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The Impact of Professional Hosts on Airbnb Performance: Neighborhood Dynamics, Market Sensitivity, and Seasonal Trends

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ABSTRACT

The short-term rental market has experienced a significant growth in the past years, by increasing its market share in the accommodation sector. Professional hosts are playing an increasingly dominant role, by perfecting skills to successfully outperform the market. The thesis revolves around the study of the differences between professional and non-professional hosts, with a particular focus on neighborhood location, seasonal market fluctuations, seasonal trends and economic segment of the listings. By employing a dataset of Airbnb listings from the city of Turin spanning across 7 years, we examine whether professional hosts are able to achieve higher RevPAN (Revenue per Available Night) and how this benefit differs across the factors previously mentioned.

According to our research, professional hosts consistently outperform non-professional hosts in popular tourist destinations, which are mainly located in the city center, because of their proficiency in pricing optimization. Additionally, they are seen to exhibit a greater revenue gap during peak demand months and higher-end listings, benefiting from their ability to maximize the effect of price positioning and dynamic pricing strategies. However, they are seen to be more sensible in less attractive areas where the power of these strategies is weaker, and they are also found to be more negatively impacted during unexpected market downturns, such as during the COVID-19 pandemic.

These findings imply that whereas professional hosting improves performance in ideal circumstances, it also puts hosts at higher risk in times of less demand. For researchers, policymakers, and Airbnb hosts looking to comprehend the changing dynamics of the short-term rental business, this study offers insightful information.

KEYWORDS

Airbnb, professional hosts, neighborhood attractiveness, market fluctuations,
seasonal trends, RevPAN, short-term rentals.

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INTRODUCTION

The rise of short-term rental platforms such as Airbnb has significantly transformed the hospitality industry, reshaping accommodation options and market dynamics worldwide. As these platforms have been becoming more and more popular, they became a place where business possibilities can be found, thanks to the revolutionary business model based on peer-to-peer accommodation. Professional hosts have therefore become a dominant force, managing multiple listings and leveraging pricing strategies to maximize revenue. The rise of hosts approaching Airbnb as a business increased interest in understanding how professional vs. non-professional hosts perform. Previous studies have identified a clear advantage of multi-unit hosts in terms of average performances, thanks to a variety of strategies and management styles that have been proved to significantly impact the revenues of the listings. However, this research aims to add one further step to the analysis on the differences between Professional and non-Professional hosts by identifying under which conditions the former gain an additional advantage over their counterparts. To do so, the differences in performance were analyzed in some selected categories.

One of the key factors that has been found to influence Airbnb performance is its location. In the cities, it has been found that properties that are located in the city center or in attractive areas for tourists typically achieve better performances on average. Several studies have been conducted that suggest how professional hosts are better at exploiting the listings value, especially trough price positioning, to increase their revenues. Therefore, an hypothesis has been developed stating that they be better at outperforming the market in high-demand areas where successful strategies such as price positioning and dynamic pricing may be more effective to bring higher revenues. Similarly, seasonality has a big impact in the accommodation sector. The Airbnb market, therefore, is strongly influenced by fluctuation in demand, which usually follows the tourism flows and changes depending on the characteristics of the location. It remains unclear, however, whether professional hosts capitalize more effectively on peak months compared to non-professional hosts, but their expertise may justify better performances during these periods similarly to how the location inside of a city could.

Other than location and seasonal fluctuations, external market conditions also influence short-term rental market, with varying impact on its performance. Another key question of the study is to evaluate the differences in reaction to unexpected market shocks, because even if professional hosts generally outperform non-professional hosts, they may do so by heavily relying on understanding and predicting the market, which may make them more vulnerable during downturns.

This thesis aims to investigating which are the performance differences between professional and non-professional hosts across several selected dimensions: neighborhood location, seasonal fluctuations, market shocks (COVID pandemic) and different economic range of the listings. To be more specific, it investigated whether professional hosts systematically outperform non-professional hosts across all market conditions, or whether their advantage varies in specific and common market conditions. The research is structured around several objectives:

1. Assessing the impact of neighborhood-specific location on professional host performance: specifically, it will aim at testing if professional hosts achieve even better performances in central neighborhoods compared to non-professionals while struggling to gain a systematical competitive advantage in lower-demand areas.
2. Evaluating seasonal revenue fluctuations: This objective seeks to understand the relationship between professional hosts and peak seasons of the market, identifying whether professional hosts systematically perform better during peak periods when demand is highest, by successfully implement winning pricing strategies such as price positioning and dynamic pricing to achieve better performances.

3. Analyzing market sensitivity to unexpected downturns and revenue stability: The study will investigate whether professional hosts experience higher volatility in revenues during market downturns compared to non-professionals, highlighting their exposure to unexpected demand fluctuations. To do so, the thesis investigates how professional hosts performed during the COVID-19 pandemic.
4. Examining the impact of market segmentation: The research will explore whether professional hosts achieve greater revenue advantages in higher-end listings, where pricing optimization may provide stronger competitive advantages.

Combining descriptive statistics and regression models with interaction effects, this study wants to provide a comprehensive understanding of how professional host performance varies across different market conditions, using a set of data from the city of Turing ranging from 2017 to 2023. The findings will contribute to the growing literature on short-term rental market dynamics by offering additional insights on the differences between Professional and non-Professional hosts.

The thesis has the following structure: the first chapter will provide a recap of the relevant literature on Airbnb, focusing on the differences between professional and non-professional hosts, the impact of location and the impact of market downturns (COVID-19) pandemic. The second chapter presents the data source with a focus on describing the variables included and then moves to provide an overview on the context of the Aribnb market in the city in Turin. This is followed by the third chapter, to describe the methodology used and to present the model developed to test the hypotheses. The fourth chapter gives an overview of the results of the regression models and interprets them, while the final chapter serves to discuss the overall implication of the research.

To summarize, the thesis has the objective to provide a detail comparison between the performances of professional versus non-professional hosts, taking into account important factors such as location, seasonality, market fluctuations and economic range of the property, to offer valuable insights into the management of professional hosts. Specifically, it will focus on understanding where they are able to find the competitive advantage that has been found in previous studies.

1. LITERATURE REVIEW: Overview on the company Airbnb and analysis of its drivers

1.1 Introduction

1.1.1 The Business Model of Airbnb

All data used in this section comes from Dolnar (2018).

Airbnb was launched in 2008 and, since then, experienced exponential growth and disrupted the hospitality and tourism sector. The company is an emblematic example of how digital platforms can transform traditional industries through innovative business models for value creation. Airbnb's value proposition consists in enabling people to list and rent out their private accommodations, by connecting them to travelers worldwide. As such, Airbnb became a predominant actor of the sharing economy. The latter consists of platforms enabling peer-to-peer value creation, by allowing individuals to earn extra income through better resource allocation and facilitated access to common information technology. Another few notable examples of companies of the sharing economy include Uber, which allows individuals to use their personal car to provide a taxi service, as well as Vinted, allowing them to sell the clothes they do not wear anymore, and finally, Kickstarter, allowing start-ups to seek financial help in exchange of benefits to donors in case of success. The essence of the sharing economy is the idea of "sharing" underused assets to create opportunities for independent actors to mutually benefit from them. This economic model represents a shift towards more flexible and technology-based forms of commercializing goods and services. It also promotes a swift from ownership to access. Digital platforms play a central role in the sharing economy, as the fundamental element to connect the actors that take part in the sharing of goods or services. What is critical for the sharing economy to function and be sustained, is to reach a high mass of users, to reach a satisfying level of supply and demand (important to note that each user can be both) to open the new market, and for the project to be scalable in the long term. This is the reason why technology is central in sharing economy environments because it allows to facilitate transaction and helps to create an ecosystem that supports and facilitates interaction between all actors: hosts, guests and service providers. Other than scalability, technology is capital to ensure trust from the users, as well as accessibility to the market, and adaptability. Trust is vital to attract and especially retain users; it is created thanks to the verification of profiles, real-time reviews and secure payment processing, all contributing to decreasing the risks of peer-to-peer transactions. Accessibility is granted by matching algorithms that optimize the process of connecting supply (hosts, in the case of Airbnb) and demand (guests, in the case of Airbnb) taking into consideration various modifiable criteria such as price, location, ratings, amenities, etcetera.

Airbnb's business model puts together technology, community and the sharing economy to create an ecosystem that creates value. This value is multi-sided, which means that it responds to the needs of two (or more) groups of people by creating interactions, which both parties can benefit from. The first group represents the individuals who have unused or underused living spaces (hence, the supply), the second is composed of individuals who are looking for a different type of accommodation than traditional hospitality can offer (hence, the demand). The two groups are strictly linked and are designed to grow together by influencing each other, as they benefit from the other. Indeed, the greater the number of listings that Airbnb offers, the more attractive it becomes for guests to use the platform, as they can choose from a wider range of possibilities. Similarly, the other way around, the greater the number of people who look for an accommodation on the platform, the more hosts are encouraged to use it to share their offers. By matching the needs of these two groups, Airbnb is able to provide value for both. The hosts benefit from income generation from their underused spaces, from a spare room in their home, to a luxurious villa, in a city center or a remote countryside, thus providing a variety of options for all possible guests' availability and financial position. Hosts can choose their property's availability, price, and the level of interaction they wish to have with the potential guests. The experience is hence highly personalized and convenient for hosts, hereby making the platform an attractive new source of income. It also provides support to help manage their offering and a security fee that provides protection in case of property damage. For guests, Airbnb offers a wide variety of accommodation types, providing more options and flexibility for their needs, taste and budget than traditional hospitality actors: from studios to spacious houses, but also castles, boathouses and treehouses for more unique experiences. Staying at an Airbnb also provides a different experience than a hotel: feeling at home at someone else's, living like a local, etc. which some travelers are looking for. Thanks to the efficient review system, guests can make informed decisions based not only on location, price and amenities, but also on the previous experiences of other travelers, which will often be more trusted than the listing itself. This trust brings comfort in the planning of a trip in an unknown place.

As introduced previously, Airbnb uses technology as the main enabling driver to create and deliver value for both hosts and guests, through its platform designed for ease of use and that includes search algorithms matching guests' preferences to available offerings using a wide range of parameters. It also offers a secure payment processing, removing this burden from both hosts and guests and a 24/7 customer support, to help its customers in case of need. The technology-driven platform hence allows a highly personalized and efficient experience.

1.1.2 Impact of Airbnb hospitality and tourism

All data used in this section comes from Buzzacchi et al. (2020).

The wide range of its cultural and natural masterpieces made Italy one of the most attractive countries for travelers (fourth most visited country in the world in 2023 according to Statista), thus creating a strong tourism sector in the country. Each year around 60 million people come from abroad to visit Italy, and around the same number of Italians moves around to visit other regions. This brings the total visitors to 120 million people each year, with 442 million nights booked. It is straightforward to understand why Airbnb found in Italy a prosperous territory to continue its growth and to consolidate its presence. For example, as of 2018, Italy was the second European country in number of Airbnb listings after France, with over 615,000 properties available, adding up to around 2.65 million beds. As a comparison, in the same period there were around 32,000 hotels with a total of 2.2 million beds offered.

Airbnb properties in Italy are mostly located in urban areas, with a higher concentration in bigger cities such as Rome, Florence, Venice and Milan. These are both touristic destinations and attractive economic hubs, resulting in a high demand for accommodation solutions. The distribution described above reflects the growing popularity of sharing economy solutions, which benefit from the high-density of offer and demand in urban areas. Airbnb has had a positive impact on touristic flows, especially in the aforementioned cities, by increasing the offering of bed nights and therefore attracting new visitors. Airbnb guests are also found to be more likely to do longer stays than hotel guests, and they tend to be more drawn to local experiences (shopping, dining, etc.) thus having a positive impact on the local economy. From a social point of view, Airbnb has been linked to over-tourism, the situation where the number of tourists visiting a place is higher than the capacity to manage them in a sustainable way. This can bring some issues:

1) Environmental degradation, with pollution, habitat destruction and increased environmental impact overall.
2) Commodification, i.e., the situation in which the will to cater to tourists' desires results in a standardization of offerings, damaging the local culture in favor of more commercial activities that can be more profitable thanks to the high number of tourists.
3) Gentrification: the proliferation of Airbnb properties in desirable locations can provoke a shortage of housing and subsequent price increases, This significantly alters the economic equilibrium of locations, forcing some individuals to relocate due to the discrepancy between house prices and rent levels, and the overall cost of living. This is an important concern that requires careful consideration and appropriate political measures in order to limit it. Consequently, numerous regions in Italy have recently introduced regulations to limit the growth of Airbnb. These regulations range from setting a limit on the number of nights a property can be rented on the platform to requiring hosts to obtain licenses.

Focusing on the hotel sector, the literature provides opposite findings regarding the impact of Airbnb. On one side, Zervas et al. (2017) and Mhlanga (2019) have identified a negative impact of Airbnb on the hotel industry in terms of occupancy rate and pricing. According to this study, the direct competition between Airbnb and hotels results in a cannibalization of demand for hotels, therefore forcing them to adapt their pricing strategies to remain competitive. On the contrary, Dogru et al. (2020) and Farronato and Fradkin (2018) describe the positive effects of Airbnb on both hospitality and tourism. Specifically, Dogru et al. (2018) found an increase in employment in the hotel sector, with the underlying implication that Airbnb stimulates tourism and the overall growth of visitors in specific places, therefore having a positive effect on hotels as well. Farronato and Fradkin (2018) focused on the relief that Airbnb provides to the hotel industry during times of peak demand. By offering more options, Airbnb is able to accommodate the excess demand that hotels would not be able to handle, hence preventing the loss of tourists to other destinations. According to them, Airbnb benefits the tourism of the area, which indirectly benefits the hotel industry. Goree (2016) proposes a third view on the topic, by stating that Airbnb has a neutral effect on traditional hospitality industries. His theory stipulates that the hotels and Airbnb's focus on different market segments by offering different services and facilities, and thus attracting different kinds of customers. For example, people looking for a more homely and authentic local experience will be more likely to choose Airbnb, while others will be more attracted by the full range of services offered by hotels (restaurants, or swimming pools, for instance).

