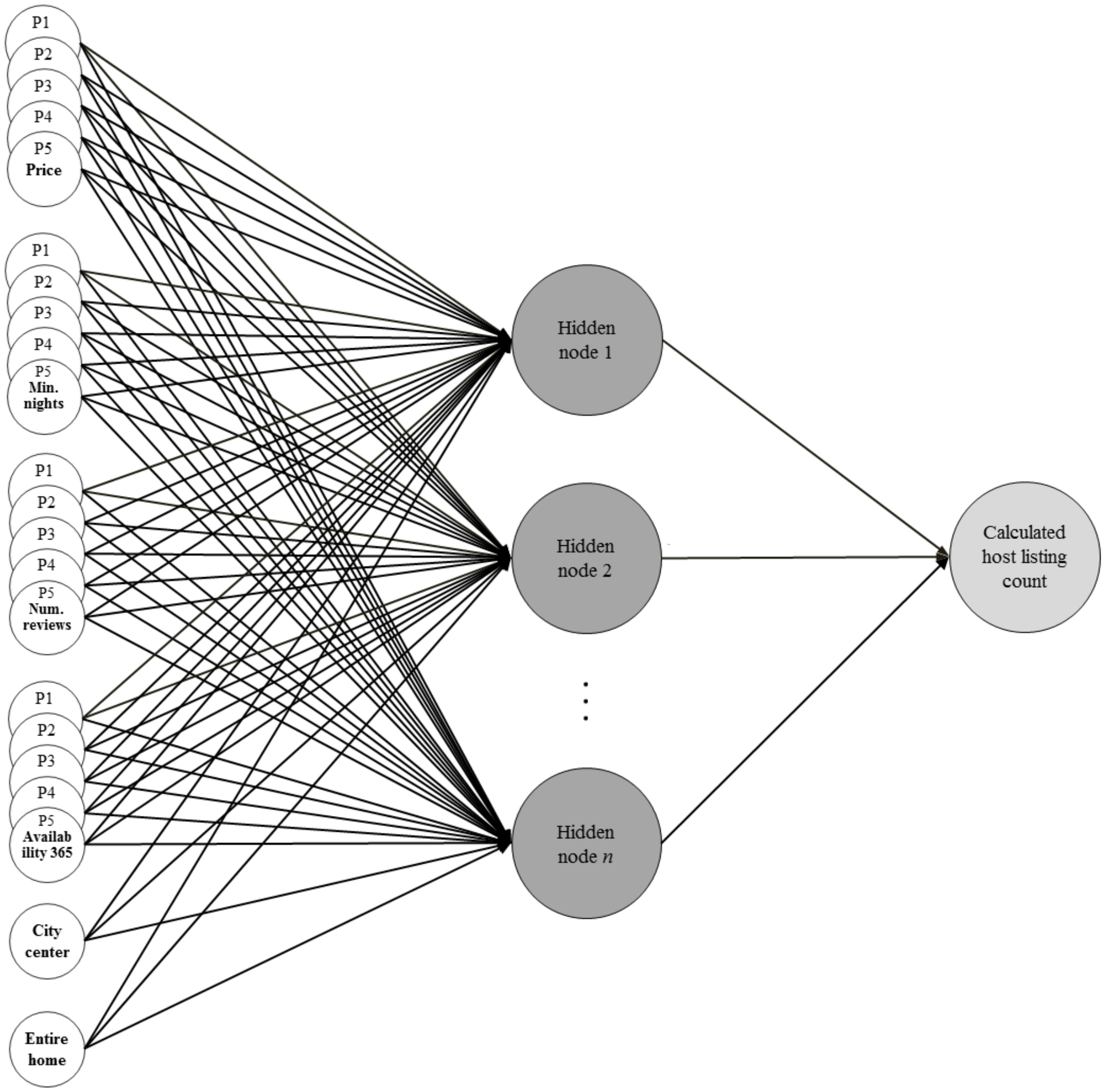
Source: The authors and Inside Airbnb.

