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# Airbnb and their performances in Milan

## Analysis of the performances of the Airbnb in Milan in relation with the distance from the "points of interest" pre, during and post Covid-19

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# 1. Introduction

The present study aims to analyze how the performance of Airbnb accommodations in the city of Milan is influenced by their proximity to various strategic points such as subway stations, parking areas, restricted traffic zones (ZTL), pedestrian areas, areas of degradation, and sports facilities. The idea to analyze these variables arose from identifying an academic gap regarding this topic in the Lombard capital.

To conduct this study, a dataset containing all the data related to various bookings and the characteristics of different accommodations between 2019 and 2022 was utilized. Additionally, other external datasets were acquired from the Milan city website regarding the aforementioned points of interest. Subsequently, with the assistance of Python and Excel, distances from strategic points for each accommodation were calculated and the listings were divided into different ranges. Finally, all this information was consolidated into a single database used for analysis.

Initially, through descriptive analyses regarding both the population and the performance of accommodations in different ranges, trends for each category of interest were examined, beginning to understand the various relationships linking performance with distances. Univariate and multivariate regression analyses were then conducted to further investigate the relationships found in the previous study, also examining the significance of the various econometric models studied.

The results obtained from this research are significant and can be useful for better understanding the dynamics of the Airbnb market in the city of Milan. This study could prove valuable to different hosts, who may adapt their strategies to maximize the performance of their accommodations.

# 2. Literature review

## 2.1. Sharing economy

The sharing economy, also known as collaborative consumption, is an economic model based on the sharing of resources among individuals, often facilitated by digital platforms. The first peer-to-peer sales website was launched in the mid-1990s when eBay introduced online offerings among consumers. One of the main features that distinguishes this type of economy is the ability to rent, share, or exchange goods and services among individuals without the need to directly own them, thereby facilitating a more efficient use of available resources.

The main business models within this framework are:

- **P2P:** peer-to-peer, a decentralized approach where two individuals collaborate to exchange goods and services directly between them or work together in their production, without the need for a third-party intermediary or the use of an incorporated company or business.
- **B2C:** business-to-consumer, indicating the practice of directly selling products and services between a company and end consumers, those who directly use such products or services.
- **B2B:** business-to-business, referring to transactions between businesses, such as between a manufacturer and a wholesaler or between a wholesaler and a retailer.
- **O2O:** online-to-offline commerce is a business strategy guiding potential customers from online channels to purchase at physical stores.

This concept emerged in response to growing concerns about resource exploitation and the environmental impact of traditional economies based on buying and owning. It has been positively received for its ability to reduce waste and promote a more sustainable lifestyle. However, there are also concerns related to unfair competition, lack of regulation, and social and economic impacts, such as the precarious nature of work for service providers on some platforms.

Regulatory challenges and debates on economic justice have been fundamental in the evolution of the sharing economy. Regulatory approaches vary from country to country, and many cities have introduced specific rules to regulate sharing economy activities to protect consumers and ensure that service providers adhere to certain standards.

The sharing economy continues to evolve and influence various economic sectors, representing a significant part of modern economic innovation. This model has attracted the attention of traditional businesses and academic researchers in recent years, generating various definitions, explanations, and evaluations of its economic, social, and environmental impacts.

Among these studies, one of the most significant was Rachel Botsman's, whose definition of the sharing economy was used in various studies to predict its success before its widespread adoption. Rachel explains how the sharing economy can be defined as an economic system based on the sharing of underutilized resources or services, either for free or for payment, directly among individuals using online platforms. (Botsman R., 2010)

The advent of the Internet, particularly smartphones with GPS capabilities and access to numerous applications, significantly contributed to the development of the sharing economy (Belk, 2010). The sharing economy was officially included in the Oxford Dictionary glossary, defining it as "an economic system in which goods or services are shared among individuals, either for free or for payment, typically via the Internet."

The growth and impact of this model have changed the perception of various industries, generating billions of dollars in the last seven years. PricewaterhouseCoopers (PwC) estimated its growth in the five main sectors:

- **Transportation**
- **Retail of consumer goods**
- **Short-term rentals**
- **Entertainment**
- **Finance**

Estimating that by 2025, the aforementioned sectors could represent $335 billion in revenues worldwide. Furthermore, Forbes predicts that the income flowing directly

through this economy into people's pockets will exceed $3.5 billion, with a growth rate of over 25% (Roh, T. H. 2016).
As early as 2011, the American newspaper Time Magazine expressed the view that the sharing economy would be one of the "10 ideas that will change the world."

Three main factors are recognized as driving people to embrace the sharing economy:

- **Economic:** The economic motive plays a significant role in the decision to participate in the sharing economy, aided by the decrease in consumer wealth. This factor has made people more open to the idea of sharing goods and services, effectively monetizing unused inventory and cutting costs.
- **Social:** Being connected and interacting with one another makes the sharing economy more effective. Sharing initially starts within one's personal network of family and close friends, but technological advancements open up opportunities for sharing among strangers.
- **Environmental:** as people begin to share, they learn to optimize unused and underused resources, reducing production costs and waste, leading to higher environmental sustainability.

Simultaneously, the concept of the sharing economy has become a subject of debate. One perspective suggests that the sharing economy has the potential to reduce environmental impact by utilizing underutilized resources, promoting social cohesion through digital technology, and stimulating entrepreneurship. Supporters argue that it can address challenges posed by economic recessions, government austerity measures, increasing socioeconomic disparities, and environmental concerns linked to consumption.
Despite efforts by sharing organizations to follow a path of sustainability, this model and its impacts face growing criticism. The sharing economy is seen as a threat to professionalism, public safety, privacy, health, and labor rights. There are concerns about its potential to encourage increased consumption and subsequent environmental impact. The rapid expansion of services provided by multinational platform giants like Airbnb and Uber has caught governmental authorities off guard, leaving them unprepared for imminent challenges. Consequently, numerous national and local administrations have initiated processes to regulate sharing economy practices.

## 2.2. The Airbnb Case:

### 2.2.1. The History:

An exemplary success story in the sharing economy is Airbnb, an innovative home-sharing startup founded in 2007 by Brian Chesky and Joe Gebbia. The idea sparked during a meeting of the Industrial Designer Society of America in San Francisco when hotels were fully booked. This prompted the brilliant idea of renting a part of their apartment to those who were unsuccessfully seeking accommodation.

In March 2008, "Airbed & Breakfast" was officially launched, securing two bookings during the SXSW festival. In August of the same year, the website was launched coinciding with the US Democratic National Convention, receiving 80 bookings. During that period, Payments, a customized platform for transactions, was introduced. Between 2008 and 2019, it processed transactions totaling approximately $70 billion between guests and hosts, across more than 40 different currencies.

In March 2009, the name was officially changed to Airbnb, expanding the offerings from single rooms to entire apartments and houses.

In November 2010, the first app was launched, featuring an instant booking function.

In 2011, the first office outside the United States was opened in Germany. Airbnb also announced reaching the milestone of one million nights booked. Around a year later, in January 2012, this number had grown to 5 million, and just a few months later, by June 2012, the milestone of 10 million nights booked was surpassed.

In July 2015, the famous logo still in use today was introduced.

*Figure 2.1 Airbnb logo*

In December 2020, Airbnb went public.

Currently, over 500 million nights have been booked, a significant indication of the ongoing evolution in the short-term rental market (The Undisrupted Growth of the Airbnb Phenomenon). To date, the following data has been collected:

- More than 7 million active listings
- 100,000 destinations with active listings
- Presence in over 220 countries
- Over 1.5 billion total check-ins completed
- Over 4 million hosts
- Over $180 billion earned in total
- $7 billion in taxes collected and remitted globally

Airbnb connects two main categories of users: hosts and guests.
Here's an overview of both categories:

## Hosts:

Hosts are individuals who offer their homes, apartments, rooms, or other properties to be rented through Airbnb. They might be property owners, tenants with landlord permission, or managers of structures such as bed and breakfasts or vacation homes. Their responsibility involves creating listings for their properties on the platform, providing details on the accommodation type, rates, house rules, and images. They can customize the listing according to their preferences.
Additionally, hosts oversee welcoming guests, including the check-in process, providing information about the accommodation and the surrounding area, and resolving any issues or questions during the guest's stay. Hosts can interact with guests at various levels, depending on the preferences of both parties.

## Guests:

Guests are individuals seeking temporary accommodation during their travels. They can be tourists, business travelers, students, or anyone in need of a place to stay. They use the Airbnb platform to search for accommodations that meet their needs. They can filter options based on criteria like location, budget, host reviews, and accommodation features. They book their desired accommodation through the platform and make payments through Airbnb's secure system, which holds the payment until after check-in to ensure guest satisfaction.

After their stay, guests have the opportunity to leave reviews about the accommodation and their experience with the host. These reviews are essential for the Airbnb community as they assist other guests in finding accommodations. Positive reviews also make hosts more appealing to future clients.

Airbnb offers a variety of accommodation types to meet diverse needs and preferences. Here are the most common types:

- **Apartments:** Self-contained living units varying in size from studios to larger multi-bedroom units. Apartments offer space and privacy and can be rented for short or long stays.
- **Vacation Homes:** Often complete accommodations like houses or villas, ideal for larger groups or families. These lodgings may include gardens, pools, or other recreational facilities.
- **Lofts:** Open and modern spaces often featuring high ceilings, large windows, and contemporary design.
- **Private Rooms:** In some homes, hosts rent private rooms to guests, allowing them to share accommodations with the owner or other guests. This is a more cost-effective option compared to renting an entire apartment.
- **Unique Lodgings:** Airbnb also offers a wide range of unique accommodations such as castles, treehouses, caravans, boats, houseboats, and caves. These options provide unusual and memorable lodging experiences.

### 2.2.2. Airbnb Business Model:

As a revolutionary innovation in the tourism industry, Airbnb offers an original business model based on modern internet technologies, focusing on cost savings, home comfort, and the opportunity to experience more authentic local experiences (Gutierrez et al., 2016; Guttentag, 2013).

Unlike other companies acting as intermediaries between businesses and consumers for travel-related bookings, such as Expedia, Bookings.com, or Tripadvisors.com, Airbnb's business model is based on direct contact between individuals offering rooms for payment (often at convenient rates) or even for free (as seen in Couchsurfing).

To summarize Airbnb's business model, the table below illustrates the key elements of the project:

| Key Partners | Key Activities | Value Proposition | Customer Relationship | Costumer Segments |
|---|---|---|---|---|
| Investors,<br>Online payment providers<br>Local Photographers | Online Platform provider<br>Maintenance and upgrade of system<br>Marketing Advertisement<br>Community Management<br>Predictive Algorithm | Monetize underutilize resources<br>Trusted community | 24/7 Support Team<br>Secure customer transaction<br>Ease of use website/app | Business and Leisure Travelers<br>Residential Owners |
| | **Key Resources** | | **Channels** | |
| | Platform<br>Host Listings | | Website, App and social media<br>Advetising<br>eWord of Mouth | |
| **Cost Structure** | | **Revenue Streams** | | |
| Online Payment<br>Development and maintenance of Platform<br>Insurance<br>Government related expense | | Guest Booking Fee 6 to 12%<br>Host Booking Fee 3% | | |

*Figure 2.2 Airbnb's business model*

This project has become the foremost pioneer of shared lodging by bridging the persistent room supply shortage. Airbnb has transformed the way people experience travel, offering the chance to feel at home away from home and to connect with the local community (Chua, E. L., Chiu, J. L., & Bool, N. C. 2019).

Its vision is to assist the community in earning money flexibly and contribute to strengthening local economies. Additionally, Airbnb offers innovative solutions to consumers by providing an online platform to access its community.

The entry of this company has disrupted the operations of the hospitality industry, becoming a significant threat to the pre-existing business model. Presently, Airbnb has, in fact, surpassed the largest hotel chains in terms of the number of rooms (Chappex,

2016) and currently holds a valuation twice that of Hilton Worldwide Holdings and Marriott International.


*Figure 2.3 Idexed sales for Airbnb vs Hotel industry*

According to Reuters in 2016, the company's valuation could reach around 30 billion dollars in the coming years, making it the fastest-growing company (even without actually owning any rooms).

Despite its growth, the impact of the disruption is still vague and unquantifiable as they act as intermediaries with limited capital costs.
Another technique recently adopted by key market players is "dynamic pricing," a revenue management strategy involving the continuous adjustment of rates based on supply and demand conditions (McGuire, 2015). Dynamic pricing originated and developed in the airline industry but has been subsequently applied in various industries, including hotels (Mauri, 2012). Airbnb's offering shares many necessary characteristics for applying dynamic pricing, such as perishability, fixed capacity, seasonality, wide demand-supply equilibrium oscillations, market segmentation, and cost structure primarily composed of fixed costs (Ivanov & Zhechev, 2012). However, dynamic rate management requires time, resources, capabilities, infrastructure (like software), benchmarking activities (competitive analysis based on sound business data), demand forecasting abilities (Kimes, 2011), a deep understanding of the destination, and the capacity to change seasonal periods, for instance, by organizing new special events during

low-traffic periods. Consequently, hotels unsurprisingly use dynamic pricing more extensively compared to Airbnb hosts (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018b). In the sharing economy context, some studies have found a positive correlation between the degree of professionalization and the adoption of dynamic pricing (Koh, Belarmino, & Kim, 2019; Kwok & Xie, 2019; Magno, Cassia, & Ugolini, 2018; Oskam, van der Rest, & Telkamp, 2018). It's challenging to understand how the number of listings rented can improve the hosts' skills or whether the higher costs associated with the dynamic pricing approach are justified. Professional hosts are defined based on the number of listings they manage, and the threshold of one is usually used to distinguish between a single-listing host and a multiple-listing host. The latter are termed "professional" or "commercial." In some studies, professional hosts are further divided into additional categories.

For example, a study (Sainaghi & Baggio, 2021) on the level of competition between Airbnb listings and hotels divided hosts into five categories:

- **Single listing**
- **Two listings**
- **Three listings**
- **Four to ten listings**
- **More than ten listings**

Although the study does not identify any competition between Airbnb and hotels, empirical results reveal significant differences in terms of the degree of professionalization. The distinction between individual and commercial hosts is meaningful. In fact, empirical results show that the listings of professional hosts exhibit lower prices but higher revenues, suggesting that professional providers are more income-oriented than focused on maximizing the ADR (Dynamic pricing in Airbnb: Individual versus professional hosts).

Like any business, we can distinguish some sources of cost and profit for Airbnb. The primary ones identified are:

## Cost Sources:

- **Attracting New Hosts:** Airbnb must invest in attracting new hosts to the platform. These costs may involve advertising campaigns, financial incentives, and promotions aimed at encouraging new host registrations.

- **Marketing and Advertising:** Airbnb invests in online advertising, sponsorships, and promotions to attract guests to the platform, increasing the service's visibility and popularity.

- **Technological Development:** Airbnb must continually improve and maintain its platform, ensuring it is intuitive and secure for users. This involves expenses for website development and ongoing application updates.

- **Operational Support:** Airbnb provides customer service and support to both hosts and guests, ensuring a positive user experience. These services require financial resources.

- **Maintenance and Property Support:** Hosts are responsible for property maintenance and cleaning. However, in case of severe issues or damages, Airbnb might be involved in the resolution costs.

- **Compliance:** In some jurisdictions, Airbnb faces costs associated with compliance with local regulations, including taxes and licenses.

## Revenue Sources:

- **Booking Fees:** Airbnb earns a percentage of the total booking fee made through the platform. The percentage varies depending on whether it's a host fee (between 3% and 5%) or a guest fee (between 6% and 14%).

- **Additional Service Fees:** Airbnb offers a range of extra services like cleaning services, airport transfers, and local experiences. The platform also earns a commission on these additional services.

- **Local Taxes:** In certain locations, Airbnb collects and remits local or regional taxes on bookings to the relevant tax authorities.

- **Long-Term Rentals:** Airbnb can also earn from hosts offering long-term rentals through the "Airbnb Long Term" program.

- **Service Fees:** Airbnb has introduced service fees, which are added to the total cost of a booking and contribute to the company's revenues.

- **Business Collaborations:** Airbnb partners with commercial associations and companies to provide special deals and promotions to users, receiving a commission or compensation based on the agreements.

### 2.2.3. A taxation problem:

Taxation and regulation have posed significant challenges for platforms like Airbnb. As Airbnb rapidly expanded globally, governments struggled to regulate the sector and tax hosts' profits consistently. The innovative nature of Airbnb, distinct from traditional accommodation industries, made it difficult to classify for taxation purposes.

In Italy, the approach to taxing Airbnb hosts' profits has evolved over time. Initially, a flat tax of 21% was applied to short-term rental income starting in 2017, regardless of personal income brackets. Although not explicitly targeting Airbnb, this tax affected all short-term rental income. Subsequently, in 2020, a new regulation stipulated that landlords renting more than four residential units would be classified as businesses and subject to business accounting and tax rules.

Proposed legislation in the Italian parliament aims to further regulate short-term rentals. The bill includes measures such as requiring a minimum stay of 2 nights for Airbnb rentals, reducing the threshold for business taxation from four to two listings, and mandating safety requirements equivalent to those for hotels.

Different countries have adopted varied taxation rules for hosts operating within their borders, posing challenges for hosts managing multiple listings across regions. In 2022, Airbnb reported collecting over $7 billion in taxes, with predictions of increased tax revenue as regulations tighten and the number of listings grows.

## 2.3. Effects of COVID-19:

Airbnb listings are more prominent in America, Europe, and the Far East. A sixth of the global supply is found in the United States, the platform's home country. Among European countries, France, Italy, Spain, the United Kingdom, and Germany are the most prominent platform markets. China, Brazil, Mexico, and Australia complete the list of the top ten countries. In contrast, countries in Africa (with the exception of South Africa) and central and southwestern Asia show a lower number of offerings. In all considered countries, the supply of Airbnb rentals grew until 2019. The pandemic led to a differential reduction in offerings in individual countries, such as in Italy and Spain, while in some countries like Brazil and Russia, the supply continued to grow in 2020 despite the pandemic context.

Businesses in the hospitality sector that managed to survive the COVID-19 crisis were forced to innovate. The triangle business model identifies ten main changes. The key elements of the business model are value proposition, value creation, and value capture (Clauss, 2016; Clauss, Abebe, Tangpong & Hock, 2021). For each element or component, the main changes to the business model triggered by the COVID-19 pandemic are discussed.

The value proposition refers to the set of solutions offered to customers (Johnson, Christensen & Kagermann, 2008). During the COVID-19 pandemic, the value proposition underwent four main changes:

- Hotels transformed into office spaces during lockdowns.
- The hospitality sector offered various new and innovative products and services.
- Accelerated digitalization of hospitality services.
- Hotels were used as quarantine facilities to isolate potentially infected individuals from the COVID-19 virus.

Value creation refers to the entire business's value chain characterized by its capabilities (Achtenhagen, Melin, & Naldi, 2013). During the pandemic period, value creation changed in at least three ways. Firstly, new procedures and certifications were introduced to ensure safe operations in the hospitality sector. Secondly, businesses in the hospitality sector reduced their capacity and increased the quality of their services. Thirdly, employment in the hospitality sector drastically changed due to the devastating effects of the COVID-19 crisis.

Value capture allows the company's value proposition to translate into revenues (Clauss, 2016). Business models in the hospitality sector underwent three major changes during COVID-19. Firstly, there was a stronger focus on domestic tourism compared to international tourism. Secondly, increased flexibility was introduced for cancellations and changes to travel arrangements. Thirdly, higher-quality and more personalized services were offered.

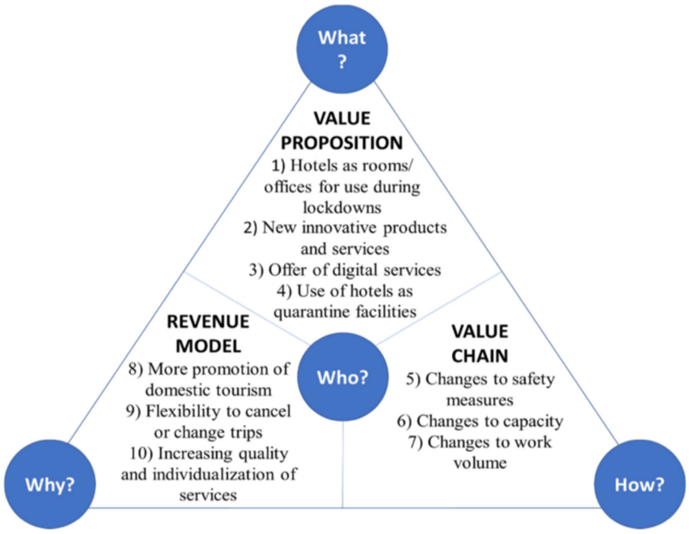



*Figure 2.4 The effect of COVID-19 in the hospitality sector*

Following the onset of the pandemic, new protocols and certifications were introduced to ensure safety within the hospitality sector. Hotels committed to adopting measures to keep their guests safe and healthy. Contact points are cleaned and disinfected more frequently, while public spaces are regularly ventilated. Many hotels require guests to complete health check forms and conduct temperature checks upon entry. Moreover, the number of guests in enclosed spaces is limited to ensure social distancing, and sanitizers are available for guest use in all public areas. Within Airbnb accommodations, hosts can obtain the 'Cleaning Protocol' certification, which includes training on preparing the lodging for guests. This training provides information on preventing COVID-19 infections, such as the use of masks and gloves by hosts and cleaners, as well as the use of appropriate disinfectants and cleaning materials.

Another significantly altered aspect due to the arrival of COVID-19 has been the reservation cancellation policy; many hotels updated their change and cancellation policies to make them more flexible in response to the crisis brought on by the pandemic (The key changes to the hospitality business model under COVID-19).

The COVID-19 pandemic has had an unprecedented negative impact on the global tourism and hospitality industry. According to UNWTO (2021), international tourist arrivals decreased by 74% between 2019 and 2020. Airbnb (www.airbnb.com), which has become synonymous with lodging sharing, was not an exception to this trend: around 1,800 employees were laid off by November 2020 due to a 72% revenue decrease since the start of the pandemic (Abril, 2020). However, as a company, Airbnb demonstrated resilience during the pandemic with a successful Initial Public Offering (IPO) on December 10, 2020 (Sonnemaker, 2020), and had approximately 6 million active listings in over 100,000 cities worldwide by December 31, 2021 (Airbnb, 2022).

Across many European countries, the COVID-19 pandemic had varying effects in terms of the timing and intensity of different pandemic waves and government countermeasures (national, regional, and/or local), such as travel restrictions, lockdowns, or other precautionary actions (e.g., ECDC, 2022). Consequently, demand variations during the pandemic affected individual Airbnb hosts in Europe differently, depending on various factors operating from a country-level (i.e., aggregate perspective) down to a neighborhood level (i.e., disaggregated perspective). This heterogeneity necessitates a detailed listing-level analysis of the effects of these demand variations on prices and revenue generation. Additionally, assuming that commercial hosts (i.e., hosts managing three or more properties in the specific base) (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Dogru, Mody, Suess, Line, & Bonn, 2020; Gunter & Onder, 2018) adopt a more sophisticated managerial approach than private hosts (Li, Moreno, & Zhang, 2016), this higher degree of professionalism might have made commercial hosts more resilient during the pandemic and could have contributed to the aforementioned heterogeneity.

The COVID-19 pandemic significantly impacted the Airbnb lodging market and the hospitality industry as a whole:

**1. Cancellations and Booking Reduction:** Due to travel restrictions and lockdown measures, many individuals canceled or postponed their Airbnb reservations, leading to a significant decrease in short-term lodging demand.

**2. Decrease in Tourism:** Travel restrictions, contagion-related anxiety, and social distancing practices have resulted in an overall reduction in tourism. Tourist destinations, in particular, experienced a decline in demand for Airbnb accommodations.

**3. Adaptation of Offerings:** To cope with the situation, some Airbnb hosts introduced discounts, promotions, or alterations to their facilities. Some focused on thorough cleaning of the premises.

**4. Safety and Hygiene Standards:** Airbnb introduced new guidelines to ensure the safety of hosts and guests. These directives included recommendations for more thorough lodging cleaning and the implementation of safety measures.

**5. Changes in Business Models:** Some hosts adjusted their business models, shifting towards long-term rentals rather than short-term ones. This change was partly driven by the increasing demand for longer-term accommodations during lockdown periods.

**6. Regional Variations:** The impact of COVID-19 on the Airbnb market differed, with significant variations across regions. In some areas, there was a gradual recovery in bookings with the relaxation of restrictions, while in others, the sector continued to struggle with a lack of tourists.

It's important to note that the situation is evolving and dynamic. The progress of the vaccination campaign and improvements in health conditions have allowed the tourism sector, including hotels and Airbnb, to adapt and recover, leading to a return to growth in terms of numbers and performance as it was before the pandemic.

## 2.4. Focus on Italy and the city Milan:

The presence of Airbnb in Italy plays a particularly significant role, especially given the country's predominantly tourist-oriented nature. Data from a study by the Bank of Italy shows that in 2019, 6% of the GDP and 6.5% of employment in Italy were attributable to tourism. This sector contributed nearly €100 billion. Therefore, delving into the details of the analysis, Italy represents the third-largest market globally for Airbnb, following only the United States (the founding country) and France. Furthermore, as declared by Matteo Frigerio, Airbnb Italy's CEO, in 2018 "9.6 million people chose Airbnb for their stay in Italy." The scale of this phenomenon appears particularly significant, especially when compared with the overall scope of incoming tourist flows into the Peninsula. In fact, out of approximately 123 million arrivals (Tourism in Italy Numbers and Development Potential - Bank of Italy) in the calendar year 2018, it's evident that about 7.8% of the individuals who arrived in our country used the platform for accommodation in Italy.