Overall, these studies offer a view of the impacts of Airbnb in the hospitality sector, suggesting that they are complex and subjected to various opinions. Hereby, it is important to consider the disparities in local markets and in types of hospitality options when studying Airbnb's effects on them.

1.2 Professional vs. non-Professional hosts

1.2.1 Definition and characteristics

A distinction is made in the literature between two types of hosts that operate in the Airbnb market: commercial and private. They differ in the level of professional engagement and in particular the number of properties that they manage on the platform. No unique cut-off number of properties to cluster the two groups is agreed upon in the literature: 10 is used in some studies, while 3 or 2 is used in others, to differentiate between single-unit and multi-unit hosts. In this analysis 3 was chose as cut-off value to be consistent with studies on the topic. Private hosts can be defined as individuals willing to increase their revenues thanks to their main or secondary accommodations and therefore see in Airbnb a more efficient way of exploiting their assets. They approach Airbnb in a more casual way, not looking to optimize their revenues by using dynamic pricing strategies or more advanced tools for managing their listings. It is important to keep in mind that Airbnb is not their main source of income, and therefore they lack the time and/or the interest to put a lot of effort in managing their accommodations on Airbnb. Private hosts, instead, may use Airbnb as their primary source of income, and are in general less responsive to adjusting their prices according to market demand variations: their response is less pronounced and often found not statistically significant. The study (Milone, Gunter, Zekan) reveals that the pricing strategies of private hosts are based on fixed effects or on conditions that affect the whole industry, rather than on targeted local market-based approach. They mostly rely on the characteristics of their listing to set the price, without taking into account the situation in terms of location, seasonality, demand fluctuations, etc. On the other hand, commercial hosts have time and effort to put into optimizing the performance of their listings on Airbnb. They display a significant variation in prices related to demand fluctuations. It was found that for every one percent increase in local Airbnb demand, commercial hosts show an increase in their average weekly price by 0,17 to 0,264 percent, with all coefficients being significant at the 99,9% confidence level. This group is more attentive to trends in demands and are quick and efficient in adapting their pricing accordingly, thanks to higher levels of management skills, and being keener on using advanced data analysis tools to optimize their pricing. Because of this, professional hosts show better performance metrics on average, such as monthly revenue per available room.

1.2.2 Differences in management strategies

The management strategies adopted by Airbnb hosts play a crucial role in determining the overall performance of a listing. Professional and non-professional hosts often approach property management differently, leading to differences in pricing and occupancy rates. Professional hosts operate multiple listings and apply structured business models, while non-professional hosts may rely on more informal management approaches, often treating their listings as secondary income sources. These differences impact several key aspects of operations, including dynamic pricing and revenue optimization. Understanding how these management strategies vary between host types provides insight into the competitive advantages and challenges faced by each group, helping to explain why professional hosts often achieve higher RevPAN.

Previous analysis investigated on which were the strategies that Airbnb hosts would use, starting from the ones that were observed to be the most successful in the hotel industry. The two main one identified were price positioning and dynamic pricing. Price positioning involves setting listing prices in a way that reflects factors such as location, property quality, amenities, and target guest segment. In general, it is defined as the difference between the listing price and the average of its competitors (Xie and Kwok, 2017). Effective price positioning ensures that a listing remains competitive while maximizing revenue and occupancy rates, and it clear that setting the right price related to its competitors is a key factor in having a successful performance. Dynamic pricing is a strategy in which prices are adjusted in real-time or periodically based on demand, market conditions, seasonality, and competitor pricing. In general, it is defined as the price fluctuation of a listing over a period of time. In the Airbnb market, dynamic pricing allows hosts to increase prices during high-demand periods and lower them during low-demand periods to optimize occupancy and revenue. It was found in the study conducted by Oskam et al. (2018) that listings which price is adjusted more often outperform in average other properties for which the price is more stable throughout a period of time.

The pricing strategies adopted by different types of Airbnb hosts are likely to have varying impacts on a listing’s revenue performance. Research has shown that host type influences the likelihood of adopting dynamic pricing strategies (Gibbs et al., 2018b; Li et al., 2016). Multi-unit hosts, who manage multiple listings and handle a higher volume of transactions daily, may develop a deeper understanding of market fluctuations and adjust their prices more effectively to maximize revenue. Their ability to learn from experience allows them to respond more efficiently to changing demand conditions. Studies have found that hosts with greater experience are more likely to use dynamic pricing strategies (Gibbs et al., 2018) and that multi-unit hosts tend to be more proficient in implementing these strategies compared to single-unit hosts.

Overall, litings managed by multi-unit hosts exhibit better performances (Kwok, Xie 2018) on average. This effect is found to be largely due to the effective price positioning strategy that professional host employ. In fact, it is found that multi-unit hosts systematically place their listing at an average higher price than their non-professional counterparts, and this has a high positive effect for them in terms of performances.

1.3 Impact of location on short-term rental performance

Location has been found to determine a crucial role to determine the performances of Aribnb listings. This is because it influences pricing and occupancy rate, which therefore means overall revenues generation. In cities, research consistently find a link between better performances and the listings being situated near area that are attractive for tourists, which usually -like in the case of Turin- are situated in the city center. On the other hand, peripheral areas usually show lower pricing power and lower performances overall.

There can be found several studies that focus on understanding the relationship between location and Airbnb pricing. The study by Gibbs et al. (2017) supports the idea that high-demand areas give better cues to predict demand fluctuation, giving experience and prepared hosts more incentive to adjust prices according to the market. In central and highly touristic areas this means that the demand is easier to predict, as the tourists flows usually follow determined fluctuations. This means that professional hosts may be able to maximize their RevPAN by implementing dynamic pricing strategies and by positioning the price more effectively than their non-professional counterparts.

The study from Toader et al. (2022) further emphasizes the importance of proximity to the city center in pricing strategies. It finds that the farther a listing is from the city center, the lower its price, confirming that central locations command a premium due to their convenience and accessibility. Moreover, as hosts gain more experience, they become more aware of the negative impact of distance on listing reputation, therefore developing the right expertise to choose the best price for the listing according to its location.

Similarly, Zhang et al. (2017) research provide additional proves to reinforce the positive relationship between closeness to urban centers and listing price. The outcome of the study demonstrates that the listings closer to the local attractions are set on an average higher price, which is also seen to decrease as the distance from those areas increases, proving how central locations give an advantage to professional hosts in terms of overall performance.

This literature framework led to the development of the first hypothesis, stating that professional hosts achieve a higher performance gap in city centers compared to non-professional hosts. Given the advantages of dynamic pricing and location-based optimization strategies that they are found to implement, it can be plausible to think that professional host can maximize their revenues outperforming non-professional hosts in center urban areas. Conversely, the situation in peripheral neighborhoods might be the opposite, as places where demand is lower and price flexibility is constrained, might cause professional hosts to lose their competitive advantage and the performance gap between the two types is likely to narrow.

1.4 Impact of COVID-19

1.2.1 Impact of COVID on the hospitality industry

The COVID-19 pandemic started out in Wuhan, China when at the end of 2019 doctors observed some cases of pneumonia that seemed to be caused by a new branch of the coronavirus. Shortly after - 30 January 2020 - the World Health Organization declared the virus as a Public Health Emergency of International Concern after having certified its high contagiousness. The expansion was very quick, reaching Europe and the US in a matter of a couple of months, causing the WHO to declare coronavirus as a pandemic. In order to diminish the diffusion of the coronavirus, governments implemented a wide range of policies:

1) Health and safety protocols: establishing hygiene guidelines to be followed in public and private spaces, such as social distancing, wearing a face mask and regularly disinfecting hands with hydro-alcoholic gels.
2) Travel restrictions: countries closed their borders or imposed quarantine requirements and negative COVID tests to access the country.
3) Lockdowns and movement restrictions: imposing limitations of the possibility to freely move depending on the criticality of the current situation, up to total lockdowns and curfews with only essential services as exception.
4) Economic stimulus: public subsidies to individuals, businesses and industries that were the most negatively affected by the pandemic, such as tourism and hospitality.

5) Vaccination campaigns: boosting the development and distribution of COVID vaccines and encouraging diffusion among the population.

The impact of these measures, especially the first three, were enormous. The world changed, with local disparities, to the opposite of the globalized move of people and goods, which was the common rule. The world economy was faced with disrupted supply chains, businesses shutting down, employees laid off and overall demand precipitating (Pantano et al., 2020). This phenomenon impacted all major industries (to various degrees) and resulted in an unprecedented world crisis.
Specifically, mobility was drastically reduced to a minimum, with a significant decrease of air travels, resulting in an average 30% loss in stock prices in the market. Air companies faced very difficult challenges due to travel bans between countries. Sea travel volumes decreased as well, with companies forced to suspend cruises and see their stock value halving or more. Sea trade was also negatively affected, with an overall reduction in trade volumes, triggering a supply chain crisis, which caused a high inflation in the western countries.
Social distancing resulted in the cancellation on many events throughout the world, like 2020 Olympic Games and 2020 European Football Championship, affecting both the economy and tourism.

Hospitality was hence one of the most impacted industries, from regulations such as travel restrictions and lockdowns, directly interfering with the main source of demand in this sector: people’s mobility. Hotels experienced sharp declines in numbers of occupants and total revenues. The UN World Tourism Organization reported a 75% decline in international tourism in 2020, resulting in an estimated loss of 1.1 trillion USD in revenues. The extended period of these measures led businesses in the hospitality sector to struggle to maintain costs with limited sources of revenues. Even during the periods of relaxed restrictions, it was a real challenge, with high associated costs for those businesses to align to health regulatory guidelines to ensure safety and therefore to attract customers back. During COVID times, customers’ behaviors changed drastically, focusing mainly on personal well-being. As a matter of fact, over 50% of customers remained hesitant to dine in restaurants or spending time in hotels, just after the reopening of activities (Gursoy, Chi, 2020). Visible sanitation efforts, effective social distancing and proper training of employees to health and safety regulations became critical customers' expectations. While these required organizational changes and expenses, they could also become opportunities for creating a competitive advantage as a higher willingness to pay from customers was observed for services that included enhanced safety protocols. Hence, businesses could potentially offset those costs by attracting additional customers.

1.2.2 Impact of COVID on Airbnb

After analyzing how COVID impacted the worldwide economy, and in particular the tourism and hospitality sectors, it is important to focus on the effects it had on Airbnb and on the measure taken to deal with it. Looking at the company, Airbnb had to lay off 25% of its staff and experienced a decrease of $13 billion in market valuation, from $31 billion in March 2020 to $18 billion in May 2020 (Yurieff, CNN, 2020). Several authors analyzed the nature and extent of these effects, with one accounting for 6 cities and comparing the volume of listings in the period 2020-2021 compared to 2019. The study, (Koutit, Nijkamp, Osth, Turk, 2022), highlighted a significance decrease in Airbnb offerings and bookings, caused by the COVID pandemic. Additionally, it found a significant peak in cancellations: a 50 to 60% increase in booking cancellations was observed in the various cities compared to 2019, stable in 2020 and continuing in 2021, indicating a strong sense of uncertainty for travelers, strongly linked to local travel restrictions. Average booking rates dropped by at least 40% to almost 100% in cities like Milan during the worst periods of the pandemic, with stricter travel restrictions and lockdowns.

Moreover, the study showed reluctance on the hosts' side to share their properties again due to risks of contamination: 30 to 50% of hosts reacted to the pandemic by removing their listing from the platform by March 2020, and increasing to 70% in 2021, compared to the same months in 2019. Many hosts preferred to switch to long-term renting in order to reduce both the risks of long vacancy periods and of guest-to-guest contamination, therefore reducing the number of offerings on the platform.

To accommodate customers in the pandemic-related uncertainty and encourage them to continue using the platform, Airbnb introduced new measures. Firstly, it modified the existing cancellation policy to allow guests to cancel their booking for free. This aimed at supporting guests who had to cancel their stay because of the pandemic but resulted in important loss of revenues for hosts due to the higher rate of last-minute cancellations. Moreover, Airbnb implemented a measure forcing hosts to implement strict cleaning requirements with the use of sanitizing products to eliminate any possible traces of COVID and required them to leave their places free for at least 24 hours between two bookings.

Commercial and private hosts were found to have different reactions to the fluctuations in demand, with the first ones being more responsive in adapting their pricing strategies accordingly. Private hosts, on the other hand, didn't implement responsive strategies, possibly due to a lack of managerial mindset and lack of utilization of pricing tools and dynamic pricing strategies. Those findings were confirmed in Barcelona by Boto-Garcìa (2022) Private hosts were found to charge lower prices on their listings on average, but commercial hosts showed a more significant price reduction following the pandemic, displaying more reactiveness to the demand drop caused by the pandemic. During 2020 and the beginning of 2021, commercial hosts applied a more dynamic pricing strategy, following the incidence of the pandemic in their area, and from February 2021 the pricing patterns of both types of hosts converged, showing a more stable market.

