Politecnico di Torino

Master of Science Degree in Engineering and Management

A.y. 2023/2024

Graduation Session: November 2024

Airbnb Market Strategy Impact: A Comparative Analysis between High and Low Population Density Areas in Lisbon in the 2019-2022 Period

Relatore:	Candidati:
Prof. Elisabetta Raguseo	Isabela Calad Lopez
Co Relatore:	Matricola
Dott. Francesco Milone	S286834

ABSTRACT

This study compares areas with high and low population densities to investigate the effect of COVID-19 on Airbnb profits in Lisbon. Using a quantitative methodology incorporating data from 2019 to 2022, it also looks at how Airbnb's marketing strategies—like its moderate cancellation policies and rapid booking options—affect hosts' economic recovery in different density situations.

The results indicated that during the most crucial stage of the pandemic, low-density areas had more resistance than densely populated ones. For instance, flexible cancellation rules worked better in low-density locations. On the other hand, instant booking, by facilitating last-minute planning, benefited both low—and high-density areas, although its effect was more pronounced in less dense areas.

This article presents an alternate perspective by acknowledging that population density plays a critical role in the recovery and profitability of short-term rental platforms during times of crises. The findings indicate that Airbnb and similar platforms may be better able to withstand and respond to future crises if they consider the density of their operating areas. The findings also offer hosts, platform management, and tourist policy decision-makers insightful information.

TABLE OF CONTENTS

1. INTRODUCTION

1.1 General Context: Impact of COVID-19 on global tourism and specifically on short-term rental platforms such as Airbnb.

The COVID-19 pandemic has had a significant impact on the global tourism sector (Ortenzi et al., 2024) due to travel bans, border closures, and restrictive lockdown measures that led to a significant drop in international tourism revenues and a significant decline in tourist arrivals in both densely populated and sparsely populated areas. Raya (2021) points out the severity of the global crisis and states that international tourist arrivals in 2020 will be 74% lower than in the previous year. A clear example is Spain, where international tourist arrivals fell by 77% in 2020 (Raya, 2021).

In densely populated metropolitan regions, such major cities and popular tourist destinations, where high infection rates have resulted in extended restrictions, recovery has been slower. According to the World Tourism Organization (UNWTO, 2022), dependence on foreign visitors and extended travel restrictions have resulted in a decline in demand for services including lodging, dining, and other tourism-related activities in these regions. The tourism industry has suffered as a result of airline flight cancellations and increased access restrictions.

On the other hand, during the pandemic, less densely populated areas, such as rural areas and nature-rich tourist destinations, have shown a different dynamic. Many tourists preferred domestic tourism because they preferred low-contact experiences in less crowded places closer to home. This change increased ecotourism and rural tourism, which recovered faster due to lower restrictions and the appeal of healthier and safer options (Cruz-Jiménez et al., 2022). After the pandemic, sustainability and local tourism have come into focus, opening up new opportunities for these regions (IUCN, 2022).

Many cities had strict lockdowns during the peak of the pandemic, which caused Airbnb hosts to lose a substantial amount of money because travel was constrained. In the United States, for instance, the number of active Airbnb listings decreased from 1.05 million in January 2020 to slightly more than 1 million in March 2020. Between January 2020 and March 2020, China's active listings decreased from 700,000 to 599,000 (Statista, 2020). Additionally, Europe had a sharp decline in Airbnb occupancy and bookings (Statista, 2020).

Airbnb showed resiliency in the face of the downturn by changing its approach and concentrating on less crowded sectors and rural regions. During this difficult time, the platform's business was helped by its geographic growth into rural areas (Adamiak, 2023). To be competitive in a dynamic market, Airbnb hosts have to adjust by introducing new cleaning procedures, providing more accommodating cancellation policies, and promoting longer stays with weekly or monthly discounts (Bresciani S. et al., 2021). This change was in line with the increasing desire for more private and secure lodging options.

In the meantime, the conventional hospitality industry has recovered slowly and widely. Many areas continue to suffer major obstacles, even though some market sectors and regions have recovered to their pre-pandemic activity levels.Demand is still below, and many hotels have not reached their pre-pandemic occupancy levels (Raya et al. 2021). This disparity highlights the differences between traditional hotels and short-term rental companies like Airbnb, which have been able to respond swiftly to changing customer demands during the pandemic.

While hotels experienced steep declines, Airbnb benefited from a desire for independent, self-contained stays. In the past, visitors have avoided hotels because of worries about crowded common areas (Mohamed F. et al., 2023). A move toward more decentralized and adaptable lodging options is shown by this preference for short-term rentals during times of increased public health concerns.

Additionally, the pandemic promoted changes in tourism toward more environmentally friendly and locally focused travel. In keeping with more general trends in ethical travel, the reassessment of travel behaviors places an emphasis on authenticity and local experiences (Brouder, P., 2020; Gössling, S., 2020).Rural development has been supported by the rise in demand for Airbnb stays in rural regions as a result of these shifting preferences (Liu et al., 2023). This change in preferences has led to an increase in demand for Airbnb visits in rural areas, which contributed to rural development (Liu et al., 2023).

In summary, COVID-19 significantly affected a number of businesses, including Airbnb. Cities and rural areas have adapted well to shifting travel patterns, although more populated areas have had difficulty shedding their reliance on foreign travel. The pandemic has changed the travel and tourism sector by promoting the adoption of new business models, environmental practices, and health and safety regulations.

1.2 Research Problem: How has population density affected the COVID recovery of revenues on Airbnb in Lisbon?

1.2.1 Context and Problem Statement

According to a report by the World Tourism Organization (UNWTO, 2020), international arrivals fell by 74% in 2020, marking a major decline in global tourism. The short-term rental industry was greatly damaged by this extraordinary worldwide downturn, and Airbnb was no exception. The platform's annual revenue fell 30% in 2020, resulting in a net loss of USD 459 million (Jelski, 2021); bookings in March-April 2020 fell by more than 100% year-on-year as cancellations outpaced new bookings (Statista 2020). In contrast, sectors such as ICT and digital services have recovered rapidly as the pandemic accelerated the adoption of digital technologies. This has allowed companies to adapt to new consumer behaviors and remain operational during the shutdown (ILO, 2022). (ILO, 2022) The construction sector has also recovered faster due to ongoing infrastructure projects and housing demand supported by government stimulus packages. The recovery was more substantial in countries that offered targeted help, like marketing campaigns and financial aid, than in those who did not (Okafor et al., 2022).

The adoption of a more sustainable tourism model and the diversification of services supplied have given the industry a much-needed boost, notwithstanding its sluggish recovery (Exceltur, 2021). International visitor arrivals from January to July 2022 nearly tripled from the same period in 2021, reaching 60% of pre-pandemic levels, according to the United Nations World Tourism Organization's (UNWTO) World Tourism Barometer (UNWTO, 2022). There is hope for the short-term rental market, which includes websites like Airbnb, thanks to this encouraging improvement.

Given the scope of this study, it is important to analyze the role of population density in the spread of COVID-19 and its impact on the dynamics of the short-term rental market. During the pandemic, urban areas with high population density experienced a faster virus spread; increased social interaction and intensive use of public transportation significantly increased the number of cases quickly (Andrade & Kasent, 2020).Despite the complexity of the relationship between infection rates and density, socioeconomic level, living conditions, and access to healthcare have a big impact on the outcomes. (Davis, A. and others, 2023)In 2018, Nagendra H. et al.M. Tilki (2010) There is a significant correlation; for example, Andrade and Kasent (2020) conducted a study focusing on the relationship between population density, poverty, and the spread of COVID-19. Other authors as Zamora Matamoros et al. (2021) discovered in their study of the relationship between traveler entry and population density in the spread of COVID-19 in Cuba, the correlation between the two, showing that higher infection rates occurred in areas with denser populations.

This pattern also had implications for real estate markets and short-term rentals, as areas with greater exposure to the pandemic suffered steeper declines in demand and rental prices (Allan et al., 2021). Publications in the literature have investigated the impact of the COVID-19 pandemic on real estate markets in different countries worldwide (Li, X. et al (2021). Ahsan and Sadak (2021) examined Turkey's housing market, urbanization, and COVID-19-related government policy changes. In the United States, studies such as those by D'Lima et al. (2020) and Zhao (2020) demonstrate that the severity of the pandemic significantly affected housing prices in the most densely populated areas. In Poland, Sołtysiak, M., & Zając, D. (2024) study the differences in the residential real estate market, depending on population density.

These findings suggest that population density is a crucial factor in understanding the spread of COVID-19 and in analyzing the effects of the pandemic on short-term rental markets. The decline in demand and widespread cancellations have had a major impact on platforms like Airbnb, which mostly depend on rentals in crowded urban areas. Looking at how less dense areas have shown greater resilience opens the possibility of conducting a detailed study examining how population density has influenced Airbnb's recovery and adaptation in different geographic contexts.

1.2.2 Development of Hypothesis

H1: Implementation of instant booking and Airbnb Revenue in High-Density Areas

The COVID-19 pandemic dramatically changed consumer behavior regarding mobility and demand for accommodation. Although existing literature has focused primarily on the residential real estate market, several studies suggest that high-density areas were hit hardest during the pandemic, a pattern that could apply to the short-term rental sector, such as Airbnb. Cancelation policies and instant booking were a options suggested by Airbnb as strategy during the pandemy, these two options offered flexible approaches, users were able to easily secure and cancel reservations thanks to this, which may have improved their performance in various locations based on population density.

Acording to Airbnb reports the Instant Booking feature—which let the visitors to reserve lodging without requiring the host's previous approval—was crucial for the period between 2019 and 2020 (Airbnb, 2022) . This promoted continuing use of the platform, providing additional protection and flexibility in densely populated urban regions where fear of transmission was more common. The istant booking acted as a buffer in both high- and low-density areas, as Adamiak (2021) notes a shift in preferences towards rural areas and less saturated markets, reducing the share of accommodation listings in urban areas from 53.6% in 2018 to 49.1% in 2021.

According to Storer (2022), establishments that implemented Instant Booking were better equipped to cater to the increasing number of last-minute tourists. Because of the uncertainties and constantly shifting travel restrictions during the epidemic, this component gained significant prominence.. For this reason, the Instant Booking option is likely associated with a higher occupancy rate and better performance on Airbnb listings, helping mitigate the pandemic's adverse effects, especially in harder-hit urban areas.

Nhamo et al. (2020) also highlight the adverse effects of COVID-19 on global tourism, including mass cancellations on short-term rental platforms such as Airbnb. In this situation, it is feasible that booking facilitating features like one-click booking and flexible cancellation policies have been essential to keeping reservations, particularly in areas with higher population densities where customers were making decisions under more uncertainty.

This study will look into whether Airbnb may replicate the trends seen in the residential real estate market during the pandemic. It will specifically look at whether using market methods like Instant Booking helped offset the negative effects on the platform's revenue because of how it behaved based on population density. Therefore, the proposed hypothesis is the following:

Hypothesis 1: In high-density areas, the **increased** implementation of **instant booking** during 2019 to 2022 had a **greater positive** effect on Airbnb **revenue**, while in low-density areas, this effect was smaller in Lisbon.

H2: Cancellation Policies and Revenue in High-Density Areas

The profitability of properties listed on Airbnb may have been affected by cancellation policies during the study period, due to the change in booking behavior, as customers preferred alternatives that allowed them to change or cancel their reservations without incurring additional charges due to the unpredictability of the pandemic and the frequent travel interruptions caused by health restrictions.

According to Pastor Ruiz and Rivera García (2022), the pandemic forced a change in consumer behavior, so Airbnb's strategy of offering guests flexible booking options and the possibility of canceling without incurring penalties is of interest to this study. This change in preferences highlighted the ability of platforms to adapt to the growing needs of users, in this case specifically the flexibility of cancellation policies.

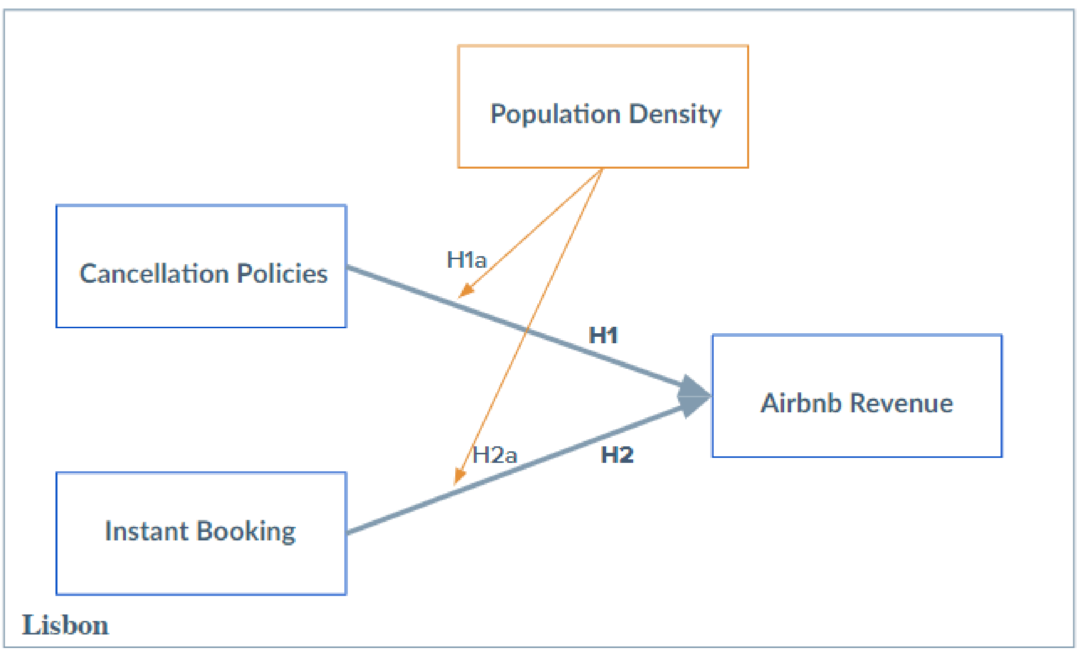
The influence of this phenomenon may have varied depending on population density. High-density areas, mainly urban tourist destinations, were more severely affected by the spread of the virus and mobility restrictions. In relation to the above, hosts in crowded regions would have been pushed to use the platform's suggested approach, which offers flexible or moderate cancellation policies as a marketing strategy to draw in hesitant tourists and reduce high cancellation rates. An Airbnb report (2023) reveals that, in Lisbon, travelers who made flexible searches were 64% more likely to stay outside the city center and were less likely to choose high-density tourist districts, such as Santa Maria Maior and Misericordia, where a 23% and 16% decrease in bookings was recorded, respectively.

On the other hand, low-density areas, more focused on natural destinations and with less social interaction, presented a lower perceived risk of contagion, which may have reduced the need to relax their cancellation policies since the demand for these destinations had a lesser impact. In order to test whether there is any relationship, the hypothesis proposed is the following:

Hypothesis 2: In low-density areas, the implementation of a moderate **cancellation policy,** Compared to flexible and strict cancellation policies, during 2019 - 2022 had a **greater positive effect** on Airbnb revenue, while in high-density areas, this effect was smaller in Lisbon

Figure 1

Hypothesis Diagram



1.3 Objectives

1.3.1 General Objective

To analyse the impact of population density on Airbnb's revenue recovery in Lisbon in the period 2019 to 2022, assessing how cancellation policies and the instant booking option influence revenue in high and low population density areas

1.3.2 Specific Objectives

To compare the variation in Airbnb revenue between high and low density areas in the study period.

To assess the effectiveness of moderate cancellation policies in areas of different population density, analysing how these strategies influenced revenue recovery during the study period

To analyse the influence of the instant booking option on Airbnb's profitability in high and low density areas, determining whether the ease of booking was an effective tool to maintain occupancy.

1.4 Justification: Relevance of understanding the dynamics between density, studied strategies: cancellation policies and instant booking, and revenues on short-term rental platforms.

Market resilience and strategic adaptation: As cities recover from the pandemic, different population densities present distinct challenges and opportunities (Hoffmann, 2021). Urban areas with high density faced higher risks of virus transmission (Andrade & Kasent, 2020) and experienced higher cancellations and lower accommodation rates (UNWTO, 2022; Allan et al.). However, because of their capacity for attracting tourists once restrictions are loosened, these regions, which are frequently prominent tourist destinations, are also in a position to recover more quickly.

A tactical tool such as Instant Booking has been essential during this rehabilitation phase, for that airbnb has made itself more appealing to last minute tourists, especially in crowded cities, by enabling guests to make reservations immediately without waiting for host approval. This instrument fits perfectly with the pandemic's immediate need for safety and simplicity. Airbnb's search algorithms provide preference to listings with Instant Booking, increasing their visibility and, in turn, their occupancy rates. This could lessen the adverse effects of the pandemic on high-density locations (Zeevou, 2024). Key insights regarding market adaptation will come from knowing how this technique has performed differently in high- and low-density areas.

As a complement of the strategies, is also crucial to examine how low density areas have handled the pandemic is also necessary. Market dynamics have changed due to passengers shifting toward more remote and sparsely inhabited places (Liu et al., 2011). Demand has surged in these places, which were frequently considered safer options during the pandemic in relation of the Instant Booking feature, this one provides convenience for tourists looking for quick, secure, and adaptable lodging options thats why a comprehensive understanding of Airbnb's market strategy during the crisis may be obtained by looking at how these tendencies have developed across different densities.

Changes in consumer behavior: The pandemic significantly reshaped consumer preferences in the travel industry, travelers increasingly sought out low-density areas perceived as safer (Liu et al., 2023; Li et al., 2021), and uncertainty caused by frequent travel restrictions made flexible booking policies more attractive (Pastor et al.) thats why the Instant Booking feature and flexible cancellation policies have become key components of Airbnb's adaptation strategy, but according to mentioned above the changes on the preferences of the customers make necessary exploring how these behavioral shifts differ between high and lowdensity regions is critical to understanding market trends, for example, one assumption could be that high-density areas may have relied more on instant and flexible bookings to counteract declining demand, while low-density areas benefited from increased interest in remote locations, which can be corroborated throughout this study.

2. LITERATURE REVIEW

2.1 Impact of COVID-19 on tourism and short-term rental platforms.

The COVID-19 pandemic has completely changed the travel business worldwide and has impacted websites that let people rent short-term homes, including Airbnb. One of the most significant alterations is the shift in the perception of danger related to the COVID-19 pandemic. A once competitive advantage, such as centrally located and easily accessible to many tourist attractions, now poses a risk to public health. It is now believed that a high population density and a geographic concentration of passengers aid in the virus's propagation (Borgoni, 2023).

Worldwide reservations for Airbnb have decreased. For example, in March 2020, reservations on the platform declined by 80% in Europe (AirDNA, 2020), and in the weeks that followed, they decreased by an additional 10% (Hu & Lee, 2020). Due to this decline in demand, Airbnb saw a 25% decline in bookings and vacancies between August 2019 and August 2020. The platform also experienced a 22% drop in revenue from active listings over the same period (Filieri et al.).