Table 3. Multi-host distribution across districts and periods (%)

| | **December** | | | | **February** | | | | **August** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **#1** | **#2-5** | **#6-10** | **#11-** | **#1** | **#2-5** | **#6-10** | **#11-** | **#1** | **#2-5** | **#6-10** | **#11-** |
| Ciutat Vella | 66.28 | 22.09 | 3.88 | 7.75 | 64.91 | 24.21 | 3.16 | 7.72 | 67.92 | 22.53 | 1.71 | 7.85 |
| Eixample | 60.92 | 24.28 | 6.03 | 8.76 | 60.44 | 25.55 | 5.55 | 8.47 | 58.54 | 26.23 | 5.70 | 9.54 |
| Gràcia | 64.56 | 21.10 | 5.06 | 9.28 | 65.02 | 21.40 | 3.29 | 10.29 | 62.64 | 23.02 | 4.91 | 9.43 |
| Horta-Guinardó | 64.41 | 20.34 | 10.17 | 5.08 | 62.12 | 22.73 | 7.58 | 7.58 | 68.49 | 19.18 | 8.22 | 4.11 |
| Les Corts | 56.00 | 26.00 | 6.00 | 12.00 | 55.10 | 22.45 | 8.16 | 14.29 | 60.71 | 25.00 | 5.36 | 8.93 |
| Nou Barris | 76.92 | 23.08 | 0.00 | 0.00 | 73.08 | 23.08 | 3.85 | 0.00 | 72.22 | 27.78 | 0.00 | 0.00 |
| Sant Andreu | 79.31 | 10.34 | 6.90 | 3.45 | 82.35 | 11.76 | 5.88 | 0.00 | 82.86 | 8.57 | 5.71 | 2.86 |
| Sant Martí | 63.11 | 22.67 | 5.33 | 8.89 | 65.95 | 20.26 | 5.17 | 8.62 | 64.89 | 20.23 | 5.34 | 9.54 |
| Sants-Montjuïc | 62.77 | 26.28 | 5.11 | 5.84 | 62.41 | 25.86 | 4.83 | 6.90 | 67.11 | 20.93 | 3.99 | 7.97 |
| Sarrià-Sant Gervasi | 59.34 | 23.08 | 4.40 | 13.19 | 57.65 | 21.18 | 5.88 | 15.29 | 58.06 | 22.58 | 4.30 | 15.05 |
| **Total** | **69.62** | **22.24** | **3.75** | **4.38** | **62.91** | **23.66** | **4.91** | **8.52** | **63.18** | **23.15** | **4.74** | **8.93** |

Source: The authors.

Figure 1. ANN model.




Source: The authors.

Table 4. Neural network prediction accuracy (RMSE)

| | **December** | | **February** | | **August** | |
|---|---|---|---|---|---|---|
| **N** | **RMSE Train** | **RMSE Test** | **RMSE Train** | **RMSE Test** | **RMSE Train** | **RMSE Test** |
| 1 | 0.069 | 0.099 | 0.060 | 0.108 | 0.076 | 0.101 |
| 2 | 0.062 | 0.097 | 0.061 | 0.128 | 0.078 | 0.110 |
| 3 | 0.067 | 0.104 | 0.063 | 0.105 | 0.076 | 0.088 |
| 4 | 0.067 | 0.139 | 0.056 | 0.088 | 0.071 | 0.106 |
| 5 | 0.064 | 0.116 | 0.056 | 0.100 | 0.080 | 0.111 |
| 6 | 0.062 | 0.137 | 0.058 | 0.102 | 0.069 | 0.102 |
| 7 | 0.065 | 0.084 | 0.060 | 0.077 | 0.079 | 0.112 |
| 8 | 0.064 | 0.098 | 0.065 | 0.133 | 0.073 | 0.099 |
| 9 | 0.063 | 0.141 | 0.059 | 0.113 | 0.081 | 0.090 |
| 10 | 0.067 | 0.109 | 0.063 | 0.104 | 0.081 | 0.109 |
| **Mean** | **0.065** | **0.112** | **0.060** | **0.106** | **0.076** | **0.103** |
| **SD** | **0.002** | **0.020** | **0.003** | **0.017** | **0.004** | **0.009** |