### 2.4.1. Introduction of Milan

Milan, situated in the northwest of Italy, is a city with a rich history and a dynamic urban environment. It's known as the country's primary economic, cultural, and fashion hub. The city is the capital of the Lombardy region and draws visitors from around the world due to its historical heritage, architecture, cuisine, and sophisticated lifestyle.
With roots tracing back to Roman times, Milan blends a long history with a contemporary atmosphere. The magnificent Milan Cathedral, an example of Gothic architecture, dominates the city center, while the Sforza Castle narrates tales of ancient dynasties and nobility.
Milan is famous for being a hub of fashion and design, hosting internationally renowned events like Fashion Week and the Furniture Fair. Its streets, such as Via Montenapoleone, are a paradise for fashion and shopping enthusiasts.

The city also offers a wide range of art and renowned museums, such as the Brera Art Gallery and the National Museum of Science and Technology "Leonardo da Vinci," catering to art and culture lovers.

Milan is a premier culinary destination, with a variety of restaurants serving traditional Milanese cuisine, featuring dishes like saffron risotto and osso buco, alongside high-quality international cuisines.
Due to its financial and commercial significance, Milan houses numerous multinational corporations and financial institutions, significantly contributing to its thriving economy. The city boasts an efficient transportation network, including subways, trains, and airports, connecting it to major Italian and European cities.
Milan hosts a diverse community of residents from around the world, offering a unique urban experience with a captivating blend of history, culture, innovation, and contemporary lifestyle. Milan spans an area of 181.67 km² and is home to a population of 1,362,551 (as of 31-7-2023).

The city of Milan is divided into 9 main zones.

• **Zone 1:** The historical center, this is the oldest area in Milan and encompasses iconic sites such as the Duomo, Galleria Vittorio Emanuele II, and Sforza Castle. It's the historical heart of the city, with cobbled streets and historic monuments.

• **Zone 2:** This area is dominated by Milano Centrale Railway Station, one of Europe's major railway hubs. It's a vibrant area with numerous commercial activities and restaurants.

• **Zone 3:** Città Studi, known for hosting several university institutions and being a center of academic and scientific excellence, also characterized by one of Milan's medieval gates. It's renowned for its public gardens, such as Parco di Porta Venezia. Also famous for its elegant shopping street, Corso Buenos Aires.

• **Zone 4:** Vittoria Forlanini, known for one of Milan's medieval gates, this area is renowned for its public gardens, like Parco di Porta Venezia. It's also recognized for its stylish shopping street, Corso Buenos Aires.

• **Zone 5:** Navigli, recognized for its canals, known as Navigli, and the surrounding bohemian neighborhood. It's a popular spot for nightlife, restaurants, and art galleries.

• **Zone 6:** Barona, Lorenteggio, a residential area characterized by a mix of modern and traditional buildings. The Basilica of San Cristoforo sul Naviglio is one of its main landmarks.

• **Zone 7:** Baggio, De Angeli, San Siro, primarily a residential area with vast green spaces and some attractions like the San Siro Stadium, shared by AC Milan and Inter Milan.

• **Zone 8:** Fiera, home to Fiera Milano, one of the world's largest exhibition centers. It's a modern area with numerous exhibition and conference facilities.

• **Zone 9:** Stazione Garibaldi, known mostly for being residential, with some industrial areas. Niguarda Hospital is one of the primary medical centers in the area.

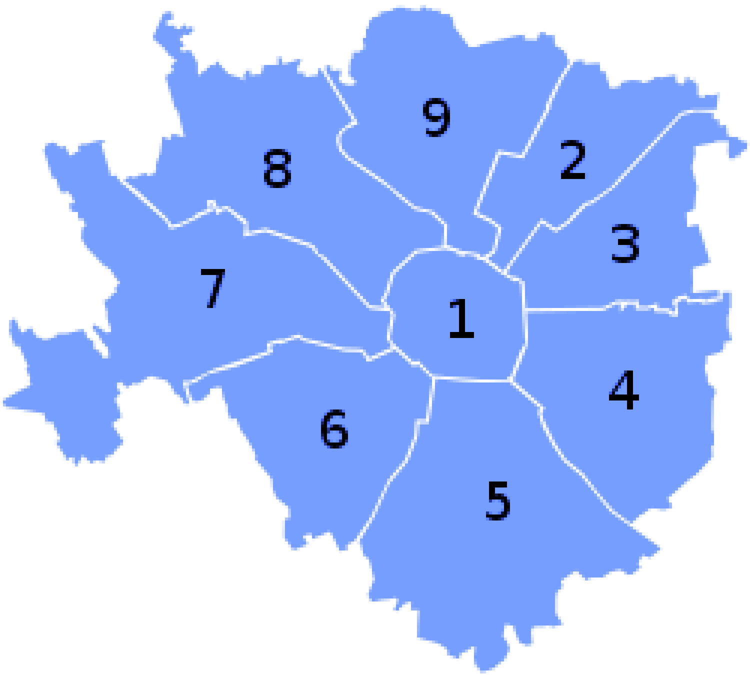



*Figure 2.5 The areas of Milan*

Since the late 1990s, one of the priorities of Milan administrations has been to produce city marketing capable of emphasizing the creative, smart, collaborative, and international nature of the Lombard capital. Starting from the bid to host the Universal Exposition of 2015, considered by some as the main driver of the city's new renaissance (Chamber of Commerce, 2017), the promotion of tourism gradually becomes a fundamental component of the urban government's business strategy. The Expo of 2015 indeed contributes to creating and promoting the "Milan Brand" globally (Rolando, 2017). Since then, tourism has become a significant sector of the urban economy (Chamber of Commerce, 2019), always characterized by strong diversification (finance, fashion and design, real estate, communications and media, research and development, innovation, business services).

Fueled by an urban agenda focused on organizing events spread across the territory and promoted in collaboration with private entities and sector associations, Milan creates a highly diversified tourist offer, managing to attract national and international visitors who come to the city for various reasons: business, conferences, cultural offerings, trade shows, and seasonal events related to the design and fashion industry.

According to data from the Municipality of Milan, tourist flows and the number of visitors stays in Milan show a continuously rising trend, with an annual growth rate of foreign visitors from 2012 to 2022 at 7%, reaching nearly 7.5 million visitors in 2019, a 9.4% increase compared to the previous year (Municipality of Milan, 2020).


*Figure 2.6 Trend of turism in Milan over the years*

### 2.4.2. The Sharing Economy in Milan

The choice to analyze the city of Milan is due to its role in both the Italian and global landscape of the "sharing economy". In 2014, it adopted an important document called "Milano Sharing City", establishing a series of guidelines and indicating attempts at regulation regarding the development of the sharing economy within the urban area.

Furthermore, the subsequent step was joining, in 2018, the so-called "Sharing Cities Declaration," something akin to a "Declaration of Shared Cities". This document acts as a sort of manual about the proper treatment of sharing economy platforms and was signed during the "Sharing Cities Summit Barcelona" event held in 2018, involving 42 cities globally.
It's fundamentally based on three simple principles:

- Distinguishing various types of sharing economy platforms based on their impact on the city.
- Providing a degree of local sovereignty to the cities involved in the agreement concerning the proliferation of digital platforms.
- Public support policies for platforms with a positive impact on the city.

With that said, Milan's role appears to be relevant when studying the sharing economy phenomenon and specifically, in this case, the Airbnb phenomenon. The urban agenda "Milano Sharing City" acknowledges Airbnb among collaborative urban economy practices (Municipality of Milan, 2014). Regulation in the sector is limited to governing the tourist tax, for which, in 2018, Airbnb signed an agreement with the Municipality of Milan for the collection and payment of the tax to the municipal coffers. Over the years, Airbnb becomes an important partner of the Municipality. In June 2018, a partnership was announced to provide over 3,000 accommodations at controlled prices in anticipation of the upcoming Olympic Games that the city will host with Cortina d'Ampezzo in 2026 (Andreis, 2019; Guerrera, 2019). This agreement, intended to limit urban sprawl and the construction of accommodation facilities, raises several questions about potential impacts on a rental housing market governed by the dynamics of short-term rentals.
In 2021, Airbnb was identified as a "solution" to the issue related to rental control. The Municipality and the platform signed an agreement aimed at promoting transient rentals (from 1 to 18 months) at agreed rents, intended for "temporary citizens" and students living in the city of Milan (Cavestri, 2021).
The distribution of Airbnbs in the city of Milan appears in a highly granular and polycentric manner, as better seen in the image below. The highest number of Airbnb lodgings is found in local identity cores with higher residential density, where high percentages of foreign residents, numerous buildings dedicated to a functional mix, public

spaces, and services, as well as good accessibility to public transport networks, are recognized. It follows that, in all likelihood, the attractiveness of these spaces may correlate with the most common location-based factors for urban activities, such as: good access to tourist and business-related services and activities, the presence of bars and restaurants, shops, cultural and entertainment activities, and, more generally, good urban quality. Specifically, the Buenos Aires-Venezia area has the highest concentration of Airbnbs in Milan. This is likely due to the residential area's expanse, the proximity to the subway line, and the central station. However, when considering the sum of Airbnbs between the Navigli and Ticinese areas, it is revealed that the area at the heart of the city's nightlife, the hub of events, and the venue for major fashion and design-related activities, also boasts the most substantial Airbnb offerings.

Other important areas include Porta Romana (which appears quite similar to the Buenos Aires zone due to various characteristics related to residential influence and the presence of diverse activities—e.g., the Fondazione Prada—that attract visitors and users of varying backgrounds) and those of Sarpi, Brera, and Isola.

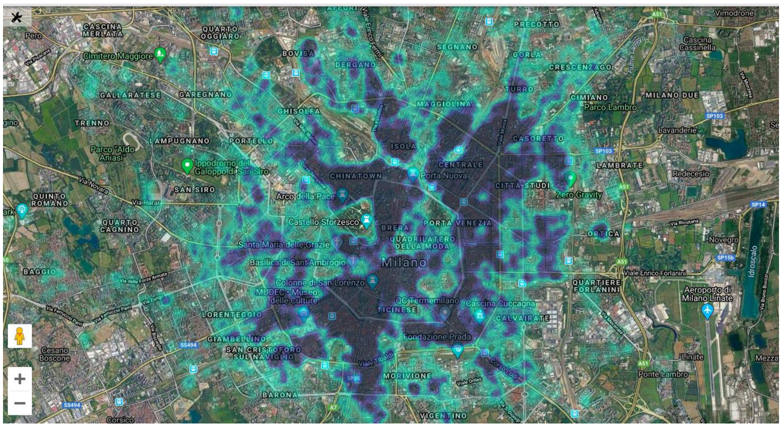



Figure 1.7 Density of Airbnbs in Milan

Breaking down the data on tourist stays in Milan between hotel and non-hotel accommodations reveals a consistent growth in both types of lodgings until 2019, followed by a collapse due to the pandemic. However, the major increase in tourist stays in Milan was observed in non-hotel structures, accounting for 45.7% of new stays between 2010 and 2019. This growth, particularly since 2012 following Airbnb's entry into the Italian market and specifically in Milan, allowed the market share of non-hotel accommodations to rise from 3.6% in 2010 to 23.3% in 2021, marking a significant increase of 19.6 percentage points.

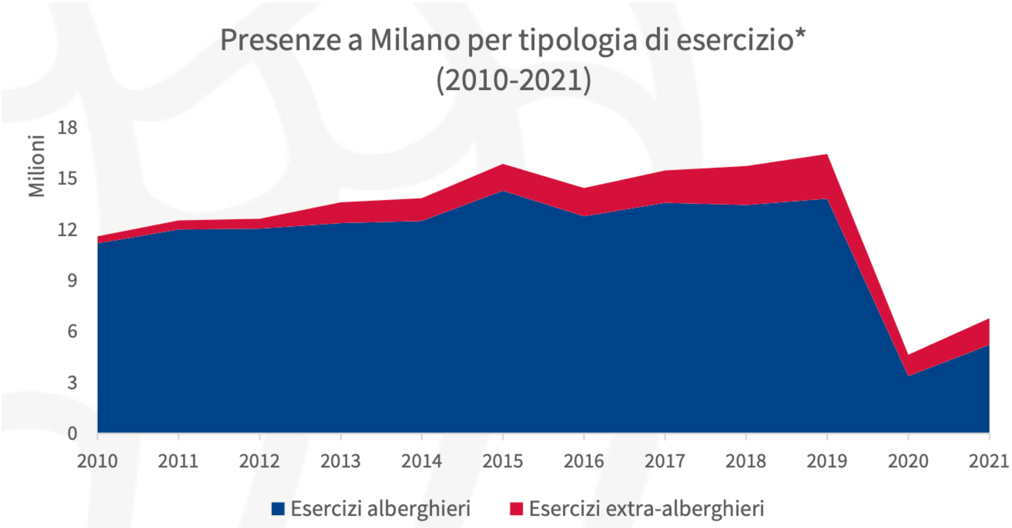



*Figure 2.8 Attendance by type of business*

The impact of Airbnb on rental prices in Milan has sparked debate and analysis among various stakeholders, including economists, urban planners, and local authorities. From these discussions, key considerations have emerged:

• **Short-Term Price Increase:** Airbnb has contributed to the surge in short-term accommodation demand in Milan, particularly in the more central and touristic zones. This surge has led to higher prices for short-term stays in these areas, making it more expensive to stay in Airbnb apartments or rooms compared to traditional long-term rentals.

• **Limited Impact on Long-Term Rental Markets:** The role of Airbnb in driving up long-term rental prices has been considered limited. Many Airbnb hosts prefer short-term rentals, meaning there are fewer units available for long-term leasing. However, the long-term rental market in Milan is primarily influenced by other factors such as supply and demand, economic growth, rental policies, and urban area expansion.

• **Local Regulation:** To address concerns regarding Airbnb and its impact on rental prices, local authorities in Milan have introduced regulations and restrictions to limit short-term rental accommodation. These measures include limits on the number of nights a unit can be rented and requirements for registration with tax authorities. These regulations aim to balance the hospitality industry while preserving access to long-term rentals.

• **Neighborhood Effect:** The impact of Airbnb can vary significantly from one neighborhood to another in Milan. Highly touristic zones, like the historical center, might experience a more pronounced increase in short-term rental prices compared to less touristic areas.

In summary, Airbnb has impacted the availability of short-term accommodations in Milan, affecting prices in certain areas. However, its effect on long-term rental prices has been deemed limited compared to other contributing factors. Local regulations have been introduced to address some of the challenges related to Airbnb use, balancing the needs of local residents with the hospitality industry. In the next sections, the goal is to provide an analysis of the various factors that influenced this market pre and post the Covid-19 pandemic.

As mentioned earlier, Milan is Italy's economic capital, and prior studies have identified three primary market segments drawn to Milan:

• **Business**
• **Trade Fairs**
• **Leisure**

Each segment shows distinct seasonality. Business segments dominate weekdays, while leisure segments prevail during weekends. Business days comprise weekdays not affected by religious (e.g., Christmas, Easter) or civic holidays (e.g., Republic Day or Labor Day). Conversely, holidays include weekends and all religious and civic holiday periods. During holidays, leisure customers are prevalent, while business is the primary target on working days. Additionally, Milan is a European leader in exhibitions. When the local

fairground (Fiera Milano) hosts high-profile events, hotels witness excellent performance in terms of both occupancy and revenues.
The hosts are divided into five groups, as previously mentioned:

- Single-list family-operated hosts
- Hosts renting out two listings
- Hosts renting out three listings
- Hosts managing four to ten listings
- Hosts renting more than ten listings

These five groups represent three different scaling effects. Logically, a host managing one to three listings can organize their business without employing external workers or by limiting such employment. Four listings are taken as the threshold to transition from a personal business model to a more professional setup, which involves external collaborators. Finally, managing more than ten listings represents a significant scale-up, fostering greater specialization and professionalization in key business functions (sales, cleaning, customer relations, and IT). Milan demonstrates a sharp demand fluctuation between holiday days, weekends, and non-fair event days versus working days, midweek, and fair event days. Many studies agree that Airbnb listings are primarily leisure-oriented. Therefore, it is expected that Airbnb listings are more effective when leisure customers are more relevant (holidays and weekends) and when the city hosts trade fairs (many fair attendees combine business and leisure). In other words, when Airbnb's key target (leisure) prevails, the differences between the five host groups (based on their size) are less nuanced. Conversely, when the city's primary objective is business, smaller hosts are less equipped to serve this goal, leading to different seasonal patterns (and consequently lower synchronization) compared to larger (scaled) hosts.

### 2.4.3. The Pandemic's Effect

The tourism sector and its related activities are among those hit the hardest by the COVID-19 pandemic, as they were affected by travel restrictions even before the suspension of activities that occurred with the DPCM on March 22, and they still struggle to regain momentum.

In terms of GDP, the direct contribution of tourism in Italy amounts to 6%. However, considering the entire supply chain and involving all "connected" activities, the impact rises to 13% and involves 15% of the national workforce.
Lombardy's tourism sector takes the lead in Italy in terms of Value Added and employees (respectively 9.7 billion euros and 245,021 employees in accommodation and catering services (Fig. 2.8). In Milan and Monza Brianza, there are nearly 112,000 employees (12,787 employed in accommodation services and 99,176 in catering) and a number of local units amounting to 20,865 (1,601 in accommodation and 19,084 in catering). The tourist appeal is common to all Lombard provinces, with Milan ranking first in the region in terms of visitor numbers (over 16 million in 2019) and sixth at the national level, preceded by Venice, Rome, Bolzano, and just behind Trento and Verona.
The image below shows the presence of tourists in Italian provinces before Covid in 2019 (expressed in thousands).

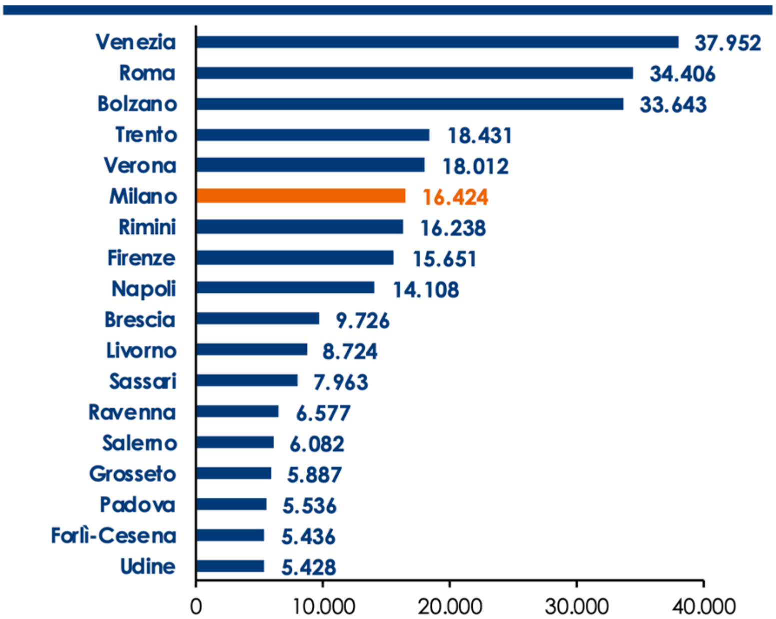



*Figure 2.8 Presence of tourists in Italian provinves in 2019*

From this chart, instead, we can observe how the presence of foreign tourists in Milan has varied, broken down by nationality.

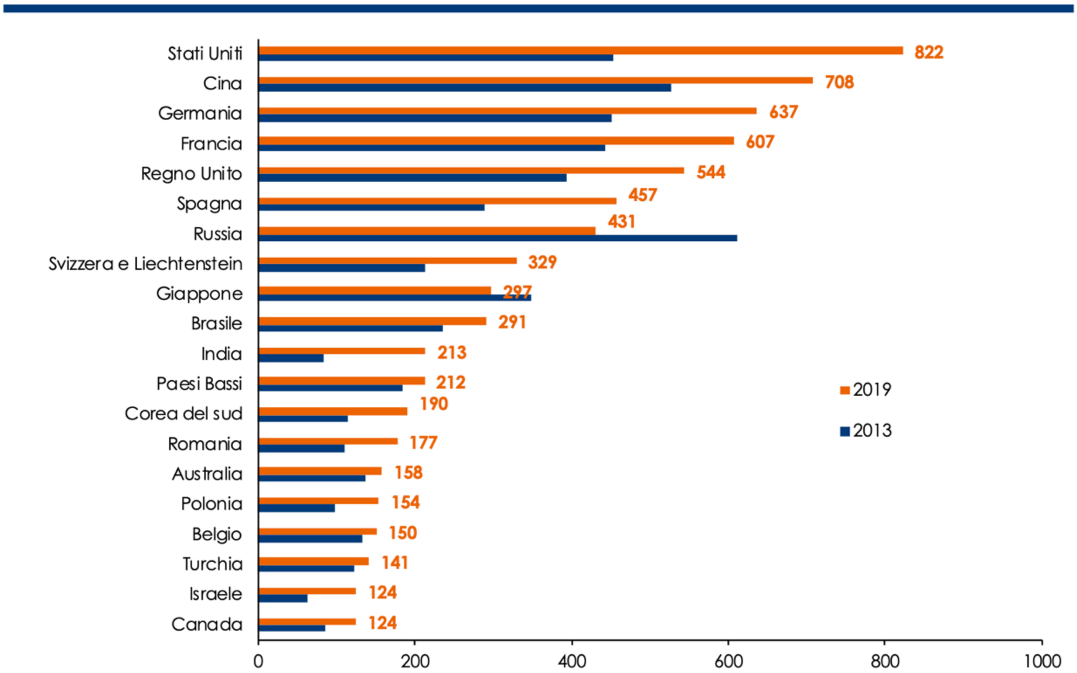



*Figure 2.9 Presence of foreign tourists in Milan*

The tourism sector in Milan began to experience the first slowdowns in early 2020 due to the decision to block flights from China in Italy (the first country affected by the epidemic and the second in terms of the incidence of foreign tourists in Milan). Subsequently, due to the discovery of the first patient testing positive for the virus in Lombardy (which raised fear among visitors) and the subsequent blockage of flights to Italy. Containment measures led to the cancellation or postponement of fairs and events, including the Salone del Mobile, a traditional moment of high influx, especially by foreign clients. In the province of Milan alone, Confesercenti estimates a drop in tourists of around 4 million.

### 2.4.4. Recovery from the Pandemic

After the decline in arrivals due to the pandemic and the partial recovery in the 2021-2022 period, in the first four months of 2023, tourist flows in Milan marked a +7.9% compared to the same period in 2019. At the regional level, the average spending per foreign tourist increased more than in other regions (+81.9% between 2019 and 2022), a factor that may be partly linked to a change in consumption habits and the type of incoming tourists. Note that the spending of foreign visitors arriving in Lombardy surpassed pre-COVID levels already in 2022, recording a +12.9% compared to 2019.

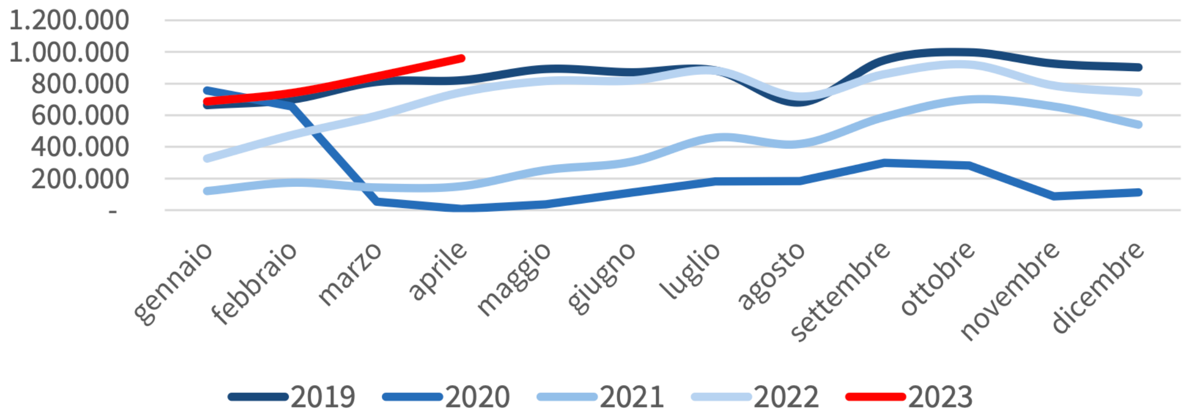



*Figure 2.9 Monthly tourist arrivals in Milan*

In 2021 and 2022, there was a progressive recovery, with 3 million visitors in 2021 and an estimated 5.8 million in 2022. According to data from the Milan Police Headquarters, in the first four months of 2023, tourist arrivals in the Metropolitan City of Milan showed a +50.9% compared to the same period last year, peaking at +28.9% in April (the month of the Salone del Mobile). Compared to the January-April 2019 period, the first four months of 2023 registered a +7.9% (+16.9% in April).