The impact was so severe that Airbnb had to lay off 25% of its workforce, including around 1,900 employees who left the company immediately. The adjustments included significant cuts in key areas such as marketing (Chesky, B. (2020). The health crisis caused by the pandemic forced cities to maintain strict controls and social distancing, causing property occupancy rates in many areas to be close to zero for several months. Chesky, B. (2020). In this setting, the growth of the tourism industry and short-term rentals (STR) has been greatly slowed by social segregation and the stoppage of most commercial operations (Gyódi, 2021).

Concerns over these platforms' long-term financial viability have been raised by the impact of COVID-19 on the short-term rental market, which has had an impact on occupancy rates and short-term revenues. One example of how the industry has endured despite these challenges is the use of flexible cancellation policies, which have attracted tenants despite creating challenges for owners who must respond quickly to changing customer needs. Therefore, to better understand the market's resilience and adaptability to external shocks, it is imperative to investigate how these policies affect platform revenues, in this case Airbnb (UNWTO, 2022).

2.2 Population density and its relationship with the spread of the pandemic and travelers' preferences.

The COVID-19 pandemic has exposed the connection between population density and the virus's transmission and how it affects travelers' decisions. Numerous studies have demonstrated that population density is a key contributing factor to the rise in infection cases. For example, in the US, population density was found to explain 57% of the variation in infection rates in a non-spatial model and up to 76% in a spatial model (Wong & Li, 2020). These findings were supported by studies in England and Wales, where population density scaling models revealed important dynamics in the spread of COVID-19 (Sutton, Shahtahmassebi, Ribeiro, & Hanley, 2022).

The faster spread of the virus in high-density urban areas is partly due to factors such as increased social interaction and heavy public transport use, which increase the likelihood of the disease spreading rapidly (Andrade & Kasent, 2020).However, there are a number of factors that affect the association between infection rates and population density, including socioeconomic status, housing conditions, and access to healthcare. The observed results are significantly influenced by these social and economic factors, which also have varying effects on the most vulnerable communities (Davis et al.).

How people travel has changed considerably as a result of these fears. Many people choose to travel to less densely populated, rural areas during the epidemic rather than crowded, dangerous areas (Castanho, Couto, & Pimentel, 2022). This trend has led to increased visits to mountainous and rural areas as travelers rediscover local destinations and support local economies (Falk, Hagsten, & Lin, 2022). A study by Falk et al. on domestic tourism demand in Northern and Southern Europe in the summer of 2020 revealed a significant increase in the number of visitors in rural areas while tourism demand in metropolitan areas declined.

Another important change in traveler behavior is the increasing preference for accommodations that are considered safer due to the risk of infectious diseases: Booking through platforms such as Airbnb is perceived as a safer option than hotels. This is because private apartments allow travelers to control their environment and reduce interaction with other guests (Krouk and Almeida, 2020). Additionally, studies have indicated that visitors feel safer staying in individual apartments as opposed to big hotels (Cheng et al.) their preferences are greatly influenced by the sense of safety as well as the potential to find housing in less populous places (Li & Zhang, 2021).

The availability of accommodations in cities has also changed due to changes in traveler preferences. According to Adamiak (2021), the percentage of the supply of lodging in urban areas fell from 53.6% in 2018 to 49.1% in 2021. This is in line with the trend of tourists choosing less-traveled markets to avoid the possible dangers that come with full, densely populated areas.

Therefore, population density has a major impact on traveler choices and the spread of COVID-19 during the epidemic. Travel has changed globally as a result of the push to lower the risk of the epidemic, which has increased demand for private accommodations and rural destinations. Smaller, less crowded tourist spots have been rediscoverable as a result.

2.3 Airbnb Market Strategy

One of the travel industry's most inventive companies, Airbnb, adjusted its business strategy to suit the COVID-19 pandemic's requirements and shifting travel trends. In 2021, the platform launched over 150 innovations and updates to satisfy the demands of rising travel trends. Since its creation, the platform has sought to alter how people travel and stay (Storer, 2022). "I'm Flexible" is one of these implementation, the feature allowis the customers to look for lodging when their dates and locations are flexible. This tactic aims to draw in a younger generation of tourists who are flexible enough to adjust to shifting conditions.

Another change in the market was the rise in domestic and non-business trave,l following the epidemic was one of the most obvious shifts in travel patterns. When individuals travel locally by automobile and stay in smaller towns outside of traditional urban centers, Airbnb saw this movement as a major opportunity to profit from local travel (Airbnb, 2021c). Demand shifted in favor of rural locations or little towns, many of which lack conventional hotels as a result of this change, which was partially motivated by the desire to avoid crowds and promote safety. Due to its decentralized business strategy, which enables it to provide lodging practically anywhere globally, Airbnb perceived a competitive advantage in this market.

Following changes in market preferences and behavior the company's 2021 strategy, which had four main pillars—educating the public about hosting, finding more hosts and guaranteeing their success, streamlining the user experience, and providing superior service—was centered on getting ready for this tourism boom (Airbnb, 2021).

Following 2022's increase in tourism, Airbnb moved to position itself to take advantage on shifts in customer preferences, of course the strategies involved reorganizing the booking process to significantly reduce the steps required to secure accommodations and enhancing search capabilities to better accommodate flexible travel plans (Storer, 2022).

Implementing Instant Booking and cancelation rules becomes essential in this instance, the Instant Booking option has been implemented to accelerate the booking process by allowing guests to make reservations without needing host approval letting enhancing the user experience and attracting last-minute travelers is a market that increased during the pandemic as a result of ambiguity surrounding travel restrictions (Storer, 2022).

On the side of the cancellation policies, this one contributed to mitigate the effects of the health crisis by reducing the high rates of cancellations. However, as Airbnb sought to maintain customer satisfaction, hosts with strict cancellation policies saw their revenues affected when they were asked to adopt flexible and moderate policies, offering full or partial refunds, which created tensions between the platform and hosts (Farmaki et al., 2020).

Despite these challenges, Airbnb's ability to adapt to circumstances and offer more flexibility to its users has been a key factor in its continued success. The analysis of this study will focus precisely on how these two key variables, Instant Booking and cancellation policies, impacted Airbnb's profitability during the pandemic. As previously evidenced, instant booking has been linked to higher occupancy rates and increased visibility in search results, and cancellation policies have influenced customer satisfaction so much, it is essential to examine how these strategies affected the financial performance of properties (Zeevou, 2024; Gyódi, 2021). The main focuses of Airbnb's marketing strategy were increase supply, maximizing user experience, and adapting to unanticipated changes in tourist demands.

2.3.1 Instant booking in the pandemic and its influence on Airbnb's profitability.

Using instant booking as a crisis management approach enables clients to reserve a house without awaiting host approval, facilitating last-minute reservations and simplifying the booking procedure (Airbnb, 2022), this feature increases customer satisfaction and improves user experience (iGMS, 2020) by offering a simple booking process, resulting in an increase in bookings, which leads to higher revenue and more reviews. o more business and positive reviews.

Additionally, Benítez-Aurioles (2018) noted that the visibility of properties is further enhanced by the rise in reviews caused by the increased of booking by the tool instant booking and the potential to become a Superhost. Properties with Instant Booking tend to appear higher in Airbnb search algorithms, giving them greater exposure and attracting more users (Zeevou, 2024), this increased visibility increases the chances of generating more bookings and, ultimately, higher revenue. In the same way Storer (2022) argues that this option was likely associated with higher occupancy rates and better financial performance, helping mitigate the pandemic's negative effects on Airbnb revenue. In fact, properties with this option were more attractive to last-minute travelers, a segment that grew during the health crisis (Storer, 2022).

Data reinforces this trend: according to AirDNA, properties that offered Instant Booking had a 7% higher average daily rate (ADR) and 10% higher revenue per available room (RevPAR) compared to those without this feature (Zeevou, 2024). Because increased booking rates and visibility contributed to higher revenues during the pandemic, it shows that the implementation of this option positively influenced the profitability of properties listed on Airbnb.

2.3.2 Cancellation policies in the pandemic and their influence on Airbnb's profitability.

Implementing the types of cancellation policies allowed us to maintain business continuity and meet guest demands. Before the pandemic, Airbnb hosts set cancellation policies, fees, and refunds based on how close the stay was to the cancellation date, which worked best for them (Hu and Lee, 2020), during the outbreak, Airbnb had to deal with extreme uncertainty and frequent changes to travel laws, to preserve customer trust against significant unpredictability and constantly evolving travel rules, for that reason the platadorm suggested the hosts to adopt a more permissive cancellation policy. This made it possible for guests to cancel their reservations without incurring heavy fees, which encouraged more people to make reservations. This was particularly effective when mobility was restricted, and the fear of the pandemic influenced travel decisions (Drago, 2023). Airbnb has also facilitated the search for accommodation with flexible cancellation policies, in line with previous strategies implemented by host's filters, and increased the visibility of these options on the platform (Gyódi, 2021).

In addition to the variety in cancellation policies, the platform adopted other measures, such as encouraging longer stays and offering monthly discounts for long-term reservations (Krouk & Almeida, 2020), and stricter safety and cleaning protocols were established. This allowed the company to remain competitive against other accommodation providers, such as traditional hotels, which have less margin to adjust their cancellation policies (Krouk & Almeida, 2020) demostraiting to be more accommodating than other players in the travel market, attracting travelers seeking more secure and flexible options during the worldwide healthcare crisis (Drago, 2023).

Because of this, Airbnb's accommodating cancellation policy during the pandemic increased user confidence and increased the platform's profitability helping hosts draw in reservations while providing tourists with the assurance that they could cancel without incurring additional costs.

2.3 Relevant Previous Studies

The literature on the impact of COVID-19 on the real estate, tourism, and short-term rental sectors has evolved significantly over the past few years, reflecting both the immediate challenges of the pandemic and the long-term strategies emerging to mitigate its effects. Early studies focused on more general aspects of how cities and urban environments responded to the pandemic and formed the basis for later, more detailed studies.

For example, Wilson and Frew (2007) highlighted the relationship between apartment location and rental prices in Portland, laying the foundation for future research on how density and location affect the real estate market; Ahsan (2020) examined the pandemic in Turkey during the COVID-19 pandemic. The impact of the pandemic on the urban environment was reviewed to explore lessons that can be learned for future pandemics. This study is important in that it links strategic decisions about the built environment to the need to adapt to a large-scale health crisis and paves the way for future studies examining how urban concentration affects the spread of the virus.

Tanrıvermiş (2020) analysis continues this approach by assessing how COVID-19 will allow the Turkish real estate sector to adapt to the new situation and emphasizing the long-term impact of the pandemic on real estate demand and housing preferences. Similarly, Uchehara et al. (2020) highlighted the importance of risk management in a crisis environment by examining how the real estate sector supply chain was disrupted. The study broadened its focus from residential to commercial and covered broader economic impacts.

In 2021, attention shifted to how these dynamics directly affect housing prices and demand. Hu et al. (2021) examined Australian house prices during the pandemic and provided empirical evidence on how regulation and lockdowns affect the housing market. At the international level, Allan et al. (2021) consider how the pandemic affected commercial property rental dynamics, arguing that the pandemic affected both the residential and commercial sectors.

Specific to short-term rentals, Adamiak (2021) and Nhamo et al. (2020) provide important insights into the impact of COVID-19 on the Airbnb industry and global tourism. These studies highlighted significant changes in the supply of platforms such as Airbnb, which had to quickly adapt to a new reality characterized by falling demand and a shift in user preferences towards less dense and more remote destinations. Similarly, Jelski (2021) documents how Airbnb exceeded its 2020 revenue forecasts despite challenges, reflecting its ability to adapt to adverse conditions.

Moriondo's (2021) study on the Madrid real estate market complements this narrative by observing how house prices have responded to the pandemic. This trend is similarly observed in studies such as Ahsan and Sadak's (2021) study on urban densities in Turkey during the pandemic, confirming that the preference for less dense areas affects rental prices and real estate investment decisions.

In parallel, Li and Zhang (2021) analyze how the crisis had an inequitable impact on housing prices in the US, highlighting that more densely populated areas were more heavily regulated and experienced larger price declines. This analysis provides a global context for studies focusing on Europe and Asia and shows that population density determines the housing market response to the pandemic.

Recent research has also begun to focus on post-pandemic recovery and long-term effects. Raya (2021) and Adamiak (2023) continue to examine the evolution of short-term rental platforms and consider how the pandemic has forced companies such as Airbnb to reorganize their business models; Borgoni (2023) and Drago (2023) and other more recent studies examine in detail how Airbnb has reorganized its strategy to attract new customers and maintain profitability in a post-pandemic scenario. Later, Ortenzi et al. (2024) examine economic strategies for post-COVID-19 recovery, providing a broader perspective on how different sectors, including tourism, have had to adapt and evolve.

In sum, these studies form a logical progression that starts with analyzing the immediate response to the pandemic and evolves into assessing long-term impacts and recovery strategies.

While early studies focused on the initial impacts on the urban environment and real estate markets, more recent studies have begun to address recovery and adaptation in specific sectors such as short-term rentals and tourism. The literature as a whole reflects the ongoing process of adaptation and recovery, with lessons learned during the pandemic being reflected in current and future decisions regarding urban planning, real estate markets, and rental platforms.

3. METHODOLOGY

3.1 Data collection.

This study adopts an inductive approach, with an exploratory perspective and a descriptive scope, to understand the relationship between population density and variables related to Airbnb's market strategies, precisely cancellation policies, and the instant booking option.

There are three main sources of information. First, a database showing Airbnb revenues for 2019-2022, provided by AirDNA. Second, a polygonal map detailing the administrative areas of Lisbon, known as freguesias, provided by the Portuguese Open Data Portal and produced by the Agência para a Modernização Administrativa (2021). Finally, a polygonal database that, through the 2021 Census, shows the population per square kilometer in Europe, provided by the European Union's GEOSTAT portal and produced by Eurostat (2024). As secondary sources, we resort to similar studies on platforms such as ScienceDirect, Google Scholar, Dialnet, and JSTOR.

The reports on Airbnb revenues between 2019 and 2022 are generated by AirDNA, a platform that offers detailed information on the short-term rental market. AirDNA extracts data from property listings on platforms such as Airbnb, achieving 689,476 Airbnb observations in Lisbon. For the reliability of the database, 200,797 observations were selected after a purification process using non-probabilistic convenience sampling.

The data purification process follows an undersampling method, where records that do not contain the complete information required for the variables of interest are eliminated. Records that meet the following criteria were selected:

- Geographic information (coordinates).

- Complete data on cancellation policies, instant booking, and dates (years and months).
- Revenues greater than zero.
- Complete information on control variables such as number of photos, rooms, maximum guest capacity, number of reviews, and blocked days.

The polygonal map is based on the spatial reference system (SRC) EPSG:4258 and groups the 24 parishes that make up the administrative division of Lisbon, according to Law No. 56/2012 (Assembleia da República, 2012). These areas cover approximately 100.05 km² (INE, 2021) and are essential for categorizing Airbnb coordinates and linking the AirDNA database with the population data provided by Eurostat.

The Eurostat grid database divides the territory into regular cells of one square kilometer, following the NUTS 2 nomenclature (Statistical et al.), a geographical classification standardized by the European Union. Each grid includes demographic data from the 2021 census, such as the total population per grid, the distribution by gender, and the count by age range. In the case of Lisbon, there are 544,851 inhabitants distributed in 88 grids of one square kilometer each.

3.1.2 Collection instruments.

STATA is a statistical analysis software widely used in economic, social, and health research due to its ability to handle large databases and run advanced analyses, such as regressions, hypothesis testing, and econometric models. In this project, STATA has been instrumental in performing various statistical techniques, including linear regressions, analysis of assumptions such as multicollinearity, distribution graphs, analysis of means, and creating dichotomous, categorical, and interactive variables. Additionally, database cleaning has been done with it to make sure the records used fit the requirements for the study.

The open-source QGIS program, on the other hand, has been utilized and is essential for the spatial analysis, display, and modification of georeferenced data. QGIS has made it possible to employ polygonal maps in this study, particularly those that depict the Lisbon parishes, which are the administrative divisions.

These maps have facilitated the analysis of the geographic impact on Airbnb revenues and the interpretation of the grid population data provided by Eurostat. Integrating spatial layers with the statistical data has allowed clear visualization of how Airbnb revenues are distributed in different areas of Lisbon, enriching the analysis by incorporating a geospatial dimension.

In addition, Microsoft Excel has been an indispensable support tool in the early stages of data management and organization. With its ability to store, organize, and perform basic and advanced calculations, Excel has been used to import and preliminary clean large volumes of information. In this study, Excel was used to filter Airbnb revenue data, perform simple operations, and create basic statistical summaries, which served as a basis for more detailed analyses in STATA. In addition, Excel has acted as an efficient bridge for the exchange of flat data between STATA and QGIS, facilitating the connection between statistical analysis and geospatial representation.

Together, these tools have allowed for a robust and multidimensional analysis. The combination of advanced statistical techniques provided by STATA, geospatial representations from QGIS, and data organization support from Excel has enriched the study of economic dynamics in the Airbnb sector, offering a more complete and accurate perspective of income distribution based on location and other key factors.