1.5 Pricing strategies

1.5.1 Factors influencing Airbnb pricing

All data used in this section comes from Toader, Valentin & Negrusa, Adina & Bode, Oana & Rus, Rozalia (2021)

Under normal circumstances, Airbnb prices vary according to different parameters.

Listing location:

1) Proximity to attractions and amenities available nearby: this has a positive effect on price, the closer to desirable locations increases the desirability of the listing, increasing its demand and subsequently its price.
2) Distance to the city center: no strong relation with price was found in the literature. This is probably subjected to the location and to the various guests' preferences and goals when travelling. If they come to visit a specific city, they

will look for central accommodations, and an increasing distance to the city center will result in loss of desirability. On the other hand, some travelers might look for quiet places in the countryside next to attractive natural destinations; in this case, the distance to the city center becomes irrelevant.

Listing attributes:

1) Number of pictures: it has a positive impact on price, because a large number of photos gives a comprehensive view of the listing, increasing its attractiveness and the perceived risk of disappointment in the eyes of customers.
2) Free breakfast: it has a negative impact on prices.
3) Accommodation type, number of rooms, facilities: they have a positive effect on prices. Optional amenities as car parking, swimming pool, Wi-Fi etc. improve the attractivity and comfort of the listing and therefore justifying an increase in price.

Listing reputation:

1) Number and scores of reviews: it is interesting to notice that a higher number of reviews, caused by a higher number of bookings, has a negative correlation with price. This can be explained because listings that are cheaper than their offered value are more frequently booked and therefore collect a higher number of reviews.
2) Cleanliness and location ratings: they have a positive effect on price as higher scores in these categories make a listing more appealing for guests.

Host attributes:

1) Host verification and profile picture: they have a positive effect on price, as they increase hosts' credibility and customers are more likely to pay more for a trusted listing.
2) Superhost status: it has mixed effect on prices. Indeed, some superhosts might use this trusted status as an attractive criterion for guests, justifying a price increase, while others might see it as an opportunity to attract more bookings, aiming to maximize the time of occupation of their property, rather than increasing the price per night.

Rental policies:

1) Cancellation policy and guest verification requirements: they have a positive effect on price, as they make the listing seem more secure and with a higher quality.
2) Smoking allowed: it has a negative impact on prices, maybe due to the reduced appeal to non-smokers, or associated negative perception of the cleanliness or state of the property.

2. CONTEXT ANALYSIS:
Introduction on the dataset and descriptive graphs to understand the context

This chapter provides an overview of the data that was used for our research, and from which the results and interpretations are retrieved. By presenting the data, including both year-on-year trends and monthly variations, this chapter aims to set the context of the analysis, and starts outlining the major findings. It gives a comprehensive understanding of the dataset and introduces how the study will be conducted.

Through a series of graphs, this chapter will first present an overview of the data, followed by an analysis of the evolution of Airbnb parameters in Turin by year and by month. The data covers full period from 2017 to 2023 and exhibits various insights into trends of the overall market and more specific aspects such as seasonality fluctuations, COVID-19 impact of both demand and offering, and professional hosts positioning into the market. The output of the analysis will serve as a basis, together with the literature review, on which the hypotheses have been developed, serving as both introduction to the topic and interesting observation that will be tested by the developed models.

2.1 Presentation of the dataset

2.1.1 Data collection

To conduct my analysis, I am using a dataset from the Management Engineering Department of Politecnico di Torino. It was directly acquired from Airbnb, to ensure the comprehensiveness and authenticity of the data.

The dataset used in this study includes 369.331 monthly samples of Airbnb listings in Turin from 2017 to 2023, providing a comprehensive and accurate foundation for the analysis. Covering multiple years allows for a detailed examination of trends in the short-term rental market, ensuring that findings are not based on temporary fluctuations but rather on sustained patterns. The extended time frame enhances the reliability of the results by capturing variations in market conditions, seasonality, and broader economic shifts. Additionally, the dataset's length improves the accuracy of the regression models by allowing for robust control of external factors that may influence listing performance. This longitudinal perspective ensures a deeper understanding of how professional hosts perform relative to non-professional hosts across different periods, making the study's conclusions more meaningful and applicable to real-world market dynamics.

The dataset includes a variety of original variables that capture crucial aspects of each listing. To further enhance the analysis, additional variables were derived from the original data. Below is a detailed breakdown of both the original and created variables used in this study.

Original Variables

The dataset originally included the following variables:

- Property ID: Unique identifier for each property.
- Reporting Month: The month during which the data was reported.
- Year: The year the data pertains to.
- Month: The month the data pertains to.
- Revenue (USD): Total revenue generated by the listing in the reporting month.
- Number of Reservations: Total number of reservations in the reporting month.
- Reservation Days: Total days the property was reserved in the reporting month.
- Available Days: Total days the property was still available for booking in the reporting month.
- Listing Type: Type of accommodation (entire home/apt, private room, shared room, hotel room).
- Country: The country in which the listing is located.
- Latitude: Geographic latitude of the listing.
- Longitude: Geographic longitude of the listing.
- State: The region where the listing is located.
- City: The city where the listing is located.
- Bedrooms: Number of bedrooms in the listing.
- Bathrooms: Number of bathrooms in the listing.
- Max Guests: Maximum number of guests the listing can accommodate.

- Airbnb Superhost: Indicator if the host has superhost status.
- Minimum Stay: Minimum number of nights required for a booking.
- Number of Reviews: Total number of reviews received.
- Number of Photos: Number of photos associated with the listing.
- Overall Rating: Average rating of the listing.
- Airbnb Host ID: Unique identifier for each host.

Created Variables

In addition to the original variables, I created several new variables to facilitate the analysis:

- TOT_available_days: Total days the property was available in the reporting month.
- Occupancy Rate: Percentage of available days the property was occupied in the reporting month.
- Revenue per day: Revenue earned per day the property was occupied in the reporting month.
- RevPAN: Revenues per available night.
- Revenues per Guest: Revenue earned per guest in the reporting month.
- Neighborhood: Specific neighborhood within the city of Turin, obtained by associating the coordinates of the listing with the official map of Turin provided by the city.
- Professional Host: Indicator if the host is a professional or non-professional, depending on the number of listings they are managing.
- Range: A variable to measure the economic value of the listing based on the average price per night, the three values are Economy, Mid-level and Luxury.
- Private Room: Indicator if the listing is a private room.
- Professional Hosts: A variable related to the professional status of hosts, created to analyze professional hosting metrics.

By combining the original and created variables, the dataset is enriched, allowing for a more detailed and nuanced analysis of the differences of professional and non-professional hosts in Turin. This structured approach ensures that all relevant aspects are covered and facilitates meaningful insights into the variations in occupancy rates and revenues across different neighborhoods and host types.

2.2.1 Descriptive graphs and interpretation

Listings number per year

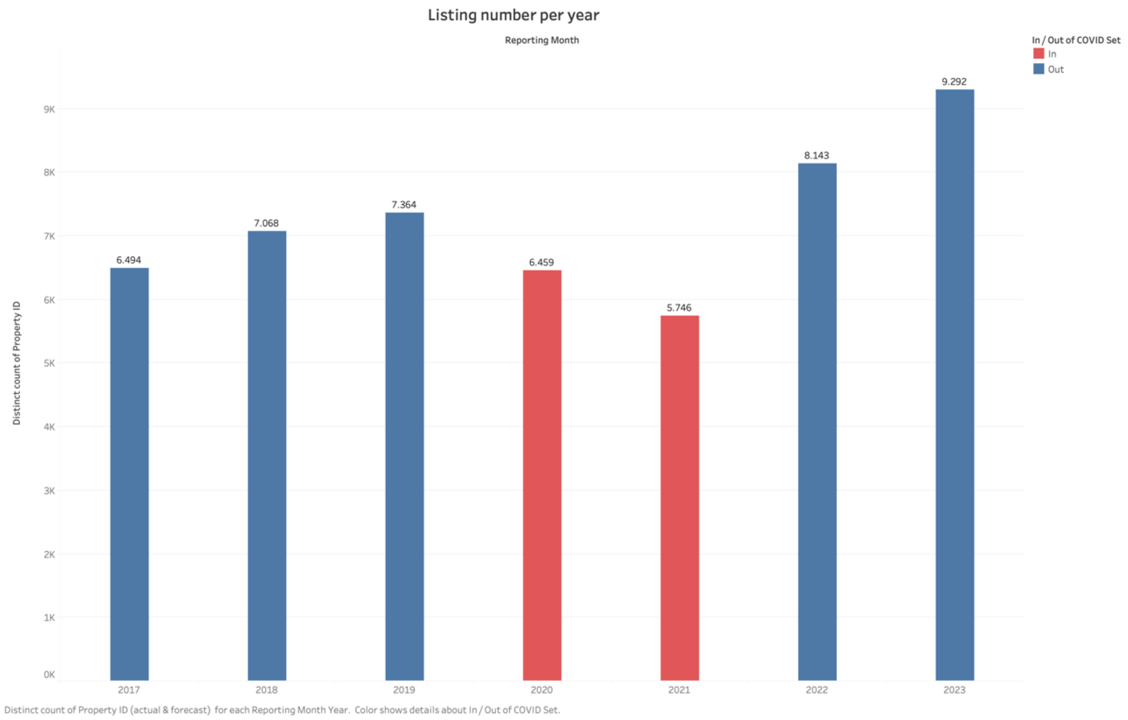


Table 1. Distinct count of listings per year

This chart shows the number of active and bookable Airbnb listings in Turin from 2017 to 2023, highlighting periods outside the COVID-19 pandemic (blue) and during the pandemic (red).

In the pre-COVID period from 2017 to 2019, there observable trend was an increasing number of listings that were registered on the platform and available to book, starting from 6,494 in 2017 up to 7,364 listings 2019, an average 6% growth per year. This upward trend indicates a growing popularity of Airbnb in Turin from the offering side, matching with the growing demand highlighted in the second graph below.

During the COVID-19 period, a decline in the number of listings is evident, even if a smaller one than what observe in the demand side (*Table 3*). In 2020, the number of listings dropped to 6,459 (less then 2017), representing a 12.29% decrease from 2019. The decline continued into 2021, with the number of listings further decreasing to 5,746, which is an additional 11.04% decrease from 2020. The reduction is clear and significant and goes in the opposite direction of what the previous trend was. This can be clearly attributed to the impact of the COVID-19 pandemic, which caused many hosts to remover their properties from the platform due to limited travel and restrictions that negatively impacted demand for accommodation.

In the post-COVID period, however, the number of listings rebounded like the demand for accommodation. Indeed, in 2022, the number of listings rose to 8,143, a substantial 41.7% increase from 2021 and already surpassing every pre-pandemic value. This upward trend continued into 2023, with listings reaching 9,292: a 14.11% increase from the previous year, showing a growing rate surpassing the pre-pandemic one.

The initial growth in listings from 2017 to 2019 represents the increasing popularity of Airbnb and short-term rental, a trend observable in the rest of the world as well. However, the onset of the pandemic in 2020 caused a significant decline in listings but the recovery observed in 2022 and 2023 suggests a renovated interest in the market.

Total number of reservations

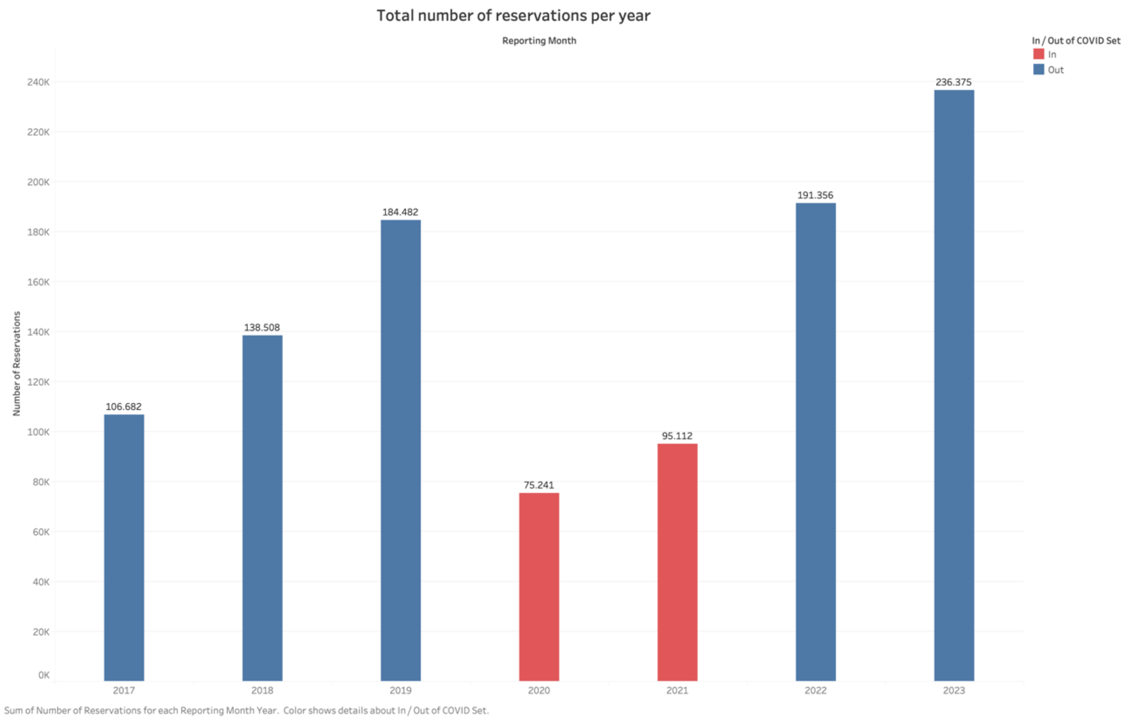


Table 3. Evolution of total number of reservations per year

The chart shows data about the total number of Airbnb reservations in the city of Turin using data from 2017 to 2023, highlighting the trend of the market in the city.