By projecting the growth in visitor numbers observed in the first four months over a yearly horizon, 2023 appears to be the year of recovery to pre-pandemic levels, with an expected number of tourists reaching 8.8 million in the best-case scenario. Alternatively, assuming that arrivals in the coming months are equal to those of last year, the growth achieved in the first four months would bring the annual total to about 6.5 million visitors (prudent scenario). According to analysts at Oxford Economics, the number of visitors to Milan in 2023 is estimated to be around 7.7 million.

Analyzing the business confidence climate in the tourism sector (accommodation, restaurants, tour guides, tour operators, and travel agencies) clearly highlights the phases of crisis and recovery that have characterized the industry in recent years: the first COVID wave (A), summer 2020 optimism (B), the second COVID wave (C), post-COVID recovery (D), spread of the Omicron variant of COVID (E), and the resurgence of international tourism (F).

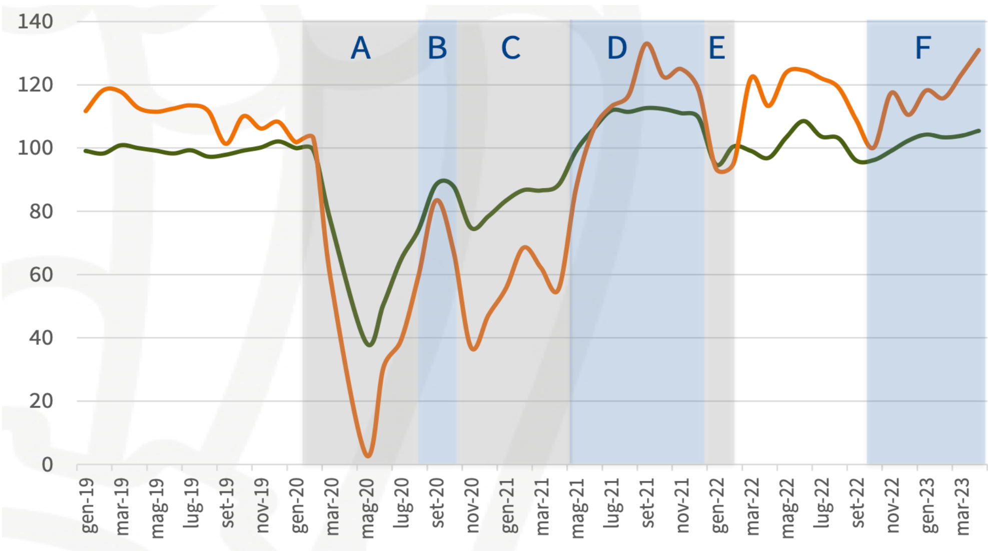



*Figure 2.10 Tourism trend in relation to the pandemic*

In 2022, the expenditure made by foreign tourists visiting Lombardy amounted to 8.3 billion euros, a figure representing 67.3% of tourist spending in the Northwestern region. Compared to 2019, Lombardy recorded a growth in tourist spending by international travelers of +12.9%, a very positive performance considering the limited growth in the Northwestern region (+1.6%) and the national decline of -0.1%.

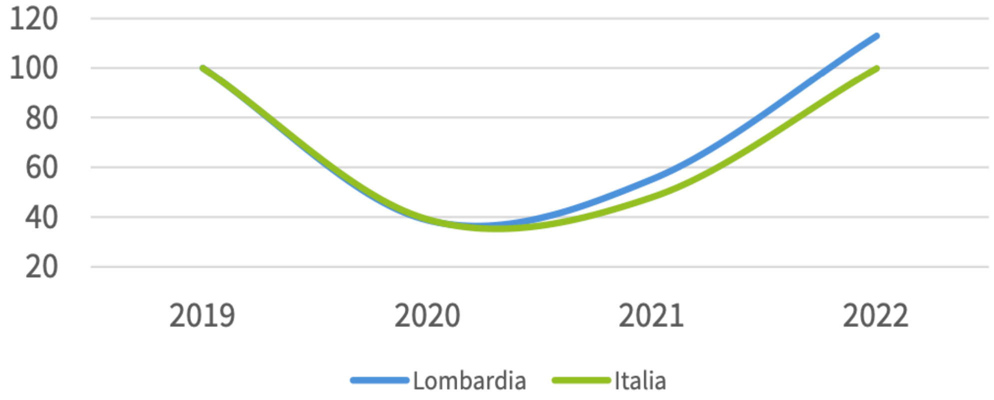



*Figure 2.11 Evolution of spending by foreign tourists*

Absolutely, the tourism sector, including phenomena like Airbnb, is showing strong signs of recovery after the challenging years of the pandemic. Already this year, there have been numbers surpassing those of 2019. In the following sections, an analysis will be conducted concerning the various factors that have influenced this recovery.

## 2.5. Literature review about the variables of distance

Only a few papers have studied the variables of distance in correlation with the short-term rent market. none of those papers has studied how the performance of the Airbnb change in relation to the variables studied in this thesis: distance to the closest metro stations, to the closest public parking, to the closest ZTL or pedestrian areas, to the closest sport facility and finally to the closest area or building in degradation conditions.

Kirkos, E. (2022) studied the correlation between the performances of the Airbnb in the city of Salonicco, in Greece, in correlation with the distance to the central square, also known as “Aristotelous”. Using the regression has found that by going further from the central square the performances of the Airbnb decrease, in particular the Revenues and the occupancy have been studied in this paper.

Zhang, Z., Chen, R. J., Han, L. D., & Yang, L. (2017) studied the prices per nights of the Airbnb in the city of Nashville, Tennessee. They studied how the prices pe nights change depending on the distance to the highway and the convention center. The results showed that going further from the convention center, identified as the city center, is strongly related to a decrease in the price per night of the listings. the same happens for the highways, indeed going further from them is related to a decrease in the price per night, even if lower than in the case of the correlation with the convention center.

Bakker, M. (2021) conducted an analysis closer to this one where have been studied how the prices of the Airbnb are affected by the distances to the closest tourist spot. The first hypothesis was: "Closer access to touristic spots is positively associated with Airbnb listing prices per night", founded to be true, indeed the author in his paper states "tourist spots have an important factor in the price determination of Airbnb, especially in areas between 0,2 km and 1 km". The analysis has been conducted in a similar way of the one showed in this thesis, splitting the distances of each listing in the city of Amsterdam into 9 ranges of distance, to have a better overview of the phenomenon. The author identified as the main turists spots: the Rijksmusuem, Anne frank House, Van Gogh Museum, The Jordaan Area, Amsterdam Lookout, Body worlds, Vondelpark, Moco Musuem, Museum Het Rembrandthuis and Artis Zoo. A same analysis can be conducted in every city to study the dependence between the prices of the Airbnb and the distance to the closest tourist spot.

Perez-Sanchez, V. R., Serrano-Estrada, L., Marti, P., & Mora-Garcia, R. T. (2018) conducted an analysis in four different cities in the coastlines of Spain taking as a reference to compute the distance from each listing the city center and the distance from the coast. Evidence shows that "accommodation prices increase incrementally by 1.3% per kilometer from the tourist area, which in all four cases are situated in the historic area of the city. However, at the same time, accommodation prices decrease incrementally as distance from the coastline increases".

Boto-García, D., & Leoni, V. (2022) studied how the performance of the short-term rent are affected from their distance to the coast in the Balearic Islands. They have taken as a reference sample in different ranges of distance from the closest point to the sea stating "we consider subsamples of listings that are located up to 500, 750, 1000, 2000, 3000, 4000 and 5000 meters away from the shoreline" going in depth also in how the coastline affects the performance of each listing.

“The purpose of this study is to identify the price determinants of sharing economy-based accommodation offers in the digital marketplace (specifically Airbnb.com). A sample of 180,533 accommodation rental offers from 33 cities listed on Airbnb.com is examined” Wang, D., & Nicolau, J. L. (2017). Between the huge number of variables studied is present also the distance of each listing to the city center. The analysis concluded with the authors stating, “The variable “distance,” representing accommodation location, has a significant negative effect, consistent with the findings of previous studies of hotel price determinants […]. The farther the accommodation from the city center, the lower its price.

In a paper published in 2019, Buhalis analyzed how the booking probability of Airbnb listings in the city of London was correlated with the distance between the various properties from the city center and the subway, in addition to the performance variables. In this study, Buhalis considered 41,124 listings in the time period between March 5, 2017, and April 4, 2017. This study demonstrated how the composition of the listings and their geographical location are important for the performance of the various Airbnb. Indeed, from these analyses, some interesting results emerged. For example, it was found that moving 1 km away from the nearest subway station decreases the booking probability by 5.39%, while moving 1 km away from the city center results in a 6.78% reduction in the booking probability. This study demonstrated also that the signal attributes, which are designated to indicate the quality of the listings, are found to be important, especially for the listings without online reviews.
(Yao, B., Qiu, R. T., Fan, D. X., Liu, A., & Buhalis, D. , 2019)

Moreover, reviewing all the papers that studied the performances or the prices per nights of the short-term rent, we notice that the most majority of them focus their attention on the distance to the city center or to the central square, or the distance to the coast for the cities near by the sea. Everyone of them, indeed, computed the distance from a single point, this last one is the same for every listing. Only in the case of the analysis conducted in Amsterdam, a more complex algorithm has been presented, indeed having more tourist points led to a computation of the distance from every point and in a second phase there will be the selection of the closest tourist spot to each listing, saving the distance between the two. A similar analysis, but with different points of interest will be conducted in this thesis, where instead of using the tourist spots of Milan, different point of interest for the tourist have been studied, like the proximity to the metro station, the closest sport facility, the closest degradation area, the closest public parking and finally the closest ZTL or pedestrian area.

# 3. Research study

## 3.1. Research framework

The analysis of this thesis focused on the performances of the Airbnb of the city of Milan in relation to some variables of distance calculated from external datasets.

In our research framework the Y axe identifies the performance variables as Revenues, Reservation days, ADR, RevPAN and occupation rate. Those have been identified as the variables of performance that can describe how a listing is performing over the year considered in our analysis (from 2019 to 2020).

- The **revenues** Are expressed in USD and indicate how much a host has earned from a listing in a month.
- The variable **reservation days** indicates how many days in a month the listing has been booked by some client.
- **ADR**, that means average daily rate, represents the average daily price of the property. It is a useful indicator because it lets us get an idea about the profitability and of the trend of tariffs over time.

$$ADR = \frac{Revenues\ (USD)}{Reservation\ days}$$

- **RevPAN**, meaning Revenue Per Available Night, is useful is useful to get an in depth focus about the performance of a listing, it is defined as:

$$RevPAN = \ Occupation\ Rate * ADR$$

$$RevPAN = \frac{Reservtion\ days}{Reservation\ days + available\ days} * \frac{Revenues\ (USD)}{Reservation\ days}$$

$$RevPAN = \frac{Revenues\ (USD)}{Reservation\ days + Available\ days}$$

- **Occupation rate** (OCC) explains the ratio between the night booked by the clients and the total available days that can be booked in a month.

$$Occupation\ rate = \frac{Reservation\ days}{Reservation\ days + Available\ days}$$

In the X axe, instead, our framework presents the independent variables, computed using Python and making calculations explained in the next chapter, about the distance from each listing to the closest "point of interest".

A "point of interest" is referred as: a metro station, a site in a degradation condition (defined in that way by the municipality of Milan), a sport facility, a public parking and finally an area with restriction, which can be a ZTL (zona traffico limitato) or a pedestrian area. From the join between the external datasets, found on the website of the municipality of Milan (https://dati.comune.milano.it), have been computed the variables of distance used in the X axe of our analysis.

Finally, as control variables for our model have been chosen some variables present in the original dataset of the Airbnb of Milan that can describe appropriately the model. On those variables some adjustments have been made to make them becoming dummy variables:

- **MaxGuest** didn't change its essence, representing still the maximum number of guests that a listing can host.
- The **ListingType** has now become a dummy variable that identifies an entire home or an apartment with 1 and any other option with 0, as private room, shared room or hotel room.
- **LTR** (long term rent) has become a dummy variable that identifies a long-term rent, so a listing that requires a minimum stay of at least 28 days is now identified with 1 and 0 otherwise.
- The **IstantBook** variable didn't change its essence too because it is already a variable that identifies with 1 the case in which the listing can be booked instantly, and 0 otherwise.

- The variable **SuperHost** didn't change its essence because it identifies with 1 the listings managed by a "super host" and with 0 the ones not.

Together with these variables has been implemented also the variable describing the NIL in which a listing has its coordinates (computed using another external source on the website of the municipality of Milan, in particular a map in the format .geojson that matched on Python with our dataset return the NIL for each listing), the year, and the month of the registration of the data.

## 3.2. Research questions

In the literature review section, we analyzed Airbnb's activity, discussing its business model and the effects this platform has had on the real estate market. We then focused on the city of Milan, starting with a study on the subdivision of various zones, discussing the main events in the city, analyzing the seasonality of tourism in the Lombardy capital, and observing how the Covid-19 pandemic and related restrictions influenced the platform's performance.

While reviewing all articles related to the city of Milan, we noticed a lack of papers that delved into analyzing the most determining factors for Airbnb hosts' performances in detail. Therefore, this study aims to fill a gap in academic literature through the acquisition and processing of data taken from the Municipality of Milan, specifically regarding the presence of metro stations, degraded areas, sports facilities, restricted zones, and parking spaces.

Analyses will be conducted on this data from the period between 2019 and 2022 in the city of Milan. These data will be concurrently compared with the performances of the platform, with the goal of identifying relationships and trends existing between strategic variables and performance indicators (revenues, occupancy rate, and certain metrics like ADR and RevPAN).

In conclusion, the research question we posed is:

How do the performances of Airbnb properties in the city of Milan vary based on qualitative variables such as the presence of subways, degraded areas, sports facilities, restricted zones, and the availability of parking?

Before starting, we formulated 5 hypotheses that will be confirmed or refuted following the analyses:

*Hypothesis 1: The presence of a metro station near the property positively influences the performance of such Airbnb.*

Analyzing the structure of the city of Milan and the location of various attractions within it, we deemed the presence of a metro station crucial for a potential customer in choosing accommodation. Proximity to subway stations, according to our reasoning, would make lodging more accessible and convenient for visitors, facilitating city exploration.

*Hypothesis 2: The presence of a degraded area near the property negatively influences the performance of such Airbnb.*

The presence of degraded areas can impact guests' perception of safety, potentially discouraging potential visitors, especially if they perceive a higher risk of crime or other security issues nearby. According to this reasoning, guests might prefer staying in safer and well-maintained areas to ensure a better-quality experience during their stay. For this reason, we believe there is a negative correlation between this factor and the property's performance.

*Hypothesis 3: The presence of parking near the property positively influences the performance of such Airbnb.*

Parking availability would make the stay more convenient for guests arriving by car. It could be a crucial deciding factor for those who prefer using their vehicle or renting one during their stay. Therefore, we anticipate a positive correlation between this factor and the property's performance.

*Hypothesis 4: The presence of ZTL/Pedestrian Areas near the property positively influences the performance of such Airbnb.*

The presence of ZTL and pedestrian areas is associated with reduced noise and traffic congestion, likely located in more central parts of the city. Therefore, we believe there is a positive correlation between this factor and the property's performance.

*Hypothesis 5: The presence of sports facilities near the property positively influences the performance of such Airbnb.*

Proximity to sports facilities is advantageous for those interested in physical activities or attending sports events. Guests participating in or observing competitions might find it convenient to stay near sports facilities. For this reason, we believe there is a positive correlation between proximity to sports facilities and the performance of the property.

# 4. Data and Methodology

In this chapter will be explained the datasets that have been used in our analysis, where those were taken and the process through which the new variables have been computed.

## 4.1. Airbnb's dataset

The analysis began from the dataset of the listings of all the Airbnb in the city of Milan. For each row of the dataset there is the description of a single listing for a specific month collecting different variables qualitative and quantitative. The Dataset presents 696565 records across the pre, post and pandemic years, indeed from 2019 to 2022. This led us to a better view on the phenomenon of the sharing economy, in housing field, in Milan.

The records of the Dataset are the following ones:

- **Property ID**: the identification string that characterize univocally a single listing making it different from every other one.
- **Reporting Month**: in the format of a date, it points the month to which the record is referring to.
- **Year**: in the format of a number, it refers to the year considered.
- **KEY_YEAR**: string concatenation between the variables "Property ID" and "Year".
- **Revenue (USD)**: refers to the revenues in Dollars of the Airbnb in the determined month considered.
- **Reservation Days**: it refers to the number of days in the considered month in which the listing has been booked.
- **Available Days**: it refers to the number of days in the considered month in which the listing has not been booked.
- **Blocked Days**: it refers to the number of days in the considered month in which the listing has been blocked (by the host?)
- **Occupation Rate**: variable computed as fraction between the variable "Reservation Days" + "Blocked Days" and the total days in the month considered.

- **ADR**: variable computed as fraction between “Revenue (USD)” and “Reservation Days” pointed indeed to the average revenues per night booked.
- **RevPAN**: variable computed as fraction between “Revenue (USD)” and “Reservation Days” + “Available Days” that pointed indeed to the average revenues per day of the listing in the determined month.
- **Listing Type**: it entails all the different possibilities of the listings from a point of view of type of the listing. Can be: Entire home/apt; Hotel room; Private room; Shared room.
- **Bedrooms**: refers to the number of bathrooms in the Airbnb.
- **Bathrooms**: refers to the number of bedrooms in the Airbnb.
- **Max Guests**: this field indicates the maximum number of guests that the property can accommodate.
- **Latitude**: this field indicates the property's latitude, which is the north-south location of the Airbnb on the surface of the Earth.
- **Longitude**: this field indicates the property's longitude, which is the east-weast location of the Airbnb on the surface of the Earth.
- **Neighborhood**: this field indicates the neighborhood within which the Airbnb is located.
- **Cancellation policy**: this field indicates how willing and available a property is regarding the cancellation policy and its timing.
- **Instantbook Enabled**: this field indicates whether the reference Airbnb provides an instant booking function, the values that can be assumed are only True or False
- **Number of Photos**: this field indicates the number of photos relating to the property inserted on the Airbnb portal by the Host.
- **Number of Reviews**: this field indicates the number of reviews left within the Airbnb portal by users who have stayed in the specific structure.
- **Minimum Stay**: this field indicates the minimum number of nights that can be booked for the specific property. This parameter is chosen by the structure host.
- **Published Weekly Rate (USD)**: (this field indicates an average weekly rate for the specific Airbnb)
- **Published Monthly Rate (USD)**: (this field indicates an average monthly rate for the specific Airbnb)

- **Airbnb Superhost**: this field indicates whether an Airbnb host is a Superhost. The criteria to be part of this category are: having completed at least 10 stays or 3 reservations, for a total of at least 100 nights, having maintained a minimum response rate of 90%, having maintained a cancellation rate of less than 1% and maintaining an overall rating of 4.8. The values that can be assumed are only True or False
- **Airbnb HostID**: this field consists of a unique numeric code associated with a single Airbnb Host; a host can have multiple properties but will always be characterized by the same code.

## 4.2. External datasets

Other than Airbnb's one there has been done an analysis on the certified website of the municipality of Milan to identify external sources for this study of Lombardia's capital. The "Geoportale of Milan" and the website of the municipality of Milan have been interesting sources for external datasets to be matched with Airbnb's one.

Five different datasets have been identified that can bring an important contribution to the research and can lead to different types of analysis for a better understanding of the Airbnb's phenomenon in the city of Milan. Each of them shows a different type of phenomenon in Milan as follows:

- Public parking
- Metro stations
- Pedestrian area
- Sports facilities
- Degradation areas and buildings

Each of them has been downloaded as a file .csv to work on it using Python. For the datasets that do not present a column that univocally identifies each record there has been created an ID using Python.

Deling with geographical coordinates means that to compute the distance between a source and each Airbnb a transformation of the parameters must be done. The Haversine formula calculates the distance between two points on the surface of a sphere (such as the Earth) given their latitude and longitude. Here's the Haversine formula in mathematical notation.

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1) * \cos(lat_2) * \sin^2(\frac{\Delta lon}{2})$$

$$c = 2 * atan2(\sqrt{a}, \sqrt{1-a})$$

$$distance = R * c$$

Where:

- $lat_1$, $lon_1$ are the latitude and longitude of each Airbnb.
- $lat_2$, $lon_2$ are the latitude and longitude of the closest source considered.
- $\Delta lat = lat_2 - lat_1$
- $\Delta lon = lon_2 – lon_1$
- R is the radius of the Earth (median radius = 6,371 kilometers)

This formula gives the distance in the same units as the radius of the Earth (e.g., kilometers). Therefore, the multiplication by 1,000 must be done.

For each external dataset two analyses have been done in order to identify the closest source to each Airbnb and also to identify the intensity of each source. For this last one there has been decided to use the NIL (Nuclueo identità locale) rather than the neighborhood, that is already present in the Airbnb's dataset, because a NIL identifies a stricter area, and the analysis would be more precise. The NIL are specified in the website of the municipality of Milan, there is a .csv file stating for each NIL important data as latitude and longitude as long as the ID, the name and the shape, but even more important has been the file .geojson that is actually a map of the city with the subdivision of the NIL with the shape. This Map has been crucial for the analysis because with the libraries of Pandas, GeoPandas, shapely.geometry and requests was possible to import it to python and work with it. In the Fig. 4.1 there is shown the map of the NIL released by the municipality of Milan, below the list of all the NIL associated to the numbers in the figure 14 split by “Municipio”.

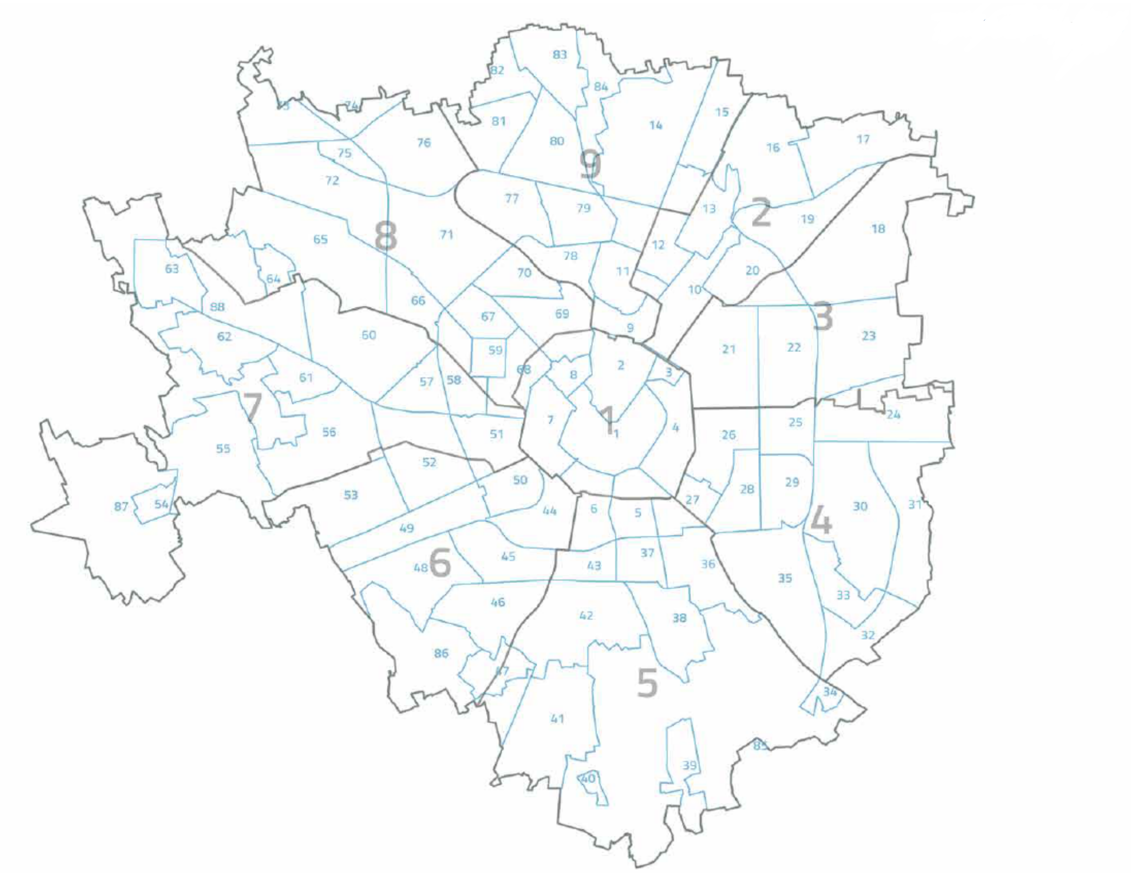



Figure 4.1 Map of NIL in Milan

**Municipio 1**
1. Duomo
2. Brera
3. Giardini Porta Venezia
4. Guastalla
7. Magenta- San Vittore
8. Parco Sempione
(5. Vigentina)
(6. Ticinese)
(68. Pagano)
(69. Sarpi)

**Municipio 2**
10. Stazione Centrale - Ponte Seveso
16. Gorla - Precotto
17. Adriano
19. Padova - Turro - Crescenzago
(11. Isola)
(12. Maciachini-Maggiolina)
(13. Greco - Segnano)
(20. Loreto - Casoretto - NoLo)

**Municipio 3**
18. Cimiano - Rottole - Q.re Feltre
21. Buenos Aires - Porta Venezia - Porta Monforte
22. Città studi
23. Lambrate - Ortica
(20. Loreto)
(24. Parco Forlanini - Cavriano)

**Municipio 4**
25. Corsica
26. XXII Marzo
28. Umbria - Molise - Calvairate
29. Ortomercato
30. Taliedo - Morsenchio - Q.re Forlanini
31. Monluè - Ponte Lambro
32. Triulzo Superiore
33. Rogoredo - Santa Giulia
35. Lodi-Corvetto
(27. Porta Romana)

**Municipio 5**
5. Porta Vigentina - Porta Lodovica
6. Porta Ticinese - Conca del Naviglio
36. Scalo Romana
34. Chiaravalle
37. Morivione
38. Vigentino - Q.re Fatima
39. Quintosole
40. Ronchetto delle Rane
41. Gratosoglio - Q.re Missaglia - Q.re Terrazze
42. Stadera - Chiesa Rossa - Q.re Torretta - Conca Fallata
43. Tibaldi
85. Parco delle Abbazie
86. Parco dei Navigli
(47. Cantalupa)

**Municipio 6**
44. Porta Ticinese - Conchetta
45. Moncucco - San Cristoforo
46. Barona
47. Cantalupa
48. Ronchetto sul Naviglio - Q.re Lodovico il Moro
49. Giambellino
50. Porta Genova
52. Bande Nere
53. Lorenteggio
86. Parco dei Navigli
(51. Washington)

**Municipio 7**
51. Porta Magenta
54. Muggiano
55. Baggio - Q.re degli Olmi - Q.re Valsesia
56. Forze Armate
57. San Siro
58. De Angeli-Monte Rosa
60. Stadio - Ippodromi
61. Quarto Cagnino
62. Quinto Romano
63. Figino
87. Assiano
88. Parco Bosco in città
(68. Pagano)

**Municipio 8**
59. Tre Torri
64. Trenno
65. Q.re Gallaratese - Q.re San Leonardo - Lampugnano
66. QT8
67. Portello
68. Pagano
69. Sarpi
70. Ghisolfa
71. Villapizzone - Cagnola - Boldinasco
72. Maggiore - Musocco - Certosa
73. MIND - Cascina Triulza
74. Roserio
75. Stephenson
76. Quarto Oggiaro - Vialba - Musocco
(88. Parco Bosco in città)

**Municipio 9**
9. Porta Garibaldi - Porta Nuova
11. Isola
14. Niguarda - Ca' Granda - Prato Centenaro - Q.re Fulvio Testi
15. Bicocca
77. Bovisa
78. Farini
79. Dergano
80. Affori
81. Bovisasca
82. Comasina
83. Bruzzano
84. Parco Nord
(12. Maciachini-Maggiolina)
(13. Greco)

*Figure 4.2 Name of the NILs of Milan*

In the next paragraph a more precise explanation of how each dataset has been implemented to create the final one having in each record the listing and the data of the external datasets.