3.2 Processing the Dataset.

3.2.1 Variables

The variables used for this research are the result of the union of the previously mentioned databases and the creation of some categorical and dichotomous variables for the purposes of the study, which are presented in Table 1

Table 1

Variables Table

Variable	Meaning	Type	No. Obs	Min	Max	Reference
id_airbnb	ID unique for each Airbnb	String	200797	8	515918	Lee, Jang, & Kim, (2020)
Year	Time var. in years from 2019- 2022	Int	200797	2019	2022	Kiczmachowska, E. E. (2022)
Month	Time var. in years from January-December	Int	200797	1	12	Kiczmachowska, E. E. (2022)
revenueusd	Monthly revenue in USD ($)	Float	200797	0	145017	Jang & Kim,(2022)
lrevenueusd	Logarithmic form of Monthly revenue in USD ($)	Float	200797	1.946	11.885	Jang & Kim,(2022)
Ins_book	Instant Booking	Float	200797	0	1	Zeevou, (2024)
cancel_pol	Cancellation policy: Flexible, Moderate, Strict	Int	200797	0	2	Jia, J., et al., (2021)
max guest	maximum number of guests	Int	200797	1	16	Gorzalek, J. A., & Sherif, N. (2023)
freguesia (Add var)	Location of each Airbnb in parishes	Int	200797	0	24	Zhang et al., (2011)
Population (t)	Number of inhabitants by each cell grid (km2), total population	Int	200797	0	22990	Zeng, Carter, and De Lacy (2005)

Pdensity (Add var)	High Population density classification of each Airbnb where: = 1 if population > 10.000 habitants per km2 = o if population < 10.000 habitants per km2	Int	200797	0	1	Zeng, Carter, and De Lacy (2005)
Int_cp_dp (Add var)	Interaction between cancellation policies and density population	Int	200797	0	3	
Int_ib_dp (Add var)	Interaction between instant book and density population classification	Int	200797	0	1	
Rooms	Number of rooms by Airbnb	Int	200797	0	24	Bresciani, S., et al (2021)
Photos	Number of rooms by Airbnb	Int	200797	0	203	Santos, M., et al. (2022)
Reviews	Number of reviews on the platform by Airbnb	Int	200797	0	203	D'Acunto, D.,et al. (2020).
Bloq_days	Number of days blocked in the platform by Airbnb	Int	200797	0	2207	Peng, Y. (2020)

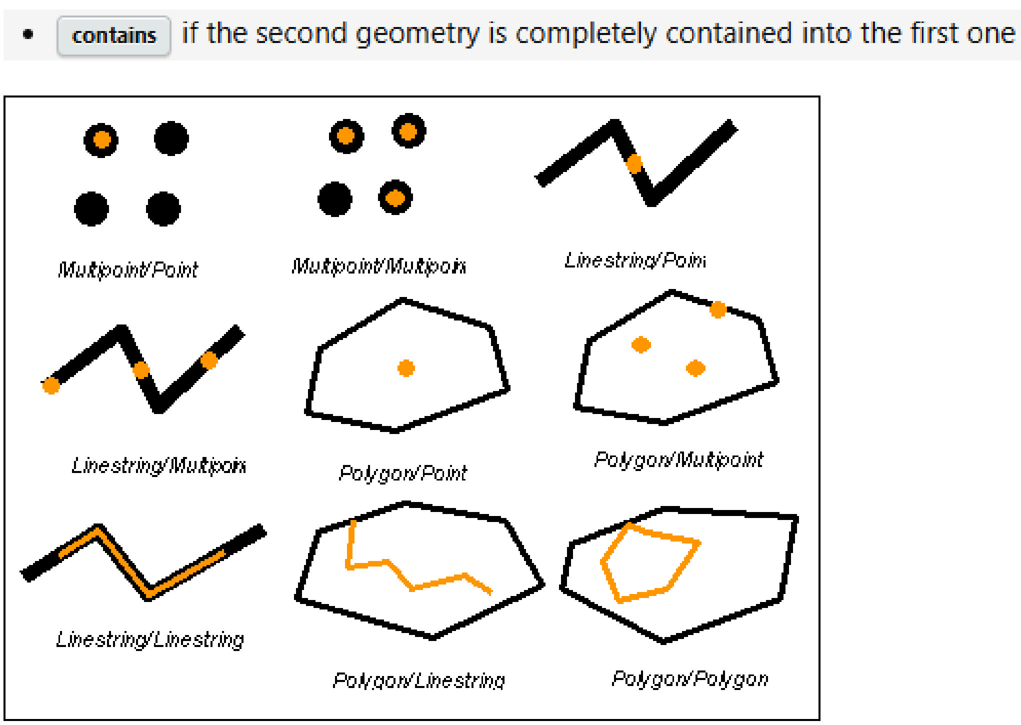
3.2.2 Geolocation of each Airbnb in parishes.

Geoprocessing tools are used to integrate the geographic information from the Airbnb database for Lisbon, covering the years 2019-2022. The coordinate data for each Airbnb is imported as a point layer in shapefile format (shp), and using the QGIS Join Attributes by Location algorithm, a cross-referencing of these coordinates with a polygon layer, also in shapefile format from the official data portal of Portugal, dados.gov.pt, is performed. This layer contains the 24 *Freguesias,* Also called parishes throughout the document (administrative divisions of Portugal that cover larger areas than neighborhoods) and uses the EPSG:4258 spatial reference system.

The Join Attributes by Location algorithm in QGIS allows you to merge the attributes of two vector layers based on their spatial relationship. In order to use it, two layers need to be defined: the destination layer (the parishes), which receives the attributes, and the union layer (the Airbnb coordinates), which provides the data to be transferred. First, the spatial relationship between both layers is established, being able to choose between different options such as "intersects," "disjoint," "contains," or "equal." In this case, the "contains" relationship is used since the points corresponding to the Airbnbs are located within the parishes. This process generates a polygonal/multipoint union, and the resulting type of matching is illustrated graphically in Figure 2.

Figure 2

Match types in the Join attributes by localization algorithm

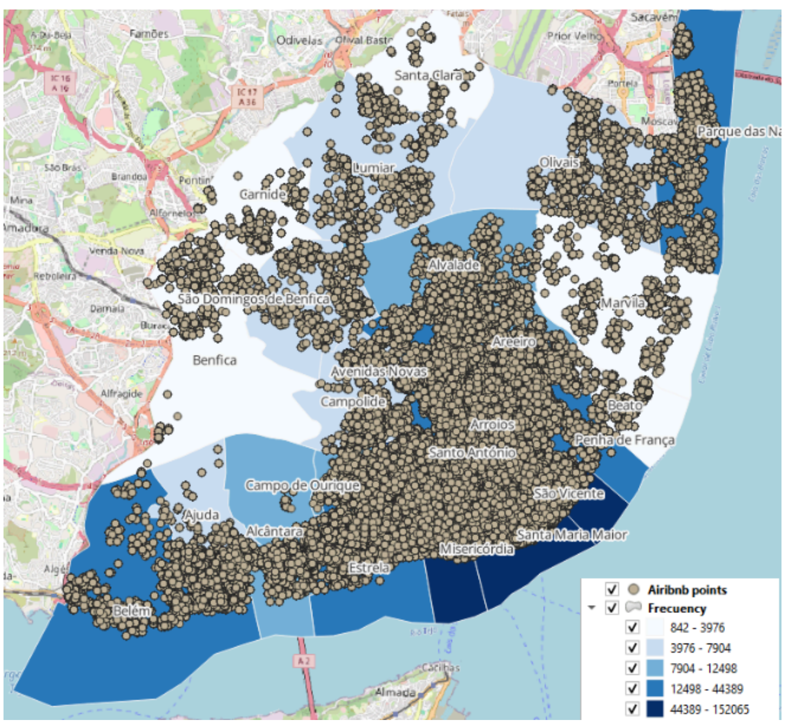


Note: Taken from Stack Exchange.

Depending on the selected relationship, QGIS identifies how the features in the target layer are related to the features in the join layer. The attributes in the join layer are then transferred to the target layer with the join type one-to-many, which considers all the data. Depending on the analysis, copying all the attributes or just some is possible. In this case, it was decided to include all the attributes for a robust database. The final result is a new layer called airbnb_freg in which each record is shown, its corresponding location in the parishes. This information is later exported to Excel and added to the database, obtaining the variable parish. From the above, and by crossing the data, it is possible to get statistics such as the frequency of Airbnbs for the total years for each parish, as well as the amount of total income or their average per year for each parish, etc. The resulting map is presented in Figure 3.

Figure 3

Airbnb Map by Fregueisa



Note: Own elaboration in QGIS using data from INE, AirDNA, and OpenStreetMap

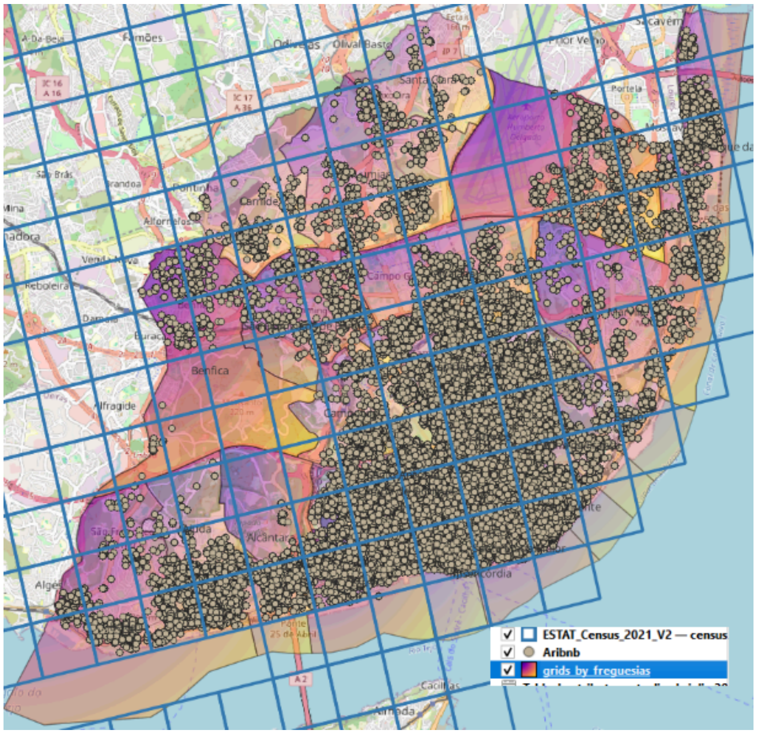
3.2.3 Population density by grid.

According to European Commission the Population grids are a powerful tool to describe our society and to study the interrelationships between human activities and the environment. They are particularly useful for analysing phenomena, and their causes, which are independent of administrative boundaries, such as flooding, commuting and urban sprawl.

To create the population density variable per grid, the Eurostat 2021 census database was used. In QGIS, the vector layer called Estat_Census_2021_V2 was imported, which organizes the European population of the year 2021 in 1 km^2 grids. Each grid contains detailed information on the number of inhabitants per square kilometer in a given area. This approach makes it possible to visualize how the population is spatially distributed at a granular level, facilitating density analysis in specific areas. The map showing this information is in Figure 4

Figure 4

Map with information about grids, Airbnb points, and fregueisa



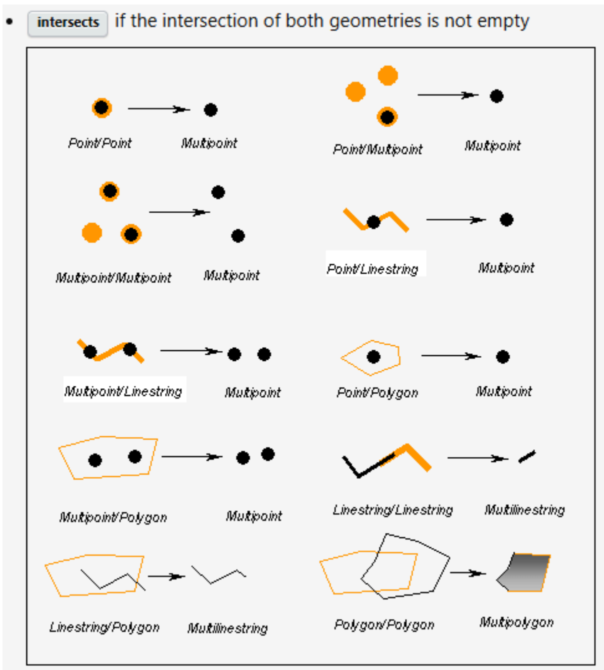
Note: Own elaboration in QGIS using data from INE, AirDNA, EuroStat and OpenStreetMap

To combine the population information from the 2021 census with the administrative areas of Lisbon, the Join Attributes by Location tool in QGIS was used. In this process, the census population grid layer (Estat_Census_2021_V2), which organizes the data in 1 km² grids, was joined to the parish layer, which contains the administrative polygons of Lisbon.

The procedure was performed using the geometric intersection function (intersects), which allowed the data from the grids to be combined with the corresponding areas of the 24 parishes. As a result, a new layer was generated that combines the population density information from 247 grids with the 24 parishes of Lisbon. This spatial join is essential to analyze how the population is distributed within each parish and its impact on Airbnb revenue. The geometric relationship between grids and parishes is illustrated graphically in Figure 5.

Figure 5

The type of match intersects



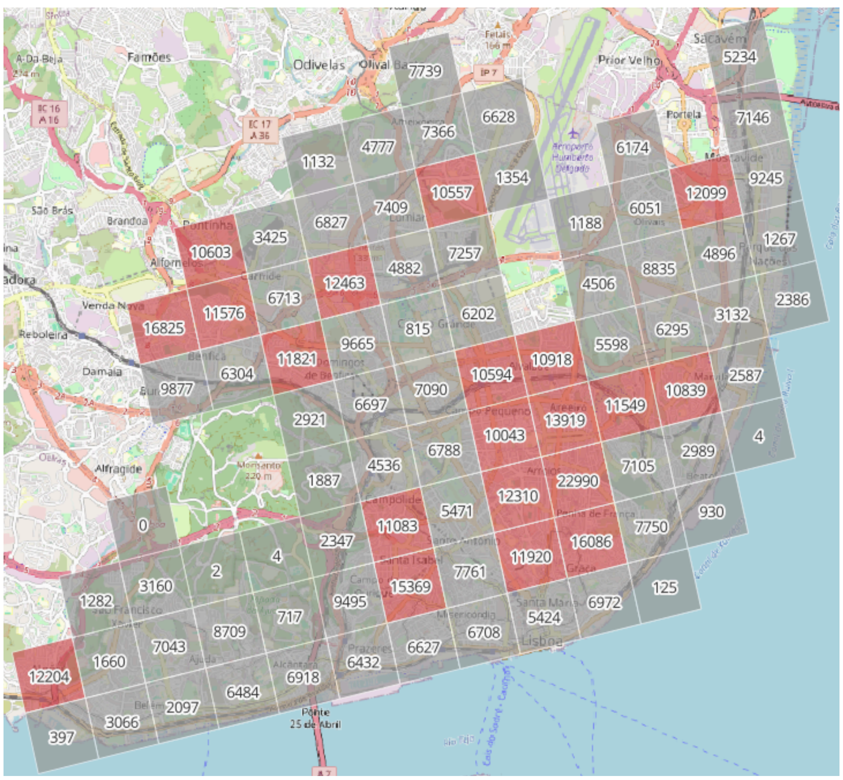
After performing the intersection between the parishes and the population grids, the Join Attributes by Location tool in QGIS is applied again, this time using the geometric function contains. This process allows the location of each Airbnb point (along with its variables such as income, ADR, etc.) to be associated with the corresponding grids according to their geographic location.

The result of this step is a new layer that assigns the information of each Airbnb to its respective grid. In this way, each Airbnb point inherits the demographic and spatial data of the grid in which it is located, enriching the original records with additional information. In addition, to restrict the analysis only to Lisbon, the parish layer acts as a geographic boundary, filtering the European grids so that only those within the 24 parishes of Lisbon are considered.

The map showing this final union and the distribution of the Airbnbs with their associated variables within Lisbon is presented in Figure 6, visualizing how the spatial and statistical data are combined in the research.

Figure 6

Resulting in a map of Airbnb by grid



The final layer is then a polygon layer containing information on both the income, instant bookings, and cancellation policies of Airbnbs, as well as the location by parish for each grid. It is important to note that there are grids that are left out of the interpolation because they did not have information on Airbnb; these are generally areas that are outside the city limits, such as green zones or non-commercial spaces that make it impossible to establish a hostel, such as the airport and the Monsanto forest park.

Finally, the classification of grids based on population density is defined by the following formula:

$$High\ density\ population\ if\ population\ >\ 10.000\ inhabitants\ per\ km2$$

Where the grids that are below 10,000 inhabitants per km2 are considered as areas without high population density, and their coding is equal to zero.

$$Grids\ without\ high\ density\ =\ 0\ if\ populataton\ <\ 10.000\ inhabitants\ per\ km2$$

Meanwhile, the grids that are above 10,000 inhabitants per km2 are considered areas with high population density, and their coding is equal to one

$$Grids\ with\ high\ density\ =\ 1\ if\ populataton\ >\ 10.000\ inhabitants\ per\ km2$$

This classification is theoretically supported by Goerlich and Cantarino (2015), which establishes that municipalities with more than 10,000 are considered in many registers as places with high population density.

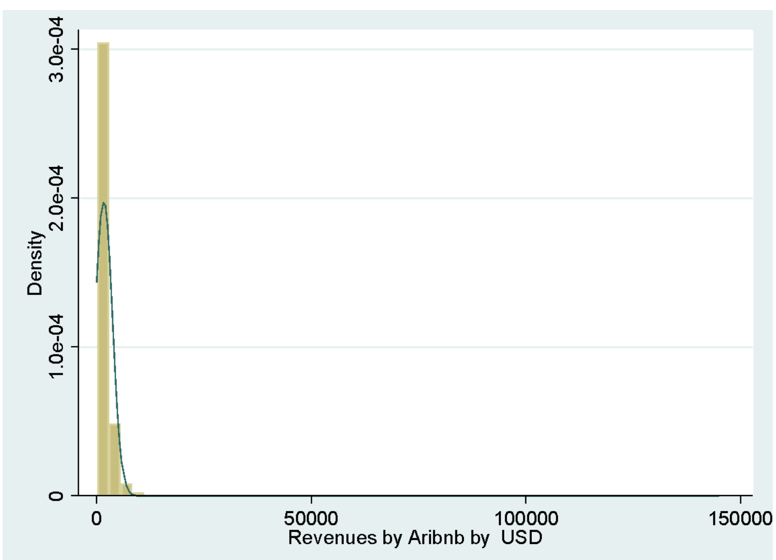
3.2.4 Logarithmic conversion of the revenue variable.

Since the distribution of the revenue variable, represented in the histogram in Figure 7, shows a strong concentration to the left (indicating a positive asymmetry), that is, most of the values are low but there are some exceptionally high revenues, the presence of extreme values or outliers is observed. This skewed distribution can distort the results of statistical analyses, such as regressions, by giving a disproportionate weight to the highest values.

To correct this distortion and obtain a more symmetrical distribution, a logarithmic transformation is applied to the revenue variable. The logarithmic transformation consists of calculating the natural logarithm of each revenue value. By doing this, very high values are reduced in greater proportion than low values, which helps to normalize the distribution and mitigate the impact of outliers. This technique is common in economic analysis when working with financial variables that present great variability. (Lütkepohl, H., & Xu, F. 2012)

Figure 7

Revenue histogram



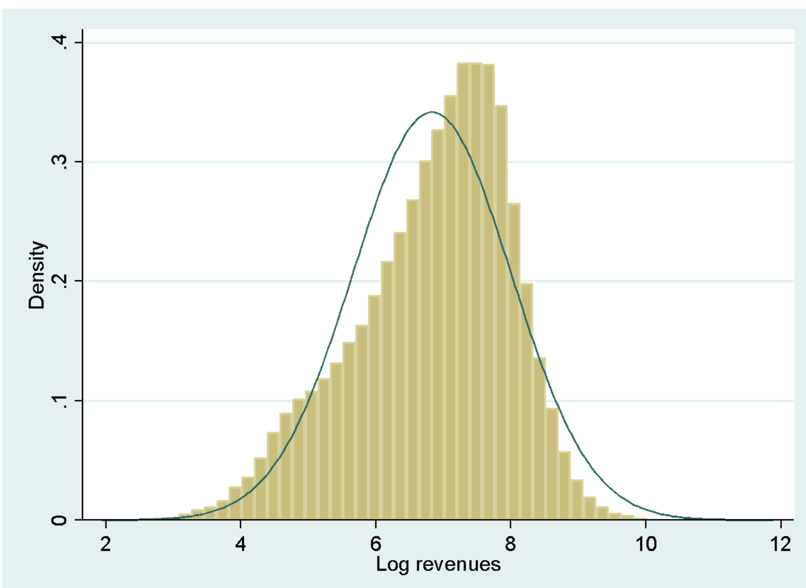
The transformation is performed by applying the natural logarithm to each value of the revenue variable using the following mathematical formula:

$$lrevenue = ln(revenue) lrevenue = \backslash ln(revenue) lrevenue = ln(revenue)$$

This procedure smooths out the differences between large and small values, reducing the influence of outliers on the results. The new transformed variable, called lrevenue, results in a more balanced distribution, which facilitates its use in linear models and other types of econometric analysis. The final distribution of the variable lrevenue can be observed in the histogram in Figure 8, which shows a more symmetrical distribution suitable for more robust statistical analysis.