In the pre-COVID period (2017-2019), the number of reservations increased consistently. In 2017, there were 106,682 reservations, which increased to 138,508 in 2018, representing a 29.85% increase. This upward trend continued into 2019, with reservations reaching 184,482, a 33.16% increase from 2018.

During the COVID-19 period (2020-2021), it clear how the pandemic negatively impacted the market thanks to travel restrictions. In 2020, it shows how the number of reservations dramatically dropped to 75,241, a 59.22% decrease from 2019. In 2021, a slight recovery can be observed, with values reaching 95,112 reservations, representing a decent 26.44% increase from 2020, but still far below pre-pandemic levels.

However, in the post-COVID period the numbers rebounded back, even surpassing pre-pandemic levels. In 2022, a stunning 101.22% increase of the number of reservations is observed, with its value arriving to191,356. This growth continued in 2023, with reservations reaching 236,375, a 23.53% increase from 2022, which is a growth rate similar to the one observed in pre-pandemic periods.

The key takeaways of the chart are two, firstly, there is a clear upward trend of the Airbnb market in Turin, growing the attractiveness of the sector year-by-year. Secondly, COVID-19 had a sudden and clear impact on the aforementioned trend, but this impact was restricted to when policies such as lockdowns and travel restrictions were implemented, as the strong rebound in 2022 and 2023 suggests.

Total revenues

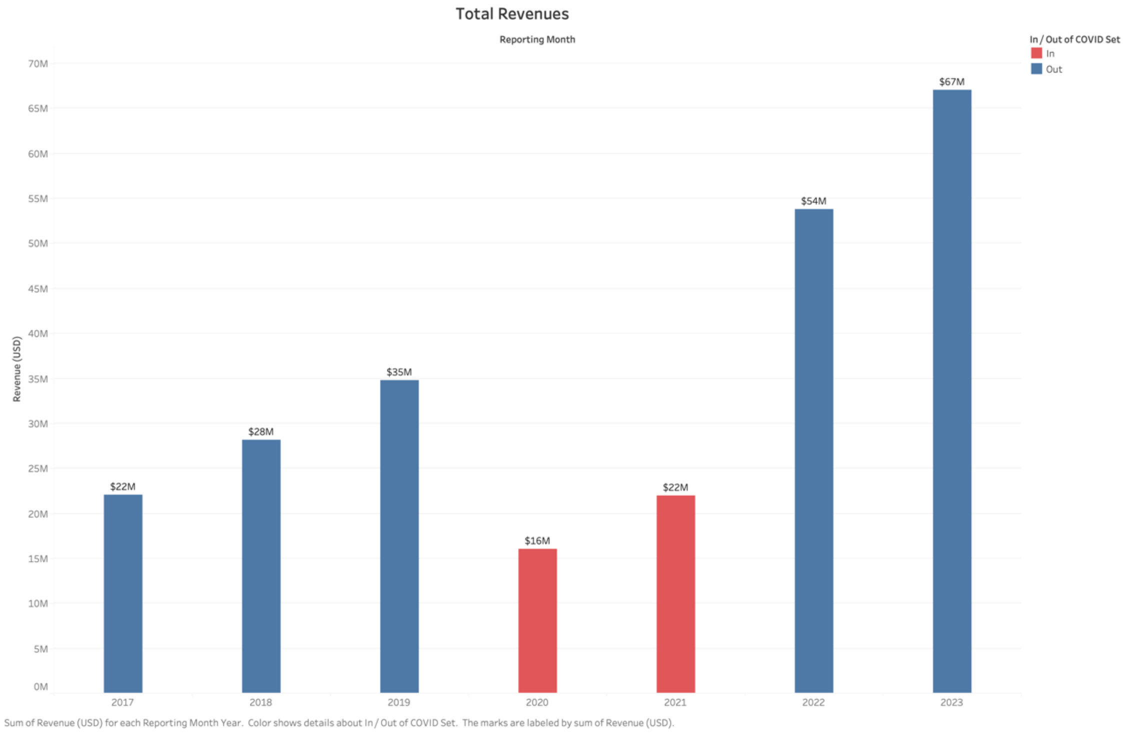


Table 4. Evolution of total revenues per year

The chart presents the total revenues generated by the Airbnb market in the city of Turin, showing the overall trend and highlighting the two years that were impacted by the COVID-19 pandemic.

In the pre-COVID period, there is a consistent increase in total revenues. In 2017, the total revenue was €22 million. This value increased to $28 million in 2018, which is a 27.27% increase, sign of a healthy and growing market. The growth continued into 2019, with revenues reaching €35 million, a further 25% increase from 2018.

The two years impacted by the COVID-19 show a clear sign of decline. Even if the market was steadily growing with a 25% increase year-by-year, in 2020, the total revenue dropped to €16 million, which is a stunning 54.29% decrease from 2019. The following year, 2021, showed a sign of recovery, especially in the last months of the years, with total revenues increasing to €22 million, representing a 37.5% increase from 2020, but still not reaching the pre-pandemic levels and only tying the values from 2017.

However, the post-COVID reaction of the market was strong, with an exceptional rebound of total revenues, which surged to €54 million, a substantial 145.45% increase from 2021, surpassing the value of 2019. The growing trend continued in 2023, with revenues reaching €67 million, representing a 24.07% increase from 2022, which matched the growing rate identified in the pre-pandemic period.

This chart clearly illustrates 2 different conclusions. Firstly, Airbnb market in the city of Turin is in a phase on rapid development, with a normal growth rate of 25% in revenues year-on-year. On the other hand, it is clear the profound impact that the COVID-19 has on Airbnb revenues, with a sharp decline followed by strong rebound in the post-pandemic years.

Average number of reservations per month

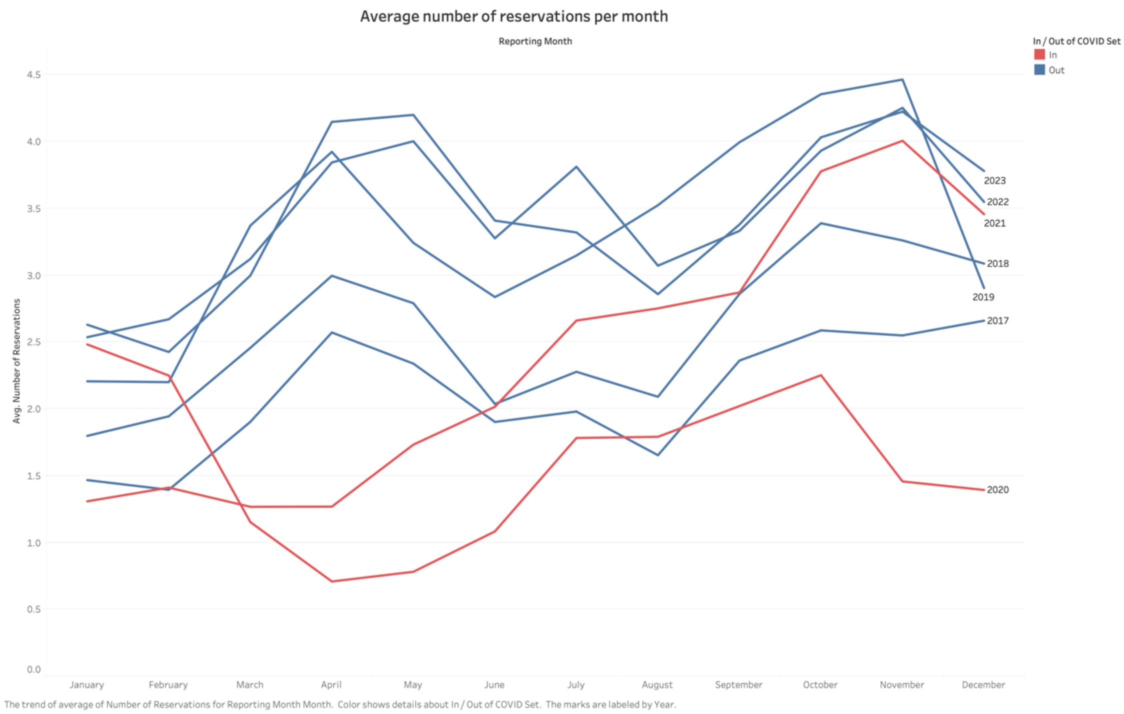


Table 5. Evolution of monthly average number of reservations per year

This chart shows the data relative to the average numbers of reservations per month for Airbnb listings in Turin, in order to identify recurring monthly trends that the market experiences. To do so the data from the years 2017 to 2023 is considered, to ensure that the trends are consistent each year and are not only relevant for a single period of time.

In the pre-COVID period, the average number of reservations per month shows a clear pattern, following the same trend in the years 2017 to 2019. The underlying trend starts with low values at the beginning the year, especially in January and February, and grows until the first peak, usually around the spring months April and May to then plunge back again during the summer months. After that, the values grow again to reach the second and highest peak of the year around the autumn months, especially November and December.

These patterns are severely disrupted by the COVID-19 pandemic, as clearly shown in the chart. During 2020 and the first months of 2021, the values followed the peak and valley of the pandemic levels, with low values when most stringent policies such as lockdowns and travel restrictions were enforced and slight recoveries when the sanitary conditions got a bit better, like in summer of 2020. This clearly shows how the unexpected pandemic disrupted the overall hospitality sector and more specifically Airbnb market.

However, in the post-COVID period, the data shows how the seasonal trend identified in the years 2017 to 2019 came back, with the same structure and exhibiting the same patterns, with peaks in the spring months of April/May and autumn months of November/December and lower values in the winter and summer months.

The chart above clearly highlights the seasonal patterns that Airbnb market presents in the city of Turin. After identifying these patterns, the HP2 was developed, investigating if Professional hosts bear an additional performance advantage during high-demand periods.

Evolution of properties managed by Professional hosts, by economic range

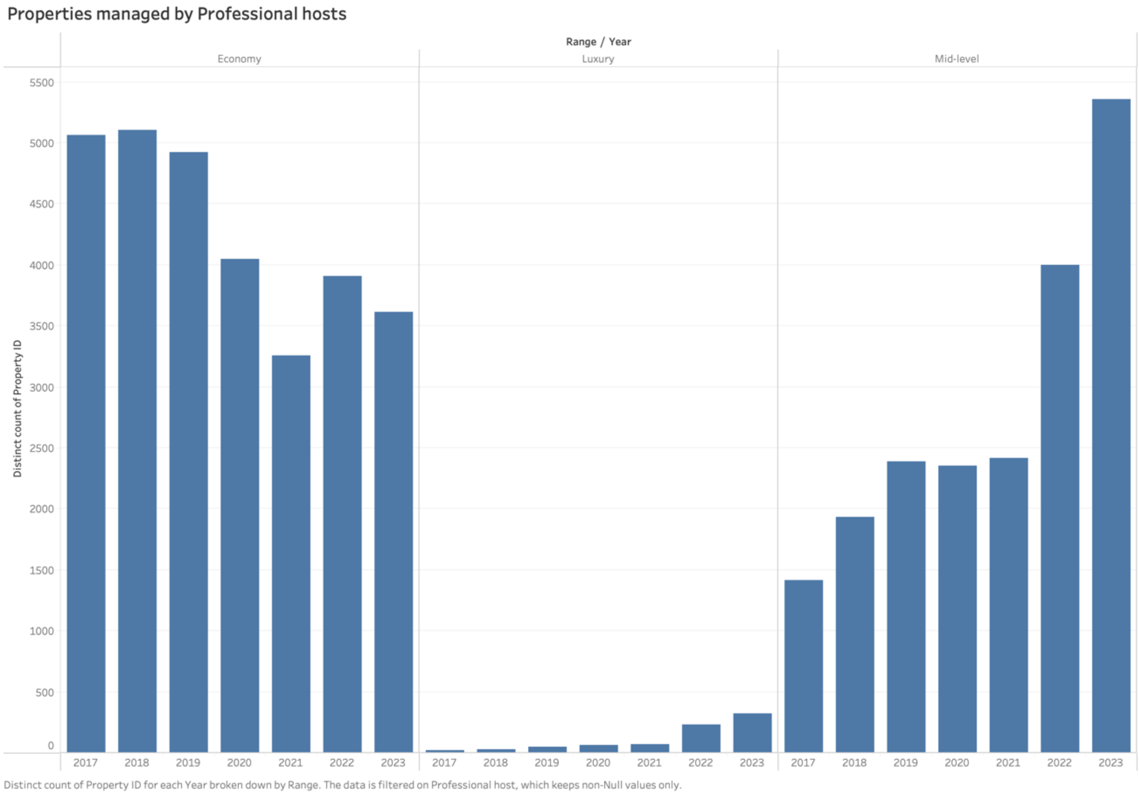


Table 6. Evolution of yearly number of listings managed by Professional hosts

This chart highlights the evolution of the number of properties managed by professional hosts year-by-year in the three different market segments (economy, mid-level, and luxury). A key trend is visible from the image in all segments. Starting from the economy listings, it started to be the most popular choice of properties managed by professional hosts but declined throughout the years. The decline may suggest that professional hosts may have exited low-margin segment to allocate resource in more profitable categories.

On the other hand, the mid-level segment as experienced an exponential growth, becoming the most popular choice of property for professional hosts. This indicates a shifting trend towards mid-level listings, moving away from the economy segment. The sharp increase in the last two years may be justified by professional hosts looking to increase their presence in a segment that may guarantee more flexibility, which could ultimately bring better profitability.