### 4.2.1. Public parking

Like many other big cities, Milan has one of the most intense traffic and number of cars all over the world. The importance of having a garage or a parking spot has increased since the city has grown exponentially and the number of people using cars in the city too. It is very important, indeed, have a public parking as close as possible to your house or hotel if you are visiting the town and you will get there by car, in this study there will be an analysis of how having a parking close to the Airbnb affects the performances of this.

The datasets of the public parking on the website of the municipality of Milan has in each record a public parking with qualitative and quantitative information about the specific parking as:

- **_id**: that is automatically generated by the dataset that identifies univocally the record.
- **id**: an identifier number of the public car park.
- **nome**: a string that states the name of the parking.
- **n_posti**: a number stating the number of spaces of the parking.
- **indirizzo**: address of the parking
- **comune**: municipality in which there is parking (for each record is specified "Milan").
- **tipo**: type of the parking that can be "Autorimessa convenzionata", "Pubblici", "Pubblici/Residenti" or "Residenti/Pubblici".
- **LONG_X_4326**: variable that describes the longitude of the parking spot.
- **LAT_Y_4326**: variable that describes the latitude of the parking spot.
- **Location**: a string variable stating all latitude and longitude of the parking spot as following (Latitude, Longitude).

### 4.2.2. Sport Facilities

Municipally owned sports facilities form the backbone of the city's sports system.

The management of the facilities is distributed to the Milanosport spa company and to the sports federations, sports promotion bodies, associations, or amateur sports clubs.

There are different types of sport facilities, from the data collected we find for example: Athletics, Dance, Basketball, Football, Fitness, and many others.

Sports activity is one of the main and fundamental activities for leading a healthy lifestyle. In fact, in the following chapters we will analyze whether and how the presence of these sports facilities can influence the performance of Airbnb.

The sports areas dataset was found on the website of the municipality of Milan reporting more variables for each sheet (which in this case it is a sports center) like:

- **Longitude**: the longitude of the sports center.
- **Latitude**: the latitude of the sports center.
- **Type**: indicates the type of sport for which the center is equipped
- **NIL**: Indicates the NIL in which the sports facility is located

### 4.2.3. Degradation

Although in recent years reconversion processes have been initiated for significant abandoned areas, equipment and systems have still been present for several years in conditions of decommissioning and functional underuse. Their redesign represents an extraordinary opportunity to redevelop significant areas of the urbanized city in terms of land and the development of new services.

These areas largely coincide with the areas of the heritage of state bodies such as the railways and the military state property, as well as private and municipally owned areas. Entire railway yards not in operation, located within the city, which at the time of their construction influenced the homogeneous development of urban systems, forming enclaves and large open spaces constituting physical barriers and separations between areas belonging to the same urban area.

The other areas concern parts of the city on which unfinished transformation procedures have been started or buildings and systems on which redevelopment or enhancement proposals have been made.

In this study there will be an analysis of how having a degraded area nearby the Airbnb affects its performance.

The degradation dataset was found on the website of the municipality of Milan reporting more variables for each sheet (which in this case it is a area of degradation) like:

- **LONG_X_4326**: the longitude of the area of degradation.
- **LAT_Y_4326**: the latitude of the area of degradation.
- **OBJECTID**: indicates the unique ID of the degradation zone.
- **TYPE_MACRO**: indicates the type of area of degradation.
- **NIL**: Indicates the NIL in which the area of degradation is located

### 4.2.4. ZTL/Restricted Areas

Zones with Restricted Traffic Access (ZTL) and pedestrian areas are urban planning strategies implemented in various cities, like Milan, to regulate vehicular traffic and enhance the livability of specific zones. These measures are designed to address concerns such as air quality, noise pollution, and pedestrian safety.

**Zones with Restricted Traffic Access (ZTL):**

- **Definition**: ZTLs are areas where access by vehicles is restricted or regulated during certain times or altogether. The primary goal is to reduce congestion, improve air quality, and create more pedestrian-friendly environments.
- **Implementation**: ZTLs are typically marked by specific signage and access control points. Only authorized vehicles, such as residents or those with special permits, are allowed to enter these zones during restricted hours.
- **Purpose**: ZTLs aim to promote sustainable transportation, decrease pollution levels, and create more pleasant urban spaces.

**Pedestrian Areas:**

- **Definition:** Pedestrian areas are zones within a city where vehicular traffic is entirely prohibited, prioritizing pedestrians and non-motorized modes of transportation.
- **Characteristics:** Pedestrian areas often feature wide sidewalks, public spaces, and amenities to encourage walking and social interaction. They are commonly found in city centers, shopping districts, and cultural or historical sites.

- **Benefits:** Creating pedestrian-friendly zones can lead to improved air quality, increased foot traffic for local businesses, enhanced safety for pedestrians, and the promotion of a more sustainable and active lifestyle.
- **Design:** Urban planners may incorporate features like benches, green spaces, and public art to make pedestrian areas more attractive and enjoyable.

It is important to note that information on ZTLs and restrictions may change over time, so it is advisable to check the latest provisions with local authorities or on the official website of the Municipality of Milan for updated information.

In this study there will be an analysis of how having a restricted area nearby the Airbnb affects its performance.

The degradation dataset was found on the website of the municipality of Milan reporting more variables for each sheet (which in this case it is an area of degradation) like:

- **LONG_X_4326**: the longitude of the restricted area.
- **LAT_Y_4326**: the latitude of the restricted area.
- **ID_AMAT**: indicates the unique ID of the restricted area.

### 4.2.5. Metro stations

Milan, a major city in Italy, features an extensive metropolitan subway system known as the Milan Metro. The metro network plays a crucial role in facilitating transportation within the city and its surrounding areas. Here's an overview of the Milan Metro stations:

**Line M1 (Red Line):**

- **Characteristics**: The Red Line, Line M1, is one of the oldest metro lines in Milan, connecting the northwest and southeast areas of the city.
- **Key Stations**: Duomo (city center), Cadorna, Loreto, and Rho Fiera (connecting to the exhibition center).

**Line M2 (Green Line):**

- **Characteristics**: The Green Line, Line M2, intersects with Line M1 and serves the northeastern and southwestern parts of Milan.
- **Key Stations**: Centrale (central railway station), Porta Garibaldi, Cadorna, and Assago.

**Line M3 (Yellow Line):**

- **Characteristics**: The Yellow Line, Line M3, runs from the northwest to the southeast, intersecting with Lines M1 and M2.
- **Key Stations**: Duomo, Centrale, Porta Romana, and San Donato.

**Line M4 (Lilac Line):**

- **Characteristics**: Line M4, currently under expansion, will connect the city center with the southwestern areas, including Linate Airport.
- **Key Stations**: Forlanini FS and Linate Airport (future extension).

**Interchanges and Connectivity:**

- **Centrale**: Milan's central railway station is a major interchange, connecting multiple metro lines and serving as a transportation hub for trains, buses, and taxis.
- **Cadorna**: A key interchange station connecting Lines M1 and M2.

The Milan Metro system has undergone modernization efforts and expansion over the years to accommodate the growing transportation needs of the city.

Navigating Milan's metro system is convenient for both locals and visitors, providing efficient access to key landmarks, business districts, and transportation hubs. The continuous development and expansion of the metro network underscore Milan's commitment to sustainable urban mobility.

The dataset of the metro has been founded in the website of the municipality of Milan stating multiple variables for each record (which in this case is a metro station) as

- **id_amat**: the number that identificate univocally the metro station.
- **Nome**: the name of the metro station as a string.

- **Line**: the number of lines that pass through this specific metro station.
- **LONG_X_4326**: the longitude of the metro station.
- **LAT_Y_4326**: the latitude of the metro station.
- **Location**: a string that states the position of the metro station as follows: (latitude, longitude)

### 4.2.6. Example of the creation of a dataset

To explain better what has been reported before is possible to see below the code used to create the variables and the datasets. The first code refers to the creation of the variables of the closest public parking to each Airbnb, with the distance expressed in meters, the name of the closest parking and the number of spaces of the public parking in case:

```
import csv
import math

def convert_to_float(value):
    try:
        return float(value)
    except ValueError:
        return None

def convert_to_int(value):
    try:
        return int(value)
    except ValueError:
        return None

def haversine(lat1, lon1, lat2, lon2):
    # Raggio della Terra in metri
    R = 6371000.0

    # Conversione delle coordinate da gradi a radianti
    lat1_rad = math.radians(lat1)
    lon1_rad = math.radians(lon1)
    lat2_rad = math.radians(lat2)
    lon2_rad = math.radians(lon2)

    # Differenze nelle coordinate
    dlat = lat2_rad - lat1_rad
    dlon = lon2_rad - lon1_rad

    # Formula di Haversine
    a = math.sin(dlat / 2)**2 + math.cos(lat1_rad) * math.cos(lat2_rad) * math.sin(dlon / 2)**2
    c = 2 * math.atan2(math.sqrt(a), math.sqrt(1 - a))

    # Distanza in metri
    distance_meters = R * c
```

```
    return distance_meters
# Load Parcheggi data
with open("C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/Dataset esterni/parcheggi_pubblici.csv",
newline="", encoding="ISO-8859-1") as fileParcheggi:
    lettoreParcheggi = csv.reader(fileParcheggi, delimiter=",")

    # Skip the header line
    next(lettoreParcheggi, None)

    datiParcheggi = [(riga[2], riga[3], convert_to_float(riga[8]), convert_to_float(riga[7]))
for riga in lettoreParcheggi if riga[0] != ""]

# Load Airbnb data
with open("C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/DB_MILAN.csv", newline="",
encoding="ISO-8859-1") as fileAirbnb:
    lettoreAirbnb = csv.reader(fileAirbnb, delimiter=",")

    # Skip the header line
    next(lettoreAirbnb, None)

    datiAirbnb = [(riga[0], convert_to_float(riga[15]), convert_to_float(riga[16]), None) for
riga in lettoreAirbnb if riga[0] != ""]

# Calculate the distance to the closest degraded point for each Airbnb listing
for i in range(len(datiAirbnb)):
    min_distance = float('inf')  # Set initial min_distance to positive infinity
    TIPO_MACRO = None
    ID_NIL = None
    NIL = None

    for j in range(len(datiParcheggi)):
        if None in (datiAirbnb[i][1], datiAirbnb[i][2], datiParcheggi[j][2],
datiParcheggi[j][3]):
            continue  # Skip rows with missing values

        d = haversine(datiAirbnb[i][1], datiAirbnb[i][2], datiParcheggi[j][2],
datiParcheggi[j][3])
        if d < min_distance:
            min_distance = d
            NOME_PARCHEGGIO = datiParcheggi[j][0]
            NUMERO_POSTI = datiParcheggi[j][1]

    datiAirbnb[i] = (datiAirbnb[i][0], datiAirbnb[i][1], datiAirbnb[i][2], NOME_PARCHEGGIO,
NUMERO_POSTI, min_distance)

# Save the results to a new CSV file
output_file_path = "C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/airbnb_with_parking_info.csv"
with open(output_file_path, mode="w", newline="", encoding="ISO-8859-1") as output_file:
    scrittore = csv.writer(output_file)

    # Write the header
    scrittore.writerow(["Listing_ID", "Latitude", "Longitude", "NOME_PARCHEGGIO",
"NUMERO_POSTI", "min_distance_parking"])

    # Write the data
    scrittore.writerows(datiAirbnb)

print(f"Data saved to {output_file_path}")
```

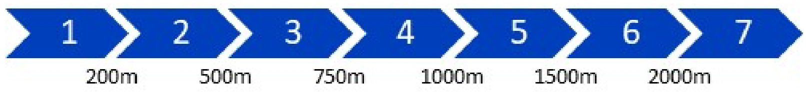
The second code, instead, refers to the creation of the dataset for the intensity of public parking per NIL, specifying the number of public parking per each NIL of the municipality of Milan:

```
import geopandas as gpd
import pandas as pd
from shapely.geometry import Point
import requests

# Load the parking dataset (CSV file)
parking_data = pd.read_csv("C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/Dataset
esterni/parcheggi_pubblici.csv", encoding="ISO-8859-1")

# Create GeoDataFrame from parking_data
geometry = [Point(xy) for xy in zip(parking_data['LONG_X_4326'], parking_data['LAT_Y_4326'])]
parking_gdf = gpd.GeoDataFrame(parking_data, geometry=geometry, crs="EPSG:4326")

# Download the NIL boundaries GeoJSON file
nil_geojson_url = "https://dati.comune.milano.it/dataset/e5a0d956-2eff-454d-b0ea-
659cb7b55c0b/resource/af78bd3f-ea45-403a-8882-91cca05087f0/download/nilzone.geojson"
nil_geojson_local_path = "C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/nilzone.geojson"
response = requests.get(nil_geojson_url)
with open(nil_geojson_local_path, "wb") as f:
    f.write(response.content)

# Load the NIL boundaries from the local GeoJSON file
nil_boundaries = gpd.read_file(nil_geojson_local_path)

# Spatial join to associate each parking facility with a NIL
joined_data = gpd.sjoin(parking_gdf, nil_boundaries, how="left", op="within")

# Group by NIL and calculate the sum of parking facilities and total number of spaces
nil_parking_stats = joined_data.groupby("NIL").agg(
    Parking_Count=('id', 'count'),
    Total_Spaces=('n_posti', 'sum')
).reset_index()

# Display or save the results
print(nil_parking_stats)

# Save the results to a new CSV file if needed
nil_parking_stats.to_csv("C:/Users/Andrea/Desktop/poli/Magistrale/Tesi/nil_parking_stats.csv",
index=False)
```

Dealing with the different datasets, for each record of the dataset of the Airbnb of Milan, has been created new variables describing the distance and the intensity of "the points of interest". In particular for each of the "point of interest" considered has been calculated:

- The distance, in meters, between each listing and the closest "point of interest" (for example the closest metro station for each Airbnb)

- The number of “point of interest” in the same NIL (Nucleo di identità locale) of the Airbnb (for example a listing in the NIL “duomo” has now a new column with the number of metro stations in the NIL “duomo”)
- Finally, a discrete variable has been computed splitting the distances in meters in multiple ranges:
  7 ranges have been created splitting the distance as follows:




in the first range you have the point of interest closer than 200m, then in then in the second range you’ll have the point of interest between 200m and 500m and so on.

# 5. Descriptive analysis

In the context of this research, descriptive analysis emerges as a crucial phase in understanding and exploring the collected data. This methodology aims to provide a detailed overview of the fundamental characteristics of the variables involved, outlining an initial framework within which more in-depth analyses (uni and multivariate regressions) will be conducted.

Descriptive analyses focus on clear and detailed presentation of the collected information, offering an initial observation of distributions, trends, and relationships present in the data. Through basic statistical calculation, creation of graphical visualizations, and exploration of key features, this phase provides a fundamental starting point for understanding the available data.

The primary goal is to provide an initial insight into the dynamics present in the data, enabling the identification of significant phenomena that may influence the overall interpretation of the analysis.

This initial process of data exploration not only provides a foundation for more advanced analyses but also offers initial feedback regarding the hypotheses formulated in the preceding section.

The ultimate purpose of this analysis is to verify how the number of Airbnb listings within the created ranges (metro, parking, ZTL, sports facilities, and degraded areas) has changed during the pre, during, and post-Covid periods.

To verify how the performance variables vary for the different ranges created (metro, parking, ZTL, sports facilities, and degraded areas).

For the descriptive statistical analysis of this paragraph, it is decided to proceed simultaneously on multiple time horizons, having data available from 2019 to 2022. The following time intervals are considered: pre-Covid (2019), Covid (2020/2021), and post-Covid (2022).

## 5.1. General performances:

We started by analyzing how certain general variables varied over the years.

Below is a summary table:

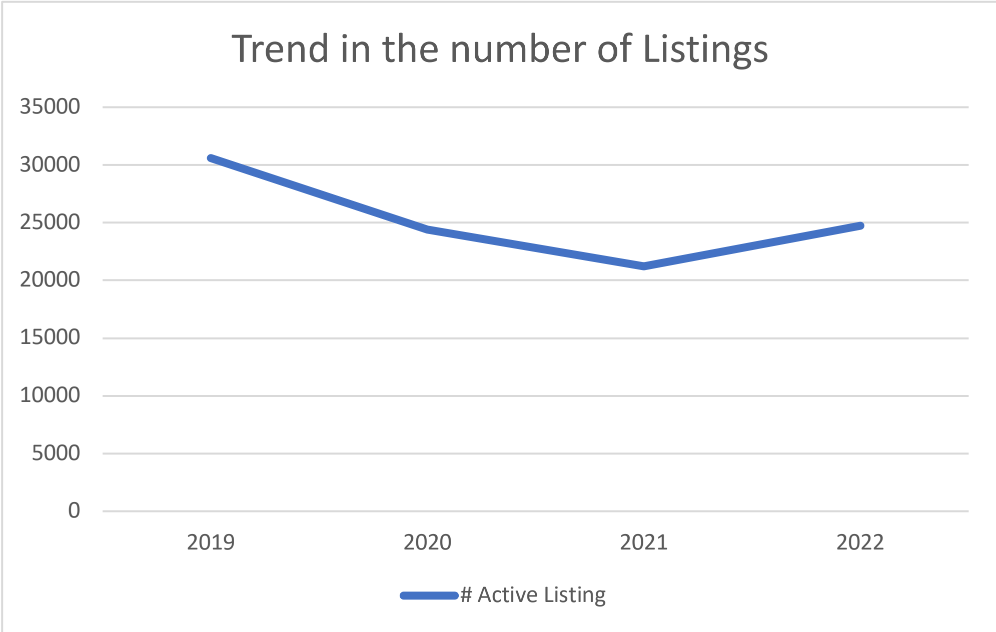
| | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|
| # active listings | 30595 | 24426 | 21217 | 24721 |
| % changes YoY | - | -20% | -13% | +17% |
| % changes from 2019 | - | -20% | -31% | -19% |
| Avg reservation days | 10.34 | 5.90 | 6.69 | 12.46 |
| Std. Err. | 0.023 | 0.021 | 0.023 | 0.027 |
| Max [Reservation days] | 31 | 31 | 31 | 31 |
| Min [Reservation days] | 0 | 0 | 0 | 0 |

*Table 5.1 General performance trend*

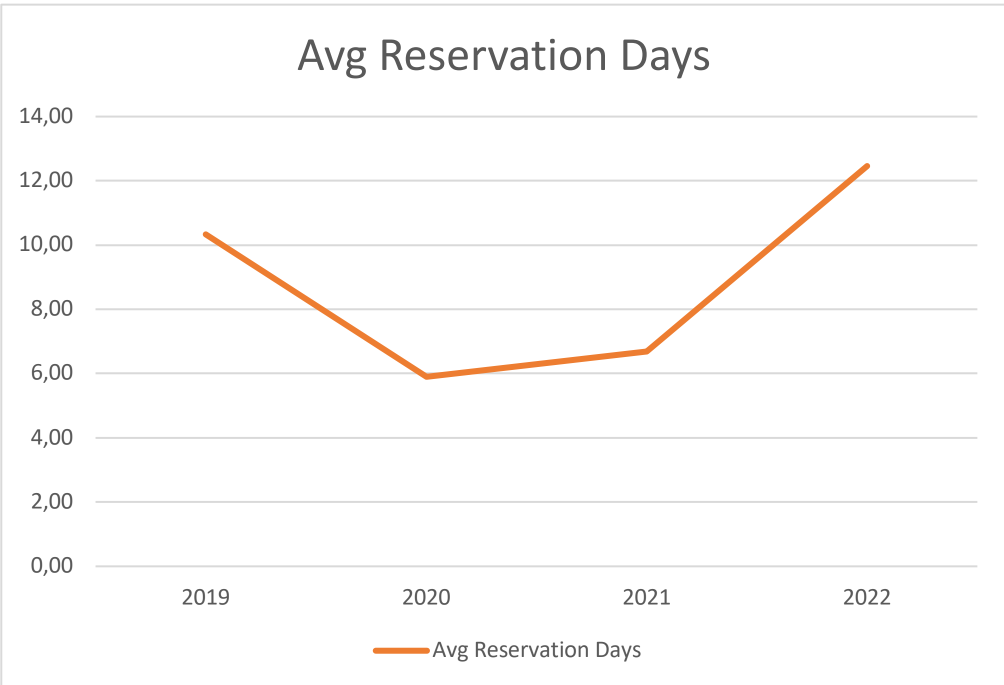
As evident from the table above, the number of active listings, i.e., properties with bookings, sharply declined starting from 2020 due to the pandemic. We observed a 20% reduction compared to the previous year, which further decreased by another 13% in 2021, reaching the lowest value. In 2022, we see this figure increase by 17%, surpassing the value recorded in 2020 but remaining far below the pre-pandemic level measured in 2019 (-19%).

Another data point we monitored was the average reservation days. In 2019, for the 30,595 active listings, we had an average of 10.34 days reserved per month. This figure decreased to 5.90 days in 2020 due to significant restrictions imposed by the government to combat the pandemic. In 2021, the value increased to 6.69 days and rose to 12.46 days in 2022. This increase is primarily attributed to a significant decrease in restrictions, thanks to the decline in the number of infections, which facilitated the recovery of tourism, in this case in the city of Milan.

Below are the graphs representing the above trends:




*Graph 5.1 Trend in the number of listings*




*Graph 5.2 Avg Reservation Days*

## 5.2. Performances variables

Subsequently to the analyses on general performances, we moved on to analyze the average values assumed by the performance variables in the various time intervals to appreciate the differences brought about by the pandemic and understand if there has been a recovery post-Covid.

Below is a summary table:

| Average | Pre-Covid | Covid | | Post-Covid |
|---|---|---|---|---|
| | 2019 | 2020 | 2021 | 2022 |
| Revenues | 1100.32 | 596.62 | 807.37 | 1769.26 |
| Reservation Days | 10.34 | 5.90 | 6.69 | 12.46 |
| OCC | 0.41 | 0.26 | 0.29 | 0.52 |
| RevPAN | 44.65 | 26.65 | 35.58 | 73.05 |
| ADR | 118.59 | 116.86 | 128.05 | 149.83 |

*Table 5.2 Trend of performance variables*

As evident from Table 2, all the performance variables follow a similar trend. In 2020, they experience a decline due to the onset of the pandemic. For instance, the host revenues nearly halve (from 1100 to 596) between 2019 and 2020. In 2021, there is a small sign of recovery that raises the values of the performance variables. An especially interesting data point is the ADR value in 2021 compared to 2019. Considering that ADR is the ratio between Revenues and Reservation Days, we can observe that the ADR value increased in 2021 (from 118 to 128). Therefore, hosts in 2021 were able to earn more per each reserved night. In summary, we can observe fewer reserved days at higher prices.

On the other hand, we notice how in 2022, the values of all these performance variables surpassed the pre-pandemic 2019 values.