Figure 8

LRevenue histogram



The interpretation of the coefficients, however, varies when the variable Lrevenue (log-transformed revenue) is employed as the dependent variable in a linear regression model. In a log-linear (log-lin) model, the coefficients must be understood in terms of percentage changes rather than a direct interpretation, in contrast to linear-linear (lin-lin) models, where a unit change in an independent variable leads to an absolute change in the dependent variable.

For example, if an independent variable's coefficient is 0.05, the logarithmic connection indicates that a one-unit rise in that variable leads to a roughly 5% increase in revenue. This kind of interpretation is common in models where logarithms are used to convert the dependent variables. It is helpful when working with variables that have a large range of values, like the revenue in this instance.

3.3 Methods of Analysis

3.3.1 Descriptive analysis

A detailed descriptive analysis is performed to characterize Airbnb revenues in Lisbon for the years 2019-2020, corresponding to before, during, and after the COVID-19 quarantine comparatively in areas with and without high population density. Descriptive statistics such as sums, averages, the number of observations, and medians were calculated for the revenues generated, also distinguishing by cancellation policies and the use of instant booking. According to Jacob (2023), descriptive analysis allows researchers to obtain a clear and precise view of the data, facilitating the identification of key characteristics and comparing variables in different temporal or spatial contexts.

3.3.2 Comparative analysis of averages

The analysis of average revenues of Airbnbs in Lisbon over the years 2019-2022 is used, corresponding to before, during, and after the COVID-19 quarantine comparatively in areas with and without high population density. In addition, the variation in revenues is calculated based on the population density of the grids; this allows us to understand the evolution of revenues over the years in each of the areas and also gives us a first approximation of the relationship between revenues and population density.

The analysis of means is explained in the following formula:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where:

$\overline{X}_1$ and $\overline{X}_2$ are the means of the average earnings of the two groups being compared.

s_1^2 and s_2^2 are the sample variances of the two groups.

n_1 and n_2 are the sample sizes of the two groups.

Field (2024) suggests that the analysis of averages is essential to identify general trends and significant differences between periods, which in this case allows us to evaluate how the quarantine affected revenues in areas of low population density. Which in this case allows us to evaluate the variation in average earnings in areas of high and low population density.

3.3.3 Regression Analysis

A multiple regression model analysis is performed to explore the impact of population density, cancellation and instant booking policies, time measured in years and months, and instant booking on Airbnb revenues from 2019 to 2022, analyzing comparatively in areas with high and without high population density, corresponding to before, during, and after the COVID 19 quarantine, controlling for variables such as the number of photos, rooms, the maximum number of guests allowed per hostel, the number of reviews and blocked days. According to Gujarati (2004), multiple regression allows not only to determine the relationship between a dependent variable and several independent ones but also to control for other factors that could influence this relationship, which is essential in a study that covers several years and different economic conditions.

The structural equation that groups the variables used in the linear regression models is the following:

$$Lrevenue = \beta 0(constant) + \beta 1\left(i.cancel_{p}\right) + \beta 2\left(inst_{book}\right) + \beta 3(pdensity) + \beta 4\left(int_{cp_{pd}}\right)$$
$$+ \beta 5\left(int_{ib_{pd}}\right) + \beta 6(i.years) + \beta 7(i.month) + \beta 8\left(max_{guess}\right) + \beta 9(rooms)$$
$$+ \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Where:

- β0: Model intercept or constant

- β1: Categorical variable of cancellation policies | flexible=0, moderate=1, strict=2

- β2: Instant booking | 1: hostel with instant booking, 0: hostel without instant booking

- β3: High population density classification | 1 if the hostel is located in a grid with population density > 10,000 inhabitants, 0 if the hostel is located in a grid with population density < 10,000 inhabitants,

- β4: Categorical variable showing the interaction between cancellation policies and high population density.

- β5: Categorical variable showing the interaction between instant booking and high population density.

- β6: Categorical variable showing the time measured in years.

- β7: Categorical variable showing the time measured in months.

- β8: Maximum guest capacity

- β9: Number of rooms

- β10: Number of photos posted on the platform per month.

- β11: Number of reviews per month

- β12: Number of days blocked for booking per month.

- ϵ: Model error term

Specifically, models were estimated to measure the isolated and direct effect of the variables of interest: population density, instant booking, and cancellation policies, all with the same control variables. Finally, the models in their independent components are the following:

Model 1: Direct effect of population density without interactions.

$$Lrevenue = \beta 0(constant) + \beta 3(pdensity) + \beta 6(i.years) + \beta 7(i.month)$$

$$+ \beta 8\left(max_{guess}\right) + \beta 9(rooms) + \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Model 2: Direct effect of instant booking without interactions.

$$\mathrm{L}revenue = \beta 0(constant) + \beta 2\left(inst_{book}\right) + \beta 6(i.years) + \beta 7(i.month)$$

$$+ \beta 8\left(max_{guess}\right) + \beta 9(rooms) + \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Model 3: Direct effect of cancellation policies without interactions

$$Lrevenue = \beta 0(constant) + \beta 1\left(i.cancel_{p}\right) + \beta 6(i.years) + \beta 7(i.month) + \beta 8\left(max_{guess}\right)$$

$$+ \beta 9(rooms) + \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Model 4: Model with interaction between population density and cancellation policies.

$$Lrevenue = \beta 0(constant) + \beta 1\left(i.cancel_{p}\right) + \beta 3(pdensity) + \beta 4\left(int_{cp_{pd}}\right) + \beta 6(i.years)$$

$$+ \beta 7(i.month) + \beta 8\left(max_{guess}\right) + \beta 9(rooms) + \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Model 5: Model with interaction between population density and instant booking.

$$Lrevenue = \beta 0(constant) + \beta 2\left(inst_{book}\right) + \beta 3(pdensity) + \beta 5\left(int_{ib_{pd}}\right) + \beta 6(i.years)$$

$$+ \beta 7(i.month) + \beta 8\left(max_{guess}\right) + \beta 9(rooms) + \beta 10(photos) + \beta 11(reviews) + \beta 12\left(bloq_{days}\right) + \epsilon$$

Model 6: Model with all interactions and variables.

$$Lrevenue = \beta0(constant) + \beta1\left(i.cancel_{p}\right) + \beta2\left(inst_{book}\right) + \beta3(pdensity) + \beta4\left(int_{cp_{pd}}\right)$$

$$+ \beta5\left(int_{ib_{pd}}\right) + \beta6(i.years) + \beta7(i.month) + \beta8\left(max_{guess}\right) + \beta9(rooms)$$

$$+ \beta10(photos) + \beta11(reviews) + \beta12\left(bloq_{days}\right) + \epsilon$$

Regression models are run with the robust option in STATA to correct for heteroscedasticity, that is when the variance of the errors is not constant across observations. This option adjusts the estimates of the standard errors, making the results more reliable and preventing heteroscedasticity from influencing the validity of statistical inferences. As a result, hypothesis tests (such as p-values) are more precise and less affected by the variability of the errors.

3.4 Ethical considerations and limitations of the study

Although this study uses secondary data from AirDNA and the National Institute of Statistics (INE), it should be noted that it handles information that could be considered sensitive, such as Airbnb hosts' income. Although the data is publicly accessible and does not involve the direct participation of individuals, it is essential to preserve the hosts' anonymity. In addition, the exclusive reliance on the data provided by AirDNA raises considerations about reliability and access to complete and accurate information.

Another significant point is that, even though no direct personal information is collected, the properties under analysis belong to certain hosts, necessitating the ethical and respectful treatment of the data with extra caution to prevent any unwarranted disclosure of information that could be connected to specific people.

However, using secondary data is one of the study's primary weaknesses, limiting the researchers' ability to control the information's quality, correctness, and degree of detail. Since the research relies on the accuracy and up-to-dateness of external sources like AirDNA and the INE, the data originates from them.

This could limit the study’s ability to analyze certain relevant factors that have not been collected or reported with sufficient granularity.

Furthermore, because COVID-19 was an unusual occurrence that significantly changed the behavior of the Airbnb rental market, the study's temporal frame—analyzing the time before, during, and after the pandemic—introduces a potential bias. This historical analysis may restrict the results' applicability to other eras not characterized by a worldwide crisis, even though it provides insightful information about the effects of COVID-19.

Finally, the study's purely quantitative approach, without using qualitative methods such as host interviews or guest surveys, prevents capturing subjective aspects or perceptions that could influence revenue, such as host experience or guest satisfaction. This may limit the comprehensive understanding of the phenomenon studied. Furthermore, the results may not be generalizable to other regions with different economic, tourist, or demographic characteristics, which reduces the results' applicability outside Lisbon's specific context.

4. RESULTS

4.1 Descriptive analysis

This section shows descriptive statistics for the analysis of monthly Airbnb revenues over time, including the total sum of revenues, the number of Airbnbs obtained from the samples, and the average revenues, all of the above distinguishing between high and low population density areas in 1 km2 grids; The analysis is done through the years 2019 - 2022, and through the months from January to December, which allows analyzing the variation of the data with respect to the possible presence of seasonal trends.

4.1.1 Statistics of revenues per month and year according to population density

Table 2 shows the sum of the total revenues of the Airbnb sample for places with low population density.

Figure 9

Sum of total revenues from Airbnb for areas with low population density

	Low population density				
Month	**2019**	**2020**	**2021**	**2022**	**Total**
Jan	$ 1'349'771.53	$ 8'205'657.55	$ 1'516'609.93	$ 3'730'043.00	$ 14'802'082.01
Feb	$ 1'067'286.80	$ 8'067'974.36	$ 954'681.70	$ 4'805'241.00	$ 14'895'183.86
Mar	$ 1'659'719.83	$ 6'134'500.13	$ 1'083'361.79	$ 6'969'430.00	$ 15'847'011.75
Apr	$ 2'268'971.46	$ 3'008'343.13	$ 1'671'506.45	$ 9'729'454.00	$ 16'678'275.04
May	$ 2'237'687.65	$ 2'913'254.98	$ 2'973'945.84	$ 10'505'773.00	$ 18'630'661.47
Jun	$ 2'098'514.80	$ 3'191'310.10	$ 4'439'591.49	$ 11'267'917.00	$ 20'997'333.39
Jul	$ 1'969'165.98	$ 4'565'959.29	$ 4'884'733.52	$ 12'805'894.00	$ 24'225'752.79
Aug	$ 1'974'045.83	$ 5'923'325.19	$ 7'287'565.53	$ 13'194'893.00	$ 28'379'829.55
Sep	$ 1'402'819.88	$ 4'828'472.45	$ 6'737'212.73	$ 11'820'406.00	$ 24'788'911.06
Oct	$ 956'026.62	$ 3'623'939.06	$ 7'496'324.71	$ 11'337'872.00	$ 23'414'162.39
Nov	$ 434'079.10	$ 2'140'638.03	$ 6'520'707.55	$ 8'505'817.00	$ 17'601'241.68
Dec	$ 430'914.95	$ 2'160'813.03	$ 5'726'883.80	$ 8'169'420.00	$ 16'488'031.78
Total	**$ 17'849'004.43**	**$ 54'764'187.30**	**$ 51'293'125.04**	**$ 112'842'160.00**	**$ 236'748'476.77**

In general terms, it can be observed that the variation in revenue has increased since 2019, with its highest point in 2022. This highlights that despite the pandemic and restrictions due to COVID-19, Airbnb revenue increased for 2020 by almost three times more than it did in 2019. However, for the year 2021, revenues show a drop of—$ 3'471'062.26, which compared to other economic activities remains positive, since while some industries experienced prolonged closures and pronounced declines, Airbnb managed to maintain high revenues thanks to its adaptation and demand in less saturated destinations. (Casasnovas, M., et al 2023)

Regarding the variation in the sum of revenues over the months, it can be observed that, outside of the years 2020 and 2021. These years are characterized by a stronger impact on the economy in relation to the pandemic. Revenues show a seasonal pattern marked by less revenues for January to March and greater revenues in July to September, which is consistent with market trends regarding summer and the holiday period in Europe (Statista, 2024). Interestingly, from November to December 2019, revenues have been considerably low. This could be related to the behavior of the accommodation seekers regarding the prevention of contagion since, although the state of emergency began on January 30, 2020, the pandemic started on November 25, 2019; the possibility that it was a market trend is also considered since it is very likely that Airbnb revenues were much lower due to the low supply of hostels compared to other years.

For the year 2020, the months of January to March present a greater amount of revenues in areas of low population density; this could be due to the fact that, due to the restrictions due to Covid-19, people were prevented from going out on the street, these accommodations became a temporary residence for those guests who were trapped in the hostels, it is unknown if there was any type of subsidized aid for this type of people at the time, or if they had an obligation to pay.

In 2021, revenues from low-density locations return to a seasonal pattern similar to that of 2019. This pattern will continue into 2022, with more progressive and less abrupt changes than in 2020 and 2021. Total revenues will double in 2022 compared to 2021, giving Airbnb a positive outlook for the accommodation business in the years to come. Table 3 shows the sum of total revenues for high-population density locations.

Table 3

Sum of total revenues from Airbnb for high population density areas

	High population density				
Month	**2019**	**2020**	**2021**	**2022**	**Total**
Jan	$ 657'319.21	$ 2'996'880.51	$ 598'316.84	$ 1'369'473.00	$ 5'621'989.56
Feb	$ 436'680.91	$ 2'792'202.10	$ 475'826.89	$ 1'647'779.00	$ 5'352'488.90
Mar	$ 674'984.29	$ 2'294'523.10	$ 555'434.82	$ 2'402'888.00	$ 5'927'830.21
Apr	$ 954'239.74	$ 1'348'451.28	$ 695'560.02	$ 3'378'341.00	$ 6'376'592.04
May	$ 887'355.06	$ 1'242'222.26	$ 1'109'636.91	$ 3'796'528.00	$ 7'035'742.23
Jun	$ 874'288.37	$ 1'339'934.75	$ 1'435'616.68	$ 4'297'408.00	$ 7'947'247.80
Jul	$ 855'490.81	$ 1'853'598.35	$ 1'734'278.87	$ 4'915'495.00	$ 9'358'863.03
Aug	$ 890'504.77	$ 2'275'256.45	$ 2'418'006.70	$ 5'115'932.00	$ 10'699'699.92
Sep	$ 492'990.54	$ 1'706'215.07	$ 2'268'633.71	$ 4'503'837.00	$ 8'971'676.32
Oct	$ 259'894.10	$ 1'330'917.04	$ 2'630'265.97	$ 4'229'503.00	$ 8'450'580.11
Nov	$ 114'129.65	$ 819'845.08	$ 2'195'901.07	$ 3'124'471.00	$ 6'254'346.80
Dec	$ 146'568.63	$ 780'723.00	$ 2'012'917.94	$ 2'940'797.00	$ 5'881'006.57
Total	**$ 7'244'446.08**	**$ 20'780'769.00**	**$ 18'130'396.42**	**$ 41'722'452.00**	**$ 87'878'063.49**

Total revenues from low-density locations are comparatively lower than total revenues from high-density locations, but the same interesting behaviors are observed, such as less abrupt seasonal patterns in 2019 and 2022, characterized by an increase in revenues from July to September; a peak in revenues in 2020 for January to March, a decrease in revenues in 2021 compared to 2020, and a generally positive trend in revenues year-over-year, with the largest amount of revenues in 2022.

However, some differentiated behaviors are observed between total revenues in low- and high-density locations, such as a larger positive percentage variation month-over-month in revenues in December 2019 (0.28%) in high-density locations, compared to low-density locations (-0.007). Although low-density areas seem to be more profitable in terms of revenues, it is not possible to suggest a possible preference for guests in less populated areas since other characteristics such as location, type of hostel, and price could be related.

Altogether, the sum of Airbnb revenues for both low—and high-density places in the sample amounts to $324,626,540.27 US dollars.

Table 4 shows the number of Airbnb listings on the platform within the sample for places with low population density.

Table 4

Airbnb listings with low-density locations

	Low population density				
Month	2019	2020	2021	2022	Total
Jan	1490	7151	2331	3048	14020
Feb	1048	6480	1593	2905	12026
Mar	1183	6341	1726	3168	12418
Apr	1288	3384	1950	3416	10038
May	1172	3169	2717	3525	10583
Jun	1128	3466	3190	3639	11423
Jul	1032	4223	3415	3794	12464
Aug	942	4625	3768	3763	13098
Sep	723	4196	3502	3619	12040
Oct	532	4141	3400	3514	11587
Nov	347	3058	3243	3394	10042
Dec	293	2933	3378	3361	9965
Total	**11178**	**53167**	**34213**	**41146**	**139704**

It is observed that, compared to the sum of total revenues, the number of Airbnb offerers in places with low population density does not present such a marked seasonal pattern. Still, an increase in offerers can be observed for June to August and a decrease in the number of offerers for November and December. The fact that the number of offerers does not follow such a marked seasonal pattern as the total revenues could indicate the persistence of Airbnb offerers to remain active throughout the year despite the decrease in revenues in some periods.

Generally, a decrease in Airbnb hostels is observed for 2021, especially between February and April. However, for the year 2022, the number of Airbnbs will grow again, and this time with less seasonal variation, which again indicates that Airbnb offerers want to remain active throughout the year. However, the number of hostels 2022 is not as high as in 2020. This could indicate increased barriers to entry into the market for 2022 or simply an economic stabilization after the increase in demand for Airbnb at the beginning of the pandemic.

For the months of January to March 2020, the number of Airbnb in low-density areas increases, as does the amount of total revenues, this could also be explained by a higher demand for hostel services in the context of pandemic restrictions at the beginning of 2020.

Table 5 shows the number of Airbnb listings on the platform within the sample for places with high population density.

Table 5

Airbnb listings with high population density

Month	High population density 2019	2020	2021	2022	Total
Jan	826	3193	1018	1246	6283
Feb	547	2761	743	1199	5250
Mar	665	2695	821	1331	5512
Apr	733	1675	839	1435	4682
May	650	1387	1118	1508	4663
Jun	622	1510	1264	1588	4984
Jul	589	1770	1411	1688	5458
Aug	543	1978	1540	1669	5730
Sep	373	1791	1434	1593	5191
Oct	204	1830	1391	1526	4951
Nov	132	1410	1313	1437	4292
Dec	110	1201	1359	1427	4097
Total	**5994**	**23201**	**14251**	**17647**	**61093**

Airbnb hostel revenues in high-density locations are comparatively lower than the number of hostels in low-density locations. Similarly, much smoother seasonal supply patterns can be observed in 2022, with a peak in supply in January to March 2020, a higher number of Airbnb hostels in 2020, and a growth in the number of hostels for 2022.

The total number of Airbnbs listed on the platform as offering accommodation services, both for low—and high-density locations, totals 200,797 observations in the sample.