Even if the luxury market obviously remains significantly smaller in volume, it is the segment that saw the biggest percentage increase in the period of the study. This proves how professional hosts have started heavily investing in high-end accommodations, likely to target a premium customer base which has a higher spending power and less influenced by price variations.

Overall, the graph shows a clear and structural transformation in how professional hosts approach the market. They have clearly progressively moved away from the economy segment and heavily invested to increase their presence in the mid-level and luxury segment of the market. This evidence serves as a basis to develop HP5, as the shift towards higher-end properties may be driven by professional hosts acquiring more experience and finding in those properties a better environment to fully maximize their pricing strategies to ultimately create a competitive advantage and outperforming non-professional hosts.

3. RESEARCH:

3.1 Research design

The study employes quantitative research based on regression models to investigate on the performance gap between professional and non-professional hosts throughout different locations in the city, market conditions, seasonal trends and properties market segment. The research uses a dataset of Airbnb listings samples divided by month over multiple years (from 2017 to 2023), allowing for both cross-sectional and longitudinal analysis. The main variable taken into account to evaluate performance is RevPAN (Revenues per Available Night) which serves as the dependent variable in all the regression models of the analysis.

To test the proposed hypotheses, multiple regression models are employed, using moderator variables to evaluate their interaction with the main independent variable, professional hosts, allowing to understand the nuances of the management style of professional hosts, by identifying where they operate best and when they tend to suffer. These interactions allow for an assessment of how the effect of being a professional host on RevPAN and occupancy rate varies across different conditions, including neighborhood attractiveness, seasonal fluctuations, and market downturns such as COVID-19. Specifically, the moderator variables are:

- **Neighborhood:** based on the Longitude and Latitude of each listing, they are assigned to a neighborhood of Turin through the official map of the city and a python script;
- **Month:** the month of the reported listing (from 1 to 12);
- **Year:** the year of the reported listing (from 2017 to 2023);
- **COVID:** a flag (0/1) assigned if the reporting period falls inside the COVID-19 pandemic;
- **Range:** it categorizes the listings based on the pricing per night (Economy, Mid-level, Luxury);

Treating neighborhoods as categorical variables enables a detailed comparison of how location influences host performance. Additionally, time-based interaction terms, Year and Minth, are included in the models, to examine whether the revenue gap between professional and non-professional hosts has widened over time or to account for how they perform during the natural fluctuations of the market. Additionally, the COVID variable allows to test their reaction to unexpected and sudden market downturn, and the Range one gives an insight on what segment of properties professional hosts are better at operating in the market. Applying a structured regression-based approach, the research has the goal to provide a complete understanding of the market positioning of professional hosts, and especially in what situation they are able to leverage on their successful management strategies to outperform non-professional hosts.

In order to study the differences between Professional and non-Professional hosts within the moderators, each variable is compared to its base level:

- the two flags (**Professional hosts** and **COVID**) compare the value 1 with the value 0;
- **Range** compares Mid-level and Luxury with Economy category;
- **Neighborhood** compares all city districts with "Centro", the most central neighborhood of Turin;
- **Month** compares all months with January;
- **Year** compares all years with 2017;

RevPAN (Revenue per Available Night) is a key performance metric in the short-term rental industry that measures the revenue generated per night a listing is available for booking. It is calculated by dividing the total revenue generated during the specific month by the number of available nights, ensuring that earnings are assessed in relation both to the asking price for the listing and also taking into account the occupancy rate that it achieved. Unlike total revenue, which can be affected by the number of blocked or unavailable nights, RevPAN provides a clearer picture of a listing's earning efficiency by incorporating both pricing strategy and occupancy rate. This makes it particularly useful and an accurate indicator of performance even for comparing it across different hosts, neighborhoods, and overall market conditions. A high RevPAN can result from higher prices, higher occupancy, or a combination of both, making it a valuable indicator of a host's ability to optimize revenue. Given its ability to reflect market trends and pricing strategies, RevPAN is used as the dependent variable in this study to evaluate the impact of professional hosting, neighborhood characteristics, seasonal fluctuations, and market downturns on Airbnb listing performance.

$$RevPAN\ (Revenues\ Per\ Available\ Night) = \frac{Revenues}{Total\ Available\ Nights}$$

The purpose of this analysis is to answer the following questions:

1) **How do professional hosts perform compared to non-professional hosts in high-demand neighborhoods with strong tourist appeal?**
2) **Do professional hosts achieve a greater revenue advantage during peak seasonal periods when market demand is at its highest?**
3) **Are professional hosts more sensitive to market fluctuations, performing significantly better in booming markets but experiencing greater losses during downturns?**
4) **How does the revenue advantage of professional hosts vary across different market segments, and is the performance gap most pronounced in higher-end listings?**

Based on theoretical frameworks in the existing literature, and general expectations five hypotheses will serve as testable propositions that aim to answer the research questions outlined above and contribute to the overall understanding of the topic:

H1: Listings managed by professional hosts tend to have better performances in the most attractive neighborhoods for tourist, specifically the central ones.

H2: Listings managed by professional hosts tend to have significantly better performances in the peak seasonal fluctuation periods of the market.

H3: As professional hosts gain experience and the market improves over time, the performance gap between their listings and those of non-professional hosts widens.

H4: During COVID period, professional hosts suffered greater losses compared to non-professional hosts, indicating higher sensitivity to market downturns.

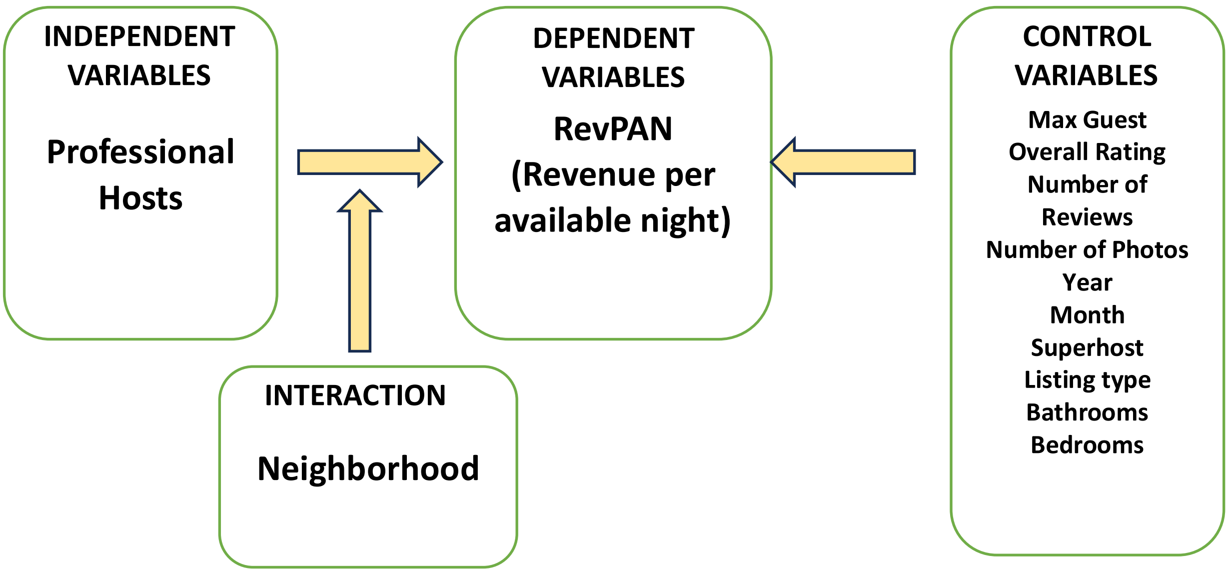
H5: The performance advantage of professional hosts increases with the listing's market segment, with the largest performance gap observed in luxury properties.

3.2 Methodology

This study employs a regression-based approach to analyze the performance differences between professional and non-professional Airbnb hosts across different market conditions, neighborhoods, and seasonal trends. The dependent variable used in the regression models is RevPAN (Revenue per Available Night), which captures both occupancy rate and pricing efficiency, making it a comprehensive measure of listing performance. The key independent variable is professional host status, which is interacted with various moderator variables to assess how its effect varies under different conditions.

Several regression models are implemented to test the hypotheses.

M1

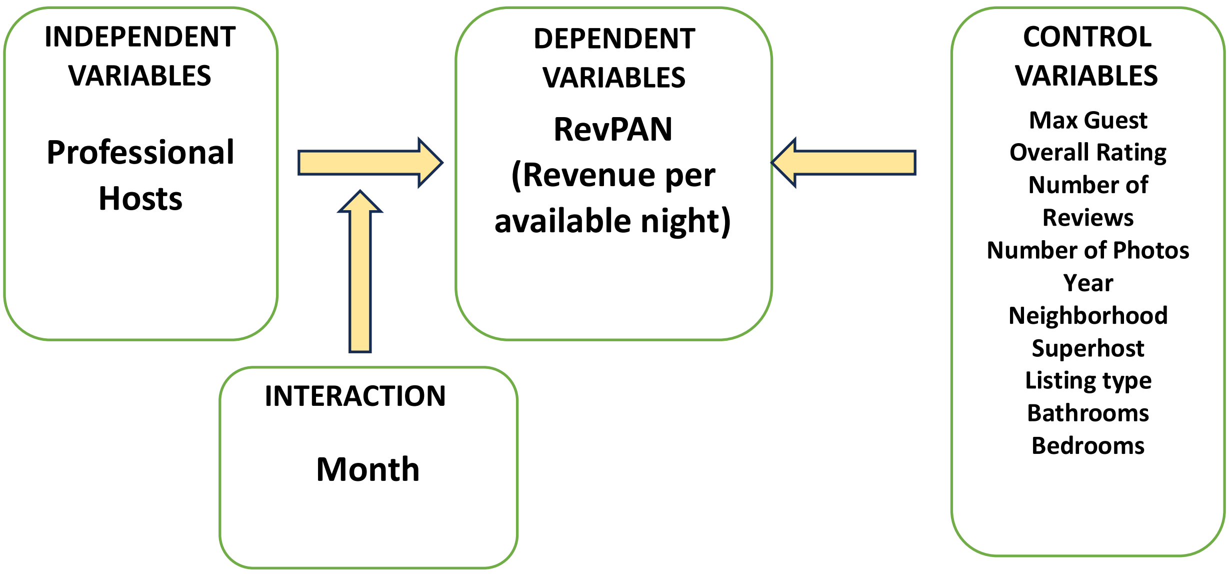


To test the first hypothesis, the model just showed was designed to investigate whether listings managed by professional hosts tend to have a higher RevPAN on average. The model uses a regression-based approach, setting Rev PAN as the dependent variable and professional host status as the main independent variable, with the goal of quantifying the statical relationship between the two variables, and therefore estimating the relationship between hosting type and revenue performance.

The focus of this model, however, is the inclusion of the variable neighborhood, treated as an interaction term to detail the analysis introducing a location-specific effect, in order to determine how the professional hosts performances differ across different areas of the city of Turin. As previously said, this moderating effect is the focus of the model, as the goal of the regression is to test the hypothesis that professional hosts performances vary greatly based on local conditions and tourist attractiveness even in the same city, to identify if a trend of professional hosts outperforming non-professional hosts in specific conditions is statistically relevant.

In order to create the best model possible, to guarantee the most accurate results, a set of control variables has been introduced in the regression to account for external factors not included in the scope of the study. These factors could influence the dependent variable (RevPAN) and could bring to inaccurate results. For example, by including variables such as guest capacity, overall rating, number of reviews, superhost status etc. the model can isolate the effect of professional hosts by reducing the risk of bias caused by property and review-related effects. Moreover, temporal variables (Month and Year) have been added, ensuring that fluctuations in demand and overall market trends are considered. Moreover, differences caused by property size and type have been taken into account by adding variables like listing type, bathrooms, and bedrooms.

M2

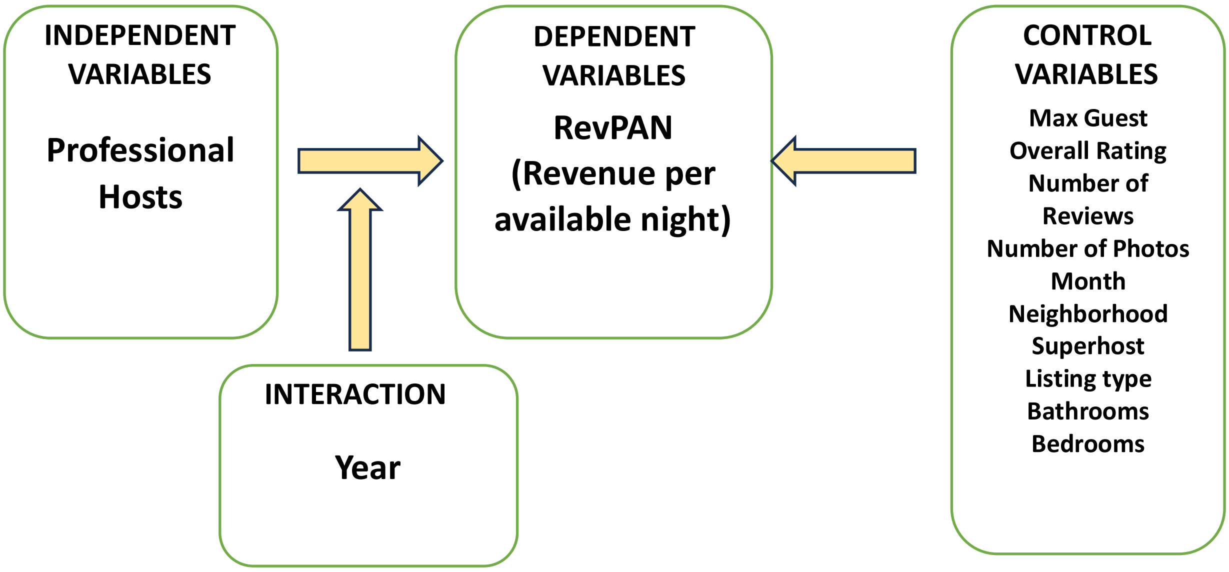


This model is designed to validate HP2, which examines whether professional hosts achieve better performances during peak seasonal periods. The regression framework integrates RevPAN as the dependent variable, and professional hosts as the main independent variable, with the goal of quantifying the statical relationship between the two variables and therefore estimating the relationship between hosting type and revenue performance.