## 5.3. New variables

We now determine the descriptive statistics for the new variables created. The objective is to initially analyze the number of properties located within the 7 ranges created for the 5 new categories (metro, parking, degradation, sports facilities, and ZTL).

Below are the 5 summary tables:

### ZTL

| Listing Airbnb in the **ZTL** ranges | Pre COVID | COVID | | Post COVID |
|---|---|---|---|---|
| | **2019** | **2020** | **2021** | **2022** |
| 1 | 8342 | 6815 | 6013 | 6841 |
| 2 | 9269 | 7473 | 6471 | 7531 |
| 3 | 5892 | 4592 | 3995 | 4648 |
| 4 | 3865 | 2987 | 2597 | 3040 |
| 5 | 2682 | 2007 | 1741 | 2100 |
| 6 | 305 | 239 | 194 | 272 |
| 7 | 240 | 313 | 206 | 289 |
| **Totale** | 30595 | 24426 | 21217 | 24721 |

*Table 5.3 Listing Airbnb in the ZTL ranges*

### Metro

| Listing Airbnb in the **Metro** ranges | Pre COVID | COVID | | Post COVID |
|---|---|---|---|---|
| | **2019** | **2020** | **2021** | **2022** |
| 1 | 4659 | 3896 | 3356 | 3702 |
| 2 | 13142 | 10699 | 9379 | 10778 |
| 3 | 5678 | 4404 | 3770 | 4446 |
| 4 | 3114 | 2395 | 2046 | 2497 |
| 5 | 2928 | 2211 | 1946 | 2365 |
| 6 | 758 | 564 | 509 | 689 |
| 7 | 316 | 257 | 211 | 244 |
| **Totale** | 30595 | 24426 | 21217 | 24721 |

*Table 5.4 Listing Airbnb in the Metro ranges*

### Degradations

| Listing Airbnb in the **Degradation** ranges | Pre COVID | COVID | | Post COVID |
|---|---|---|---|---|
| | **2019** | **2020** | **2021** | **2022** |
| 1 | 3960 | 3063 | 2715 | 3218 |
| 2 | 12235 | 9524 | 8221 | 9631 |
| 3 | 7954 | 6394 | 5577 | 6479 |
| 4 | 4090 | 3376 | 2939 | 3351 |
| 5 | 2115 | 1769 | 1561 | 1794 |
| 6 | 168 | 136 | 120 | 139 |
| 7 | 73 | 164 | 84 | 109 |
| **Totale** | 30595 | 24426 | 21217 | 24721 |

*Table 5.5 Listing Airbnb in the Degradation*

### Parking

| Listing Airbnb in the **Parking** ranges | Pre COVID | COVID | | Post COVID |
|---|---|---|---|---|
| | **2019** | **2020** | **2021** | **2022** |
| 1 | 3141 | 2510 | 2223 | 2512 |
| 2 | 9453 | 7620 | 6724 | 7685 |
| 3 | 6579 | 5279 | 4679 | 5458 |
| 4 | 4050 | 3162 | 2718 | 3176 |
| 5 | 3410 | 2628 | 2222 | 2608 |
| 6 | 1956 | 1539 | 1296 | 1563 |
| 7 | 2006 | 1688 | 1355 | 1719 |
| **Totale** | 30595 | 24426 | 21217 | 24721 |

*Table 5.6 Listing Airbnb in the Parking ranges*

### Sport Facility

| Listing Airbnb in the **Sport** ranges | Pre COVID | COVID | | Post COVID |
|---|---|---|---|---|
| | **2019** | **2020** | **2021** | **2022** |
| 1 | 1926 | 1517 | 1321 | 1546 |
| 2 | 10610 | 8280 | 7254 | 8440 |
| 3 | 10491 | 8317 | 7181 | 8415 |
| 4 | 5104 | 4100 | 3532 | 4054 |
| 5 | 2121 | 1779 | 1587 | 1895 |
| 6 | 335 | 315 | 291 | 306 |
| 7 | 8 | 118 | 51 | 65 |
| **Totale** | 30595 | 24426 | 21217 | 24721 |

*Table 5.7 Listing Airbnb in the Sport ranges*

The data in the tables above show how the various properties are distributed within the ranges. Starting from the restricted areas (ZTL, pedestrian areas, etc.), we see that in the initial data analysis year, 2019, range 2 is the most populated with 9269 listings. Additionally, we notice how this number has significantly decreased over the years, dropping to 7473 in 2020, 6471 in 2021, and reaching 7531 in 2022. This trend is repeated for the other 6 ranges as well.

Regarding the metro, degraded areas, and parking, we observe the same situation as mentioned previously, with range 2 leading in 2019 with 13142 properties for the metro, 12235 for degraded areas, and 9453 for parking. This lead is maintained by this range in 2020, 2021, and 2022.

Concerning degraded areas, we can notice how for range 7 (i.e., for apartments located more than 2 km from the nearest degraded area), the number of listings increases significantly from 2019 to 2020 with the onset of Covid (from 73 to 164).

The last area analyzed is related to sports facilities. We observe that ranges 2 and 3 are predominant with 10610 and 10491 listings, respectively. The trend over the years remains very similar to what was observed for other areas, showing a decrease in the number of structures in all ranges except for range 7, where we have seen an increase from 8 to 65 Airbnb between 2019 and 2022.

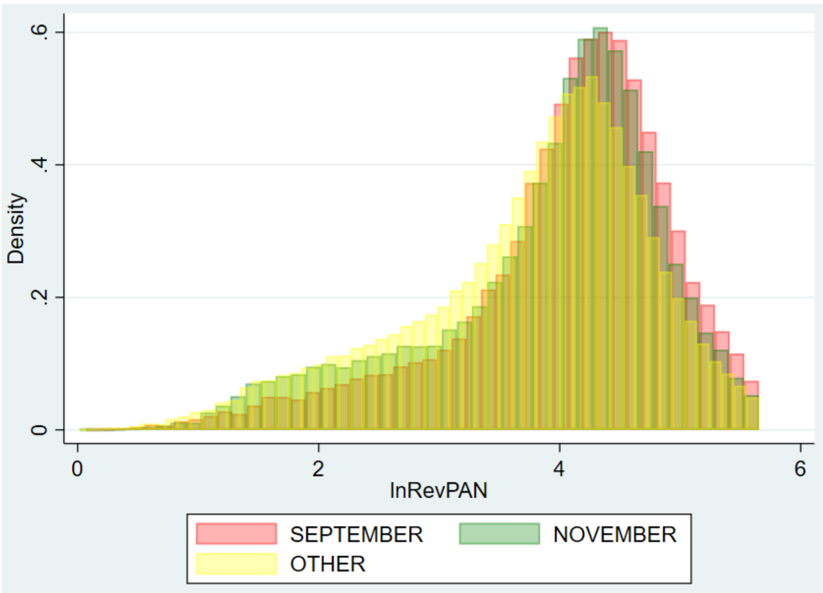
## 5.4. Seasonality analysis:

As explained in the literature review section, Milan is a city rich in events that attract a high volume of tourists. In this section, we aimed to analyze the seasonality of tourism in the Lombard capital. Tourism seasonality in Milan can be influenced by various factors, including cultural events, weather conditions, and national holidays. Tourism seasonality may also vary based on visitor segments (e.g., business tourism, cultural tourism, shopping) and global tourism industry trends. However, overall, Milan is an attractive destination for tourists throughout the year, offering a rich variety of cultural, artistic, gastronomic, and entertainment experiences.

To conduct these analyses, we used Stata, grouping bookings from various years by month and analyzing which months maximized the performance variables' values. We then created graphs to highlight the results obtained.

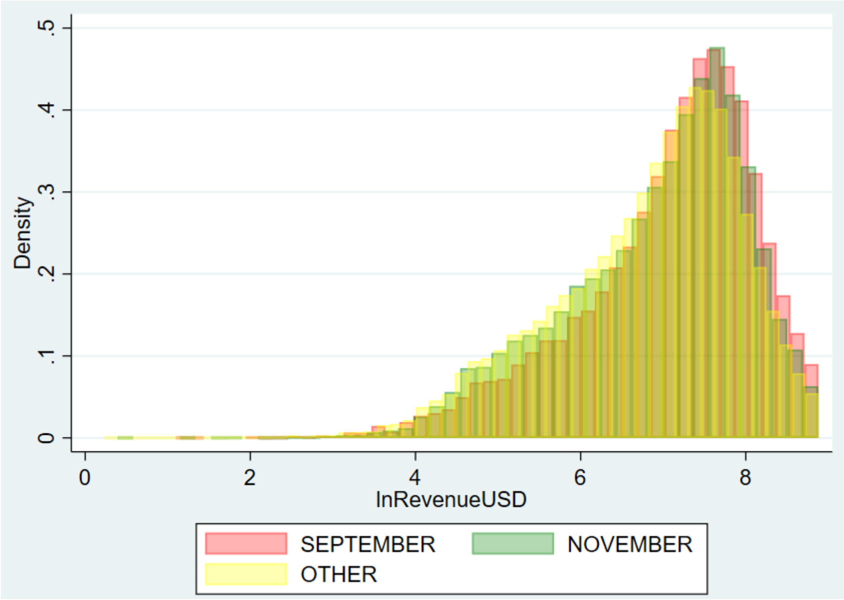
Below are the graphs:

### Ln(RevPAN)



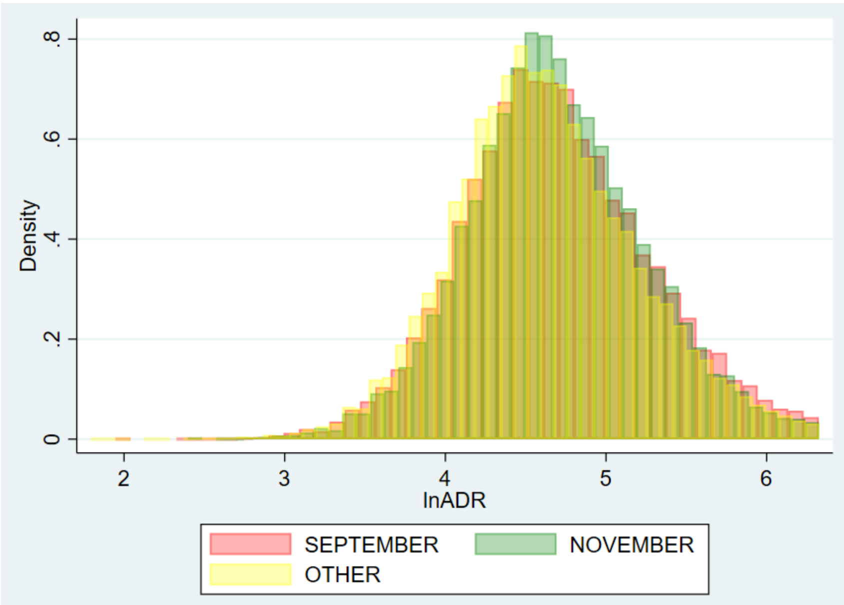

*Graph 5.3 RevPAN trend over the months*

## Ln(RevenueUSD)




*Graph 5.4 lnRevenueUSD trend over the months*

## Ln(ADR)




*Graph 5.5 lnADR trend over the months*

In the graphs above, we analyzed the seasonality concerning some performance variables, namely:

- Natural logarithm of RevPAN
- Natural logarithm of Revenues
- Natural logarithm of ADR

We used the natural logarithm of the performance variables because it can offer several advantages, such as better statistical stability, increased linearity in models, and improved interpretability of percentage changes in the data.

For each of these variables, we examined the density in three different periods of the year: September, November, and the remaining months. The choice to separate the months of September and November was driven by the presence of numerous events that occur annually and are potential sources of tourism for Milan.

Here are some of the most significant events that take place in those months:

**September:**

1. Milan Fashion Week: September is the month of fashion in Milan, with Milan Fashion Week showcasing the latest spring/summer or autumn/winter fashion collections. This event attracts thousands of designers, buyers, journalists, and fashion enthusiasts from around the world.
2. MiArt: This is a fair for modern and contemporary art held in September. MiArt provides a platform for emerging and established artists, art galleries, and collectors to exhibit and purchase artworks.
3. Milan Film Festival: A significant film event held in September, featuring screenings of independent films, short films, and documentaries from around the world.

**November:**

1. Festival of Science: Organized by the National Museum of Science and Technology Leonardo da Vinci, this festival promotes scientific culture through interactive exhibitions, conferences, workshops, and labs.
2. Milan Wine Week: An event dedicated to wine lovers, where you can taste a wide selection of wines from various Italian and international regions. It takes place in various wine bars and venues across the city.
3. Milan Jazzin' Festival: A jazz festival held annually in November, featuring concerts by national and international jazz artists at various locations throughout the city.

These events, as we can see from the graphs above, influence the performance variables, registering peaks and superior performance in the months of September and November.

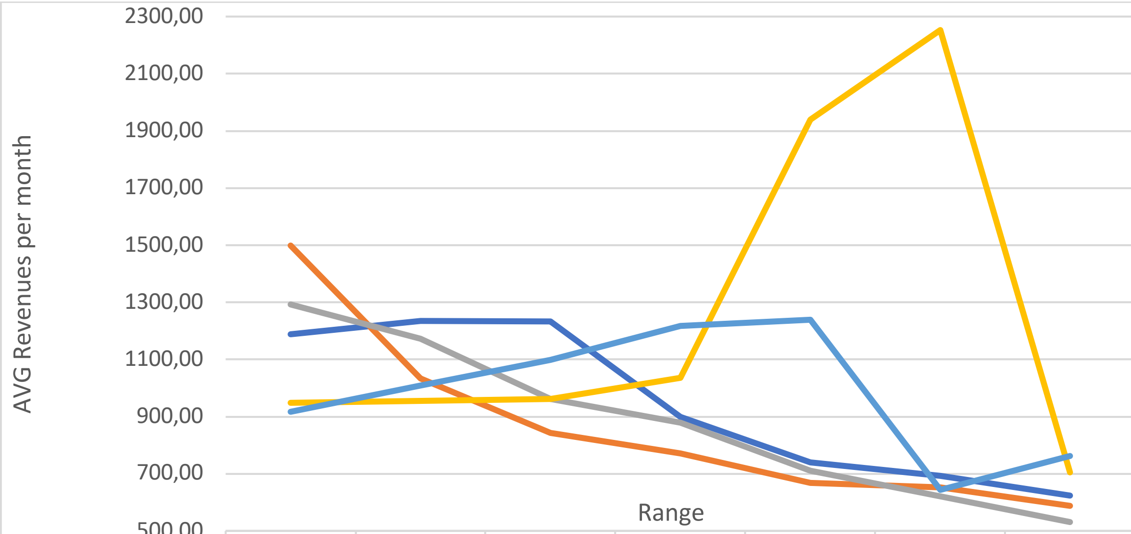
## 5.5. Performance related to the range of distance

The descriptive analysis continued using Stata and Excel in order to understand if the closeness of a "point of interest" affects the performance of an Airbnb in the period considered, indeed from 2019 to 2022.

This analysis has been done using the seven ranges computed and explained in the chapter above. After calculating the presence of those "point of interest" in each NIL, the performances of the Airbnb have been studied in relation to the range of distance from the closest "point of interest" for each of them.

Following an analysis of the performances split by each parameter.

## Revenues




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Parking | 1187,63 | 1234,74 | 1233,42 | 899,85 | 739,34 | 692,76 | 623,52 |
| ZTL | 1498,67 | 1032,40 | 843,33 | 771,08 | 667,09 | 651,15 | 587,61 |
| Metro | 1292,38 | 1171,99 | 960,74 | 879,08 | 711,47 | 620,15 | 530,85 |
| Sport | 948,72 | 954,62 | 961,47 | 1034,70 | 1939,35 | 2252,85 | 704,70 |
| Degradation | 915,79 | 1008,96 | 1098,88 | 1217,87 | 1238,96 | 643,50 | 761,13 |

*Table 5.7 Avg Revenues per month*

In the *Table 5.7*, in the X axe are presented the ranges of distance from the Airbnb and the closest "point of interest", instead in the Y axe the average of the revenues per month of the listing in the same range of distance.

Some macro-trends can be deducted from the graph and the data, indeed, as is possible to imagine, having the Airbnb closer to a public parking, a metro station or also a ZTL or pedestrian area results in a better performance of the listing, to higher revenues. In the next pages will be deducted the fact that enhanced the revenues of these listings. Higher revenues can be associated with higher prices, or a higher number of nights booked by the clients of the platform.

Regarding the Sport facilities there is a pick in correspondence to the range 5 and 6, meaning that listings that are between 1km and 2km from the closest sport facility will get higher revenues than other areas. This data is explained by the fact that in the NIL of

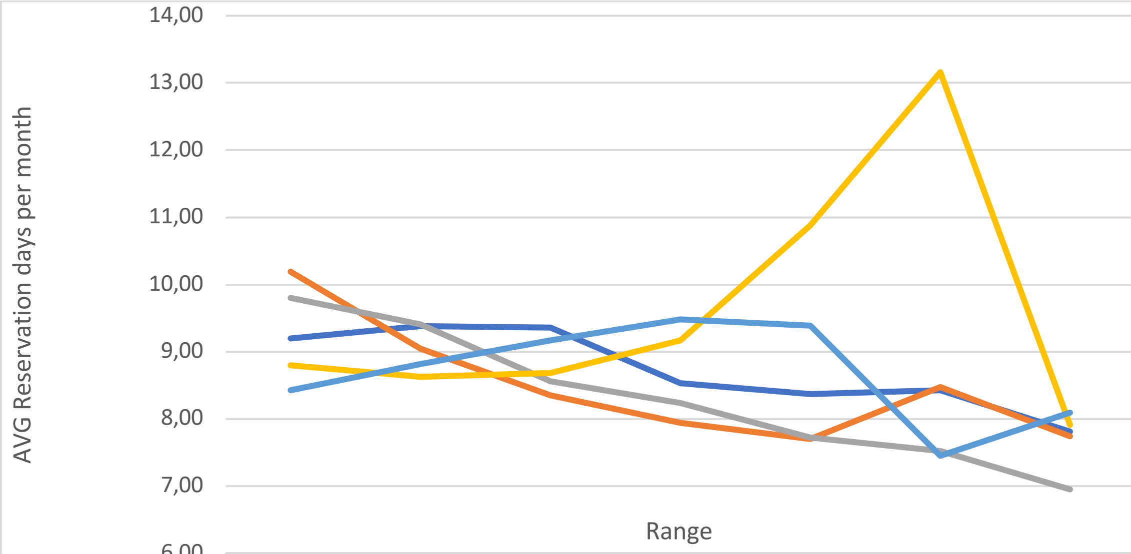
*Figure 3.1 Map of the sport facilities in the city center*

the city center there are not sport facilities, the closest facilities to Duomo and Brera are just outside them.

in the *figure 5.1* in blue are evidenced the sport facilities that are closer to the city center. In red, instead, the center of Milan, as we can see there are no sport facilities in the center and the distance between the closest and the center is between 1km and 2km explaining the pick in the range 5 and 6. Different things happened for the range 7, instead, where the sports facilities are further distant than 2000m. in this range are present only the listings at the border Milan that also show worst performances.

For the degradation, instead, identifying a trend using the ranges of distance is difficult. Indeed, there is a building in a degradation condition in the NIL "Duomo", meaning that the listings in "Duomo" and "Brera" are in the range of degradation 1, 2 or 3. What we expected, instead, happened till the range 5, where the revenues increase as we move away from the buildings and area in degradation conditions, an anomalous trend, instead, is shown by the data in the range 6 and 7 where there are the listings further than 1500m from the closest building in degradation conditions and presents the lowest average revenues between every range considered.

## Reservation days



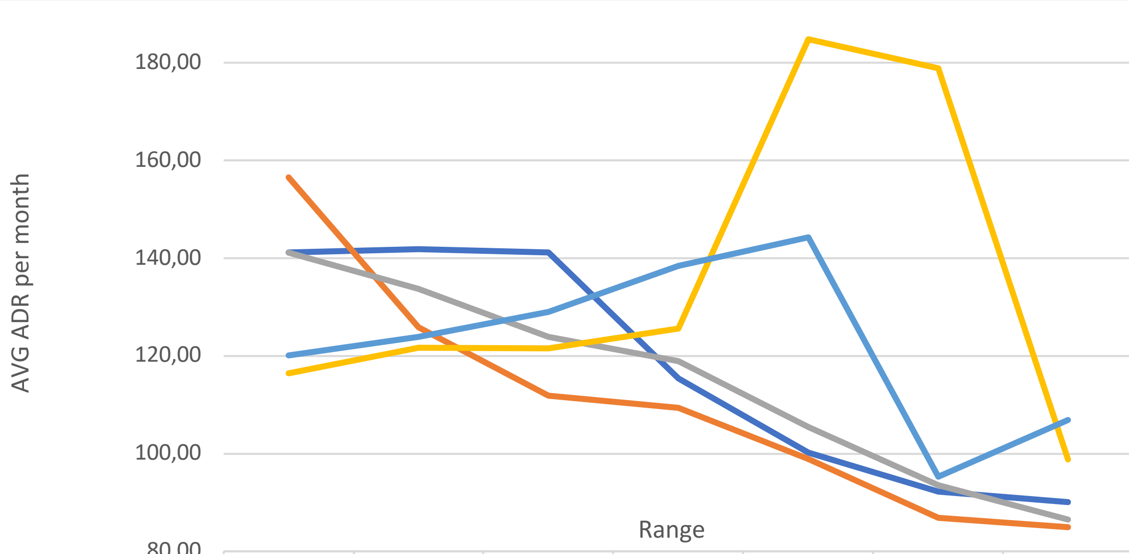

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Parking | 9,20 | 9,38 | 9,36 | 8,53 | 8,37 | 8,43 | 7,81 |
| ZTL | 10,19 | 9,04 | 8,35 | 7,94 | 7,70 | 8,47 | 7,74 |
| Metro | 9,80 | 9,41 | 8,56 | 8,24 | 7,72 | 7,52 | 6,95 |
| Sport | 8,80 | 8,63 | 8,68 | 9,17 | 10,88 | 13,16 | 7,91 |
| Degradation | 8,43 | 8,82 | 9,17 | 9,48 | 9,39 | 7,45 | 8,09 |

*Table 5.8 Avg Reservation days per month*

*Table 5.8* shows the average reservation days per month, dividing the listings into the ranges explained before. As expected, the reservation days were lowered by moving further from the closest metro station, the closest ZTL and the closest public parking.

For the reservation days the same discourse explained for the revenues applied. Indeed, the pick are in correspondence of the range five and six, where comprehends part of the area of "Duomo" and "Brera". The same happened also for the degradation, with the reservation days that increases by moving further form the closest degradation area, but for the range 6 and 7.

## ADR




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Parking | 141,17 | 141,84 | 141,13 | 115,43 | 100,14 | 92,25 | 90,07 |
| ZTL | 156,53 | 125,89 | 111,91 | 109,42 | 98,87 | 86,81 | 84,94 |
| Metro | 141,12 | 133,76 | 123,86 | 118,89 | 105,43 | 93,58 | 86,50 |
| Sport | 116,40 | 121,63 | 121,56 | 125,56 | 184,80 | 178,89 | 98,81 |
| Degradation | 120,14 | 123,90 | 128,96 | 138,46 | 144,26 | 95,27 | 106,85 |

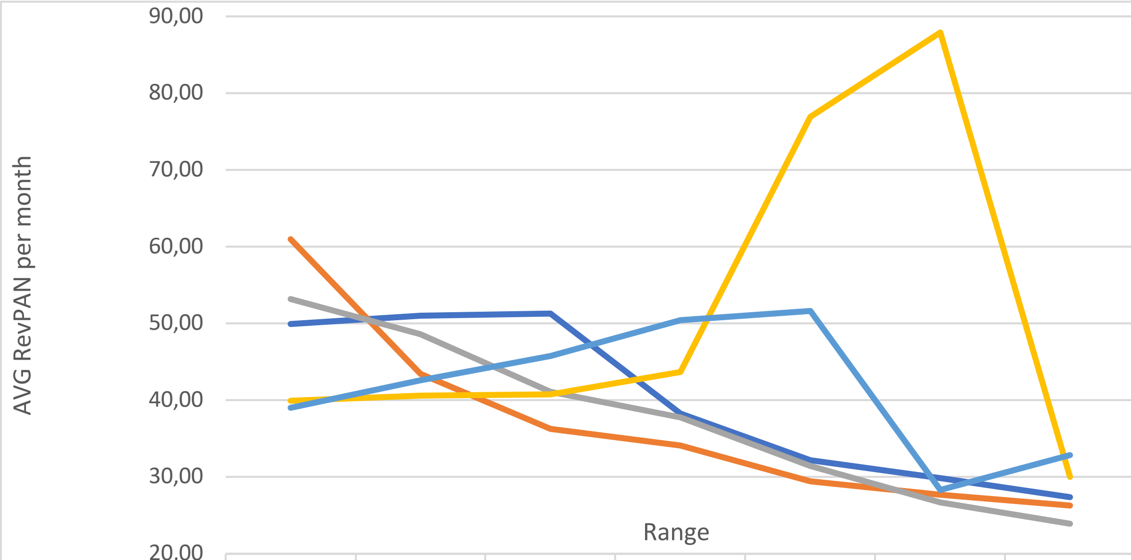
*Table 5.9 Avg ADR per month*

In *table 5.9* is shown how the ADR (Average daily rate) changed depending on the ranges of distance from each "point of interest". The ratio between the revenues and the days reserved by the client drops for ZTL, metro and public parking by moving further from these points.