Figures 6 and 7 show the average monthly revenues of Airbnbs for places with low and high population density, respectively.

Table 6

Average revenues of Airbnb in places with low population density

Month	Low population density 2019	2020	2021	2022	Total
Jan	$ 905.89	$ 1'147.48	$ 650.63	$ 1'223.77	$ 1'055.78
Feb	$ 1'018.40	$ 1'245.06	$ 599.30	$ 1'654.13	$ 1'238.58
Mar	$ 1'402.98	$ 967.43	$ 627.67	$ 2'199.95	$ 1'276.13
Apr	$ 1'761.62	$ 888.99	$ 857.18	$ 2'848.20	$ 1'661.51
May	$ 1'909.29	$ 919.30	$ 1'094.57	$ 2'980.36	$ 1'760.43
Jun	$ 1'860.39	$ 920.75	$ 1'391.72	$ 3'096.43	$ 1'838.16
Jul	$ 1'908.11	$ 1'081.21	$ 1'430.38	$ 3'375.30	$ 1'943.66
Aug	$ 2'095.59	$ 1'280.72	$ 1'934.07	$ 3'506.48	$ 2'166.73
Sep	$ 1'940.28	$ 1'150.73	$ 1'923.82	$ 3'266.21	$ 2'058.88
Oct	$ 1'797.04	$ 875.14	$ 2'204.80	$ 3'226.49	$ 2'020.73
Nov	$ 1'250.95	$ 700.01	$ 2'010.70	$ 2'506.13	$ 1'752.76
Dec	$ 1'470.70	$ 736.72	$ 1'695.35	$ 2'430.65	$ 1'654.59
Total	**$ 1'596.80**	**$ 1'030.04**	**$ 1'499.23**	**$ 2'742.48**	**$ 1'694.64**

Table 7

Average Airbnb revenues in high-density locations

Month	High population density 2019	2020	2021	2022	Total
Jan	$ 795.79	$ 938.58	$ 587.74	$ 1'099.10	$ 894.79
Feb	$ 798.32	$ 1'011.30	$ 640.41	$ 1'374.29	$ 1'019.52
Mar	$ 1'015.01	$ 851.40	$ 676.53	$ 1'805.33	$ 1'075.44
Apr	$ 1'301.83	$ 805.05	$ 829.03	$ 2'354.24	$ 1'361.94
May	$ 1'365.16	$ 895.62	$ 992.52	$ 2'517.59	$ 1'508.84
Jun	$ 1'405.61	$ 887.37	$ 1'135.77	$ 2'706.18	$ 1'594.55
Jul	$ 1'452.45	$ 1'047.23	$ 1'229.11	$ 2'912.02	$ 1'714.71
Aug	$ 1'639.97	$ 1'150.28	$ 1'570.13	$ 3'065.27	$ 1'867.31
Sep	$ 1'321.69	$ 952.66	$ 1'582.03	$ 2'827.27	$ 1'728.31
Oct	$ 1'273.99	$ 727.28	$ 1'890.92	$ 2'771.63	$ 1'706.84
Nov	$ 864.62	$ 581.45	$ 1'672.43	$ 2'174.30	$ 1'457.21
Dec	$ 1'332.44	$ 650.06	$ 1'481.18	$ 2'060.82	$ 1'435.44
Total	**$ 1'208.62**	**$ 895.68**	**$ 1'272.22**	**$ 2'364.28**	**$ 1'438.43**

Low-density areas show higher average annual revenues than high-density areas. However, they show a similar seasonal trend. The difference is noticeable in all years, especially in 2022, where the average in low-density areas was $2,742.48, compared to $2,364.28 in high-density areas.

In both areas, an increase in revenues is observed in the summer months (June to August), peaking in August. Low-density areas reach higher peaks in summer compared to high-density areas. For example, in August 2022, low-density areas achieved an average income of $3,506.48 compared to $3,065.27 in high-density areas.

In 2020, revenues decreased compared to 2019, reflecting the impact of the pandemic. However, 2021 shows a recovery, especially in low-density areas. In 2021, revenues in low-density areas increased significantly compared to high-density areas, possibly due to a preference for less crowded locations. Low-density areas tend to be more profitable in terms of average revenues, especially in peak seasons. This could indicate that guests value less dense and quiet spaces more, especially during periods of high demand.

The significant increase in the summer months suggests that adjusting prices upwards during this season could further increase revenues. Low-density areas could take advantage of this seasonality to compensate for the lower demand months in winter.

4.1.2 Statistics for the Revenue per year according to population density and strategy

4.1.2.1 Statistics for Revenue per year according to population density and Instant Booking

Table 8

Sum of total Revenue according to population density and the use of instant reservation

	2019	2020	2021	2022	Total general
Low pdensity	**$ 17'849'004.43**	**$ 54'764'187.30**	**$ 51'293'125.04**	**$ 112'842'160.00**	**$ 236'748'476.77**
IB False	$ 4'190'577.39	$ 12'659'234.24	$ 11'840'025.87	$ 32'819'796.00	$ 61'509'633.50
IB True	$ 13'658'427.04	$ 42'104'953.06	$ 39'453'099.17	$ 80'022'364.00	$ 175'238'843.27
high pdensity	**$ 7'244'446.08**	**$ 20'780'769.00**	**$ 18'130'396.42**	**$ 41'722'452.00**	**$ 87'878'063.49**
IBFalse	$ 1'547'387.43	$ 5'314'184.88	$ 5'297'699.47	$ 14'183'873.00	$ 26'343'144.78
IB True	$ 5'697'058.65	$ 15'466'584.12	$ 12'832'696.95	$ 27'538'579.00	$ 61'534'918.72
Total	**$ 25'093'450.51**	**$ 75'544'956.30**	**$ 69'423'521.46**	**$ 154'564'612.00**	**$ 324'626'540.27**

Data analysis on total revenues for Airbnbs in high- and low-density areas reveals important trends, especially in the context of instant booking (IB True) availability. Low-density areas generated higher total revenues compared to high-density areas. In low-density areas, Airbnb, with instant bookings, accumulated a total of $175.2 million, representing approximately 74% of revenues in these areas. On the other hand, in the same areas, Airbnb without instant booking generated $61.5 million, a significantly lower figure, suggesting that the instant booking option could be associated with higher revenue capture, possibly due to guests' preference for the convenience and speed of booking confirmation.

In high-density areas, total revenues are also higher for those with instant booking, reaching $61.5 million compared to $26.3 million for those without this option. This suggests that, although to a lesser extent than in low-density areas, instant booking is still a competitive advantage in urban or densely populated areas. However, the difference in revenues between

Airbnb with and without instant booking is smaller in these areas, which could indicate that in high-demand areas, instant booking is less of a driver of guest choice compared to lower-density areas.

In terms of annual growth, both densities show a significant increase in total revenues from 2019 to 2022, largely driven by the recovery from the pandemic. In low-density areas, total annual revenues grew by 533%, from $17.8 million in 2019 to $112.8 million in 2022, while in high-density areas, the increase was 478%, from $7.2 million to $41.7 million over the same period. These data reflect not only a market recovery but also a possible expansion of tourism in low-density areas, where instant booking appears to be a key tool to maximize revenues.

Table 9

Number of Airbnbs by population density and instant booking usage

	2019	2020	2021	2022	Total
Low pdensity	**11178**	**53167**	**34213**	**41146**	**139704**
IB False	3221	15178	10013	14449	42861
IB True	7957	37989	24200	26697	96843
high pdensity	**5994**	**23201**	**14251**	**17647**	**61093**
IBFalse	1717	7180	4936	6887	20720
IB True	4277	16021	9315	10760	40373
Total	**17172**	**76368**	**48464**	**58793**	**200797**

Analysis of data on the number of Airbnb hosts in high- and low-density areas and the availability of instant booking (IB True) reveals patterns of growth and differences between these types of bookings. In general, low-density areas saw a higher number of hosts than high-density areas, especially those with the instant booking option. Between 2019 and 2022, the number of hosts in low-density areas increased from 11,178 to 41,146, representing a growth of 268%. In high-density areas, growth was 194%, from 5,994 hosts in 2019 to 17,647 in 2022.

Instant booking appears to play an important role in attracting hosts, as in both areas, hosts with IB True account for a higher proportion. In low density, 69% of total offerers used instant booking (96,843 out of 139,704), while in high density, 66% opted for this option (40,373 out of 61,093). The difference between IB True and IB False in low-density areas suggests that hosts in these areas may rely more on instant booking to attract guests, likely due to the need to compete with other accommodations or to increase visibility in less urbanized areas. In contrast, although instant booking is also popular in high density, offerer growth in IB True is lower, which could indicate that in urban areas, other factors such as location or property features have greater comparative relevance.

The overall increase in both densities could also reflect the recovery and expansion of the Airbnb market after the pandemic, with a substantial increase in supply as more hosts implement instant booking options to capture demand. Taken together, these patterns suggest that instant booking is not only a tool to increase competitiveness but could be incentivizing the expansion of supply in lower-density areas.

Table 10

Average Airbnb revenues by population density and instant booking usage

	2019	2020	2021	2022	Total
Low pdensity	**$ 1'596.80**	**$ 1'030.04**	**$ 1'499.23**	**$ 2'742.48**	**$ 1'694.64**
IB False	$ 1'301.02	$ 834.05	$ 1'182.47	$ 2'271.42	$ 1'435.10
IB True	$ 1'716.53	$ 1'108.35	$ 1'630.29	$ 2'997.43	$ 1'809.51
high pdensity	**$ 1'208.62**	**$ 895.68**	**$ 1'272.22**	**$ 2'364.28**	**$ 1'438.43**
IBFalse	$ 901.22	$ 740.14	$ 1'073.28	$ 2'059.51	$ 1'271.39
IB True	$ 1'332.02	$ 965.39	$ 1'377.64	$ 2'559.35	$ 1'524.16
Total	**$ 1'461.30**	**$ 989.22**	**$ 1'432.48**	**$ 2'628.96**	**$ 1'616.69**

The analysis of average revenues for Airbnbs in high- and low-density areas, considering the instant booking option (IB True), shows some important differences and growth patterns over time. In low-density areas, average revenues were higher almost every year, especially for Airbnbs that use instant booking. In 2019, average revenues for Airbnb with instant booking in low density were $1,716.53, compared to $1,301.02 for those without instant booking. This trend continued through 2022, when average revenues for IB True in low density reached $2,997.43, an increase of 74.6% from 2019, while revenues for IB False grew to a lesser extent by 74.5%.

In high-density areas, the results also indicate that Airbnb with instant booking tends to generate higher average revenues. In 2019, average revenues for IB True were $1,332.02 versus $901.22 for IB False, a considerable difference. By 2022, revenues for IB True increased by 92.2%, reaching $2,559.35, while those for IB False grew by 128.5% to $2,059.51. Although the percentage growth for IB False in high density was higher, in absolute terms, IB True is still more profitable.

The difference between Airbnb with and without instant booking appears to be more marked in low-density areas, where instant booking allows for higher demand and potentially improved occupancy. Although there is also a difference in high density, it is less pronounced, possibly due to high competition and greater supply in these areas.

4.1.2.2 Statistics for Revenue per year according to population density and Cancellation Policies.

Table 11

Sum of Airbnb revenues by population density and cancellation policies

	2019	2020	2021	2022	Total general
Low pdensity	**$ 17'849'004.43**	**$ 54'764'187.30**	**$ 51'293'125.04**	**$ 112'842'160.00**	**$ 236'748'476.77**
Flexible	$ 2'153'274.71	$ 13'453'073.18	$ 9'783'745.67	$ 13'201'423.00	$ 38'591'516.56
Moderate	$ 6'570'287.59	$ 22'269'026.99	$ 25'083'449.55	$ 53'777'784.00	$ 107'700'548.12
Strict	$ 9'125'442.13	$ 19'042'087.14	$ 16'425'929.83	$ 45'862'953.00	$ 90'456'412.10
High pdensity	**$ 7'244'446.08**	**$ 20'780'769.00**	**$ 18'130'396.42**	**$ 41'722'452.00**	**$ 87'878'063.49**
Flexible	$ 1'063'010.28	$ 3'965'418.96	$ 3'215'395.94	$ 5'123'111.00	$ 13'366'936.18
Moderate	$ 2'808'496.86	$ 8'539'122.03	$ 7'878'836.05	$ 18'095'284.00	$ 37'321'738.94
Strict	$ 3'372'938.94	$ 8'276'228.01	$ 7'036'164.43	$ 18'504'057.00	$ 37'189'388.38
Total general	**$ 25'093'450.51**	**$ 75'544'956.30**	**$ 69'423'521.46**	**$ 154'564'612.00**	**$ 324'626'540.27**

The analysis of total revenues for Airbnbs in high- and low-density areas, segmented by the type of cancellation policy (flexible, moderate, and strict), shows a sustained increase from 2019 to 2022, especially in low-density areas. In these areas, moderate and strict cancellation policies generate the highest cumulative revenues, with $107.7 million and $90.5 million, respectively, compared to $38.6 million under the flexible policy. This growth, especially between 2020 and 2022, is partly due to the recovery of tourism after the pandemic. In high-density areas, the moderate policy also leads to total revenues of $37.3 million, closely followed by the strict policy of $37.1 million. The flexible policy, although less profitable, shows moderate growth, reaching $13.3 million.

The analysis suggests that Airbnbs in low-density areas and with less flexible cancellation policies perform better in revenues, possibly due to stable demand in areas with less competition. In high-density areas, on the other hand, the difference between policies is less pronounced, likely due to greater competition and variety of offerings, which has less impact on guests' decisions regarding cancellation policy. In terms of percentage growth, both densities experienced notable year-over-year profit increases, highlighting that the recovery and expansion of the Airbnb market appears to have occurred more evenly across all cancellation policies and population densities in recent years.

Table 12

Number of Airbnbs by population density and cancellation policies

	2019	2020	2021	2022	Total general
Low pdensity	**11178**	**53167**	**34213**	**41146**	**139704**
Flexible	1773	12569	7005	5624	26971
Moderate	4055	21410	16075	19149	60689
Strict	5350	19188	11133	16373	52044
High pdensity	**5994**	**23201**	**14251**	**17647**	**61093**
Flexible	1120	4919	2804	2538	11381
Moderate	2174	8842	6028	7638	24682
Strict	2700	9440	5419	7471	25030
Total general	**17172**	**76368**	**48464**	**58793**	**200797**

Analysis of the number of Airbnb hosts segmented by density areas and cancellation policies shows significant variations in growth over the years. In low-density areas, the number of hosts increased sharply from 11,178 in 2019 to 53,167 in 2020, followed by fluctuations and a relative decline in 2021 but a recovery in 2022, with a cumulative total of 139,704. Among the cancellation policies in this category, the moderate one attracted the largest number of hosts (60,689), while the strict one came in second (52,044). This suggests a preference for moderate policies in areas with less competition and greater stability in booking demand.

In high-density areas, the total number of hosts also grew, but to a lesser extent, reaching 61,093 in the cumulative total. Here, the moderate and strict policies are almost balanced in the number of offerers, with 24,682 and 25,030, respectively. The flexible policy, on the other hand, represents a smaller fraction in both densities, indicating a lower preference for this modality in both high- and low-density areas.

As for annual growth, significant growth is observed in 2020 for all categories, probably driven by the expansion of the alternative accommodation market. However, the recovery from 2021 to 2022 was more stable, showing a market adjustment after the pandemic. The difference between cancellation policies suggests that stricter policies may be more popular in high-density areas, where supply and competition are higher. In contrast, in low-density areas, the moderate policy is more predominant, probably due to a demand that is less sensitive to cancellation conditions.

Table 13

Average Airbnb Revenues by population density and cancellation policies

	2019	2020	2021	2022	Total general
Low pdensity	**$ 1'596.80**	**$ 1'030.04**	**$ 1'499.23**	**$ 2'742.48**	**$ 1'694.64**
Flexible	$ 1'214.48	$ 1'070.34	$ 1'396.68	$ 2'347.34	$ 1'430.85
Moderate	$ 1'620.29	$ 1'040.12	$ 1'560.40	$ 2'808.39	$ 1'774.63
Strict	$ 1'705.69	$ 992.40	$ 1'475.43	$ 2'801.13	$ 1'738.08
High pdensity	**$ 1'208.62**	**$ 895.68**	**$ 1'272.22**	**$ 2'364.28**	**$ 1'438.43**
Flexible	$ 949.12	$ 806.14	$ 1'146.72	$ 2'018.56	$ 1'174.50
Moderate	$ 1'291.86	$ 965.75	$ 1'307.04	$ 2'369.11	$ 1'512.10
Strict	$ 1'249.24	$ 876.72	$ 1'298.42	$ 2'476.78	$ 1'485.79
Total general	**$ 1'461.30**	**$ 989.22**	**$ 1'432.48**	**$ 2'628.96**	**$ 1'616.69**

Analysis of average Airbnb revenues, broken down by high- and low-density areas and cancellation policies, reveals significant differences in revenue behavior. In low-density areas, average revenues show considerable growth between 2019 and 2022, going from $1,596.80 to

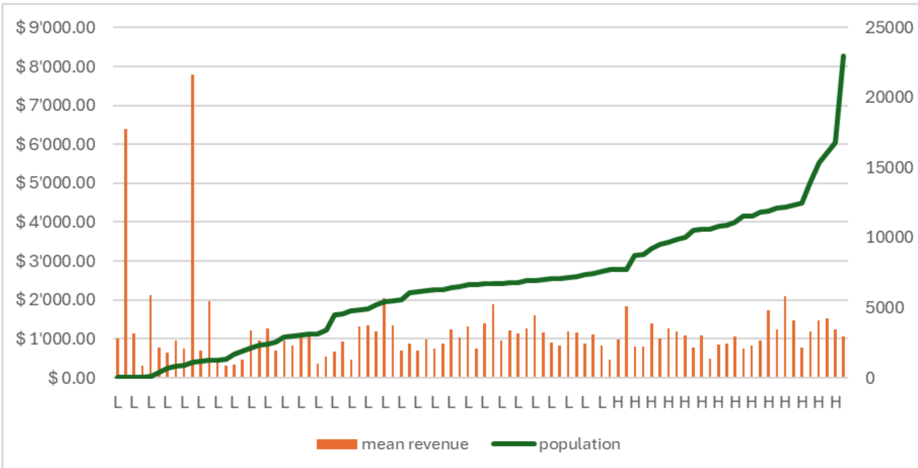
$2,742.48, representing an increase of 71.7%. Moderate and strict cancellation policies show higher revenues in this area, reaching averages of $1,774.63 and $1,738.08, respectively, over the entire period. Accommodations with flexible policies also increased their revenues, although at a slower pace, with an average of $1,430.85 over the entire period. In high-density areas, revenue growth was equally notable, though lower in comparison, with a 95.6% increase from $1,208.62 in 2019 to $2,364.28 in 2022. Within this area, listings with moderate cancellation policies also stand out, reaching an average of $1,512.10 over the full period, followed by strict policies with $1,485.79. Flexible policies in high-density underperformed, with a total average of $1,174.50.