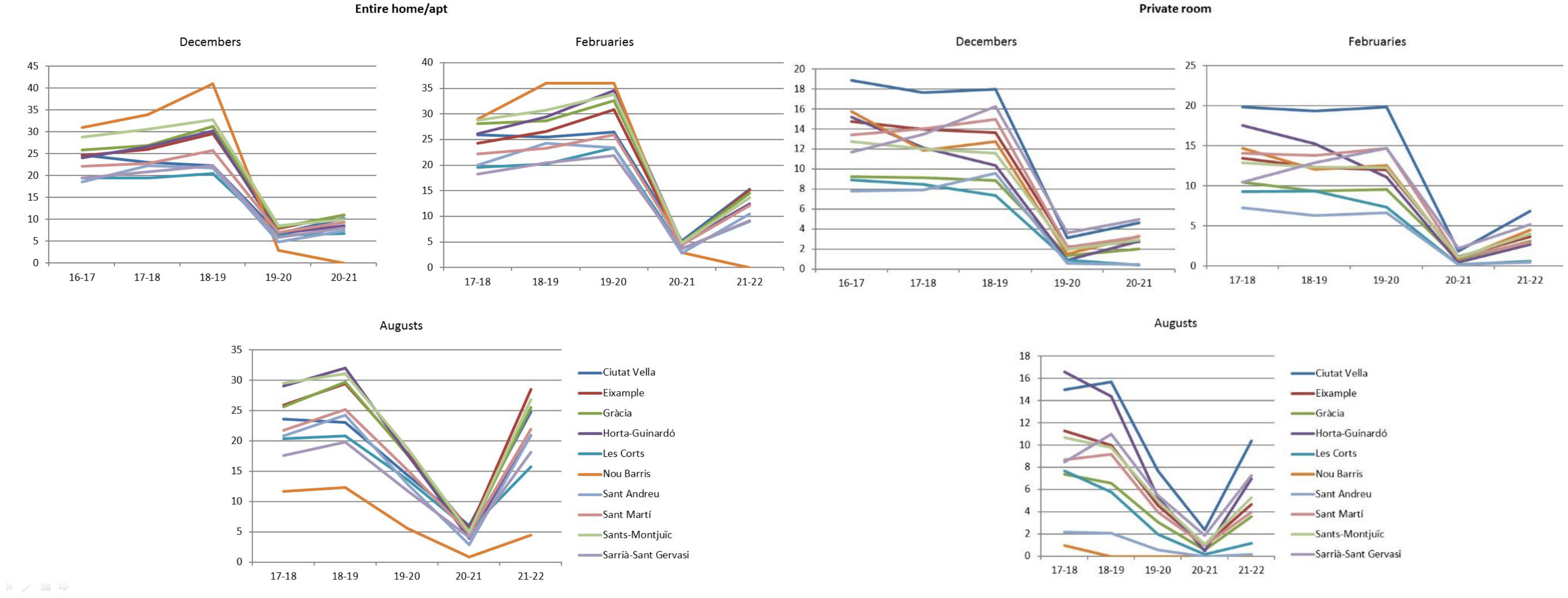
Source: The authors.

Table 5. Model results using *calculated_host_listings_count* (multi-host) as dependent variable (format 2 (focus on seasonality))