In order to validate the hypothesis, the variable Month was included as an interaction term, in order to estimate the effect on performances of seasonal fluctuations, to ultimately find if any statistical correlation exists between high-demand peak seasons and professional hosts outperforming their non-professional counterparts. As Airbnb market experiences clear cycle of peaks and valleys, obviously driven by the touristic appeal of different times of the year, which changes from place to place, it is interesting to assess whether professional hosts are better at capitalizing on the periods of intense demand, when the pricing and occupancy rate are higher and there are more opportunities to outperform the average market.

In order to create the best model possible, to guarantee the most accurate results, a set of control variables has been introduced in the regression to account for external factors not included in the scope of the study. These factors could influence the dependent variable (RevPAN) and could bring to inaccurate results. For example, by including variables such as guest capacity, overall rating, number of reviews, superhost status etc. the model can isolate the effect of professional hosts by reducing the risk of bias caused by property and review-related effects. Moreover, the variable Year has been added, ensuring that the overall growing trend of the market is considered, and the monthly variations are more accurate. Moreover, differences caused by property size and type have been taken into account by adding variables like listing type, bathrooms, and bedrooms.

M3

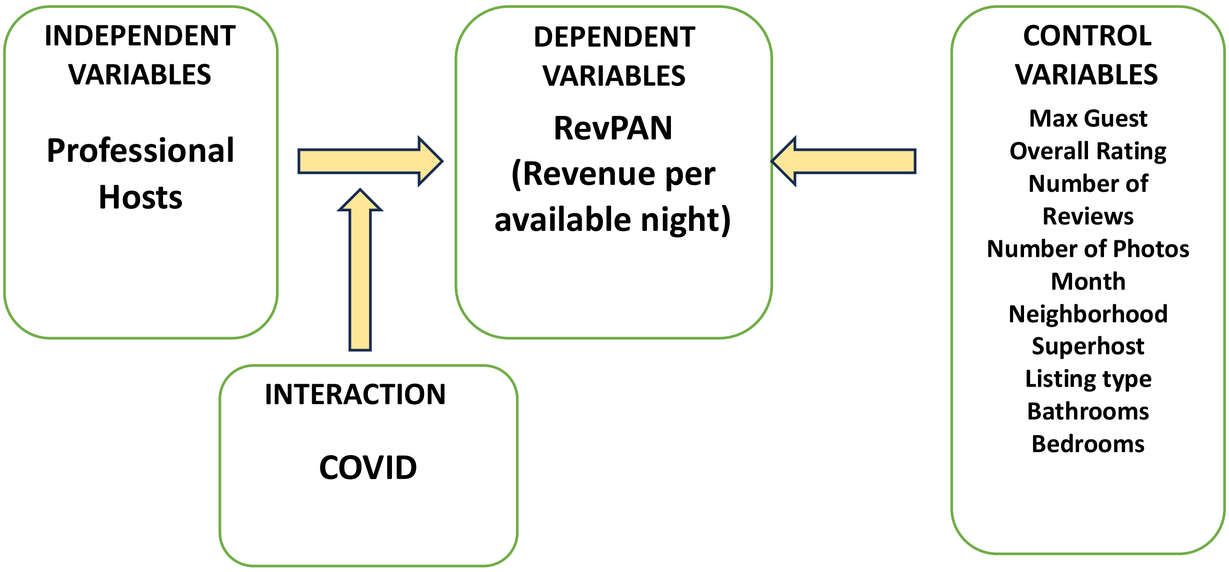


This model is designed to validate HP3, which aims at finding out if the revenue advantage of professional hosts increases over time as they gain experience of local-based factors. The regression framework integrates RevPAN as the dependent variable, and professional hosts as the main independent variable, with the goal of quantifying the statical relationship between the two variables and therefore estimating the relationship between hosting type and revenue performance.

By including the variable year as an interaction term, the regression enables to identify if the difference in the performance gap between professional and non-professional hosts has been widening as the market and the skill of the hosts evolve. This is important because as the short-term rental market matures, professional hosts may become better at optimizing their pricing strategies and adapting to market trends.

In order to create the best model possible, to guarantee the most accurate results, a set of control variables has been introduced in the regression to account for external factors not included in the scope of the study. These factors could influence the dependent variable (RevPAN) and could bring to inaccurate results. For example, by including variables such as guest capacity, overall rating, number of reviews, superhost status etc. the model can isolate the effect of professional hosts by reducing the risk of bias caused by property and review-related effects. Moreover, the variable Month has been added, ensuring that the monthly variations caused by surge in demand in certain periods of the year are accounted for. Additionally, differences caused by property size and type have been taken into account by adding variables like listing type, bathrooms, and bedrooms.

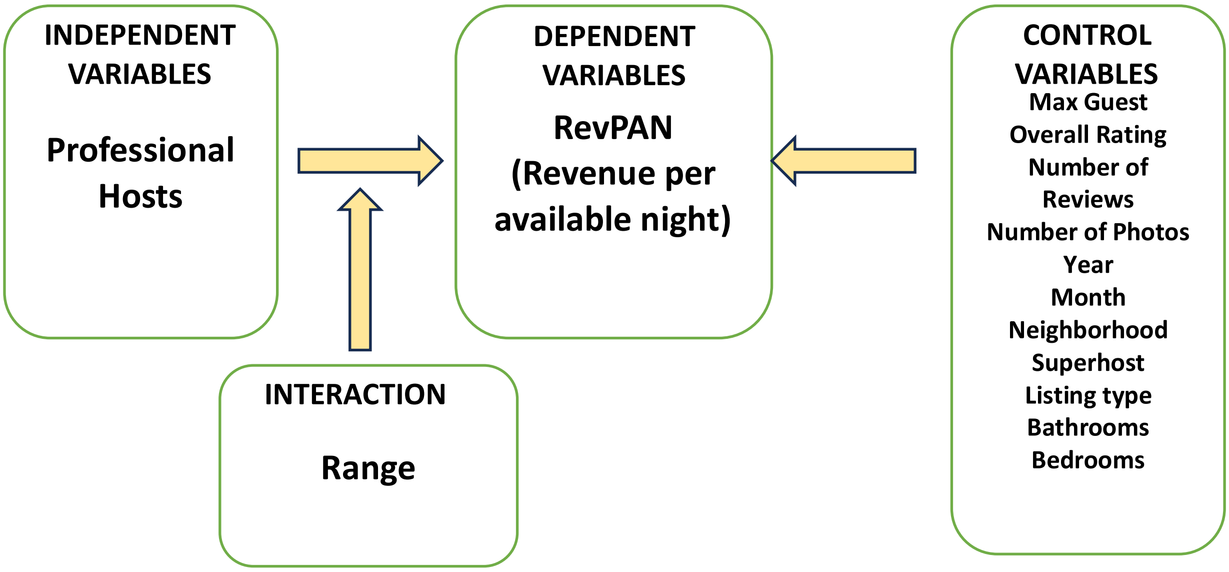
M4



In order to test the HP4, this model has been designed, with the goal of identifying if the professional hosts suffer greater losses during unexpected market downturns. In this case, the COVID-19 period, which caused of the biggest crisis in recent years, and specifically impacted heavily the overall hospitality and Airbnb market, has been selected as the interacting term. Since COVID-19 caused a dramatic and sudden drop in accommodation demand, as polices like lockdowns and travel restrictions were applied worldwide, professional hosts who rely on predictable market fluctuations and high-demand periods (as tested by the previous models) might have suffered even greater losses than non-professional hosts. The aim of the model is therefore to find if the performance gap between the two types of hosts narrowed during this period.

In order to create the best model possible, to guarantee the most accurate results, a set of control variables has been introduced in the regression to account for external factors not included in the scope of the study. These factors could influence the dependent variable (RevPAN) and could bring to inaccurate results. For example, variables such as guest capacity, overall rating, number of reviews, superhost status help isolate the effect of professional hosts by incorporating property-related and review-based characteristics. Moreover, the variable Month has been added, ensuring that the monthly variations caused by surge in demand in certain periods of the year are accounted for. Additionally, differences caused by property size and type have been taken into account by adding variables like listing type, bathrooms, and bedrooms.

M5



In order to validate HP5, this model has been designed, with the objective of identifying how the gap between professional and non-professional hosts varies in different market segments. To do so, the variable Range has been introduced as in interaction term, enabling to quantify the difference in performances. The listings fall into three categories, based on the average price range: Economy, Mid-level, and Luxury. This interaction term could provide valuable insights, as professional hosts may be better equipped to successfully exploit the pricing flexibility that higher-end listings offer. On the other hand, budget listing may prove to be less able to give professional hosts a competitive advantage.

In order to create the best model possible, to guarantee the most accurate results, a set of control variables has been introduced in the regression to account for external factors not included in the scope of the study. These factors could influence the dependent variable (RevPAN) and could bring to inaccurate results. For example, by including variables such as guest capacity, overall rating, number of reviews, superhost status etc. the model can isolate the effect of professional hosts by reducing the risk of bias caused by property and review-related effects. Moreover, temporal variables (Month and Year) have been added, ensuring that fluctuations in demand and overall market trends are considered. Moreover, differences caused by property size and type have been taken into account by adding variables like listing type, bathrooms, and bedrooms.

By using the aforementioned regression-based models, the study will be able to provide detailed insights on how professional hosts perform across different market condition compared to non-professional hosts. Overall, a set of interaction terms have been chosen to identify if there is a statical relationship between professional hosts systematically outperforming the market during specific positive market conditions (such central and attractive neighborhoods, peak-demand seasons and high-end properties) while struggling to gain a significant competitive advantage in worse conditions, such as peripheral neighohoods and market downturns like the COVID-19 pandemic.

3.3 Results analysis

This section presents the results that have been obtained by the regression analysis conducted based on the previously explained models, which have the objective to test the five hypotheses on the differences between professional and non-professional hosts performances. Across the models, the variable RevPAN (Revenue per Available Night) has been used as the dependent variable. This has been identified in the previous literature as the most used variable to estimate a listing's performance, as it considers both the pricing of the listing and the occupancy rate, both key metrics in identifying the successfulness of a property on Airbnb. The models examine how the revenue advantage of professional hosts varies across different market conditions, focusing on both positive ones, such as attractive neighborhoods, peak fluctuations and high-end listings, and negative ones, such as the COVID-pandemic, peripheral neighborhoods and low-end properties.

The results are structured to address each hypothesis individually, focusing on the main findings of each one to then accorporate them into the overall considerations in the conclusion chapter. Each model includes the variable professional host, in order to assess if they systematically outperform non-professional hosts like the literature suggests. By doing so a baseline is set to then move on analyzing the effect of each moderating variable, to investigate how external factors like seasonality, overall market trend, neighborhood attractiveness, economic range of the listing and unexpected downturn influence the RevPAN. By identifying which are these effects, the study will provide a better understanding of the overall Airbnb market.

Once the direct effect of the moderator is established and analyzed, the study then explores the interaction between each one of them and the Professional host variable, to identify how the differences between performances shift when subject to the overall market effects. This will help gaining insights on how the moderating effect of market segment, location, seasonality, and economic shifts impact the two types of hosts, specifically to see which conditions amplify or weaken their performance gap. By identifying which are these effects, the study will provide a better understanding of their differences, going beyond the mere distinction between the two and focusing on how the react to the selected market dynamics. The goal is to find under which conditions bring a strong competitive edge to professional hosts and under which ones their strength diminishes.

Finally, the effects of the control variables are presented to show the robustness of the results and to display the effects of external factors that are not included in the analysis but that still have a significant effect on Airbnb performances. These variables belong to different categories, such as listings characteristics like the number of bedroom and bathrooms, the maximum number of guests, the overall rating and the number of reviews. Additionally, as the dataset incorporates 7 years of data, the variable Yeas has been used to account for overall shifting trends in the market, and the Month variable was used to isolate the effect of natural seasonal fluctuations in a business like Airbnb that heavily relies on tourism flows. By integrating all of these components, the results provide a detail examination of the drivers of the difference in Airbnb performances between professional and non-professional hosts.