Comparing the two densities, it can be seen that in low-density areas, Airbnb tends to generate higher average revenues, especially with moderate cancellation policies. In contrast, in high-density areas, revenues are more balanced between moderate and strict policies. Strict and moderate cancellation policies appear to be more profitable in both density types, suggesting a lower preference for flexibility in terms of cancellation in these areas.

4.1.3 Spatial Analysis

Figure 9

Average Airbnb revenues per grid based on population (km2)



The chart shows the variation in average Airbnb revenues in Lisbon for the years 2019-2022, comparing low and high-population-density areas. On the left vertical axis, the orange bars represent the average revenues in dollars, while the right vertical axis shows the amount of population per square kilometer, represented by the green line. On the horizontal axis, low-population-density areas are marked with the letter "L" and high-density areas with the letter "H".

In terms of revenues, it is noted that these are relatively low and constant in most low-density areas, with some exceptions where a considerable and punctual increase in average revenues is observed. These exceptions could be related to specific locations that, despite having low population density, have high-demand Airbnb properties, perhaps due to unique characteristics or their tourist appeal. As one moves into high-density areas, the pattern of average revenues shows greater variability, with some spikes. In general, they tend to remain in a similar range to low-density areas.

Population growth is gradual in high-density areas, especially at the end of the series, when the population experiences a considerable increase. This suggests that high-density areas tend to have a higher concentration of people and, possibly, a higher potential demand for Airbnb. However, this does not seem to translate proportionally into the level of average revenues.

A key insight is that, although high-density areas have a higher population, this does not always correlate with a significant increase in average revenues, which could indicate that additional factors, such as property supply, accommodation type, or seasonality, influence Airbnb revenues. It is also interesting to note that population concentration in high-density areas increases strongly towards the end of the series, which could represent a market opportunity to increase revenues in these areas if this growing demand is captured.

Figure 10

Population graph by grid (Km2)

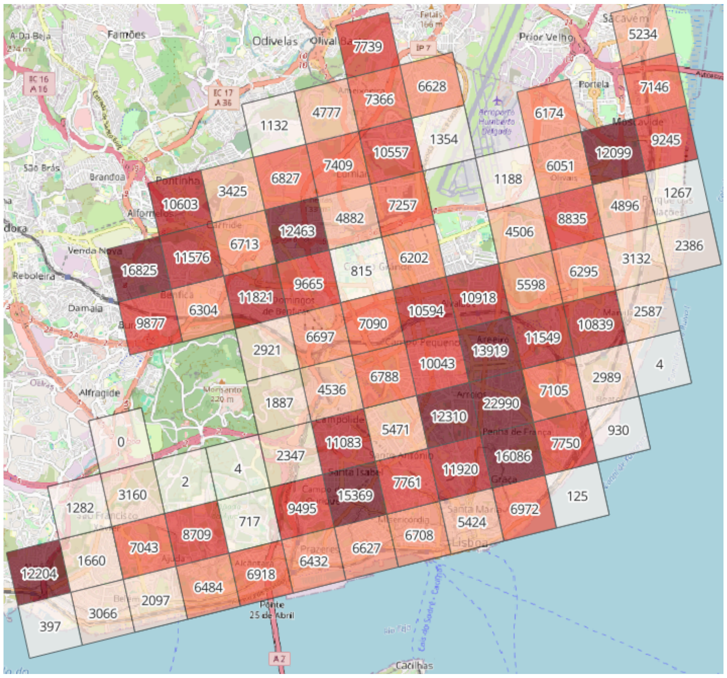
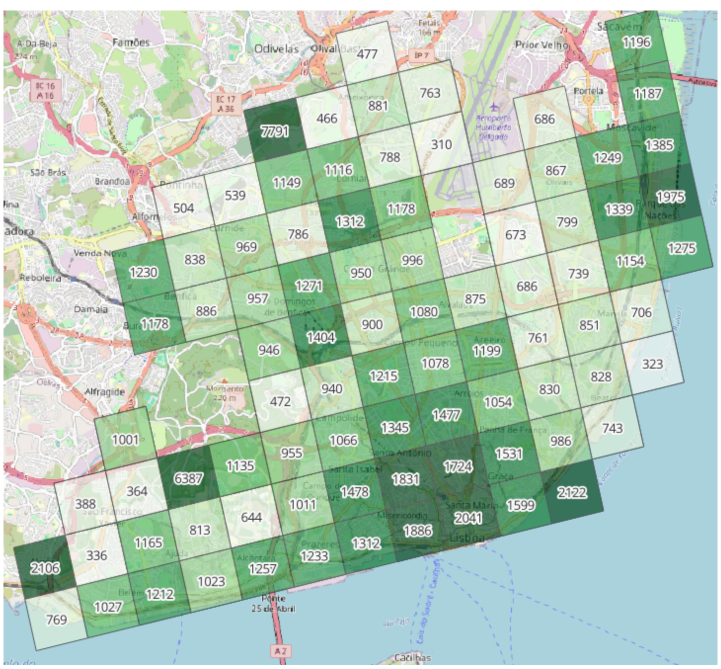


Figure 11

Graph of average Airbnb Revenue per grid (Km2)



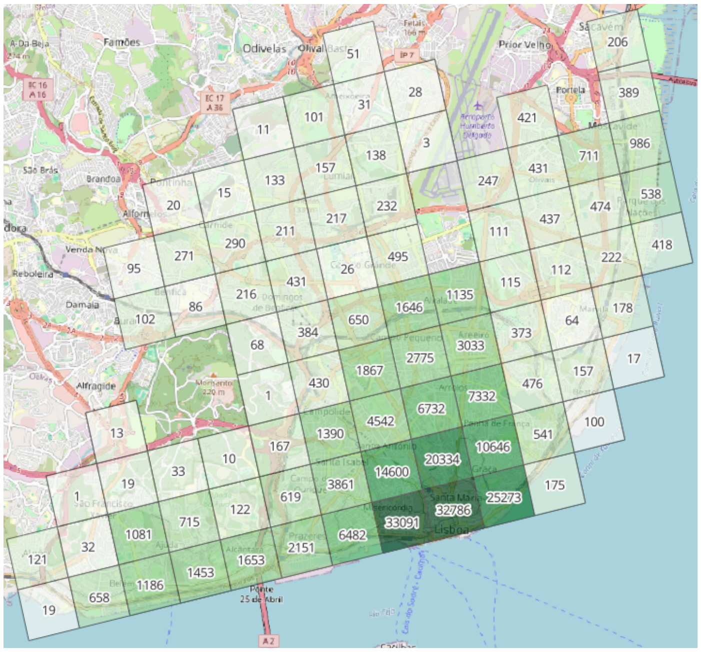
In the first map (Figure 10), which represents population density in Lisbon, areas with a high concentrations of inhabitants are shown in darker colors, especially in central and northern regions, while peripheral areas and some areas near the river show lower density, highlighted in lighter colors. In contrast, the second map (Figure 11) shows average Airbnb revenues, where the highest values are found mainly in areas near the river and in some central areas, but they do not correlate consistently with areas with higher population density.

Comparing both maps, it can be seen that in areas with population densities higher than 10,000 inhabitants per square kilometer (such as in certain central and northern areas of Lisbon), average Airbnb revenues do not always reach the highest values. This suggests that, although these areas have a high concentration of people, demand for Airbnb may be limited, or there may be a saturation of supply that lowers average revenues. In contrast, some areas with lower population density, especially those closer to the river and in the city center, show higher revenues, indicating that other factors, such as proximity to tourist spots or the exclusivity of the area, could influence the success of Airbnb.

An important insight from this spatial analysis is that high population density does not guarantee higher average revenues on Airbnb. Areas that combine moderate population density with tourist attractions or a prime location appear to be the most profitable. Therefore, a strategy focused on capturing demand in areas of low or moderate density but with tourist potential could be more profitable than focusing exclusively on areas of high population density.

Figure 12

Graph showing the number of Airbnb listings per grid (Km2)



It can be seen in Figure 12 that over the 4 years of the study period (2019 - 2022), the largest number of Airbnb hostels on offer was concentrated in the south of the city, mostly in the parishes of Santa Maria and Misericordia, places close to the south coast, and located within the historic center of the city. In the north of the city, in the parishes of Lumiar and Carnide, the number of Airbnb hostels on offer is comparatively lower. This could be related to a greater amount of tourist demand in the summer period when tourist consumers seeks central places close to the beach Finimize. (2024). However, compared to average incomes, the distribution is much less dispersed and does not follow a direct correlation; this could be related to characteristics such as the type of accommodation, or simply because there is little supply and therefore little competition, average earnings may be concentrated in these places that retain a considerable demand for those areas far from the center, which could give indications of investment opportunities. Likewise, the demand for places close to the eastern coast of Lisbon can also be seen in the average income graph. However, compared to the south coast, the eastern coast presents less market saturation, which, due to a lower amount of competition, could be a market opportunity.

4.2 Comparative analysis of averages

Table 14

Difference of means test for Airbnb by population density

Year	obs1 Low PD	obs2 High PD	Mean1 Low PD	Mean2 High PD	Diff	St Err	t value	p-value
2019	11178	5994	1596.798	1208.617	388.182	24.767	15.65	0
2020	53167	23201	1030.041	895.684	134.357	9.074	14.8	0
2021	34213	14251	1499.229	1272.219	227.01	16.202	14	0
2022	41146	17647	2742.482	2364.28	378.202	25.009	15.1	0

The analysis of the difference in means between high and low-population density areas in Lisbon for the years 2019-2022 indicates statistically significant differences in the average revenues from Airbnb in these areas. In each year, low population density (Low PD) areas have higher average revenues compared to high population density (High PD) areas. These differences are especially noticeable in 2019 and 2022, where the difference in means is $388.18 and $378.20, respectively. Across all four years, the p-value is zero, confirming the statistical significance of the differences in all comparisons for each year.

The observed trend shows that low-density areas tend to generate higher revenues on Airbnb than high-density areas. This could be related to the exclusivity or specific characteristics of these less dense areas, which could be more attractive to tourists looking for less crowding, or to the fact that the lower supply of properties in these areas allows for higher average prices. Furthermore, the stability of the differences across years suggests a consistent relationship independent of annual fluctuations that could be influenced by other factors (such as the pandemic in 2020).

An important insight from this analysis is that low-density areas have an advantage in terms of average revenues, which could guide investment strategies to maximize revenues on Airbnb. Furthermore, since the differences remain significant over the years, it seems that demand in these areas is not as affected by population density, and that other factors, such as location and area attractiveness, play a fundamental role in profitability.

4.3 Econometric analysis

4.3.1 Direct relationship of the Variable on the Revenues

This linear regression model on Table 15 analyses Airbnb revenues in Lisbon considering several variables including Instant booking, years, months of the year and specific listing characteristics such as number of rooms, photos, reviews and days blocked. The dependent variable "Lrevenue" represents the logarithm of Airbnb's revenues, allowing us to observe how these variables proportionally affect revenues.

Table 15

Linear regression model: Airbnb revenues in Lisbon effect of instant booking "inst_book"

Linear regression 1

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
inst_book	.303	.005	66.86	0	.294	.312	***
Years: 2019	0	.	.	.	.	.	
2020	-.445	.008	-52.40	0	-.461	-.428	***
2021	-.025	.009	-2.81	.005	-.043	-.008	***
2022	.694	.008	83.02	0	.678	.711	***
Month: base Jan	0	.	.	.	.	.	
Feb	.144	.01	14.07	0	.124	.164	***
Mar	.129	.01	13.13	0	.11	.149	***
Apr	.179	.011	16.72	0	.158	.2	***
May	.251	.011	23.59	0	.23	.272	***
Jun	.33	.01	32.46	0	.31	.35	***
Jul	.433	.01	44.30	0	.414	.452	***
Aug	.654	.009	70.12	0	.636	.673	***
Sep	.6	.009	64.00	0	.582	.618	***
Oct	.48	.01	46.46	0	.459	.5	***
Nov	.294	.011	27.12	0	.272	.315	***
Dec	.273	.01	26.21	0	.253	.293	***
max_guess	.128	.002	70.63	0	.125	.132	***
rooms	.04	.004	11.03	0	.033	.047	***
photos	.004	0	26.65	0	.004	.004	***
reviews	.001	0	36.32	0	.001	.001	***
bloq_days	-.05	0	-202.20	0	-.05	-.049	***
Constant	5.772	.012	492.52	0	5.749	5.795	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.409	Number of obs	200421
F-test	8986.169	Prob > F	0.000
Akaike crit. (AIC)	525384.436	Bayesian crit. (BIC)	525598.808

*** *p<.01, ** p<.05, * p<.1*

This linear regression model analyses Airbnb revenues in Lisbon, considering the effect of enabling "instant booking" (inst_book).

The significant positive coefficient for "inst_book" (0.303) suggests that enabling instant booking is associated with an increase in Airbnb revenues. This result implies that listings that allow instant booking tend to generate higher revenues, possibly because this system makes the booking process more streamlined and attractive for guests looking for convenience and speed. The magnitude of the coefficient indicates a considerable increase in revenues, suggesting that implementing this option may be an effective strategy for hosts who wish to maximize their revenues.

As for the temporal analysis, the year 2020 shows a decrease in revenues (coefficient of -0.445), reflecting the impact of the pandemic on tourism. However, for 2022, the model shows a significant recovery in revenues (coefficient of 0.694), possibly due to the recovery of tourism activity. The months variable also reflects seasonality, with increases in revenues during the summer months, especially in August (coefficient of 0.654). This suggests that demand for accommodation on Airbnb is particularly high in the summer season, which is typical for tourist destinations such as Lisbon.

The analysis of listing characteristics shows that listings with more rooms, photos, and reviews tend to generate higher revenues. This is logical since these factors can make the listing more attractive and visible to guests. On the other hand, blocked days ("bloq_days") have a significant negative impact on revenues (-0.05), indicating that lower availability reduces potential revenues.

With an R-squared of 0.409, the model explains approximately 41% of Airbnb revenues' variability, suggesting good explanatory power. However, it also indicates that other factors not considered in the model could influence revenues.

The use of instant booking appears to be an effective tool to increase hosts' revenues, and its implementation can be a key recommendation to improve the financial performance of listings. In addition, seasonality and specific characteristics of listings should be considered to maximize revenues, especially by taking advantage of summer demand. The recovery of revenues in 2022 signals a positive trend in the sector, and this analysis can help Airbnb hosts and managers in Lisbon optimize their strategies to adapt to demand trends and maximize the attractiveness of their listings.

Table 16

Linear regression model: Airbnb revenues in Lisbon effect of Cancellation policies "Cancel p"

Linear regression 2

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Cancel P: base flexible	0	.	.	.	.	.	
Moderate	.135	.006	23.29	0	.124	.147	***
Strict	-.016	.006	-2.65	.008	-.027	-.004	***
Years: base 2019	0	.	.	.	.	.	
2020	-.457	.009	-53.25	0	-.474	-.44	***
2021	-.05	.009	-5.53	0	-.068	-.032	***
2022	.652	.008	77.23	0	.636	.669	***
Month: base Jan	0	.	.	.	.	.	
Feb	.144	.01	14.00	0	.124	.164	***
Mar	.13	.01	13.15	0	.111	.15	***
Apr	.178	.011	16.53	0	.157	.199	***
May	.253	.011	23.64	0	.232	.274	***
Jun	.332	.01	32.39	0	.312	.352	***
Jul	.435	.01	44.28	0	.416	.454	***
Aug	.656	.009	69.68	0	.637	.674	***
Sep	.604	.009	63.93	0	.585	.622	***
Oct	.478	.01	45.83	0	.458	.499	***
Nov	.294	.011	26.89	0	.272	.315	***
Dec	.275	.011	26.22	0	.255	.296	***
max_guess	.136	.002	74.55	0	.132	.14	***
rooms	.028	.004	7.77	0	.021	.035	***
photos	.005	0	28.79	0	.004	.005	***
reviews	.001	0	38.35	0	.001	.001	***
bloq_days	-.05	0	-205.30	0	-.051	-.05	***
Constant	5.926	.012	482.21	0	5.902	5.95	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.399	Number of obs	200421
F-test	8275.052	Prob > F	0.000
Akaike crit. (AIC)	528935.451	Bayesian crit. (BIC)	529160.031

**** $p<.01$, ** $p<.05$, * $p<.1$*

This regression model examines how cancellation policies affect Airbnb revenues in Lisbon in conjunction with additional variables such as years, months, number of rooms, photos, reviews, and days blocked. The dependent variable "lrevenue" (logarithm of revenue) allows the coefficients to be interpreted in proportional terms to analyze how each variable influences Airbnb revenues.

The model uses the flexible policy as a basis for comparison regarding cancellation policies. The moderate policy has a significant positive coefficient (0.135), suggesting that opting for a moderate policy is associated with an increase in revenue compared to the flexible policy. This may indicate that guests are willing to pay more when the policy is somewhat stricter, probably due to the perception that the property has a higher value or a preference towards booking stability. On the other hand, the strict policy has a negative coefficient (-0.016), indicating a reduction in revenue compared to the flexible policy. This may be because guests find a strict cancellation policy less attractive and may avoid booking on these listings.

Regarding the temporal analysis, the negative coefficient for 2020 (-0.457) reflects the impact of the pandemic on revenues, while the positive and significant coefficient for 2022 (0.652) suggests a strong revenue recovery consistent with the rebound in tourist activity. A clear seasonality in revenues is also observed, with increases in the summer months, especially in August (coefficient of 0.656), which is expected in a tourist destination such as Lisbon.

Other variables related to listing characteristics, such as the number of rooms, photos, and reviews, are also significant and positive. These factors contribute to increasing revenues, probably because listings with more rooms and photos are perceived as higher quality or capacity, and positive reviews strengthen guest trust. Blocked days, on the other hand, have a significant negative effect (-0.05) on revenues, which is logical since they limit the property's availability and therefore reduce potential revenues.

With an R-squared of 0.399, the model explains approximately 40% of the variability in Airbnb revenues. This indicates that although the factors included are relevant, other elements that could be influencing revenues are not accounted for in this model.

The analysis reveals that cancellation policies have a notable impact on revenues. The moderate policy is more advantageous than the flexible and strict ones. In addition, seasonal factors and listing characteristics contribute significantly to Airbnb revenues in Lisbon, while the post-pandemic recovery and monthly variation highlight the importance of good pricing and availability planning.