For the sport facilities is possible to notice a pick in the range five and six with an average daily rate that overtake 180$ per night. This because the listings in "Duomo" and "Brera" are at a distance between 1km and 2km from the closest sport facility.

The degradation line follows the same as the one for the revenues and reservation days, increasing the average daily rate by moving further from the degradation area, until the range six and seven where there is a drastic drop.

## RevPAN




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Parking | 49,90 | 51,05 | 51,29 | 38,29 | 32,16 | 29,89 | 27,38 |
| ZTL | 60,97 | 43,42 | 36,23 | 34,09 | 29,42 | 27,71 | 26,29 |
| Metro | 53,18 | 48,61 | 41,06 | 37,76 | 31,41 | 26,68 | 23,92 |
| Sport | 39,91 | 40,64 | 40,80 | 43,71 | 76,91 | 87,90 | 30,02 |
| Degradation | 39,06 | 42,56 | 45,77 | 50,45 | 51,63 | 28,32 | 32,83 |

*Table 5.10 Avg RevPAN per month*

In *table 5.10* is shown how the RevPAN changes depending on the ranges of distance. As before the line of parking, ZTL and metro drop by going further from them. The two picks for the sport facility are still present in range 5 and 6, with the pick in range 6 that exceeds the double of range 1, 2, 3 and 7, showing the importance of having an Airbnb in the city center.

While the degradation follows the same path until range six where has a drastic drop. As shown in the picture below, the degradation points of the city of Milan are distributed all over the territory.

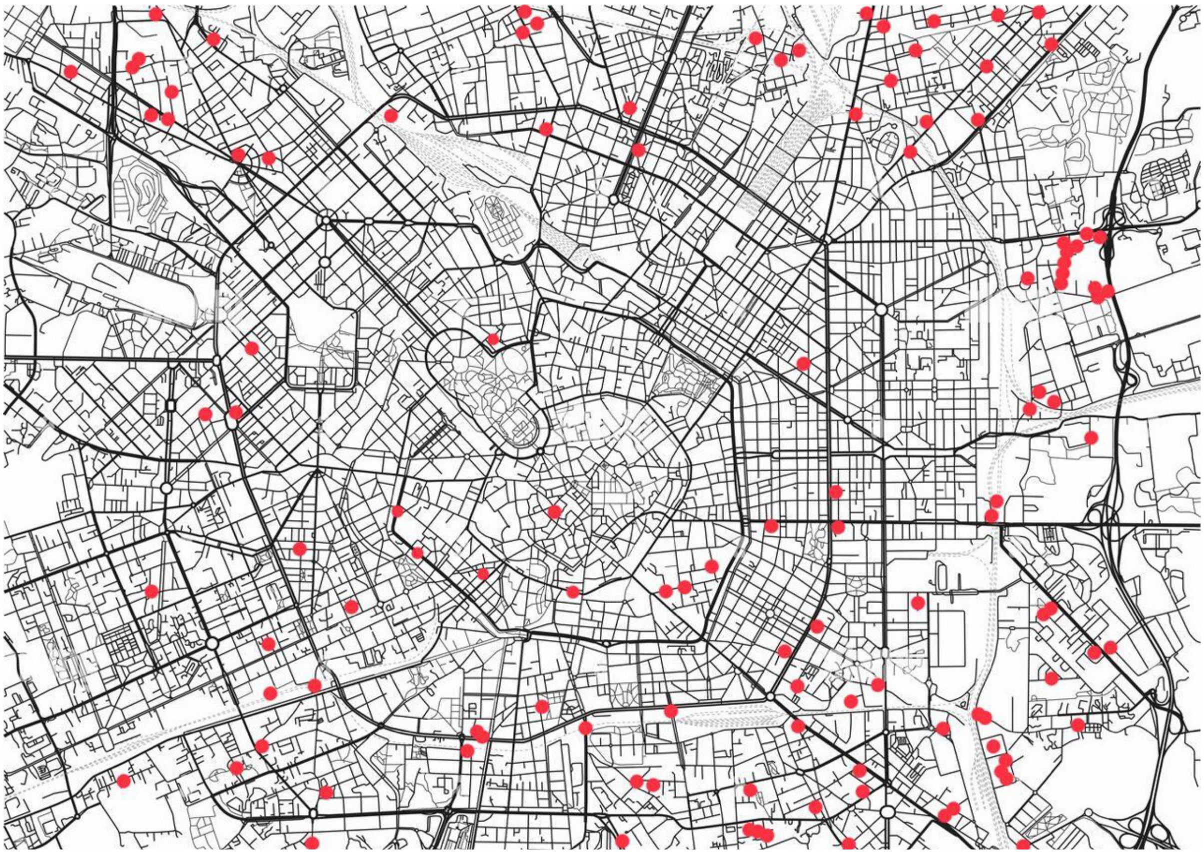
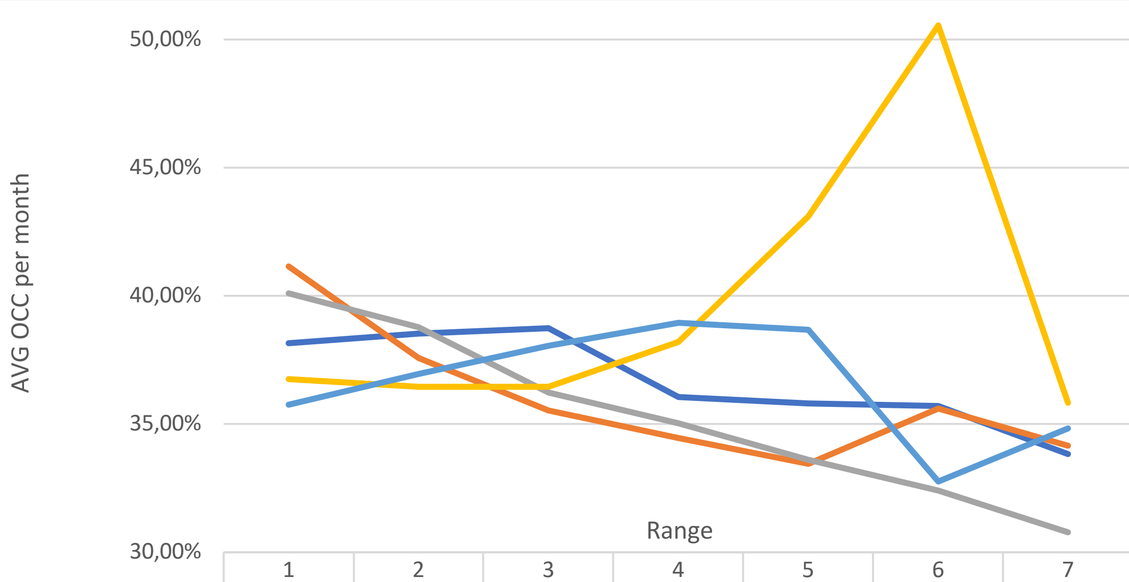


*Figure 5.2 Map of the degradation buildings and area of Milan.*

## OCC




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Parking | 38,16% | 38,54% | 38,74% | 36,06% | 35,80% | 35,71% | 33,83% |
| ZTL | 41,15% | 37,58% | 35,52% | 34,45% | 33,45% | 35,60% | 34,15% |
| Metro | 40,10% | 38,78% | 36,22% | 35,04% | 33,60% | 32,41% | 30,78% |
| Sport | 36,75% | 36,45% | 36,46% | 38,21% | 43,09% | 50,55% | 35,83% |
| Degradation | 35,75% | 36,96% | 38,06% | 38,95% | 38,69% | 32,76% | 34,82% |

*Table 5.11 Avg OCC per month*

In *table 5.11* the trend of the occupation rate shows that going further from the closest metro station, the closest ZTL or pedestrian area and the closest public parking the reservation days drop with respect to the number of available days to be rented. The metro ling evidence a drastic drop of the occupation rate from 40.10% of the range 1 (so being closer than 200m to the closest metro station) to 30.78% of range 7, having a metro station further than 2000m.

The other trends are similar to what has been explained before, with the occupancy rate of the city center to more than 50% that is reflected in the pick at range 5 and 6 of the sport facility.

# 6. Regression analysis

Regression analysis is a fundamental statistical technique used to examine relationships between variables. In the context of this thesis, regression analysis will be a crucial methodological tool to further explore and better understand the factors influencing the performance of Airbnb hosts in the city of Milan.

The regression analysis will be presented as an essential methodological tool to address research questions and test formulated hypotheses. The main objective will be to identify significant variables that impact Airbnb host performance and understand the nature of these relationships.

Specifically, we will use regression analysis to examine how qualitative variables such as the presence of subways, degraded areas, parking facilities, Restricted Traffic Zones (ZTL), and sports facilities influence Airbnb host performance. Through the application of regression models, we will explore the magnitude and direction of these relationships, identifying factors that have a significant impact on performance and providing an empirical basis for better understanding the functioning of the short-term rental market in the city of Milan.

Regression analysis will also be presented as a tool to evaluate the effectiveness of any interventions or policies that may be proposed to improve Airbnb host performance or better manage the short-term rental market in the city. Through the interpretation of estimated coefficients and analysis of results, we will provide valuable insights for stakeholders in the sector, such as hosts, tourism operators, and local authorities.

In summary, regression analysis plays a key role in the methodological approach of my thesis, offering a robust statistical framework to examine complex relationships between variables and contributing to the overall understanding of the Airbnb rental phenomenon in the city of Milan.

## 6.1. Univariate analysis

Univariate regression analysis aims to explore the relationship between two variables, where one variable (the independent variable) is used to predict or explain changes in another variable (the dependent variable). In the thesis, univariate regression analysis will serve as a preliminary step to investigate the relationship between each independent variable (such as proximity to the metro, parking availability, restricted traffic areas, sports facilities, and degraded areas) and the dependent variables representing Airbnb host performance metrics (such as RevPAN, Revenues, Reservation Days, ADR, and OCC). Through univariate regression analysis, we aim to assess the strength and direction of the relationship between each independent variable and performance metrics, individually. Additionally, univariate regression analysis will establish a foundation for subsequent multivariate regression analysis, where we will examine the combined influence of multiple independent variables on Airbnb host performance while controlling for any confounding factors. The equations referenced, with a linear-linear univariate regression model and a log-linear model, are as follows:

$$RevPAN_i = \alpha + \beta \, Distance_i$$

$$lnRevPAN_i = \alpha + \beta \, Distance_i$$

In this case, an example of equations with RevPAN as the dependent variable has been provided, and the equations remain the same for all other performance variables, except for OCC, where only the linear-linear model is used since it wouldn't make sense to use the logarithmic model since it is already a percentage. It is also specified that the independent variable Distance$i$ is generically presented to provide an example of these equations, but during the analysis, it is appropriately replaced with all distance variables from the various categories analyzed (metro, degradation, ZTL, sports facilities, and parking).

### 6.1.1. Revenues:

As previously anticipated, it is decided to study the relationship between the dependent variable Revenues and the independent variable Distance, repeated for all categories (metro, ZTL, degradation, sports facilities, and parking), first with a linear model (LIN-LIN), and subsequently with a logarithmic model (LOG-LIN), as summarized in the tables below:

| Revenues USD | Cons | Beta | P value | R^2 |
|---|---|---|---|---|
| **Metro** | 1753.738 | -0.4716 | 0.000 | 0.0203 |
| **Degradation** | 1366.144 | 0.2637 | 0.000 | 0.0038 |
| **ZTL** | 1824.065 | -0.6695 | 0.000 | **0.0405** |
| **Parking** | 1761.951 | -0.3343 | 0.000 | 0.0278 |
| **Sport facility** | 1084.988 | 0.6937 | 0.000 | 0.0267 |

*Table 6.1 Univariate regression for the dependent variable Revenues*

| Ln(Revenues USD) | Cons | Beta | P value | R^2 |
|---|---|---|---|---|
| **Metro** | 7.0266 | -0.0004 | 0.000 | 0.0162 |
| **Degradation** | 6.7412 | 0.0002 | 0.000 | 0.0027 |
| **ZTL** | 7.071 | -0.0005 | 0.000 | **0.0300** |
| **Parking** | 7.0368 | -0.0003 | 0.000 | 0.0231 |
| **Sport facility** | 6.5770 | 0.0004 | 0.000 | 0.0146 |

*Table 6.2 Univariate regression for the dependent variable Ln(Revenues)*

The equations referred to, with a linear-linear univariate regression model and with a log-linear model, are as follows:

$$Revenuesi \ = \ \alpha \ + \ \beta \ Distance_{i}$$

$$lnRevenuesi \ = \ \alpha \ + \ \beta \ Distance_{i}$$

The results of the LIN-LIN model are as follows:

$Revenues \ = \ 1753{,}738 - \ 0{,}4716 \ DistanceMetro$

$Revenues \ = \ 1366{,}144 \ + \ 0{,}2637 \ DistanceDegradation$

$Revenues \ = \ 1824{,}065 - \ 0{,}6695 \ DistanceZTL$

$Revenues \ = \ 1761{,}951 - \ 0{,}3343 \ DistanceParking$

$Revenues \ = \ 1084{,}988 \ + \ 0{,}6937 \ DistanceSport$

Observing the first table above, we can notice that the t-value is less than -2.58 ($p < 1\%$), indicating the rejection of the null hypothesis, meaning that the coefficient β is statistically significant. Therefore, taking the example of the Metro category, a unit increase in the distance between the property and the nearest metro station implies a decrease of 0.4716 in the value of the dependent variable Revenues. This result confirms our initial hypothesis that having a metro station near the property positively influences its performance. Looking at the model's precision, the variance explained by it is relatively low (R^2 of 0.0203, i.e., 2.03%). However, by using a continuous variable, we have improved the significance compared to the same regression conducted with a dummy independent variable, which would have provided less information. To achieve a more significant model, as we will see later, it is necessary to combine multiple variables.

Additionally, it can be noted that a similar relationship to that of the metro is observed for parking lots and restricted traffic areas (ZTL), meaning that an increase in the distance for these categories leads to a reduction in the value of Revenues. Conversely, for degradation areas and sports facilities, the relationship is opposite, meaning that an increase in distance leads to an increase in Revenues. Particularly, an increase of one unit in the distance to a sports facility results in Revenues increasing by 0.6937 dollars. This latter result contradicts our initial hypotheses, so we will evaluate if this trend reoccurs in subsequent regressions.

A significant value is observed in the variance explained by the model with the distance from restricted traffic areas (ZTL), which is relatively high ($R^2$ of 0.0405, i.e., 4.05%).

Similarly, the results of the LOG-LIN model are as follows:

$$ln\ (Revenues) \ = \ 7{,}0266 - \ 0{,}0004\ DistanceMetro$$

$$ln\ (Revenues) \ = \ 6{,}7412 \ + \ 0{,}0002\ DistanceDegradation$$

$$ln\ (Revenues) \ = \ 7{,}0710 - \ 0{,}0005\ DistanceZTL$$

$$ln\ (Revenues) \ = \ 7{,}0368 - \ 0{,}0003\ DistanceParking$$

$$ln\ (Revenues) \ = \ 6{,}5770 \ + \ 0{,}0004\ DistanceSport$$

Observing the second table above, we can also note that the t-value is less than -2.58 ($p < 1\%$), indicating the rejection of the null hypothesis, meaning that the coefficient β is statistically significant at the 99% level. Therefore, taking the example of the Metro category, a unit increase in the distance between the property and the nearest metro station implies a decrease of 0.04% in the value of the dependent variable Revenues. The trends, even for the other categories, remain similar and consistent with those of the linear-linear model. Comparing the value of $R^2$, we can see that it has decreased from 2.03% to 1.62%. As observed, this trend repeats all analyzed categories. One explanation could be that the logarithmic model might not be fully capturing the relationship between the variables, leading to an information loss compared to the linear model.

### 6.1.2. Reservation days:

As the second univariate regression model, we analyzed the relationship between the dependent variable Reservation Days and the independent variable Distance, repeated for all categories (metro, ZTL, degradation, sports facilities, and parking), first with a linear model (LIN-LIN), and subsequently with a logarithmic model (LOG-LIN), as summarized in the tables below:

| Reservation days | Cons | Beta | P value | R^2 |
|---|---|---|---|---|
| Metro | 14.8589 | -0.0014 | 0.000 | 0.0033 |
| Degradation | 13.8542 | 0.0005 | 0.000 | 0.0003 |
| ZTL | 14.9122 | -0.0017 | 0.000 | 0.0046 |
| Parking | 14.5994 | -0.0006 | 0.000 | 0.0017 |
| Sport facility | 13.0981 | 0.0017 | 0.000 | 0.0031 |

*Table 6.3 Univariate regression for the dependent variable Reservation days*

| Ln(Reservation days) | Cons | Beta | P value | R^2 |
|---|---|---|---|---|
| Metro | 2.4808 | -0.0001 | 0.000 | 0.0029 |
| Degradation | 2.3933 | 0.00005 | 0.000 | 0.0003 |
| ZTL | 2.4865 | -0.0001 | 0.000 | 0.0042 |
| Parking | 2.4604 | -0.00005 | 0.000 | 0.0016 |
| Sport facility | 2.3336 | 0.0001 | 0.000 | 0.0027 |

*Table 6.4 Univariate regression for the dependent variable Ln (Reservation days)*

The results of the LIN-LIN model are as follows:

$$Reservation\ days = 14{,}8589 - 0{,}0014\ DistanceMetro$$

$$Reservation\ days = 13{,}8542 + 0{,}0005\ DistanceDegradation$$

$$Reservation\ days = 14{,}9122 - 0{,}0017\ DistanceZTL$$

$$Reservation\ days = 14{,}5994 - 0{,}0006\ DistanceParking$$

$$Reservation\ days = 13{,}0981 + 0{,}0017\ DistanceSport$$

Observing the first table above, we can note that the t-value is less than -2.58 ($p < 1\%$), indicating the rejection of the null hypothesis, meaning that the coefficient β is statistically significant. Therefore, taking the example of the Metro category again, a unit increase in the distance between the property and the nearest metro station implies a decrease of 0.0014 days in the dependent variable Reservation Days. This result confirms our initial hypothesis that having a metro station near the property positively influences its performance, in this case, increasing the number of days reserved by guests. Looking at the precision of the model, the variance explained by it is very low (R^2 of 0.0033, i.e., 0.33%). This indicates that this performance variable is not strongly influenced by the independent variable studied. In summary, we can say that the distance does not greatly influence the duration of guests' stays, unlike what we saw in the previous model regarding customers' willingness to pay.

Additionally, a similar relationship to that of the metro is observed for parking lots and restricted traffic areas (ZTL), meaning that an increase in the distance for these categories leads to a reduction in the value of Reservation Days. Conversely, for degradation areas and sports facilities, the relationship is opposite, meaning that an increase in distance leads to an increase in Reservation Days. Particularly, an increase of one unit in the distance to a sports facility results in Reservation Days increasing by 0.0017 days. This latter result contradicts our initial hypotheses again. As seen for the metro, the R^2 value for all these categories is very low, never exceeding 0.42%.

Similarly, the results of the LOG-LIN model are as follows:

$ln\ (Reservation\ days)\ =\ 2{,}4808 - \ 0{,}0001\ DistanceMetro$

$ln\ (Reservation\ days)\ =\ 2{,}3933\ +\ 0{,}00005\ DistanceDegradation$

$ln\ (Reservation\ days)\ =\ 2{,}4865 - \ 0{,}0001\ DistanceZTL$

$ln\ (Reservation\ days)\ =\ 2{,}4604 - \ 0{,}00005\ DistanceParking$

$ln\ (Reservation\ days)\ =\ 2{,}3336\ +\ 0{,}0001\ DistanceSport$

Observing the second table above, we can also note that the t-value is less than -2.58 (p < 1%), indicating the rejection of the null hypothesis, meaning that the coefficient β is statistically significant at the 99% level. Therefore, taking the example of the Metro category again, a unit increase in the distance between the property and the nearest metro station implies a decrease of 0.01% in the value of the dependent variable Reservation Days. The trends, even for the other categories, remain similar and consistent with those of the linear-linear model. Comparing the value of R^2, we can see that it has further decreased from 0.33% to 0.29%, making this model even less significant.

### 6.1.3. ADR

Following an example of the formula used in the univariate regression analysis of the average daily rate:

$$ADR = \alpha + \beta Distance$$

$$\ln ADR = \alpha + \beta Distance$$

For the ADR, in the univariate regression, the correlation between the variable and the distance to the closest “point of interest” was studied with two criteria: the LIN-LIN and the LOG-LIN one.

The variable “Distance” reported before refers to the distance, in meters, between each listing and the closest “point of interest”. Indeed, for each dependent variable five univariate regressions were made, one for each “point of interest”: metro station, degradation area, public parking, ZTL/pedestrian area, and sport facility.

| ADR | Cons | beta | p value | R^2 |
|---|---|---|---|---|
| **Metro** | 136.0909 | -0.0283 | 0.0000 | 0.0203 |
| **Degradation** | 136.0909 | -0.0283 | 0.0000 | 0.0203 |
| **ZTL** | 141.0142 | -0.0417 | 0.0000 | **0.0438** |
| **Parking** | 139.0923 | -0.0233 | 0.0000 | **0.0375** |
| **Sport facility** | 95.4257 | 0.0423 | 0.0000 | 0.0283 |

*Table 6.5 Univariate regression for the dependent variable ADR*

*Table 6.5* shows the correlations between the ADR and each independent variable using a LIN-LIN correlation. For each of these analyses the P-value is below 1%, so we can discard the null hypothesis, stating that the β is significative.

The β in each regression is negative, but for the correlation with the sport facility. A negative value of β means that for each meter that the listing is further from the closest “point of interest” the ADR drops for the value of β. In particular, the most negative β is the one of the ZTL, this means that the more we are closer to a ZTL and the more the ADR will be high, instead for each meter going further from the closest ZTL will reduce by 0.0417 [$ per night].

Looking at the precision of the model, the variance explained by it appears to be very low, going from an $R^2$ of 0.0203 to at a maximum of 0.0438, this because only one single variable at each time has been used, indeed for a better study of the model in the next chapter the variables are studied together in the multivariate regression.

| Ln(ADR) | Cons | beta | p value | R^2 |
|---|---|---|---|---|
| **Metro** | 4.7651 | -0.0002 | 0.0000 | 0.0293 |
| **Degradation** | 4.7651 | -0.0002 | 0.0000 | 0.0293 |
| **ZTL** | 0.6051 | -0.0000333 | 0.0000 | **0.0611** |
| **Parking** | 4.7980 | -0.0002 | 0.0000 | **0.0596** |
| **Sport facility** | 4.4442 | 0.0003 | 0.0000 | 0.0308 |

*Table 6.6 Univariate regression for the dependent variable Ln(ADR)*

In *table 6.6* the LOG-LIN regression model for the ADR is shown. This kind of model, using logarithms, focused its attention on how the dependent variable changes in % for each unitary change in the independent variable, which in our case are the distances to the closest "point of interest". This model shows again the negative correlation between going further from the first four points of interest as a percentage, explaining in a better way the model with a $R^2$ higher than in the LIN-LIN analysis.

The opposite trend, instead, characterizes the correlation with the sport facilities. Going further of 1 meter from the closest sport facility led to an increase in the ADR of 0.03%. This lets us understand that having a sport facility closer to your Airbnb is correlated to having a lower ADR.

### 6.1.4. OCC

Following an example of the formula used in the univariate regression analysis of the average daily rate:

$$OCC = \alpha + \beta Distance$$

The Occupancy rate, in the univariate regression, was studied only with the LIN-LIN model and not the LOG-LIN one, because by being a percentage value its logarithm is meaningless. The distance refers to each single distance from the closest "point of interest", which change for each of them.

| OCC | coeff | beta | p value | R^2 |
|---|---|---|---|---|
| **Metro** | 0.6059 | -0.0001 | 0.0000 | 0.001 |
| **Degradation** | 0.5852 | 7.95e-06 | 0.0000 | 0.0001 |
| **ZTL** | 0.6051 | -0.0000333 | 0.0000 | 0.0016 |
| **Parking** | 0.5992 | -0.0000127 | 0.0000 | 0.0006 |
| **Sport facility** | 0.5677 | 0.0000355 | 0.0000 | 0.0011 |

*Table 6.7 Univariate regression for the dependent variable OCC*

*Table 6.7* shows the correlations between the dependent variable, which in this case is the occupancy rate, and each distance from the closest "point of interest" one at each time.

The P-value for all these analyses was below 1%, so is possible to consider the β as a significative value. The β of these analyses were so low, negative for the metro stations, the ZTL and the public parking meaning that moving further from them led to a decrease in the occupancy rate of the listings. The opposite, instead, happens for the degraded areas and the sports facilities, having a positive beta show that being closer to them led to a lower occupancy rate to the listing.

Looking at the precision of the model, the variance explained by it appears to be very low, going from an $R^2$ of 0.0006 to at a maximum of 0.0016, this is because only one single variable at each time has been used.