| | **Relative importance (%)** | | |
|---|---|---|---|
| | **December** | **February** | **August** |
| P1_price | 17.1631 | 15.4314 | 7.9389 |
| P1_minimum_nights | 63.1647 | 87.8222 | 23.5483 |
| P1_number_of_reviews | 35.1768 | 100.0000 | 21.6658 |
| P1_availability_365 | 2.9366 | 6.6487 | 4.2532 |
| P2_price | 16.7987 | 16.4818 | 8.0268 |
| P2_minimum_nights | 55.5775 | 60.7792 | 22.5064 |
| P2_number_of_reviews | 21.0816 | 69.4088 | 13.3230 |
| P2_availability_365 | 4.0090 | 5.7153 | 5.2650 |
| P3_price | 13.5698 | 19.7490 | 9.0618 |
| P3_minimum_nights | 57.3656 | 70.6562 | 25.1365 |
| P3_number_of_reviews | 21.2246 | 61.2952 | 15.0757 |
| P3_availability_365 | 4.1321 | 11.3358 | 3.8296 |
| P4_price | 22.8217 | 23.2467 | 10.0691 |
| P4_minimum_nights | 54.8509 | 69.1760 | 31.9179 |
| P4_number_of_reviews | 29.3143 | 64.0745 | 11.8834 |
| P4_availability_365 | 3.8343 | 7.6284 | 4.9380 |
| P5_price | 20.6031 | 17.4728 | 10.2265 |
| P5_minimum_nights | 100.0000 | 80.2180 | 100.0000 |
| P5_number_of_reviews | 23.9654 | 57.6201 | 15.9544 |
| P5_availability_365 | 4.3056 | 9.3980 | 4.7600 |
| citycenter | 8.6371 | 19.0868 | 8.2687 |
| entirehome | 4.5450 | 15.1649 | 5.3304 |

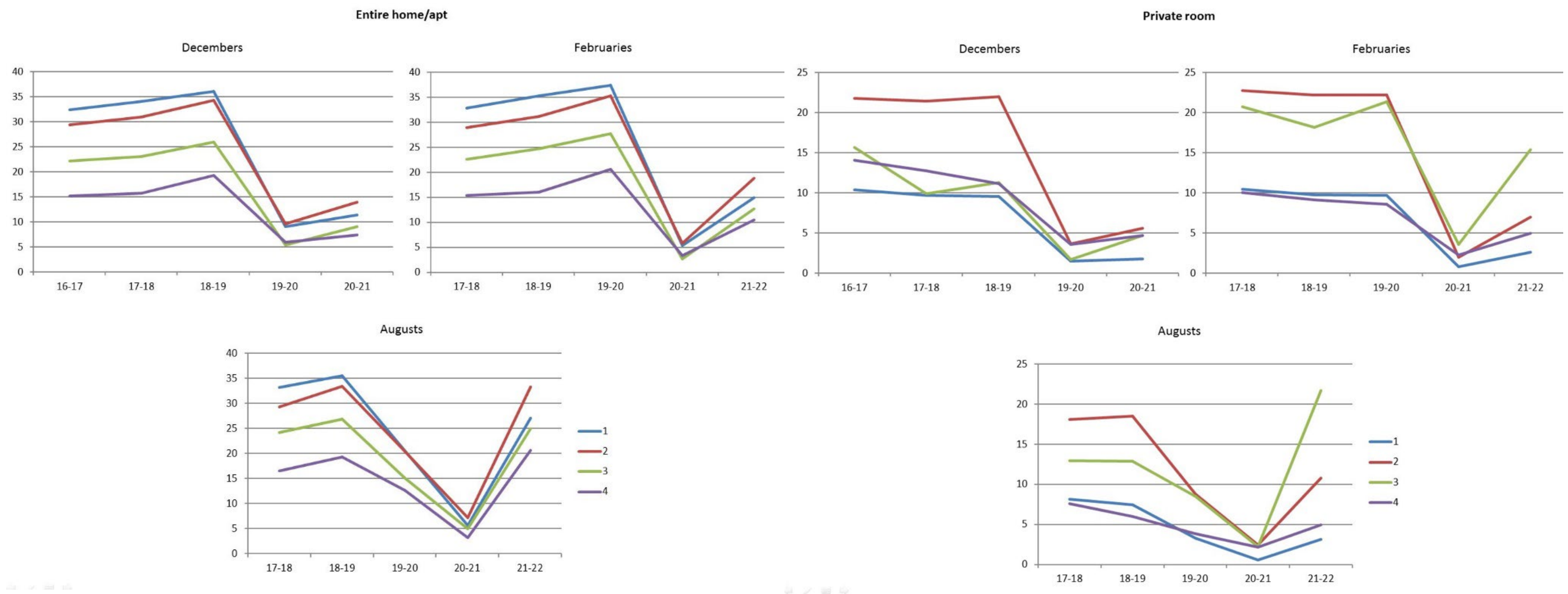
Source: The authors

Figure 2. Longitudinal evolution of number of reviews (previous year) by tourist season and district




Source: The authors.