Table 17

Linear regression model: Airbnb revenues in Lisbon effect of Population density "Pdensity"

Linear regression 3

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pdensity	-.179	.005	-39.43	0	-.188	-.17	***
Years: base 2019	0	.	.	.	.	.	
2020	-.453	.009	-53.11	0	-.47	-.437	***
2021	-.038	.009	-4.24	0	-.056	-.021	***
2022	.668	.008	79.49	0	.651	.684	***
Month: base Jan	0	.	.	.	.	.	
Feb	.144	.01	13.98	0	.123	.164	***
Mar	.131	.01	13.24	0	.112	.151	***
Apr	.18	.011	16.76	0	.159	.202	***
May	.253	.011	23.71	0	.233	.274	***
Jun	.331	.01	32.33	0	.311	.351	***
Jul	.435	.01	44.22	0	.415	.454	***
Aug	.655	.009	69.65	0	.637	.674	***
Sep	.603	.009	63.89	0	.584	.621	***
Oct	.478	.01	45.80	0	.457	.498	***
Nov	.293	.011	26.89	0	.272	.315	***
Dec	.274	.011	26.12	0	.254	.295	***
max_guess	.13	.002	71.15	0	.127	.134	***
rooms	.038	.004	10.61	0	.031	.046	***
photos	.005	0	29.08	0	.004	.005	***
reviews	.001	0	33.84	0	.001	.001	***
bloq_days	-.05	0	-204.26	0	-.051	-.05	***
Constant	6.04	.011	526.71	0	6.017	6.062	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.400	Number of obs	200421
F-test	8721.918	Prob > F	0.000
Akaike crit. (AIC)	528586.125	Bayesian crit. (BIC)	528800.497

**** $p<.01$, ** $p<.05$, * $p<.1$*

Regarding population density ("pdensity"), the significant negative coefficient (-0.179) indicates that areas with higher population density tend to have lower average revenues on Airbnb. This supports the previous finding that low-population density areas tend to generate higher revenues, probably because exclusivity and lower saturation increase their attractiveness to guests.

The temporal analysis shows that revenues decreased in 2020 (-0.453) compared to the base year 2019, which is consistent with the pandemic's negative impact on global tourism. However, in 2022, a significant increase in revenues is observed (coefficient of 0.668), which could reflect a recovery in Airbnb demand in Lisbon, possibly driven by the gradual reopening of tourism and increased interest in travel.

The coefficients for the months show a clear seasonality, with an increase in revenues during the summer months (particularly in August, with a coefficient of 0.655), suggesting a high tourist demand in this season. This seasonality is typical in tourist cities such as Lisbon, where summer usually attracts more tourists.

Furthermore, the characteristics of the listings also influence revenues. The number of rooms and photos has a positive impact, suggesting that listings with more rooms and more photos tend to generate higher revenues. This could be because these listings are more attractive or suitable for large groups. The number of reviews also has a positive effect, indicating that listings with more reviews can inspire trust and attract more bookings. On the other hand, blocked days ("bloq_days") have a significant negative coefficient (-0.05), suggesting that listings with more blocked days generate less revenues, which is logical since they are less available for bookings.

The model has an R-squared of 0.40, indicating that it explains 40% of Airbnb revenues' variability. Although not extremely high, this value suggests that other factors not captured in the model also affect Airbnb revenues.

A key insight from this analysis is that, in addition to location in low-density areas, hosts can optimize their revenues by adjusting factors such as the number of photos, the number of rooms, and the availability of accommodation. Furthermore, seasonality should be considered in pricing strategies, as revenues tend to be higher in summer. Finally, the recovery observed in 2022 shows a recovery in demand, which may represent an opportunity to strengthen the short-term rental market in Lisbon.

4.3.2 Interaction of population density and variables on Revenues

Table 18

Interaction of population density and instant booking "int_ib_dp" on revenue

Linear regression 4

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pdensity	-.187	.008	-22.56	0	-.203	-.171	***
inst_book	.293	.005	54.71	0	.282	.303	***
Int_ib_dp	.021	.01	2.18	.029	.002	.04	**
Years: base 2019	0	.	.	.	.	.	
2020	-.447	.008	-53.04	0	-.464	-.431	***
2021	-.029	.009	-3.25	.001	-.046	-.011	***
2022	.694	.008	83.59	0	.678	.71	***
Month: base Jan	0	.	.	.	.	.	
Feb	.143	.01	14.09	0	.124	.163	***
Mar	.129	.01	13.17	0	.11	.149	***
Apr	.18	.011	16.87	0	.159	.201	***
May	.25	.011	23.57	0	.229	.271	***
Jun	.329	.01	32.47	0	.309	.349	***
Jul	.432	.01	44.35	0	.413	.451	***
Aug	.654	.009	70.29	0	.636	.672	***
Sep	.599	.009	64.13	0	.581	.617	***
Oct	.478	.01	46.50	0	.458	.499	***
Nov	.293	.011	27.16	0	.272	.314	***
Dec	.271	.01	26.10	0	.251	.291	***
max_guess	.123	.002	67.62	0	.119	.126	***
rooms	.051	.004	14.02	0	.044	.058	***
photos	.004	0	26.91	0	.004	.004	***
reviews	.001	0	32.79	0	.001	.001	***
bloq_days	-.049	0	-201.35	0	-.05	-.049	***
Constant	5.844	.012	487.19	0	5.821	5.868	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.414	Number of obs	200421
F-test	8322.802	Prob > F	0.000
Akaike crit. (AIC)	523847.942	Bayesian crit. (BIC)	524082.730

*** *p*<.01, ** *p*<.05, * *p*<.1

This linear regression model examines how population density, instant booking, and the interaction between the two affect Airbnb revenues (represented as the log of Revenues). It also controls for additional factors such as years, months, listing characteristics, and other relevant elements.

Population density (pdensity) has a negative and statistically significant coefficient of -0.187, suggesting that, on average, listings located in high-density areas tend to generate lower revenues compared to those in low-density areas. This negative relationship could be explained by the high supply of listings in densely populated areas, which could lead to more intense competition and, consequently, lower prices.

The instant booking variable (inst_book) has a positive coefficient of 0.293, which is also significant. This indicates that listings that allow instant booking generate more revenue than those that require a prior reservation request. This may reflect guests' preference for the convenience and speed offered by this option, which could lead to these listings being booked more frequently.

The interaction between population density and instant booking (Int_ib_dp) has a positive coefficient of 0.021, albeit smaller but significant at the 5% level. This result suggests that in high-population-density areas, the instant booking option has an additional positive effect on revenues. This implies that hosts may benefit even more from offering the instant booking option in areas where competition is higher, probably because it helps differentiate the listing and attract guests looking for convenience in a saturated market.

In temporal terms, the model shows a negative impact on revenues in 2020 (-0.447) and a strong recovery in 2022 (0.694), consistent with the behavior of the tourism industry before, during and after the COVID-19 pandemic. Furthermore, a clear seasonality in revenues is observed, with significant increases in the summer months, especially in August (coefficient of 0.654), which is typical for tourist destinations.

Among other variables, the number of rooms and photos in the listing, reviews, and blocked days significantly affect revenues. In particular, blocked days have a considerable negative effect (-0.049), as they limit the property's availability for bookings. Meanwhile, the number of rooms and photos increases revenues, reflecting guests' perception of higher value and attractiveness.

With an R-squared of 0.414, the model explains approximately 41% of Airbnb revenues' variability, indicating that other factors not captured in the model could also influence revenues.

This analysis reveals that population density negatively impacts Airbnb revenues but that the instant booking option can partially mitigate this disadvantage, especially in areas with high density. Hosts in more saturated areas may benefit from offering instant bookings to improve their competitiveness and capture more revenue. Seasonal patterns and listing characteristics also play a significant role in revenue performance, suggesting that a well-thought-out listing availability and presentation strategy is crucial to maximizing revenue in this competitive market.

Table 19

Interaction of population density and cancellation policies "int_cp_dp" on revenue

Linear regression

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pdensity	-.188	.011	-17.04	0	-.209	-.166	***
Cancel P: base flexible	0	.	.	.	.	.	
Moderate	.121	.007	17.83	0	.107	.134	***
Strict	-.008	.007	-1.20	.228	-.022	.005	
Int_cp_pd: base flexible	0	.	.	.	.	.	
Moderate	.042	.013	3.27	.001	.017	.067	***
Strict	-.01	.013	-0.74	.459	-.035	.016	
Years: base 2019	0	.	.	.	.	.	
2020	-.459	.009	-53.80	0	-.476	-.443	***
2021	-.053	.009	-5.85	0	-.07	-.035	***
2022	.653	.008	77.87	0	.637	.67	***
Month: base Jan	0	.	.	.	.	.	
Feb	.144	.01	14.02	0	.124	.164	***
Mar	.13	.01	13.17	0	.111	.15	***
Apr	.179	.011	16.67	0	.158	.2	***
May	.252	.011	23.59	0	.231	.272	***
Jun	.331	.01	32.38	0	.311	.351	***
Jul	.435	.01	44.31	0	.415	.454	***
Aug	.655	.009	69.83	0	.637	.673	***
Sep	.602	.009	64.04	0	.584	.621	***
Oct	.477	.01	45.87	0	.457	.497	***
Nov	.293	.011	26.93	0	.271	.314	***
Dec	.273	.01	26.09	0	.253	.294	***
max_guess	.13	.002	71.38	0	.127	.134	***
rooms	.039	.004	10.83	0	.032	.046	***
photos	.005	0	29.06	0	.004	.005	***
reviews	.001	0	34.67	0	.001	.001	***
bloq_days	-.05	0	-204.41	0	-.051	-.05	***
Constant	5.99 6	.013	472.93	0	5.972	6.021	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.403	Number of obs	200421
F-test	7379.794	Prob > F	0.000
Akaike crit. (AIC)	527373.547	Bayesian crit. (BIC)	527628.751

**** $p<.01$, ** $p<.05$, * $p<.1$*

This linear regression model explores how population density, cancellation policies, and the interaction between the two factors affect Airbnb profits. It also controls for years months, and listing characteristics to capture the independent effects of each variable better.

Population density (pdensity) has a significant negative coefficient of -0.188, indicating that listings in areas with high population density tend to generate less profit than those in less dense areas. This suggests that, in densely populated areas, competition between listings is likely more intense, reducing average profitability.

Regarding cancellation policies, on average, listings with a moderate policy earn 12.1% higher profits than those with a flexible policy, as reflected by the significant positive coefficient (0.121). This suggests that guests value greater certainty when booking, preferring listings that do not have an overly permissive cancellation policy, which can be interpreted as greater security for hosts. On the other hand, the coefficient for the strict policy (-0.008) is not significant, suggesting that an overly restrictive policy has no clear effect on profits and might not be an effective strategy to increase profitability.

The interaction between population density and moderate cancellation policy (Int_cp_pd) shows a positive coefficient of 0.042, which is significant. This indicates that in high-density areas, a moderate cancellation policy has an additional positive effect on profits. This finding suggests that a moderate cancellation policy in high-competition locations can make listings more attractive to guests by offering a balance between flexibility and commitment, which could increase bookings and, consequently, profits. In contrast, the interaction between density and strict policy has no significant effect, reinforcing the idea that an overly rigid cancellation policy does not bring additional benefits in terms of profits, even in high-density areas.

Temporal effects are also noticeable in the model: the year 2020 has a significant negative impact, with a coefficient of -0.459, due to the COVID-19 pandemic, while the year 2022 shows a strong recovery (0.653), reflecting the reactivation of tourism. Likewise, the summer months present increases in revenues, especially in August, with a coefficient of 0.655, which is consistent with the seasonal demand in tourist destinations.

Among the other variables, the number of rooms, photos, and reviews have significant positive effects on revenues. This suggests that by improving the presentation and reputation of the listing, hosts can attract more guests and maximize their revenues. In addition, blocked days have a significant negative impact on revenues (-0.05), as they limit the availability of space for reservations.

With an R-squared of 0.403, the model explains about 40% of the variability in Airbnb listing revenues, indicating that other external factors may also be influencing revenues.

The analysis suggests that hosts in densely populated areas may benefit from opting for a moderate cancellation policy, which appears to be preferred by guests in these competitive contexts. The results indicate that excessive flexibility or rigidity are not optimal strategies for maximizing revenues in densely populated areas. This balance in cancellation policy, along with good listing presentation and optimization of listing availability, can help hosts improve their profitability in a saturated market.

Table 20

Interaction of population density vs instant booking "int_ib_dp" and cancellation policies "int_cp_dp" on revenue

lrevenue	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
pdensity	-.189	.013	-14.47	0	-.215	-.164	***
Cancel_p: base flexible	0	.	.	.	.	.	
Moderate	.112	.007	16.67	0	.099	.125	***
Strict	.012	.007	1.79	.074	-.001	.026	*
inst_book	.284	.005	52.64	0	.274	.295	***
Int_ib_dp	.015	.01	1.53	.126	-.004	.034	
Int_cp_dp: base flexible	0	.	.	.	.	.	
Moderate	.036	.013	2.87	.004	.012	.061	***
Strict	-.013	.013	-0.98	.325	-.038	.013	
Years (2019 - 2~2019	0	.	.	.	.	.	
2020	-.451	.008	-53.49	0	-.468	-.435	***
2021	-.04	.009	-4.52	0	-.058	-.023	***
2022	.681	.008	82.09	0	.665	.697	***
Month: base Jan	0	.	.	.	.	.	
Feb	.144	.01	14.12	0	.124	.163	***
Mar	.129	.01	13.12	0	.11	.148	***
Apr	.179	.011	16.78	0	.158	.2	***
May	.249	.011	23.47	0	.228	.269	***
Jun	.329	.01	32.52	0	.309	.349	***
Jul	.432	.01	44.42	0	.413	.451	***
Aug	.654	.009	70.42	0	.636	.672	***
Sep	.599	.009	64.25	0	.581	.617	***
Oct	.478	.01	46.55	0	.458	.498	***
Nov	.292	.011	27.19	0	.271	.313	***
Dec	.27	.01	26.08	0	.25	.291	***
max_guess	.123	.002	67.97	0	.12	.127	***
rooms	.051	.004	14.05	0	.044	.058	***
photos	.004	0	26.88	0	.004	.004	***
reviews	.001	0	33.55	0	.001	.001	***
bloq_days	-.049	0	-201.57	0	-.05	-.049	***
Constant	5.802	.013	440.66	0	5.776	5.828	***

Mean dependent var	6.831	SD dependent var	1.167
R-squared	0.416	Number of obs	200421
F-test	7126.150	Prob > F	0.000
Akaike crit. (AIC)	522996.784	Bayesian crit. (BIC)	523272.404

**** p<.01, ** p<.05, * p<.1*

This linear regression model analyzes the impact of population density, cancellation policies, instant booking, and their interactions on Airbnb listing revenues. By including these factors and their combinations, the model provides a more detailed view of how these elements affect hosts' revenues.

Population density (pdensity) has a significant negative coefficient of -0.189, suggesting that listings in densely populated areas generate less revenue, likely due to increased competition in these areas. This negative effect is important for hosts in saturated markets, who might need additional strategies to stand out.

Cancellation policies also influence revenues. Listings with a moderate policy have a positive coefficient of 0.112, indicating that these listings generate higher revenues compared to those offering flexible cancellations. This suggests that the moderate policy may offer a good balance for guests, providing security for both travelers and hosts. In contrast, listings with a strict policy show a slight positive coefficient (0.012) that is barely significant at the 10% level ($p<0.1$). This implies that a strict policy does not significantly increase revenues compared to a flexible policy, and hosts might not benefit significantly from this increased rigidity.

The instant booking option (inst_book) has a positive and highly significant impact on revenues, with a coefficient of 0.284. This suggests that the ease and speed of this option is attractive to guests and may increase demand for listings that offer it, resulting in higher revenues for hosts.

As for interactions, the interaction between population density and moderate cancellation policy (Int_cp_dp) is significant and positive, with a coefficient of 0.036. This indicates that, in high-density areas, the moderate policy has an additional positive effect on revenues, suggesting that this type of policy is well received in markets with high competition. However, the interaction between population density and strict policy is not significant, reinforcing the idea that this policy does not provide additional benefits in densely populated areas.

On the other hand, the interaction between population density and instant booking (Int_ib_dp) is not significant, implying that although instant booking alone is favorable, its impact is not amplified or reduced in high-density areas. This suggests that instant booking has an independent value that does not vary considerably depending on the density of the area.

Temporal effects, such as in years and months, are also consistent with seasonal patterns and the impact of the pandemic. The year 2020 presents a significant decrease in revenues due to COVID-19 (-0.451), while in 2022 there is a strong recovery (0.681). In terms of months, August is the most profitable month (0.654), reflecting a high demand for seasonal tourism.

Among the additional control variables, the number of rooms, photos, and reviews have significant positive effects on revenues, suggesting that better listing presentation and offering more amenities attract more guests. Blocked days, however, have a negative impact (-0.049), as they limit availability for new bookings.

With an R-squared of 0.416, the model explains 41.6% of Airbnb revenues' variability, which is considerable but also indicates that other factors not captured in the model may be influencing revenues.

The analysis suggests that hosts in densely populated areas could benefit from adopting moderate cancellation policies, as these balance flexibility and safety for guests. Instant booking is another effective strategy to increase revenues, regardless of population density. To maximize revenues, hosts should consider not only these policies but also improve the presentation and availability of their listings. This model offers strategic guidance on how hosts can adapt based on the market context to maximize their revenues.

Finally, to address the hypotheses raised, it can be stated that since the study models that include the instant booking variable and its interactions do not support hypothesis 1, it is refuted. Instead, the results suggest that the presence of instant booking is associated with higher average income in low-density population areas, in contrast to high-density areas. The positive coefficients of between 0.28 and 0.30 on Airbnb revenues in these areas indicate that instant booking was more effective in less dense areas, possibly due to travelers' preference for quieter and less crowded environments during the pandemic. This implies that, in situations of uncertainty, instant booking could be a more beneficial tool in low-density areas, which contradicts the original statement of the hypothesis. On the other hand, the results of the models that include the cancellation policy variable and its interactions are consistent with hypothesis 2. Compared to flexible policies, moderate cancellation policies are associated with higher average income in low-density population areas. Positive coefficients, ranging from 0.46 to 1.35, suggest that moderate cancellation policies generated a favorable effect on revenue in low-density areas. On the other hand, strict cancellation policies showed a limited impact on revenue: in some models, these policies are less significant, and in others, they are statistically insignificant with a P value >10. In all cases, strict policies have a negative coefficient, with values between -0.01 and -0.016 on revenue, indicating a negative effect on profitability at Airbnb.

The analysis shows that instant booking has a significantly positive effect in low-density areas, contrary to hypothesis 1. This finding suggests that travelers opted for less crowded destinations and that the ease of instant booking increased the attractiveness of these accommodations. Regarding cancellation policies, moderate policies in low-density areas effectively boosted revenue compared to high-density areas, supporting hypothesis 2.

5. DISCUSSION

The results obtained in this study on the impact of population density and Airbnb strategies during the COVID-19 pandemic present both similarities and differences with previous studies. On the one hand, the findings confirm the relationship between population density and resilience in crisis times, as previous research suggested (Cruz-Jiménez et al., 2022; Andrade & Kasent, 2020). In the literature, low-density areas have been perceived as safer and more attractive destinations during the pandemic, and this analysis reinforces this observation, showing how travelers preferred less dense areas, favoring recovery in these places.

In line with the studies by Storer (2022) and Pastor Ruiz and Rivera García (2022), this research indicates that flexibility in cancellation policies and the ease of instant booking were crucial factors in retaining travelers in times of uncertainty. However, the results suggest that these strategies' effectiveness varies according to population density, which extends the existing literature. Thus, it is observed that cancellation policies were more effective in low-density areas, while instant booking showed benefits in both areas, although to different degrees.