### 6.1.5. RevPAN

Following an example of the formula used in the univariate regression analysis of the average daily rate:

$$RevPAN = \alpha + \beta Distance$$

$$\ln RevPAN = \alpha + \beta Distance$$

For the RevPAN, in the univariate regression, the correlation between the variable and the distance to the closest "point of interest" was studied with two criteria: the LIN-LIN and the LOG-LIN one. The distance refers to each single distance from the closest "point of interest", which change for each of them.

| RevPAN | Cons | beta | p value | R^2 |
|---|---|---|---|---|
| Metro | 72.7664 | -0.0176 | 0.0000 | 0.0191 |
| Degradation | 58.3889 | 0.0097 | 0.0000 | 0.0035 |
| ZTL | 75.3575 | -0.0249 | 0.0000 | **0.0380** |
| Parking | 73.4366 | -0.0129 | 0.0000 | 0.0282 |
| Sport facility | 47.8902 | 0.0257 | 0.0000 | 0.0249 |

*Table 6.8 Univariate regression for the dependent variable RevPAN*

*Table 6.8* shows the correlation between RevPAN (dependent variable) and as independent variable the distance in meters to the closest "point of interest".

The P-value is below 1%, indeed is possible to consider the β significative. Having a negative β, going further from the closest metro station, ZTL/pedestrian area and public parking show a lower RevPAN as supposed before. The exact opposite happens, instead, for the degradation area and the sport facilities.

| Ln(RevPAN) | Cons | beta | p value | R^2 |
|---|---|---|---|---|
| Metro | 3.9430 | -0.000299 | 0.0000 | 0.0146 |
| Degradation | 3.7070 | 0.0001491 | 0.0000 | 0.0022 |
| ZTL | 3.9809 | -0.0004105 | 0.0000 | 0.0273 |
| Parking | 3.9587 | -0.0002257 | 0.0000 | 0.0227 |
| Sport facility | 3.5623 | 0.0003687 | 0.0000 | 0.0136 |

*Table 6.9 Univariate regression for the dependent variable Ln(RevPAN)*

In *table 6.9*, the same correlation has been studied using logarithms, showing a better explanation of the model (with higher $R^2$). The signs, obviously, remained the same, with the beta now showing the change of the RevPAN as a percentage and no more as a numerical value as before.

The P-values are all below the limit of 1% letting us consider the betas as significative values.

## 6.2. Multivariate Analysis

For the multivariate regression 3 different models were studied. In all three models as dependent variables were used the performance variables of the Airbnb and their natural logarithms, as control variables the ones explained before and ad independent variables the distance ones computed before. The differences between the three analysis that were done wat that in the first one has been only studied the correlation between the variables described before, instead in the second was also introduced the correlation with the long-term variable and finally in the third the implementation of the Superhost variable.

These multivariate analyses have been done to understand the correlation, if any, between the dependent variables and the independent ones, also introducing the control variables in order to study a model that can better explain the phenomenon.

Each analysis began with the first model where only the control variables were studied. In the following formula is reported an example of the M1 model with the RevPAN as dependent variable.

$$RevPAN_{i,t} = \alpha + \beta_1 MaxGuests + \beta_2 EntireHome + \beta_3 IstantBook \\ + \beta_4 SuperHost + \beta_5 LTR + \beta_6 NIL + \beta_7 Year + \beta_8 Month$$

The same happened also for the LOG-LIN study where the RevPAN as independent variable was substituted with the ln (RevPAN).

$$lnRevPAN_{i,t} = \alpha + \beta_1 MaxGuests + \beta_2 EntireHome + \beta_3 IstantBook \\ + \beta_4 SuperHost + \beta_5 LTR + \beta_6 NIL + \beta_7 Year + \beta_8 Month$$

Then the models M2, M3, M4, M5 and M6 were studied introducing, in each single one, the correlation with a distance variable computed before. In depth:

- M2: correlation with the distance to the closest metro station
- M3: correlation with the distance to the closest degradation area
- M4: correlation with the distance to the closest ZTL/pedestrian area
- M5: correlation with the distance to the closest sport facility
- M6: correlation with the distance to the closest public parking

Finally in the Model M7 all those variables were implemented arriving to the final model with all the control variables and all the distance variables as independent ones.

All these analyses described have been done for all the performances variables as dependent and for their logarithms, with the exception for the occupancy rate which, being a value expressed as a percentage, its logarithms would be meaningless.

### 6.2.1. Revenues

The model has been studied for the revenues and the natural logarithm of them, showing in M1 the correlation between the first model, having only the control variables described before. The control variable of MaxGuests, entire apartment, instantbook and superhost show a positive correlation with the dependent variables "Revenues" and "ln(Revenues)", the opposite, instead, happen for the long term rent, associated with a decrease of the revenues.

In the following models (M2, M3, M4, M5 and M6) have been studied these variables of control plus one single variable of distance computed before. Recalling that these variables of distance computed the distance in meters from a listing to the closest "point of interest", two of them shows a positive correlation, meaning that for each meter that a listing is further from the closest "degradation area" and "sport facility" its revenues are higher. In depth for each meter going further from the closest degradation area, the revenues increase of 0.145$ per month and for each meter going further from the closest sport facility the revenues increase of 0.053$ per month, all these values are strengthened by the P-value being <1%. The opposite trends are shown by the metro stations, the ZTL or pedestrian areas and finally by the public parking. These models show a negative correlation between going further from these "point of interests" and the revenues of the listings, indirectly is shown also that getting closer to one of them is correlated with better performances. For each meter getting closer to the closest metro stations the revenues will be 0.184$ per month higher, for each meter getting closer to the closest ZTL or pedestrian areas the revenues will be 0.154$ per month higher and finally by getting 1 meter closer to the closest public parking the revenues show an increase of 0.125$ per month. These values can be considered significative due to the fact that their P-values are below 1%.

The models referring to the logarithm of the revenues do not show in a clear way the trends because we are considering how the revenues change by moving meter by meter, so study the change in percentage of them didn't result in the best way to study the model.

In the final model (M7) all the variables of control and all the independent variables have been grouped together in order to study a final model complete of all the variables. In the tables attached at the end of the paper all these tables are grouped to show in a better way what happened in the model.

### 6.2.2. ADR

The model was studied for the variable ADR and its natural logarithm, showing in M1 the correlation between the performance variable and general variables. In this model, a positive correlation is observed between the control variables MaxGuests, Entire Apartment, and LTR with the dependent variables ADR and ln (ADR), while the opposite occurs for Instantbook and Superhost, associated with a decrease in the value of ADR.

In the subsequent models (M2, M3, M4, M5, and M6), we added one by one the calculated distance variables (Metro, degradation, ZTL, sports facilities, and parking). Two of these distance variables show a positive correlation, meaning that for every meter an ad moves away from the nearest "degradation area" and "sports facility," the ADR value increases. In particular, for every meter moving away from the nearest degradation area, revenues increased by \$0.011 per month, and for every meter moving away from the nearest sports facility, revenues increased by \$0.005 per month, all of these values are supported by a p-value <1%. Conversely, opposite trends are recorded for metro stations, restricted traffic areas (ZTL) or pedestrian areas, and public parking. These models show a negative correlation between moving away from these "points of interest" and the ADR of listings, indirectly demonstrating that getting closer to one of them is correlated with better performance. For every meter approaching the nearest metro stations, revenue will increase by \$0.014 per month, for every meter approaching the nearest ZTL or pedestrian areas, revenue will increase by \$0.011 per month, and finally, approaching the nearest metro station by 1-meter, public parking will result in a revenue increase of \$0.011 per month. These values can be considered significant since their p-values are less than 1%.

However, the Log-Lin models, still for the ADR performance variable, do not clearly show trends. This is undoubtedly since we are considering how revenues change meter by meter, so studying their percentage variation is not very meaningful, given that even the variations in the linear model are very small for this variable.

In the final model (M7), all control variables and independent variables were grouped together to study a comprehensive model with all variables.

### 6.2.3. OCC:

The model was studied for the OCC variable, showing in M1 the correlation between the performance variable and general variables. From this regression, we can observe a positive correlation between the control variables Instantbook, Entire Apartment, and Superhost with the dependent variable OCC, while the opposite occurs for MaxGuests and LTR, associated with a decrease in the value of OCC.

In the subsequent models (M2, M3, M4, M5, and M6), we added one by one the calculated distance variables (Metro, degradation, ZTL, sports facilities, and parking). These distance variables calculate the distance in meters from a listing to the nearest "point of interest." Observing the obtained data, we can see that the Beta values are equal to zero, suggesting that there is no significant relationship between this variable and the dependent variable (performance) when considering the distance from the points of interest. The fact that OCC (Occupancy Rate) is a percentage could significantly influence the relationship with the distance from the points of interest, especially when considering the variation meter by meter. Therefore, the occupancy rate may not vary significantly for each additional or removed meter of distance from the points of interest, especially considering that we are analyzing a very large area. We can notice that for all values within this regression, the p-value is <1%.

In the final model (M7), all control variables and independent variables were grouped together to study a comprehensive model with all variables, but we obtained the same data as in the previous models.

### 6.2.4. RevPAN:

The model was studied for the RevPAN variable and its natural logarithm, showing in M1 the correlation between the performance variable and general variables. In this model, we can observe a positive correlation between all control variables MaxGuests, Entire Apartment, LTR, Instantbook, and Superhost with the dependent variable RevPAN. However, considering ln(RevPAN), the opposite occurs for the control variable LTR. In fact, for the Lin-Lin model, a positive coefficient of 3.722 is found, while in the Log-Lin model, a value of -0.088 is obtained. These values are supported by a p-value < 1%.

In the subsequent models (M2, M3, M4, M5, and M6), we added one by one the calculated distance variables (Metro, degradation, ZTL, sports facilities, and parking). Two of these distance variables show a positive correlation, meaning that for every meter an ad moves away from the nearest "degradation area" and "sports facility," the value of RevPAN increases. In particular, for every meter moving away from the nearest degradation area, the value of RevPAN increases by $0.005 per month, and for every meter moving away from the nearest sports facility, revenues increase by $0.002 per month, all of these values are supported by a p-value <1%. Conversely, opposite trends are recorded for metro stations, restricted traffic areas (ZTL) or pedestrian areas, and public parking. These models show a negative correlation between moving away from these "points of interest" and the RevPAN of listings, indirectly demonstrating that getting closer to one of them is correlated with better performance. For every meter approaching the nearest metro stations, revenue will increase by $0.007 per month, for every meter approaching the nearest ZTL or pedestrian areas, revenue will increase by $0.005 per month, and finally, approaching the nearest metro station by 1 meter, public parking will result in a revenue increase of $0.004 per month. These values can be considered significant since their p-values are less than 1%.

However, the Log-Lin models, still for the RevPAN performance variable, do not clearly show trends. This is undoubtedly due to the fact that we are considering how revenues change meter by meter, so studying their percentage variation is not very meaningful, given that even the variations in the Lin-Lin model are very small for this variable.

In the final model (M7), all control variables and independent variables were grouped together to study a comprehensive model with all variables.

## 6.3. Multivariate regression with SuperHost

Following the previously analyzed multivariate regression models, in this paragraph, the performance variables of Airbnb listings were examined in relation to the SuperHost status to verify if this variable has an interactive effect with other variables in determining the dependent variable. Indeed, by multiplying this dummy variable by the variables representing distances from points of interest, we can verify if and how being a SuperHost has additional effects on them.

For these regressions, 6 models were identified:

**M1:** Classic introductory model that relates the dependent performance variable with control variables such as Max Guest, Entire Apartment, Instantbook, SuperHost, and LTR, always comparing listings for each NIL, Year and Month.

**M2-M3-M4-M5-M6:** In addition to the control variables used in M1, two new variables are introduced, one being the distance variables and the second being the product between the previously mentioned distance variable and the SuperHost dummy variable. This is repeated for each model from M2 to M6, always changing the type of point of interest (metro, degradation, ZTL, sports facilities, and parking).

Observing the results, we can see that regarding the OCC variable, we obtain the same results as in the previous regressions, i.e., a beta equal to 0 for all models. As seen previously, this could be related to the fact that, being a percentage value linked to a very large area, a change of one meter in the distance between the structure and the various reference points may not be significant enough to vary the occupancy rate by one percentage point.

Regarding the variable Revenues and its natural logarithm, we can observe the following:

- Regarding the distance from the metro, we see a beta value of -0.178 $ per month, meaning that an increase of one meter in the distance between the listing and the point of interest decreases the Revenues by \$0.178. Additionally, we see a beta value of -0.029 \$ per month when considering the variable Distance*SuperHost. This suggests that being a SuperHost makes the distance between the nearest metro and the listing even more significant. Specifically, it implies that an increase of one meter in the distance between the listing and the point of interest decreases the Revenues by \$0.178 + \$0.029 in the case of a SuperHost. All these values are supported by a p-value <1%. This trend is also repeated for ZTL, sports facilities, and parking.

- Regarding model M3, which pertains to the distance from the nearest degradation area, we see a beta value of 0.150 \$ per month, indicating that an increase of one meter in the distance between the listing and the point of interest increases the Revenues by \$0.150. Additionally, we see a beta value of -0.024 \$ per month when considering the variable Distance*SuperHost. This suggests that being a SuperHost makes the distance from the nearest degradation area to the structure less significant. Specifically, it implies that an increase of one meter in the distance between the listing and the point of interest increases the Revenues by \$0.150 - \$0.024 in the case of a SuperHost. However, it is notable that for the variable Distance*SuperHost, the p-value is > 1%. This may indicate that the variable does not significantly contribute to explaining the variation in the dependent variable, or there may be additional heterogeneity or noise not captured by the variables considered in the model.
- As for the natural logarithm of Revenues, we observe that the beta coefficients in models M2 to M6 are zero for the distance variables and Distance*SuperHost. This is because we are considering how revenues change meter by meter, so studying the percentage variation is not very meaningful, given that even the variations in the linear model are very small for this variable.

Moving on to analyze the trend of the ADR variable and its natural logarithm, concerning the distance from the metro, we observe a beta value of -0.014 \$ per month, indicating that an increase of one meter in the distance between the listing and the point of interest decreases the ADR by \$0.014. Additionally, we see a beta value of 0.000 \$ per month when considering the variable Distance*SuperHost, suggesting that being a SuperHost does not further influence the trend of this performance variable. For models M4 and M5

(ZTL and sports facilities), we observe that the beta coefficients related to the regression with the distance variable and with the latter multiplied by the SuperHost dummy have the same sign. For instance, in model M4, we see a beta value of -0.011 $ per month, meaning that an increase of one meter in the distance between the listing and the point of interest decreases the ADR by $0.011, and we see a beta value of -0.001 $ per month when considering the variable Distance*SuperHost. This implies that an increase of one meter in the distance between the listing and the point of interest decreases the ADR by $0.011 + $0.001 in the case of a SuperHost. All these values are supported by a p-value <1%. However, for models M3 and M6 (Degradation and Parking), we observe that the beta coefficients related to the regression with the distance variable and with the latter multiplied by the SuperHost dummy have opposite signs. Taking model M3 as an example, we see a beta value of 0.012 $ per month, indicating that an increase of one meter in the distance between the listing and the degradation area increases the ADR by $0.012, and we see a beta value of -0.003 $ per month when considering the variable Distance*SuperHost. This implies that an increase of one meter in the distance between the listing and the degradation area increases the ADR by $0.012 - $0.003 in the case of a SuperHost. Therefore, we can notice that being a Superhost slightly attenuates the effect on the distance from the degradation area to the structure, but the trend remains the same.

Regarding the natural logarithm of ADR, we observe that the beta coefficients in models M2 to M6 are zero for the distance variables and distance * SuperHost, repeating the same situation identified for the performance variables listed previously.

Finally, the last variable analyzed is RevPAN and its natural logarithm. In this case, we can observe that there is no disagreement in signs between the coefficients obtained from the regressions with the distance variable and with the latter multiplied by the SuperHost dummy. Specifically, for models M2, M4, M5, and M6, we see that being a SuperHost further reinforces the relationship between the distance and the RevPAN performance variable. For example, in model M2, we observe a beta value of -0.006 $ per month, indicating that an increase of one meter in the distance between the listing and the point of interest (metro station) decreases the RevPAN by $0.006, and we see a beta value of -0.001 $ per month when considering the variable Distance*SuperHost. This suggests that being a SuperHost makes the distance between the nearest metro and the listing even more significant. Specifically, it implies that an increase of one meter in the distance between the listing and the point of interest decreases the RevPAN by $0.006 + $0.001 in the case of a SuperHost.

We notice that these variations are minimal, but these values are justified by the fact that we are analyzing a large area, and the movement is equal to one meter. All these values are supported by a p-value <1%. The only model that "differs" is M3, which pertains to degradation. In this case, we find a beta value of 0.000 $ per month when considering the variable Distance*SuperHost. Therefore, we can deduce that being a SuperHost does not further influence the relationship between the distance from the degradation area to the structure and the RevPAN performance variable. Additionally, for the natural logarithm of RevPAN, we observe that the beta coefficients in models M2 to M6 are zero for the distance variables and distance * SuperHost.

## 6.4. Multivariate regression with LTR

the analysis, finally continued with the introduction of the dummy variable long term rent, described before. This variable, which can assume the values 0 or 1, has been multiplied with the distance variables computed before, in order to understand what happen to the listings in correlation with the distance and the LTR at the same time. The models studied refers to the dependent variables of the performance variables described before and their logarithms to study the LIN-LIN model and the LOG-LIN one, this last one resulting difficult to respond to questions since differences in percentage on a so little movement in meters are so small. In the tables attached at the bottom of this thesis there are presented all the values that will be described in this chapter, to have a full overview of the model and a better explanation of what has been found.

Regardless the revenues, as studied before for each meter going further from the closest metro stations, ZTL and public parking the revenues reduce. Introducing the interaction of these variables of distance with the long-term rent is possible to notice that the distance to the closest metro stations multiplied by the dummy variable of LTR is correlated with a positive value, showing that for the long-term rent listings, going further from the closest metro, public parking and ZTL increases the revenues per month. This can be explained by saying that having to booking an Airbnb for more than 1 month, guests are more willing to move away from the center where there is more concentration of ZTL, metro and parking, because a listing in the center is more think for visitors that want to enjoy the city for just a weekend or few days. For the degradation area, the long-term rent multiplier has no effects on the revenues per month of the listings. For the sports facilities the regression analysis stated that going further from them increases the revenues of the listings, the opposite happens, instead, introducing the multiplication with the LTR, indeed the listings accepting reservation only for more than 28 days, show a decrease of the revenues for each meter going further from the closest sport facility of 0.356$ per month.

Regarding the Average Daily Rate (ADR) the distance between a listing and the closest metro station follows the same trend as the proximity with the closest public parking. For each meter going further form the closest metro stations the revenues per month drop of 0.014$ per month, even more amplified for the listings offering a long-term rent, presenting a decrease in the revenue per month of ulterior 0.007$ per month for each meter going further from the closest metro station. For the listings proposing only long-term rent, is possible to say that the ADR drops of 0.014$ + 0.007$ for each meter going further from the closest metro station. For each meter going further from the closest degradation area or building, the ADR of the Airbnb increase of 0.011$ per day, even more amplified for the listing proposing only long-term rent, increasing their average daily rate by further 0.027$ per day. The opposite trend instead is shown by the proximity with the pedestrian areas, indeed, for each meter going further from the closest ZTL the ADR of the listings drops of 0.011$ per day, for the Airbnb offering only bookings of more than 28 days the ADR drops of only 0.004$ per day.

Regardless of the RevPAN, for each meter going further from the closest metro station and from the closest ZTL the RevPAN decrease, but this phenomenon is less effective for the listings proposing only long-term rent. For example, for each meter going further from the closest metro the RevPAN of the Airbnb drops 0.007$, considering only the listing proposing the long-term rent, the RevPAN drops of only 0.003$. Going away from a degradation area result in an increase in the RevPAN of the Airbnb, this phenomenon is even amplified for the LTR listings. The opposite trend is shown instead by the sport facilities. Step away from sport facilities results in better performances regarding the

RevPAN, evidence not verified for the listings offering only LTR, indeed their RevPAN reduces by 0.009$ for each meter going further from the closest sport facility.

All the data described in this chapter can be considered significative, having a P-value below 1%. The analysis has been conducted also for the LOG-LIN model, but the changes of the performance variables in percentage do not show in a clear way what happens by moving only meter by meter. A better way to understand the LOG-LIN model could be done using the distinction done before of the ranges.

# 7. Conclusions

The analysis conducted in this thesis have been chosen because of the lack of research in this sector, in particular the dependence between the distance from the "points of interests" to the Airbnb have never been studied before. The research is based on the fact that, in our opinion, the distance from an Airbnb to a metro station, to a public parking, to a sport facility, to a ZTL and finally to an area in degradation condition can affect the choice of the customers, and as a consequence the performances of the Airbnb.

This analysis can be useful not only to understand the model of Airbnb and the main factors affecting the performance, but also for the hosts to develop better choices from a strategical and managerial point of view. Not only for the hosts that currently have listings on the platforms, but also from new potential hosts that want to enter in the sector or people looking to purchase a new apartment to be placed on the Airbnb platform.

At the beginning of the thesis five hypotheses have been drawn up. Our analysis has been made with the aim of verifying the validity of the predetermined hypothesis or to refute them. Afterwards are reported the five hypotheses with the results founded:

*Hypothesis 1: The presence of a metro station near the property positively influences the performance of such Airbnb.*

First of all, with the univariate regression and afterwards with the multivariate regression has been found that for each meter going further from the closest metro station the performances of the listings decrease. Both in case of the regressions, where the continuous variables of the distance in meters have been used, and in the case of the division in ranges, the performances of the Airbnb dropped by stepping away from the closest metro stations. In particular the average of the revenues per month in the range 1 are 1292.38$ per month and in range 7 are 530.85$ per month. Also, the β in the regressions shows a negative value for every dependent variable studied. With the data collected and the analysis done has been possible to confirm our hypothesis 1.

*Hypothesis 2: The presence of a degraded area near the property negatively influences the performance of such Airbnb.*

The dataset regarding the degradation conditions refers to all the buildings and areas declared as is by the municipality of Milan. The regression shows a positive sign in the beta for all the performance variables studied, indeed is possible to say that for each meter going further from the closest area or building in degradation condition, the performances of the Airbnb increase. Revenues = 1366,144 + 0,2637*Distance Degradation.
This regression states that for each meter going further from the closest area in degradation conditions, the monthly revenues of the listings drop of 0.2637$ per month. A particular trend is evidenced in the division in ranges, indeed is possible to notice that for the first 5 ranges, stepping away from the closest degradation point results in better performances. In range 6 and 7 drop drastically, showing that listings further than 1500m from the closest degradation point have worst performance even with respect to the listings in range 1.

*Hypothesis 3: The presence of parking near the property positively influences the performance of such Airbnb.*

The analysis conducted in this thesis showed evidence of the confirmation of this hypothesis. Indeed, in the regression the β associated to the distance from the listings to the closest public parking show a negative sign, indicating that for each meter going further from the closest public parking the performances of the Airbnb drop. In the univariate regression with the revenues as dependent variable, the formula found has been *Revenues = 1761,951 – 0,3343*DistanceParking* showing that for each meter going further from the closest public parking the revenues of the Airbnb dropped of 0.3343$ per month. The same trend is evidenced also in the Average daily rate which decreases by 0.0233$ per night for each meter stepping away from the closest public parking. Also in the subdivision of the distance by ranges was possible to found that the average of the RevPAN per month in range 1 is almost the double of the one in range 7.

*Hypothesis 4: The presence of ZTL/Pedestrian Areas near the property positively influences the performance of such Airbnb.*

Analyzing the distances of various listings from restricted areas such as pedestrian zones and ZTLs, both through an analysis for individual structures and for different ranges, yielded significant results. During the analyses conducted by dividing the listings into 7 ranges, we noticed that transitioning from Range 1, which contains structures closest to the metro, to Range 7, which contains the farthest structures, the performances decreased steeply. For example, in the case of Revenues, we observed a decrease from an average monthly value of $1498.67 to $587.61. Examining the city structure of Milan, we identified a high concentration of these areas in the historic center, suggesting that Range 1 presumably consists of structures located in the center of Milan, thus justifying such a high average value of Revenues. During the univariate and multivariate regressions, we further confirmed our hypotheses. Indeed, analyzing the beta coefficients in the various regressions consistently revealed negative values, indicating a decline in performance associated with increasing distance of the structure from these zones. Additionally, we observed that in all regressions, the R^2 value associated with the model containing the distance from ZTLs was consistently the highest, reaching a peak of 6.11% for the ADR performance variable, thus demonstrating a high explanation of such a model.

*Hypothesis 5: The presence of sports facilities near the property positively influences the performance of such Airbnb.*

Moving on to the analysis regarding the performance variables in relation to the distance from Airbnb to sports facilities, we obtained interesting results. Starting with the analysis of these performances through the division into ranges, we noticed that the trend of these variables followed an alternating and non-constant pattern. Considering the Revenues and recalling that range 1 contains structures with a sports facility very close to the property while range 7 contains structures with a greater distance from the sports facilities, we observe a linear growth in the value of the variable from range 1 to range 4 (from $948.72 to $1034.70) and subsequently an exponential growth up to range 6 reaching a peak of $2252.85, then dropping drastically to $704.70 for range 7. Through analyses of Milan's layout, we managed to explain this phenomenon by understanding that the Airbnbs in range 7 were located in the peripheral areas of Milan where the prices per night are lower. From this analysis, we began to intuit that moving away from these points of interest would lead to better performance for the property. This intuition was subsequently confirmed first through univariate regressions and later in multivariate regressions where we consistently found positive regression beta coefficients associated with p-values < 1%. Therefore, we can see how this study has reversed the initial hypothesis

Further analysis may be conducted analyzing in a separate way the years taken in consideration in order to understand how and if the trends changed during the pandemic crisis. Moreover, may be monitored the website of the municipality of Milan to look forward for releases of new datasets or the updating of the ones used in this analysis, in order to study how the new distance variables may affect the performances of Airbnb.