Multivariate regressions

The first Model translates into the following regression:

RevPAN = β0 + β1 Neighborhood * β2 Professionalhost + β3 MaxGuests + β4 OverallRating + β5 NumberofReviews + β6 NumberofPhotos + β7 Year + β8 Month + β9 AirbnbSuperhost + β10 ListingType + β10 Bathrooms + β10 Bedrooms + ε

	Coef.	**Std. Err.**	**t**	**P>|t|**
Neighborhood				
Aurora	-6.692075	.2787495	-24.01	0.000
Barriera di Milano	-12.7552	.5071235	-25.15	0.000
Borgata Vittoria	-12.91913	.6906297	-18.71	0.000
Borgo Po e Cavoretto	-5.94324	.4141563	-14.35	0.000
Cenisia	-5.780035	.3898726	-14.83	0.000
Crocetta	-3.981493	.3597667	-11.07	0.000
Falchera	-15.1803	1.379713	-11.00	0.000
Le Valette	-14.55485	.7547787	-19.28	0.000
Madonna del Pilone	-7.018673	.5184692	-13.54	0.000
Madonna di Campagna	-12.57217	.6559873	-19.17	0.000
Mercati generali	-9.72589	.4861490	-20.01	0.000
Mirafiori Nord	-10.21291	.67501	-15.13	0.000
Mirafiori Sud	-16.49215	.8141261	-20.26	0.000
Nizza millefonti	-9.248148	.4326388	-21.38	0.000
Parella	-8.352315	.4475216	-18.66	0.000
Pozzo Strada	-7.797689	.4938421	-15.79	0.000
Regio Parco	-13.74555	.8912311	-15.42	0.000
San Donato	-8.246631	.3111247	-26.51	0.000
San Paolo	-7.978027	.536993	-14.86	0.000
San Salvario	-5.289939	.2575821	-20.54	0.000
Santa Rita	-8.292171	.4929319	-16.32	0.000
Vanchiglia	-4.679907	.3256689	-14.37	0.000
Professionalhost	10.04259	.2523535	39.80	0.000
Neighborhood#Professionalhost				
Aurora#1	-6.809062	.4973998	-13.69	0.000
Barriera di Milano#1	-12.22572	1.054151	-11.60	0.000
Borgata Vittoria#1	-8.118996	1.652473	-4.91	0.000
Borgo Po e Cavoretto#1	-4.449913	.9760969	-4.56	0.000
Cenisia#1	2.817871	.7370388	3.82	0.000
Crocetta#1	4.704371	.6086103	7.73	0.000
Falchera#1	-7.28715	1.980303	-3.68	0.000
Le Valette#1	.1673647	2.221044	0.08	0.940
Madonna del Pilone#1	-9.511316	1.077175	-8.83	0.000
Madonna di Campagna#1	-9.025713	1.679462	-5.37	0.000

Mercati generali#1	2.106421	1.073605	1.96	0.050
Mirafiori Nord#1	-6.372733	1.626065	-3.92	0.000
Mirafiori Sud#1	-5.023566	1.495035	-3.36	0.001
Nizza millefonti#1	-1.617487	.7837473	-2.06	0.039
Parella#1	-9.174845	1.035949	-8.86	0.000
Pozzo Strada#1	-7.833089	1.09551	-7.15	0.000
Regio Parco#1	-12.47732	2.934658	-4.25	0.000
San Donato#1	-2.470963	.6356584	-3.89	0.000
San Paolo#1	-2.712231	1.146941	-2.36	0.018
San Salvario#1	-4.627382	.4455185	-10.40	0.000
Santa Rita#1	-6.273814	.9089764	-6.90	0.000
Vanchiglia#1	-8.229898	.6107582	-13.47	0.000
MaxGuests	3.83059	.0548153	69.88	0.000
OverallRating	.180766	.0130387	13.86	0.000
NumberofReviews	.0656321	.001109	59.18	0.000
NumberofPhotos	.0442142	.0021536	20.53	0.000
Year 2018	2.547016	.2320922	10.97	0.000
Year 2019	5.636221	.2299267	24.51	0.000
Year 2020	-5.92229	.2422974	-24.44	0.000
Year 2021	6.595933	.2516834	26.21	0.000
Year 2022	10.39758	1.185924	8.77	0.000
Year 2023	6.758682	1.186235	5.70	0.000
Month 2	-.4628157	.3191456	-1.45	0.147
Month 3	.0998681	.3168178	0.31	0.755
Month 4	8.907211	.3130883	28.45	0.000
Month 5	8.41946	.3079814	27.34	0.000
Month 6	1.323835	.3072862	4.31	0.000
Month 7	4.560729	.303779	15.01	0.000
Month 8	2.295324	.3051442	7.52	0.000
Month 9	7.483416	.3050289	24.53	0.000
Month 10	11.70673	.3085168	37.95	0.000
Month 11	14.32336	.3072919	46.61	0.000
Month 12	10.40775	.3049918	34.12	0.000
AirbnbSuperhost	6.152383	.1554211	39.59	0.000
Hotel room	17.17058	.8855105	19.39	0.000
Private room	-9.768449	.170538	-57.28	0.000
Shared room	-14.32736	.5011684	-28.59	0.000
Bathrooms	6.423257	.1879385	34.18	0.000

Bedrooms	2.665767	.133353	19.99	0.000
_cons	-7.413611	.3695953	-20.06	0.000

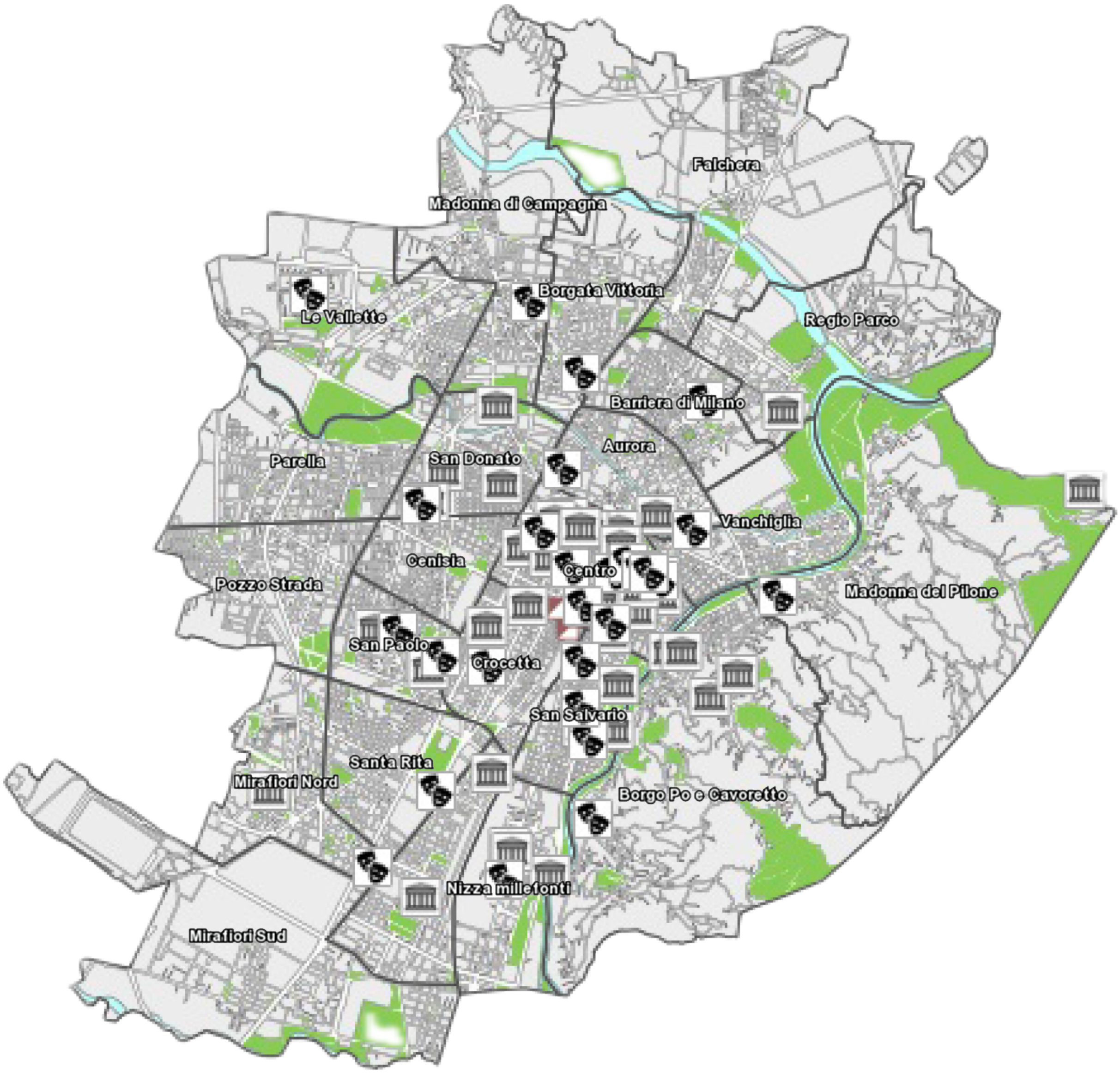
The regression model bas the goal to examine whether professional hosts achieve better performances in the central areas of Turin, where the market is supposed to be bear higher revenues. The coefficient for professional host status is 10.04 ($p < 0.001$), indicating that, on average, professional hosts earn €10.04 more per available night compared to non-professional hosts across the city.

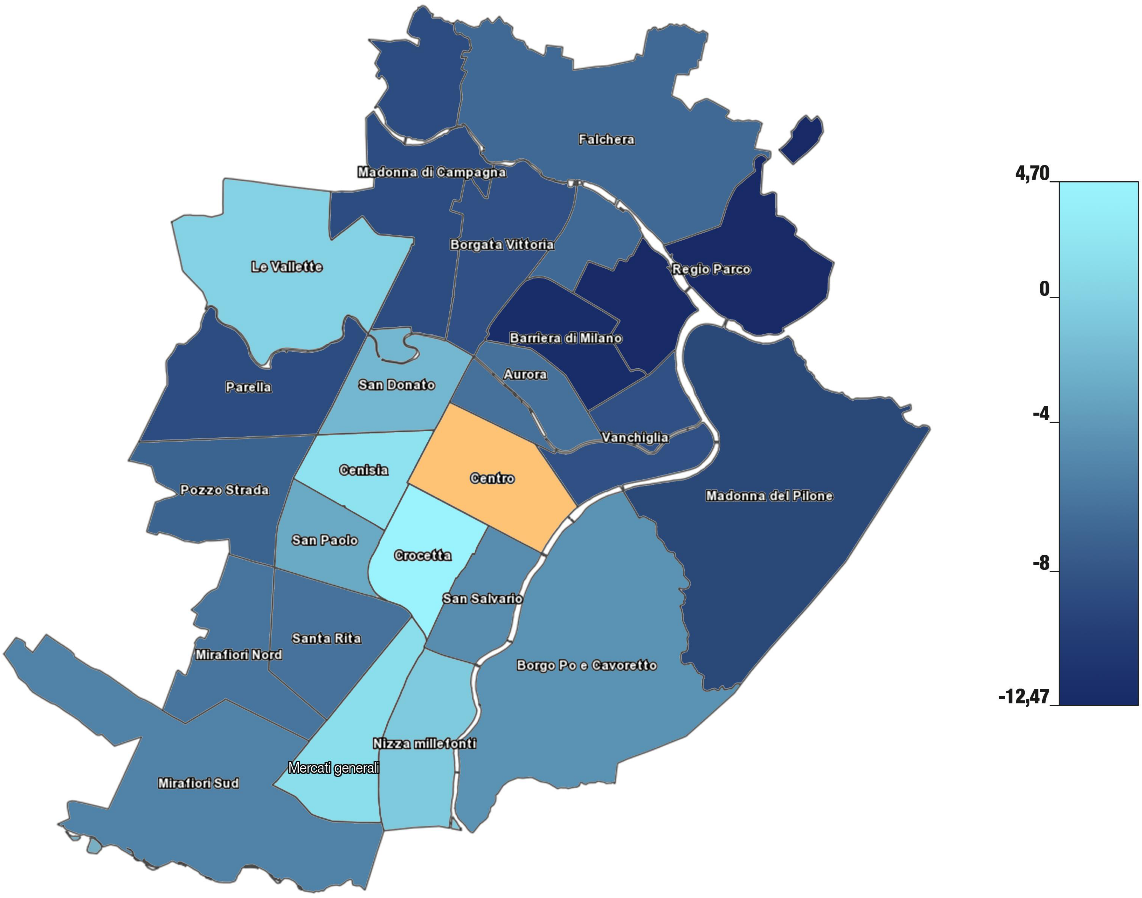
The baseline neighborhood for the regression is set to Centro, which means that all other neighborhoods RevPAN are compared to Centro. As clearly shown by all the coefficients being negative, Centro is the area where the the Airbnb market is most successful, with listings in this place outperforming the others. This is explained by Centro being the most central and touristic area of Turin, justifying higher demand and price premiums for the properties in it. A trend is clearly showing, with neighborhoods close to Centro showing a smaller gap in performances, which grows moving towards peripheral areas.

The interaction term shows how the revenue advantage of professional hosts is not uniform across different locations. Most neighborhoods exhibit negative coefficient, highlighting how the performance gap is almost maximum in the Centro. Notably, Cenisia (€2.81, $p = 0.001$) and Crocetta (€4.70, $p < 0.001$) show the highest positive interaction effects, suggesting that professional hosts gain a stronger advantage in these areas, with both neighborhoods being situated next to the Centro. Additionally, neighborhoods such as San Donato (-€2.20, $p = 0.001$) and San Paolo (-€2.71, $p = 0.032$) have interaction terms close in value to Centro, showing a smaller difference than other areas. A common characteristic of these neighborhoods is their proximity to the city center, validating the hypothesis that professional hosts systematically outperform non-professional hosts in the central areas on the city, leveraging the higher demand and lower price sensitivity to maximize their revenues and gain a clear competitive advantage.