Figure 3. Longitudinal evolution of number of reviews (previous year) by tourist season and multi-host




Source: The authors.

Table 6. Price evolution from multi-hosting profile in $US per night (annual difference).

| | | December | | | | | February | | | | | August | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Multi-host type | Accommodation type | **16-17** | **17-18** | **18-19** | **19-20** | **20-21** | **17-18** | **18-19** | **19-20** | **20-21** | **21-22** | **17-18** | **18-19** | **19-20** | **20-21** | **21-22** |
| #1 | Entire home/apt | 5.5 | 2.6 | 5.1 | -10.6 | 5.2 | 3.5 | 4.1 | 5.6 | -12.9 | 16.0 | -1.1 | 4.6 | -4.7 | 21.2 | 19.3 |
| | Private room | 1.4 | 0.6 | 1.2 | 0.3 | 0.0 | 0.7 | 0.7 | 1.1 | -0.5 | 1.2 | -0.9 | 1.0 | 0.2 | 0.4 | 1.1 |
| | Shared room | 3.3 | 0.2 | 1.1 | 0.2 | 0.0 | 4.4 | 0.2 | 1.2 | 0.0 | 0.0 | -0.4 | 1.5 | 0.4 | -0.4 | -1.4 |
| | Total | 3.2 | 1.5 | 2.9 | -4.4 | 2.2 | 1.9 | 2.1 | 3.0 | -5.7 | 7.3 | -1.0 | 2.4 | -1.7 | 8.3 | 8.1 |
| #2-5 | Entire home/apt | 9.0 | -0.2 | 7.2 | -16.8 | -1.9 | 6.8 | 2.2 | 7.6 | -25.7 | 24.3 | -0.3 | 1.9 | -22.6 | 30.3 | 33.0 |
| | Private room | 0.3 | 1.2 | 2.0 | -2.8 | 3.9 | -0.2 | 1.9 | 2.0 | -2.9 | 4.6 | -1.7 | 1.4 | -1.0 | 0.5 | 7.4 |
| | Shared room | -2.3 | 4.6 | 1.4 | 9.9 | -13.6 | 0.2 | 2.1 | 1.7 | -1.4 | -54.2 | 0.2 | 5.0 | -107.8 | 107.8 | -88.5 |
| | Total | 4.7 | 0.5 | 4.6 | -9.8 | 0.7 | 3.6 | 2.1 | 5.0 | -15.1 | 14.2 | -0.9 | 1.7 | -13.6 | 17.7 | 20.7 |
| #6-10 | Entire home/apt | 10.5 | 2.2 | 4.5 | -24.9 | 0.9 | 10.3 | 0.2 | 8.1 | -37.7 | 46.8 | -3.0 | 7.6 | -16.8 | 36.6 | 50.7 |
| | Private room | 2.1 | 3.6 | -2.2 | -7.8 | 9.8 | 2.2 | 4.9 | -5.0 | -10.7 | 10.1 | 4.0 | -1.8 | -19.7 | 20.2 | 24.5 |
| | Total | 9.8 | 2.4 | 4.0 | -23.5 | 1.6 | 9.6 | 0.6 | 7.0 | -35.3 | 43.5 | -2.4 | 6.8 | -17.1 | 35.2 | 48.4 |
| #11- | Entire home/apt | 6.5 | -2.5 | 1.6 | -10.4 | 4.8 | 3.3 | 2.9 | 1.3 | -24.2 | 34.4 | 2.8 | 0.8 | -38.3 | 57.7 | 40.5 |
| | Private room | 0.2 | -1.3 | -4.0 | -14.0 | 6.2 | -1.6 | -9.4 | 0.2 | -9.5 | 2.7 | 0.3 | -6.8 | -10.8 | 2.0 | 4.8 |
| | Shared room | -2.8 | 12.7 | 2.2 | -18.4 | 5.6 | -3.1 | 12.5 | 2.1 | -0.1 | -5.5 | 15.2 | 0.8 | -17.4 | 18.7 | 1.2 |
| | Total | 6.0 | -1.9 | 1.4 | -10.8 | 4.9 | 2.9 | 2.7 | 1.2 | -22.8 | 31.8 | 3.0 | 0.4 | -36.2 | 53.4 | 37.3 |
| Total | Entire home/apt | 7.3 | 0.2 | 4.3 | -13.7 | 3.0 | 5.0 | 2.8 | 4.9 | -22.5 | 27.6 | 0.3 | 3.0 | -22.4 | 38.2 | 33.9 |
| | Private room | 1.0 | 0.9 | 1.3 | -1.1 | 1.5 | 0.4 | 0.9 | 1.2 | -1.6 | 2.4 | -1.0 | 0.8 | -0.8 | 0.8 | 3.4 |
| | Shared room | -0.7 | 6.7 | 1.6 | -5.4 | -1.0 | 0.0 | 6.1 | 1.7 | -0.4 | -16.3 | 7.7 | 1.7 | -27.3 | 28.0 | -15.0 |
| | Total | 4.7 | 0.6 | 3.1 | -8.8 | 2.3 | 3.1 | 2.1 | 3.4 | -14.0 | 17.1 | -0.2 | 2.1 | -13.8 | 23.1 | 21.1 |