# 8. Attachments

## 8.1. Multivariate regression tables

| Revenues | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | -0.184*** | | | | | -0.110*** |
| | | (0.008) | | | | | (0.008) |
| Degrado | | | 0.145*** | | | | 0.138*** |
| | | | (0.008) | | | | (0.008) |
| ZTL | | | | -0.154*** | | | -0.114*** |
| | | | | (0.007) | | | (0.007) |
| Sport | | | | | 0.053*** | | 0.068*** |
| | | | | | (0.009) | | (0.009) |
| Parcheggi | | | | | | -0.125*** | -0.094*** |
| | | | | | | (0.006) | (0.006) |
| Max Guest | 186.651*** | 186.506*** | 187.063*** | 186.678*** | 186.578*** | 187.133*** | 187.243*** |
| | (1.692) | (1.690) | (1.692) | (1.691) | (1.692) | (1.691) | (1.690) |
| Entire APT | 248.729*** | 249.675*** | 247.861*** | 249.068*** | 248.442*** | 246.081*** | 246.370*** |
| | (4.377) | (4.372) | (4.375) | (4.376) | (4.377) | (4.377) | (4.373) |
| Instantbook | 395.250*** | 392.271*** | 393.158*** | 392.839*** | 395.104*** | 394.676*** | 389.069*** |
| | (3.660) | (3.658) | (3.658) | (3.661) | (3.660) | (3.658) | (3.657) |
| Superhost | 152.051*** | 151.326*** | 150.618*** | 152.448*** | 152.385*** | 151.806*** | 150.790*** |
| | (4.277) | (4.273) | (4.274) | (4.274) | (4.276) | (4.275) | (4.269) |
| LTR | -81.141*** | -81.481*** | -81.193*** | -82.176*** | -81.014*** | -80.516*** | -81.531*** |
| | (14.991) | (14.980) | (14.979) | (14.990) | (14.990) | (14.992) | (14.972) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.282 | 0.283 | 0.283 | 0.283 | 0.282 | 0.283 | 0.284 |

| Ln(Revenues) | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | | 0.000*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.000*** | | | | 0.000*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | 0.000*** | | | 0.000*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.000*** | | 0.000*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | 0.000*** | 0.000*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.372*** | 0.372*** | 0.371*** | 0.372*** | 0.372*** | 0.370*** | 0.370*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.366*** | 0.364*** | 0.365*** | 0.365*** | 0.366*** | 0.366*** | 0.362*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.198*** | 0.198*** | 0.198*** | 0.199*** | 0.199*** | 0.198*** | 0.198*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| LTR | -0.268*** | -0.269*** | -0.268*** | -0.269*** | -0.268*** | -0.268*** | -0.269*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.252 | 0.253 | 0.253 | 0.253 | 0.252 | 0.253 | 0.254 |

| Y = ADR | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | -0.014*** | | | | | -0.008*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.011*** | | | | 0.011*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | -0.011*** | | | -0.008*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.005*** | | 0.006*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | -0.011*** | -0.009*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | 17.653*** | 17.640*** | 17.689*** | 17.653*** | 17.645*** | 17.699*** | 17.707*** |
| | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) |
| Entire APT | 18.311*** | 18.385*** | 18.237*** | 18.337*** | 18.282*** | 18.073*** | 18.079*** |
| | (0.273) | (0.272) | (0.272) | (0.273) | (0.273) | (0.272) | (0.272) |
| Instantbook | -9.926*** | -10.161*** | -10.099*** | -10.104*** | -9.941*** | -9.985*** | -10.421*** |
| | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) |
| Superhost | -13.792*** | -13.845*** | -13.911*** | -13.764*** | -13.758*** | -13.812*** | -13.892*** |
| | (0.226) | (0.226) | (0.226) | (0.226) | (0.226) | (0.226) | (0.226) |
| LTR | 12.492*** | 12.467*** | 12.491*** | 12.412*** | 12.506*** | 12.533*** | 12.472*** |
| | (0.930) | (0.928) | (0.927) | (0.929) | (0.930) | (0.927) | (0.925) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.304 | 0.306 | 0.305 | 0.305 | 0.304 | 0.306 | 0.308 |

| Y = lnADR | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | -0.000*** | | | | | -0.000*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.000*** | | | | 0.000*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | -0.000*** | | | -0.000*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.000*** | | 0.000*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | -0.000*** | -0.000*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.119*** | 0.119*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.295*** | 0.296*** | 0.295*** | 0.296*** | 0.295*** | 0.293*** | 0.294*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Instantbook | -0.056*** | -0.058*** | -0.057*** | -0.057*** | -0.056*** | -0.056*** | -0.060*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | -0.093*** | -0.093*** | -0.094*** | -0.093*** | -0.093*** | -0.093*** | -0.094*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| LTR | 0.018*** | 0.018*** | 0.018*** | 0.017** | 0.018*** | 0.018*** | 0.018*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.398 | 0.400 | 0.399 | 0.399 | 0.398 | 0.400 | 0.403 |

| Y = RevPAN | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | -0.007*** | | | | | -0.004*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.005*** | | | | 0.005*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | -0.005*** | | | -0.004*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.002*** | | 0.003*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | -0.004*** | -0.003*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | 8.179*** | 8.173*** | 8.192*** | 8.180*** | 8.176*** | 8.196*** | 8.199*** |
| | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) |
| Entire APT | 13.656*** | 13.692*** | 13.627*** | 13.669*** | 13.645*** | 13.561*** | 13.574*** |
| | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) |
| Instantbook | 12.835*** | 12.725*** | 12.762*** | 12.749*** | 12.829*** | 12.814*** | 12.614*** |
| | (0.138) | (0.138) | (0.138) | (0.138) | (0.138) | (0.138) | (0.138) |
| Superhost | 7.157*** | 7.131*** | 7.107*** | 7.171*** | 7.170*** | 7.148*** | 7.113*** |
| | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) |
| LTR | 3.722*** | 3.711*** | 3.717*** | 3.686*** | 3.727*** | 3.746*** | 3.710*** |
| | (0.613) | (0.612) | (0.612) | (0.613) | (0.613) | (0.613) | (0.612) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 | 0.317 |

| Y = lnRevPAN | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | -0.000*** | | | | | -0.000*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.000*** | | | | 0.000*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | -0.000*** | | | -0.000*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.000** | | 0.000*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | -0.000*** | -0.000*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.439*** | 0.440*** | 0.439*** | 0.440*** | 0.439*** | 0.438*** | 0.438*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.305*** | 0.303*** | 0.304*** | 0.304*** | 0.305*** | 0.305*** | 0.302*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.237*** | 0.236*** | 0.236*** | 0.237*** | 0.237*** | 0.236*** | 0.236*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| LTR | -0.088*** | -0.088*** | -0.088*** | -0.088*** | -0.088*** | -0.087*** | -0.088*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 | 0.300 |

| OCC | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | | 0.000*** |
| | | (0.000) | | | | | (0.000) |
| Degrado | | | 0.000*** | | | | 0.000*** |
| | | | (0.000) | | | | (0.000) |
| ZTL | | | | 0.000*** | | | 0.000*** |
| | | | | (0.000) | | | (0.000) |
| Sport | | | | | 0.000*** | | 0.000*** |
| | | | | | (0.000) | | (0.000) |
| Parcheggi | | | | | | 0.000*** | 0.000*** |
| | | | | | | (0.000) | (0.000) |
| Max Guest | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Entire APT | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Instantbook | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | 0.115*** | 0.115*** | 0.115*** | 0.115*** | 0.115*** | 0.115*** | 0.115*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| LTR | -0.019*** | -0.019*** | -0.019*** | -0.019*** | -0.019*** | -0.019*** | -0.019*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| ID NIL | yes | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes | yes |
| N | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 |
| R2 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 |

## 8.2. Multivariate regression tables Distance * SuperHost

| Revenues | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.178*** | | | | |
| | | (0.008) | | | | |
| Metro * Superhost | | -0.029*** | | | | |
| | | (0.009) | | | | |
| Degrado | | | 0.150*** | | | |
| | | | (0.008) | | | |
| Degrado * Superhost | | | -0.024* | | | |
| | | | (0.013) | | | |
| ZTL | | | | -0.142*** | | |
| | | | | (0.007) | | |
| ZTL * Superhost | | | | -0.058*** | | |
| | | | | (0.010) | | |
| Sport | | | | | 0.047*** | |
| | | | | | (0.009) | |
| Sport * Superhost | | | | | 0.036** | |
| | | | | | (0.017) | |
| Parcheggi | | | | | | -0.123*** |
| | | | | | | (0.006) |
| Parcheggi * Superhost | | | | | | -0.005 |
| | | | | | | (0.005) |
| Max Guest | 186.651*** | 186.541*** | 187.026*** | 186.722*** | 186.582*** | 187.124*** |
| | (1.692) | (1.690) | (1.692) | (1.691) | (1.692) | (1.691) |
| Entire APT | 248.729*** | 249.578*** | 248.025*** | 248.814*** | 248.263*** | 246.098*** |
| | (4.377) | (4.372) | (4.375) | (4.376) | (4.375) | (4.377) |
| Instantbook | 395.250*** | 392.209*** | 393.073*** | 392.936*** | 395.209*** | 394.720*** |
| | (3.660) | (3.658) | (3.659) | (3.660) | (3.659) | (3.659) |
| Superhost | 152.051*** | 166.010*** | 163.787*** | 179.771*** | 130.683*** | 155.966*** |
| | (4.277) | (6.942) | (8.206) | (7.049) | (10.142) | (6.646) |
| LTR | -81.141*** | -81.721*** | -81.243*** | -82.358*** | -81.275*** | -80.524*** |
| | (14.991) | (14.980) | (14.978) | (14.987) | (14.989) | (14.992) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.282 | 0.283 | 0.283 | 0.283 | 0.282 | 0.283 |

| Ln(Revenues) | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * Superhost | | | 0.000*** | | | |
| | | | (0.000) | | | |
| ZTL | | | | 0.000*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * Superhost | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Max Guest | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.372*** | 0.373*** | 0.372*** | 0.372*** | 0.372*** | 0.370*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.366*** | 0.364*** | 0.365*** | 0.365*** | 0.366*** | 0.366*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.198*** | 0.188*** | 0.229*** | 0.189*** | 0.220*** | 0.184*** |
| | (0.004) | (0.006) | (0.007) | (0.006) | (0.008) | (0.006) |
| LTR | -0.268*** | -0.269*** | -0.269*** | -0.269*** | -0.268*** | -0.268*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.252 | 0.253 | 0.253 | 0.253 | 0.252 | 0.253 |

| ADR | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.014*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | -0.000 | | | | |
| | | (0.001) | | | | |
| Degrado | | | 0.012*** | | | |
| | | | (0.001) | | | |
| Degrado * Superhost | | | -0.003*** | | | |
| | | | (0.001) | | | |
| ZTL | | | | -0.011*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | -0.001** | | |
| | | | | (0.001) | | |
| Sport | | | | | 0.005*** | |
| | | | | | (0.001) | |
| Sport * Superhost | | | | | 0.004*** | |
| | | | | | (0.001) | |
| Parcheggi | | | | | | -0.012*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | 0.003*** |
| | | | | | | (0.000) |
| Max Guest | 17.653*** | 17.641*** | 17.684*** | 17.654*** | 17.646*** | 17.703*** |
| | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) |
| Entire APT | 18.311*** | 18.383*** | 18.257*** | 18.332*** | 18.264*** | 18.064*** |
| | (0.273) | (0.272) | (0.272) | (0.273) | (0.272) | (0.272) |
| Instantbook | -9.926*** | -10.162*** | -10.109*** | -10.102*** | -9.929*** | -10.012*** |
| | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) |
| Superhost | -13.792*** | -13.608*** | -12.311*** | -13.197*** | -15.884*** | -16.155*** |
| | (0.226) | (0.372) | (0.444) | (0.365) | (0.516) | (0.351) |
| LTR | 12.492*** | 12.463*** | 12.483*** | 12.408*** | 12.481*** | 12.536*** |
| | (0.930) | (0.928) | (0.927) | (0.929) | (0.930) | (0.927) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.304 | 0.306 | 0.305 | 0.305 | 0.304 | 0.306 |

| Ln(ADR) | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * Superhost | | | 0.000*** | | | |
| | | | (0.000) | | | |
| ZTL | | | | 0.000*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * Superhost | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Max Guest | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.118*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.295*** | 0.296*** | 0.295*** | 0.295*** | 0.295*** | 0.293*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Instantbook | -0.056*** | -0.058*** | -0.057*** | -0.057*** | -0.056*** | -0.056*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | -0.093*** | -0.081*** | -0.087*** | -0.073*** | -0.116*** | -0.097*** |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.002) |
| LTR | 0.018*** | 0.017*** | 0.018*** | 0.017*** | 0.018*** | 0.018*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.398 | 0.400 | 0.399 | 0.399 | 0.398 | 0.400 |

| RevPAN | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.006*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | -0.001*** | | | | |
| | | (0.001) | | | | |
| Degrado | | | 0.005*** | | | |
| | | | (0.000) | | | |
| Degrado * Superhost | | | -0.000 | | | |
| | | | (0.000) | | | |
| ZTL | | | | -0.005*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | -0.003*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.002*** | |
| | | | | | (0.000) | |
| Sport * Superhost | | | | | 0.002*** | |
| | | | | | (0.001) | |
| Parcheggi | | | | | | -0.004*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | -0.001*** |
| | | | | | | (0.000) |
| Max Guest | 8.179*** | 8.175*** | 8.192*** | 8.182*** | 8.176*** | 8.195*** |
| | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) |
| Entire APT | 13.656*** | 13.686*** | 13.629*** | 13.657*** | 13.635*** | 13.563*** |
| | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) |
| Instantbook | 12.835*** | 12.722*** | 12.761*** | 12.754*** | 12.835*** | 12.818*** |
| | (0.138) | (0.138) | (0.138) | (0.138) | (0.138) | (0.138) |
| Superhost | 7.157*** | 7.889*** | 7.249*** | 8.498*** | 5.938*** | 7.565*** |
| | (0.156) | (0.255) | (0.300) | (0.256) | (0.369) | (0.243) |
| LTR | 3.722*** | 3.698*** | 3.717*** | 3.676*** | 3.712*** | 3.745*** |
| | (0.613) | (0.612) | (0.612) | (0.612) | (0.612) | (0.612) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 |

| Ln(RevPAN) | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * Superhost | | | 0.000*** | | | |
| | | | (0.000) | | | |
| ZTL | | | | 0.000*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * Superhost | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Max Guest | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.439*** | 0.440*** | 0.439*** | 0.440*** | 0.439*** | 0.438*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.305*** | 0.303*** | 0.304*** | 0.304*** | 0.305*** | 0.305*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.237*** | 0.231*** | 0.259*** | 0.231*** | 0.255*** | 0.230*** |
| | (0.003) | (0.005) | (0.006) | (0.005) | (0.007) | (0.005) |
| LTR | -0.088*** | -0.088*** | -0.088*** | -0.088*** | -0.088*** | -0.087*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 |

| OCC | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * Superhost | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * Superhost | | | 0.000*** | | | |
| | | | (0.000) | | | |
| ZTL | | | | 0.000*** | | |
| | | | | (0.000) | | |
| ZTL * Superhost | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * Superhost | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Parcheggi * Superhost | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Max Guest | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Entire APT | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Instantbook | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | 0.115*** | 0.108*** | 0.122*** | 0.107*** | 0.130*** | 0.111*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| LTR | -0.019*** | -0.018*** | -0.019*** | -0.018*** | -0.018*** | -0.019*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 |
| R2 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 |

## 8.3. Multivariate regression tables Distance * LTR

| Y=Revenues | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.188*** | | | | |
| | | (0.008) | | | | |
| Metro * LTR | | 0.191*** | | | | |
| | | (0.030) | | | | |
| Degrado | | | 0.145*** | | | |
| | | | (0.008) | | | |
| Degrado * LTR | | | 0.000 | | | |
| | | | (0.048) | | | |
| ZTL | | | | -0.160*** | | |
| | | | | (0.007) | | |
| ZTL * LTR | | | | 0.336*** | | |
| | | | | (0.037) | | |
| Sport | | | | | 0.059*** | |
| | | | | | (0.009) | |
| Sport * LTR | | | | | -0.356*** | |
| | | | | | (0.061) | |
| Parcheggi | | | | | | -0.126*** |
| | | | | | | (0.006) |
| Parcheggi * LTR | | | | | | 0.066*** |
| | | | | | | (0.017) |
| Max Guest | 186.651*** | 186.545*** | 187.063*** | 186.798*** | 186.609*** | 187.151*** |
| | (1.692) | (1.690) | (1.692) | (1.691) | (1.692) | (1.691) |
| Entire APT | 248.729*** | 249.913*** | 247.861*** | 248.994*** | 248.506*** | 246.300*** |
| | (4.377) | (4.373) | (4.376) | (4.376) | (4.377) | (4.378) |
| Instantbook | 395.250*** | 392.044*** | 393.158*** | 392.030*** | 394.956*** | 394.425*** |
| | (3.660) | (3.658) | (3.658) | (3.661) | (3.660) | (3.659) |
| Superhost | 152.051*** | 151.369*** | 150.618*** | 152.391*** | 152.627*** | 151.783*** |
| | (4.277) | (4.273) | (4.274) | (4.274) | (4.277) | (4.275) |
| LTR | -81.141*** | -189.288*** | -81.267*** | -252.082*** | 123.017*** | -133.635*** |
| | (14.991) | (24.533) | (28.356) | (24.900) | (37.418) | (22.970) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.282 | 0.283 | 0.283 | 0.283 | 0.282 | 0.283 |

| Y=lnRevenues | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | 0.000* | | | |
| | | | (0.000) | | | |
| ZTL | | | | -0.000*** | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * LTR | | | | | -0.000* | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | -0.000*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | -0.000 |
| | | | | | | (0.000) |
| Max Guest | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** | 0.111*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.372*** | 0.373*** | 0.371*** | 0.372*** | 0.372*** | 0.370*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.366*** | 0.364*** | 0.365*** | 0.364*** | 0.366*** | 0.366*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.198*** | 0.198*** | 0.198*** | 0.199*** | 0.199*** | 0.198*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| LTR | -0.268*** | -0.323*** | -0.314*** | -0.319*** | -0.217*** | -0.255*** |
| | (0.014) | (0.022) | (0.028) | (0.022) | (0.033) | (0.021) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.252 | 0.253 | 0.253 | 0.253 | 0.252 | 0.253 |

| Y=ADR | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.014*** | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | -0.007*** | | | | |
| | | (0.002) | | | | |
| Degrado | | | 0.011*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | 0.027*** | | | |
| | | | (0.003) | | | |
| ZTL | | | | -0.011*** | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | 0.007*** | | |
| | | | | (0.002) | | |
| Sport | | | | | 0.006*** | |
| | | | | | (0.001) | |
| Sport * LTR | | | | | -0.014*** | |
| | | | | | (0.004) | |
| Parcheggi | | | | | | -0.011*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | -0.005*** |
| | | | | | | (0.001) |
| Max Guest | 17.653*** | 17.639*** | 17.678*** | 17.655*** | 17.646*** | 17.697*** |
| | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) | (0.104) |
| Entire APT | 18.311*** | 18.375*** | 18.271*** | 18.336*** | 18.284*** | 18.056*** |
| | (0.273) | (0.272) | (0.272) | (0.273) | (0.273) | (0.272) |
| Instantbook | -9.926*** | -10.153*** | -10.093*** | -10.122*** | -9.947*** | -9.964*** |
| | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) | (0.223) |
| Superhost | -13.792*** | -13.847*** | -13.904*** | -13.766*** | -13.749*** | -13.809*** |
| | (0.226) | (0.226) | (0.226) | (0.226) | (0.226) | (0.226) |
| LTR | 12.492*** | 16.557*** | -2.134 | 8.871*** | 20.822*** | 16.905*** |
| | (0.930) | (1.518) | (1.885) | (1.520) | (2.258) | (1.420) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.304 | 0.306 | 0.305 | 0.305 | 0.304 | 0.306 |

| Y=lnADR | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | -0.000** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | 0.000*** | | | |
| | | | (0.000) | | | |
| ZTL | | | | -0.000*** | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | 0.000*** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * LTR | | | | | -0.000*** | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | -0.000*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | -0.000*** |
| | | | | | | (0.000) |
| Max Guest | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.118*** | 0.119*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.295*** | 0.296*** | 0.295*** | 0.296*** | 0.295*** | 0.293*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Instantbook | -0.056*** | -0.058*** | -0.057*** | -0.057*** | -0.056*** | -0.056*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | -0.093*** | -0.093*** | -0.094*** | -0.093*** | -0.093*** | -0.093*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| LTR | 0.018*** | 0.035*** | -0.078*** | -0.020* | 0.090*** | 0.061*** |
| | (0.007) | (0.011) | (0.014) | (0.010) | (0.016) | (0.010) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 | 4.09e+05 |
| R2 | 0.398 | 0.400 | 0.399 | 0.399 | 0.398 | 0.400 |

| Y = RevPAN | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.007*** | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | 0.004*** | | | | |
| | | (0.001) | | | | |
| Degrado | | | 0.005*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | 0.004* | | | |
| | | | (0.002) | | | |
| ZTL | | | | -0.006*** | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | 0.009*** | | |
| | | | | (0.001) | | |
| Sport | | | | | 0.002*** | |
| | | | | | (0.000) | |
| Sport * LTR | | | | | -0.011*** | |
| | | | | | (0.003) | |
| Parcheggi | | | | | | -0.005*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | 0.000 |
| | | | | | | (0.001) |
| Max Guest | 8.179*** | 8.174*** | 8.191*** | 8.183*** | 8.177*** | 8.196*** |
| | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) | (0.065) |
| Entire APT | 13.656*** | 13.696*** | 13.632*** | 13.667*** | 13.648*** | 13.562*** |
| | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) | (0.167) |
| Instantbook | 12.835*** | 12.720*** | 12.763*** | 12.728*** | 12.824*** | 12.812*** |
| | (0.138) | (0.138) | (0.138) | (0.139) | (0.138) | (0.138) |
| Superhost | 7.157*** | 7.132*** | 7.108*** | 7.169*** | 7.177*** | 7.148*** |
| | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) |
| LTR | 3.722*** | 1.552 | 1.677 | -0.773 | 9.893*** | 3.438*** |
| | (0.613) | (1.008) | (1.171) | (1.016) | (1.540) | (0.931) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 | 0.315 |

| Y = lnRevPAN | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.000*** | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | 0.000** | | | | |
| | | (0.000) | | | | |
| Degrado | | | 0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | 0.000* | | | |
| | | | (0.000) | | | |
| ZTL | | | | -0.000*** | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | 0.000** | | |
| | | | | (0.000) | | |
| Sport | | | | | 0.000*** | |
| | | | | | (0.000) | |
| Sport * LTR | | | | | -0.000* | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | -0.000*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | -0.000** |
| | | | | | | (0.000) |
| Max Guest | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.109*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Entire APT | 0.439*** | 0.440*** | 0.439*** | 0.440*** | 0.439*** | 0.438*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Instantbook | 0.305*** | 0.303*** | 0.304*** | 0.304*** | 0.305*** | 0.305*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Superhost | 0.237*** | 0.236*** | 0.236*** | 0.237*** | 0.237*** | 0.236*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| LTR | -0.088*** | -0.121*** | -0.125*** | -0.120*** | -0.044 | -0.058*** |
| | (0.012) | (0.019) | (0.024) | (0.019) | (0.029) | (0.019) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 | 4.11e+05 |
| R2 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 | 0.299 |

| Y = OCC | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|
| Metro | | -0.000 | | | | |
| | | (0.000) | | | | |
| Metro * LTR | | 0.000*** | | | | |
| | | (0.000) | | | | |
| Degrado | | | -0.000*** | | | |
| | | | (0.000) | | | |
| Degrado * LTR | | | -0.000* | | | |
| | | | (0.000) | | | |
| ZTL | | | | -0.000 | | |
| | | | | (0.000) | | |
| ZTL * LTR | | | | -0.000 | | |
| | | | | (0.000) | | |
| Sport | | | | | -0.000 | |
| | | | | | (0.000) | |
| Sport * LTR | | | | | 0.000 | |
| | | | | | (0.000) | |
| Parcheggi | | | | | | 0.000*** |
| | | | | | | (0.000) |
| Parcheggi * LTR | | | | | | -0.000 |
| | | | | | | (0.000) |
| Max Guest | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Entire APT | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** | 0.053*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Instantbook | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** | 0.121*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Superhost | 0.115*** | 0.115*** | 0.115*** | 0.115*** | 0.115*** | 0.115*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| LTR | -0.019*** | -0.033*** | -0.005 | -0.013** | -0.024*** | -0.017*** |
| | (0.004) | (0.006) | (0.008) | (0.006) | (0.009) | (0.006) |
| ID NIL | yes | yes | yes | yes | yes | yes |
| Year | yes | yes | yes | yes | yes | yes |
| Mese | yes | yes | yes | yes | yes | yes |
| N | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 | 4.14e+05 |
| R2 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 | 0.126 |

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