On the other hand, previous studies document Airbnb's resilience and its ability to adapt during the pandemic (Adamiak, 2023; Bresciani et al., 2021). The results of this thesis reinforce this perspective and demonstrate that the platform and its hosts in Lisbon managed to recover occupancy in low-density areas through adaptive strategies. This finding is consistent with previous research, which suggests that rental platforms can attract travelers in times of volatility thanks to the flexibility of their offers and policies.

Regarding practical implications, cities with areas of diverse population density can benefit from market segmentation that promotes low-density areas as safe and sustainable destinations in times of crisis. Promoting peripheral or rural areas can reduce pressure on densely populated areas and strengthen the resilience of the sector as a whole. In addition, flexible cancellation policies are key to attracting and retaining travelers in uncertain environments. Tourism authorities and rental platforms could coordinate to standardize policies that offer flexibility and security to travelers, highlighting these characteristics in the promotion of lower-density areas.

Finally, this study underlines the importance of sustainable and resilient tourism planning, especially in low-density areas. Urban and land-use planning policies should encourage the development and diversification of less dense areas, which could mitigate the effects of future crises and support more decentralized and ecological tourism.

6. CONCLUSIONS

In conclusion, the analysis of Airbnb earnings in Lisbon during the years 2019 to 2022 offers a detailed understanding of how population density strategies, cancellation policies, and instant booking options impact the financial performance of listings. The findings show that low-density areas tend to generate higher average revenues, which could be attributed to lower competition and a potential appeal to less saturated environments. Furthermore, moderate cancellation policies emerge as the optimal option to maximize earnings in both high- and low-density areas, offering a balance between flexibility and security. The instant booking option also stands out as an effective tool to increase earnings, particularly in more competitive markets, by facilitating a fast and convenient guest experience.

This study underlines the importance of considering contextual factors such as density and cancellation conditions when designing pricing and availability strategies in the short-term rental market. The results suggest that hosts could benefit from adapting their policies and optimizing the features of their listings, especially in peak seasons, to capitalize on demand. The 2022 recovery confirms the Lisbon Airbnb market's potential for growth, pointing to a resurgence in travel and creating chances for growth in less crowded locations. In a competitive and changing market, this research offers a strong foundation for strategic choices that assist in optimizing revenue.

7. REFERENCES

Adamiak, C. (2023). Cambios en la oferta de Airbnb durante la pandemia de COVID-19. Revista de Estudios Turísticos, 15, 1-15. https://ejtr.vumk.eu/index.php/about/article/download/3166/613/7140

Agência para a Modernização Administrativa. (2021). Distritos, concelhos, freguesias e heráldica de Portugal. Portal de dados abertos da Administração Pública. https://dados.gov.pt/pt/

Ahsan, M. M. (2020). Strategic decisions on urban built environment to pandemics in Turkey: Lessons from COVID-19. Journal of Urban Management, 9(3). https://doi.org/10.1016/j.jum.2020.07.001

Ahsan, M. M., & Sadak, C. (2021). Exploring housing market and urban densification during COVID-19 in Turkey. Journal of Urban Management, 10(2), 218-229. https://doi.org/10.1016/j.jum.2021.06.002

Airbnb. (2020, March 30). A letter to hosts. Airbnb Newsroom. https://news.airbnb.com/a-letter-to-hosts/

Airbnb. (2021, June 30). New Flexible Destinations feature now live to more easily find unique stays. Airbnb Newsroom. https://news.airbnb.com/unique-stays-hosts-earn-morethan-300-million-since-start-of-pandemic/

Airbnb. (2023, April 18). Cómo Airbnb dispersa los viajes en las principales ciudades de Europa. https://news.airbnb.com/es/como-airbnb-dispersa-los-viajes-en-las-principales-ciudades-de-europa/

Allan, R., Liusman, E., Lu, T., & Tsang, D. (2021). The COVID-19 pandemic and commercial property rent dynamics. Journal of Risk and Financial Management, 14(8), 360. https://doi.org/10.3390/jrfm14080360

Assembleia da República. (2012). Lei n.º 56/2012. Diário da República, 1.ª série, n.º 124, 29 de junho de 2012. https://www.diasri.gov.pt

Andrade, R., & Kasent, M. (2020). Comportamiento epidemiológico del COVID-19 en las entidades federativas de México. Semantic Scholar. https://doi.org/10.1101/2020.06.01.20120298

Benítez-Aurioles, B. (2018). Why are flexible booking policies priced negatively? Tourism Management, 67, 312–325. https://doi.org/10.1016/j.tourman.2018.02.008

Borgoni, G. (2023). Airbnb e strategie di riposizionamento: Un’analisi pre e post Covid-19 nella città di Roma (Tesi di laurea magistrale, Politecnico di Torino). http://webthesis.biblio.polito.it/id/eprint/29663

Bresciani, S., Ferraris, A., Santoro, G., Premazzi, K., Quaglia, R., Yahiaoui, D., & Viglia, G. (2021). The seven lives of Airbnb: The role of accommodation types. Annals of Tourism Research, 88, 103170. https://doi.org/10.1016/j.annals.2021.103170

Business Insider. (2023). Los hoteles se recuperan, aunque por debajo de los niveles prepandemia. https://www.businessinsider.es/hoteles-recuperan-aunque-debajo-niveles-prepandemia-967071

Casasnovas, M., Bagó, J., Abellan, R., Cousin, N., & Ricord, P. (2023). Portugal hotel market snapshot 2023. Retrieved from https://assets-eu-01.kc-usercontent.com/6bb3df3c-b648-01ae-2357-22fa5c7d5f19/93b732c7-e612-4890-88f4-31d2996a52eb/Portugal%20Hotel%20Market%20Performance%202023.pdf

Castanho, R. A., Couto, G., & Pimentel, P. (2022). Introductory chapter: Post-COVID tourism – Tendencies and management approaches – An introduction. In Post-COVID Tourism (pp. 1-18). IntechOpen. https://doi.org/10.5772/intechopen.87574

Chesky, B. (2020). A message from co-founder and CEO Brian Chesky. Airbnb News. https://news.airbnb.com/a-message-from-co-founder-and-ceo-brian-chesky/

Davis, A. M., & Gollust, S. E. (2023). Assessing COVID-19 pandemic policies and behaviours and their economic and educational trade-offs across US states from Jan 1, 2020, to July 31, 2022: An observational analysis. The Lancet, 401(10383), 157-169. https://doi.org/10.1016/S0140-6736(23)00461-0

Dogru, T., Mody, M., & Suess, C. (2019). Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets. Tourism Management, 72, 27–38. https://doi.org/10.1016/j.tourman.2018.11.008

Dogru, T., Mody, M., Suess, C., Line, N., & Bonn, M. (2020). Airbnb 2.0: Is it a sharing economy platform or a lodging corporation? Tourism Management, 78, 104049.

Drago, L. (2023). Effetti della pandemia di Covid-19 sulla customer base di Airbnb (Tesi de laurea magistrale, Politecnico di Torino). http://webthesis.biblio.polito.it/id/eprint/26551

D'Acunto, D., Tuan, A., Dalli, D., Viglia, G., & Okumus, F. (2020). Do consumers care about CSR in their online reviews? An empirical analysis. International Journal of Hospitality Management, 85, 102342. https://doi.org/10.1016/j.ijhm.2019.102342

European Commission. (2024.). Population grids. Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_grids

Exceltur. (2021). Impacto del COVID-19 y escenarios de recuperación para el sector turístico español. Esade EcPol Insight, 31. https://www.esade.edu/ecpol/wp-content/uploads/2021/07/AAFF_ESP_EsadeEcPol_Insight31_ImpactoTurismo_final2-1_compressed.pdf

Farmaki, A., Miguel, C., Drotarova, M. H., Aleksić, A., Časni, A. Č., & Efthymiadou, F. (2020). Impacts of Covid-19 on peer-to-peer accommodation platforms: Host perceptions and responses. International journal of hospitality management, 91, 102663. https://doi.org/10.1016/j.ijhm.2020.102663

Falk, M. T., Hagsten, E., & Lin, X. (2022). Domestic tourism demand in the North and the South of Europe in the Covid-19 summer of 2020. Annals of Regional Science, 69(2), 537–553. https://doi.org/10.1007/s00168-022-01147-5

Finimize. (2024, October 12). Portugal's record-breaking summer sees surge in tourist arrivals. Retrieved from https://finimize.com/content/portugals-record-breaking-summer-sees-surge-in-tourist-arrivals

Field, A. (2024). Discovering statistics using IBM SPSS statistics. Sage Publications.

Filieri, R., Milone, F. L., Paolucci, E., & Raguseo, E. (2023). A big data analysis of COVID-19 impacts on Airbnb's bookings behavior applying construal level and signaling theories. International Journal of Hospitality Management, 111, 103461. https://doi.org/10.1016/j.ijhm.2023.103461

Goerlich, J. M., & Cantarino, A. (2015). Estimaciones de la población rural y urbana a nivel municipal. Revista de Estadística, 57(186), 1-28. Retrieved from https://www.ine.es/ss/Satellite?blobcol=urldata&blobheader=application%2Fpdf&blobheadername1=Content-Disposition&blobheadervalue1=attachment%3B+filename%3Dart_186_1.pdf&blobkey=urldata&blobtable=MungoBlobs&blobwhere=393%2F264%2Fart_186_1%2C0.pdf

Gorzalek, J. A., & Sherif, J. (2020). Real estate markets in crisis: Post-COVID recovery strategies. Journal of Property Investment & Finance, 38(6), 473–491. https://doi.org/10.1108/jpif-05-2020-0047

Gujarati, D. N. (2004). Basic econometrics (4th ed.). New York: McGraw-Hill/Irwin.

Gyódi, K. (2021). Airbnb and hotels during COVID-19: different strategies to survive. International Journal of Culture, Tourism and Hospitality Research, ahead-of-printof(ahead-of-print). https://doi.org/10.1108/ijcthr-09-2020-0221

Gyódi, K., & Nawaro, Ł. (2021). Determinants of Airbnb prices in European cities: A spatial econometrics approach. Tourism Management, 86, 104319. https://doi.org/10.1016/j.tourman.2021.104319

Hoffmann, S. (2021). Challenges and opportunities of area-based conservation in reaching biodiversity and sustainability goals. Biodiversity and Conservation, 30(1), 1-24. https://doi.org/10.1007/s10531-021-02340-2

Hu, M. R., & Lee, A. D. (2020). Airbnb, COVID-19 risk and lockdowns: Local and global evidence. Coronavirus & Infectious Disease Research eJournal. https://doi.org/10.2139/ssrn.3589141

Hu, M. R., Lee, A. D., & Zou, D. (2021). COVID-19 and housing prices: Australian evidence with daily hedonic returns. Finance Research Letters, 101960. https://doi.org/10.1016/j.frl.2020.101960 iGMS. (2020, May 26). What Is Airbnb Instant Book and How to Use It Effectively iGMS. https://www.igms.com/what-is-instant-book-on-airbnb/

International Labour Organization. (2022). COVID-19 and sustainable recovery in the tourism sector: Technical meeting on COVID-19 and sustainable recovery in the tourism sector (Geneva, 25–29 April 2022). https://doi.org/10.1080/14649365.2022.2056542

Jacob, J. (2023). Review of Flick, Uwe (2020). Introducing research methodology: Thinking your way through your research project (3rd ed.). Qualitative Sociology Review, 19(2), 114–116. https://doi.org/10.18778/1733-8077.19.2.06

Jia, J., Jin, G. Z., & Wagman, L. (2021). Platform as a rule-maker: Evidence from Airbnb's cancellation policies (Working Paper No. 28878). National Bureau of Economic Research. http://www.nber.org/papers/w28878

Jelski, C. (2021). Airbnb says it beat its revenue projections for 2020. Travel Weekly. https://www.travelweekly.com/Travel-News/Hotel-News/Airbnb-says-it-beat-its-revenue-projections-for-2020

Kiczmachowska, E. E. (2022). The impact of the COVID-19 pandemic on peer-to-peer accommodation businesses: The case of Airbnb. Journal of Management and Business Administration. Central Europe, 30(2), 135-152. https://doi.org/10.22367/jem.2022.30.2.12

Lee, Y.-J. A., Jang, S., & Kim, J. (2020). Tourism clusters and peer-to-peer accommodation. Annals of Tourism Research, 83, 102960.

Li, C.-Y., & Tsai, M.-C. (2022). What makes guests trust Airbnb? Consumer trust formation and its impact on continuance intention in the sharing economy. Tourism Management, 93, 104-119. https://doi.org/10.1016/j.tourman.2021.104119

Li, X., & Zhang, C. (2021). Did the COVID-19 pandemic crisis affect housing prices evenly in the U.S.? Sustainability, 13(21), 12277. https://doi.org/10.3390/su132112277

Lütkepohl, H., & Xu, F. (2012). The role of the log transformation in forecasting economic variables. Empirical Economics, 42(3), 619–638. https://doi.org/10.1007/s00181-010-0440-1

Matamoros, L. Z., Sagaró del Campo, N., Valdés García, L. E., & Benitez Jimenez, I. (2020). Entrada de viajeros y densidad poblacional en la propagación de la COVID-19 en Cuba. Semantic Scholar. https://doi.org/10.1101/2020.06.01.20120298

Moriondo, M. (2021). Efectos del COVID-19 en el mercado de vivienda de Madrid (Tesis de maestría, Universidad Torcuato Di Tella). https://repositorio.utdt.edu/bitstream/handle/20.500.13098/11674/MEU_Moriondo_2021.pdf?isAllowed=y&sequence=1

Nagendra, H., Bai, X., Brondizio, E. S., & Lwasa, S. (2018). The urban south and the predicament of global sustainability. Nature Sustainability, 1(7), 341-349. https://doi.org/10.1038/s41893-018-0101-5

Nhamo, G., Dube, K., & Chikodzi, D. (2020). Impacts and implications of COVID-19 on the global hotel industry and Airbnb. En A. M. Becken & A. M. Stoeckel (Eds.), Counting the cost of COVID-19 on the global tourism industry (pp. 183-204). Springer. https://doi.org/10.1007/978-3-030-56231-1_82

Noya, L., & Comenge, R. (2020). COVID-19's impact on short-term rentals: The consumer perspective. Journal of Management Studies, 58(1), 15–30. https://doi.org/10.1111/joms.12654

Okafor, L., Usman, K., & Sasidaran, G. (2022). COVID-19 economic policy response, resilience and tourism recovery. Tourism Economics, 28(2), 321-343. https://doi.org/10.1016/j.tourman.2022.100786

Organización Mundial del Turismo. (2022). El turismo internacional se sitúa al 60% de los niveles anteriores a la pandemia en enero-julio de 2022. https://doi.org/10.18111/wtbarometeresp.2022.20.5.01

Ortenzi, G. P., Andrade, A. A. D., Facó, J. F. B., & Gasi, F. (2024). A Discussion About Strategies for Economic Recovery Post-COVID-19 Pandemic. International Journal of Advanced Engineering Research and Sciences. https://doi.org/10.22161/ijaers.116.4

Pastor Ruiz, R., & Rivera García, J. (2022). El rol de la agencia de viajes ante la nueva situación post Covid-19: Decálogo de propuestas para su recuperación. *PASOS. Revista de Turismo y Patrimonio Cultural, 20*(1), 55-68. https://doi.org/10.25145/j.pasos.2022.20.1.05

Peng, Y. (2020). The analysis of blocking behavior and pricing: The case of Airbnb. Business & Entrepreneurship Journal, 9(1), 1-28. https://doi.org/10.47260/bej/911

Pine, R., & Lam, T. (2020). Hotel quarantine for COVID-19: Perspective from a developing country. Journal of Tourism, 8(2), 231-248. https://doi.org/10.1002/jtr.11455

Raya, J. M. (2021). El impacto de la pandemia en el turismo: Modelos, estancias y mercado de alquiler. *EsadeEcPol.* https://www.esade.edu/ecpol/es/publicaciones/el-impacto-de-la-pandemia-en-el-turismo-modelos-estancias-y-mercado-de-alquiler/

Santos, M., Correia, A., Ribeiro, R., & Batista, F. (2022). What are Airbnb hosts advertising? A longitudinal essay in Lisbon. *Consumer Behavior in Tourism and Hospitality, 17*(3), 312-325. https://doi.org/10.1108/CBTH-10-2021-0253

Sevtsuk, A., Hernandez, D., & Peralta Quiros, T. (2021). Long-term effects of COVID-19 on tourism and hospitality. World Tourism Organization, 16(5), 26–47. https://doi.org/10.18111/9789284415310

Statista. (2024). Summer travel in Europe - statistics & facts. Retrieved October 28, 2024, from https://www.statista.com/topics/12400/summer-travel-in-europe/

Storer, J. N. (2022). A study of Airbnb in London: The effect of the COVID-19 pandemic on the strategies of hosts and the consequential impact on economic returns (Master's thesis, Politecnico di Torino). http://webthesis.biblio.polito.it/id/eprint/22883

Șolt, B. H. (2021). Changes in cities and urban services in the COVID-19 pandemic. International Journal of Management and Social Researches, 8(15), 218–229.

Sołtysiak, M., & Zając, D. (2024). Differences in the local residential real estate market in Poland depending on population density. *Real Estate Management and Valuation, 32*(2), 45-56. https://doi.org/10.2478/remav-2024-0015

Sutton, J., Shahtahmassebi, G., Ribeiro, H. V., & Hanley, Q. S. (2022). Population density and spreading of COVID-19 in England and Wales. *PLoS ONE, 17*(3), e0261725. https://doi.org/10.1371/journal.pone.0261725

Tanrıvermiş, H. (2020). Possible impacts of the COVID-19 outbreak on the real estate sector and possible changes to adopt: A situation analysis and general assessment from a Turkish perspective. Journal of Urban Management, 9, 263–269.

Uchehara, I., Hamma-Adama, M., Obiri, K. A., Jafarifar, N., & Moore, D. (2020). Impacts and risk management of the COVID-19 pandemic on the real estate supply chain. International Journal of Real Estate Studies, 14, 41–53.

Wilson, B.; Frew, J. (2007) "Apartment Rents and Locations in Portland, Oregon: 1992-2002", Journal of Real Estate Research, Vol. 29, No. 2

Wong, D. W. S., & Li, Y. (2020). Spreading of COVID-19: Density matters. *PLoS ONE, 15*(12), e0242398. https://doi.org/10.1371/journal.pone.0242398

Zeng, B., Carter, R. W., & De Lacy, T. (2005). Short-term perturbations and tourism effects: The case of SARS in China. *Current Issues in Tourism, 8*(4), 306–322.

Zeevou. (2024). Airbnb Instant Book: What hosts need to know. Zeevou. https://zeevou.com/blog/airbnb-instant-book-what-hosts-need-to-know/#1_Enhanced_Booking_Volume

Zhang, Z., Ye, Q., & Law, R. (2011). Determinants of hotel room price: An exploration of travelers' hierarchy of accommodation needs. *International Journal of Contemporary Hospitality Management, 23*(7), 972–981. https://doi.org/10.1108/09596111111167551