Source: The authors.

Table 7. Barcelona: Evolution of rental prices (euros/month)

| District | 2019 | 2020 | 2021 |
|---|---|---|---|
| Ciutat Vella | 945.53 | 913.66 | 846.40 |
| Eixample | 1,093.70 | 1,075.44 | 1,007.57 |
| Sants-Montjuïc | 841.49 | 846.88 | 799.69 |
| Les Corts | 1,156.95 | 1,112.50 | 1,054.14 |
| Sarrià-Sant Gervasi | 1,316.57 | 1,305.73 | 1,246.40 |
| Gràcia | 957.73 | 950.36 | 896.35 |
| Horta-Guinardó | 794.88 | 799.32 | 768.82 |
| Nou Barris | 704.52 | 705.51 | 684.49 |
| Sant Andreu | 796.31 | 797.82 | 764.07 |
| Sant Martí | 941.71 | 929.91 | 888.34 |

Source: The authors.

Table 8. Evolution of rental market in Barcelona (euros/month)

| Quarter | Average monthly rent |
|---|---|
| Q1 2019 | 944.43 |
| Q2 2019 | 968.89 |
| Q3 2019 | 1,005.79 |
| Q4 2019 | 995.59 |
| Q1 2020 | 980.48 |
| Q2 2020 | 960.06 |
| Q3 2020 | 979.42 |
| Q4 2020 | 939.10 |
| Q1 2021 | 905.39 |
| Q2 2021 | 903.28 |
| Q3 2021 | 932.31 |
| Q4 2021 | 934.21 |
| Q1 2022 | 965.00 |
| Q2 2022 | 997.00 |

Source: The authors.

Table 9. Evolution of rental market in Barcelona (number of new leases)

| **Year** | **Number of new leases** |
|---|---|
| 2011 | 38,156 |
| 2012 | 41,047 |
| 2013 | 44,819 |
| 2014 | 44,411 |
| 2015 | 40,623 |
| 2016 | 42,182 |
| 2017 | 49,953 |
| 2018 | 53,524 |
| 2019 | 51,294 |
| 2020 | 40,416 |
| 2021 | 57,158 |
| 1S 2022 | 23,670 |
| | |

Source: The authors

Table 10. Barcelona: Evolution of residential population 2019-2021

| District | Growth rate |
|---|---|
| City | 0.60% |
| Downtown | 3.64% |
| Peripheral districts | 1.01% |
| Other districts | 0.10% |

Source: The authors.