Focusing on the opposite phenomenon, we see that there are some neighborhoods where professional hosts don’t outperform non-professional hosts, and in certain cases the positive effect previously identified is even negatively surpassed by the mixed effect, indicating how they perform worse in some neighborhoods. The strongest negative interactions are found in Barriera di Milano (-€12.22, $p < 0.001$), Borgata Vittoria (-€8.11, $p < 0.001$), and Regio Parco (-€12.47, $p < 0.001$), Madonna del Pilone (-€9.51, $p < 0.001$), Madonna di Campagna (-€9.02, $p = 0.001$), and Parella (-€9.17, $p < 0.001$). A common characteristic of these neighborhoods is being located far from the city center, where demand is likely lower due the lowest appeal for tourists, and a higher number of long-term stays could reduce the competitive advantage of professional hosts.

Overall, the hypothesis is validated by the regression model, with the results that clearly show how the performances of professional hosts are sensibly better in high-demand tourist neighborhoods, specifically in the city center. The central areas are the ones that exhibit a higher revenue performance overall, but this model shows how professional host are able to successfully leverage the high-demand and price flexibility to systematically outperform non-professional hosts in these areas, gaining a clear competitive advantage reflected in a higher RevPAN. On the other hand, it is clear how professional hosts lose this competitive advantage in lower demand areas, like peripheral neighborhoods where also price sensitivity is higher for guests looking for cheaper accommodation options.


Falchera
Madonna di Campagna
Borgata Vittoria
Le Vallette
Regio Parco
Barriera di Milano
Aurora
San Donato
Parella
Vanchiglia
Cenisia
Centro
Pozzo Strada
Madonna del Pilone
San Paolo
Crocetta
San Salvario
Santa Rita
Mirafiori Nord
Borgo Po e Cavoretto
Nizza millefonti
Mirafiori Sud


Falchera
Madonna di Campagna
Le Vallette
Borgata Vittoria
Regio Parco
Barriera di Milano
Aurora
Parella
San Donato
Vanchiglia
Cenisia
Centro
Pozzo Strada
Madonna del Pilone
San Paolo
Crocetta
San Salvario
Santa Rita
Mirafiori Nord
Borgo Po e Cavoretto
Nizza millefonti
Mercati generali
Mirafiori Sud
4,70
0
-4
-8
-12,47

The second Model translates into the following regression:

RevPAN = β0 + β1 Month * β2 Professionalhost + β3 MaxGuests + β4 OverallRating + β5 NumberofReviews + β6 NumberofPhotos + β7 Year + β8 Neighborhood + β9 AirbnbSuperhost + β10 ListingType + β10 Bathrooms + β10 Bedrooms + ε

	Coef.	Std. Err.	t	P>|t|
Month				
Month 2	-.9629366	.3758678	-2.56	0.010
Month 3	-.2710227	.3734412	-0.73	0.468
Month 4	7.545016	.3689945	20.45	0.000
Month 5	7.272469	.3624151	20.07	0.000
Month 6	1.016808	.3619523	2.81	0.005
Month 7	3.73047	.3580141	10.42	0.000
Month 8	1.936002	.3602637	5.37	0.000
Month 9	6.195378	.3599748	17.22	0.000
Month 10	9.711245	.3640776	26.67	0.000
Month 11	11.19343	.3626697	30.86	0.000
Month 12	8.393089	.3600479	23.31	0.000
Professionalhost	3.118511	.5005951	6.23	0.000
Month#Professionalhost				
Month 2#Professionalhost	1.829375	.7126276	2.57	0.010
Month 3#Professionalhost	1.416587	.7064897	2.01	0.045
Month 4#Professionalhost	4.903941	.6982489	7.02	0.000
Month 5#Professionalhost	4.106208	.6880713	5.97	0.000
Month 6#Professionalhost	1.147153	.6850637	1.67	0.090
Month 7#Professionalhost	2.99325	.677124	4.42	0.000
Month 8#Professionalhost	1.364173	.6783997	2.01	0.044
Month 9#Professionalhost	4.565356	.6791222	6.72	0.000
Month 10#Professionalhost	7.079702	.6862655	10.32	0.000
Month 11#Professionalhost	11.00993	.6832936	16.11	0.000
Month 12#Professionalhost	7.124929	.6779147	10.51	0.000
MaxGuests	3.825064	.0547137	69.91	0.000
OverallRating	.1898479	.0130241	14.58	0.000
NumberofReviews	.0650507	.0011076	58.73	0.000
NumberofPhotos	.0426717	.0021533	19.82	0.000
Year				
2018	2.531178	.2321831	10.90	0.000
2019	5.598503	.2299539	24.35	0.000

2020	-5.93418	.2422961	-24.49	0.000
2021	6.617488	.2517133	26.29	0.000
2022	9.713112	1.184664	8.20	0.000
2023	6.004612	1.185039	5.07	0.000
Neighborhood				
Aurora	-8.882246	.2312479	-38.41	0.000
Barriera di Milano	-15.84124	.4447357	-35.62	0.000
Borgata Vittoria	-14.8234	.6265451	-23.66	0.000
Borgo Po e Cavoretto	-7.250151	.3735905	-19.41	0.000
Cenisia	-5.293095	.3306042	-16.01	0.000
Crocetta	-2.449337	.2908608	-8.42	0.000
Falchera	-18.29726	.9904388	-18.47	0.000
Le Valette	-15.23002	.708348	-21.50	0.000
Madonna del Pilone	-9.552759	.4542865	-21.03	0.000
Madonna di Campagna	-14.5324	.6027676	-24.11	0.000
Mercati generali	-9.806544	.4333369	-22.63	0.000
Mirafiori Nord	-11.8577	.6138379	-19.32	0.000
Mirafiori Sud	-18.12541	.6842235	-26.49	0.000
Nizza millefonti	-9.91053	.3613412	-27.43	0.000
Parella	-10.50119	.4020932	-26.12	0.000
Pozzo Strada	-9.831286	.4399452	-22.35	0.000
Regio Parco	-15.66307	.8479224	-18.47	0.000
San Donato	-9.199025	.2702584	-34.04	0.000
San Paolo	-8.978908	.474103	-18.94	0.000
San Salvario	-6.859196	.2125282	-32.27	0.000
Santa Rita	-10.05317	.3776489	-26.62	0.000
Vanchiglia	-7.139085	.2757053	-25.89	0.000
AirbnbSuperhost	6.2089	.155257	39.99	0.000
LystingType				
Hotel Room	18.89165	.881891	21.42	0.000
Private Room	-9.829082	.170171	-57.76	0.000
Shared Room	-14.77592	.4995	-29.54	0.000
Bedrooms	2.656785	.1332525	19.94	0.000
Bathrooms	6.389609	.1879252	34.00	0.000
cons	-5.18381	.3854079	-13.45	0.000

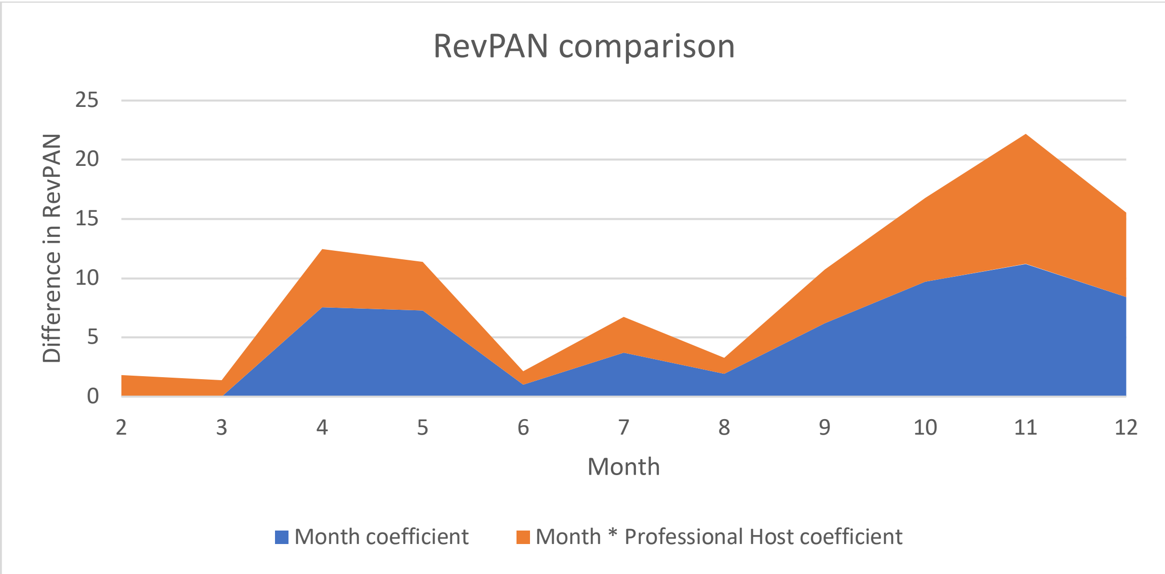
The results for HP2, which examines whether professional hosts achieve significantly better performances during peak seasonal periods, indicate that professional hosting has a positive overall effect on RevPAN, with strong seasonal variations.

The main effects of the month variable indicate strong seasonality in RevPAN. The baseline month considered in this model is January, so all month coefficients represent the difference in RevPAN compared to January's value. The coefficients are highest in October (€9.71, $p < 0.001$), November (€11.19, $p < 0.001$), and December (€8.39, $p < 0.001$), indicating how the autumn period presents the highest value of revenue per available, due to the increase demand in this period. In addition to these peak months, April (€7.54, $p < 0.001$) and May (€7.27, $p < 0.001$) also show high RevPAN values, indicating significantly strong market performance. Conversely, February (-€0.96, $p = 0.010$) and March (-€0.27, $p = 0.468$, not significant) show the lowest values, showing little to no significant difference to January, making the winter period the lowest in the term of revenues. As shown in the context analysis section, a clear seasonal trend has been identified, with the highest months in terms of RevPAN being in the Autumn period, followed by the lowest months in the Winter, with a growth during Spring and a subsequent decline in the summer.

The interaction terms between professional host status and month provide insight into how the revenue advantage of professional hosts fluctuates throughout the year. The interaction effects are highest in October (€7.08, $p < 0.001$), November (€11.09, $p < 0.001$), and December (€7.12, $p < 0.001$), followed by April (€4.90, $p < 0.001$) and May (€4.10, $p < 0.001$). These findings highlight how professional hosts achieve the greater revenue gap during the peak market seasons of the year. This suggests that during high-demand periods, professional hosts are able to make the most out of pricing strategies such as dynamic pricing and price positioning to successfully outperform non-professional hosts leading to a significantly larger RevPAN gap.

During the lower-demand months, the revenue advantage of professional hosts is clearly smaller. For example, in February (€1.83, $p = 0.010$), March (€1.42, $p = 0.045$), and June and August (both not significant), there are not significant differences between the RevPAN of the two types of hosts, showing how professional hosts don't have the competitive edge to outperform non-professional hosts during these periods.

The second hypothesis is strongly supported by the results of the regression model, clearly showing a link between high-revenues periods and professional hosts outperforming non-professional hosts. The seasonal advantage seen in the results is likely due to professional hosts being able to leverage on the successful strategies that have been identified to positively impact RevPAN during peak periods where the growth in demand allows for a greater flexibility to increase price without negatively impacting on overall performance.



The third Model translates into the following regression:

RevPAN = β0 + β1 Year * β2 Professionalhost + β3 MaxGuests + β4 NumberofReviews + β5 NumberofPhotos + β6 Month + β7 Neighborhood + β8 AirbnbSuperhost + β9 ListingType + β10 Bathrooms + β11 Bedrooms + ε

	Coef.	Std. Err.	t	P>|t|
Year				
2018	2.080029	0.2403651	8.65	0.000
2019	4.981243	0.2402656	20.73	0.000
2020	-5.304351	0.2595152	-20.44	0.000
2021	3.955803	0.2694378	14.68	0.000
2022	23.81038	0.2675831	88.98	0.000
2023	20.96238	0.2484153	84.38	0.000
Professionalhost	-1.131208	0.3438229	-3.29	0.001
Year#Professionalhost				
2018#1	3.777177	0.4684233	8.06	0.000
2019#1	5.82454	0.4617736	12.61	0.000
2020#1	4.106507	0.4891899	8.39	0.000
2021#1	11.42764	0.5038384	22.68	0.000
2022#1	16.18079	0.4905247	32.99	0.000
2023#1	13.27104	0.4644977	28.57	0.000
MaxGuests	3.81752	0.0504142	75.72	0.000
NumberofReviews	0.0728264	0.0010712	67.98	0.000
NumberofPhotos	0.0559703	0.0021037	26.61	0.000
Neighborhood				
Aurora	-7.878018	0.2167505	-36.35	0.0
Barriera di Milano	-14.47939	0.4071998	-35.56	0.0
Borgata Vittoria	-13.76255	0.5723717	-24.04	0.0
Borgo Po e Cavoretto	-6.780822	0.3396817	-19.96	0.0
Cenisia	-5.049406	0.3057138	-16.52	0.0
Crocetta	-2.0035	0.2682708	-7.47	0.0
Falchera	-16.64418	0.930203	-17.89	0.0
Le Valette	-13.78577	0.6481867	-21.27	0.0
Madonna del Pilone	-9.275354	0.4078244	-22.74	0.0
Madonna di Campagna	-13.707	0.5453536	-25.13	0.0
Mercati generali	-8.817096	0.4011339	-21.98	0.0
Mirafiori Nord	-10.98121	0.559777	-19.62	0.0
Mirafiori Sud	-16.94678	0.5985458	-28.31	0.0
Nizza millefonti	-9.192428	0.337778	-27.21	0.0

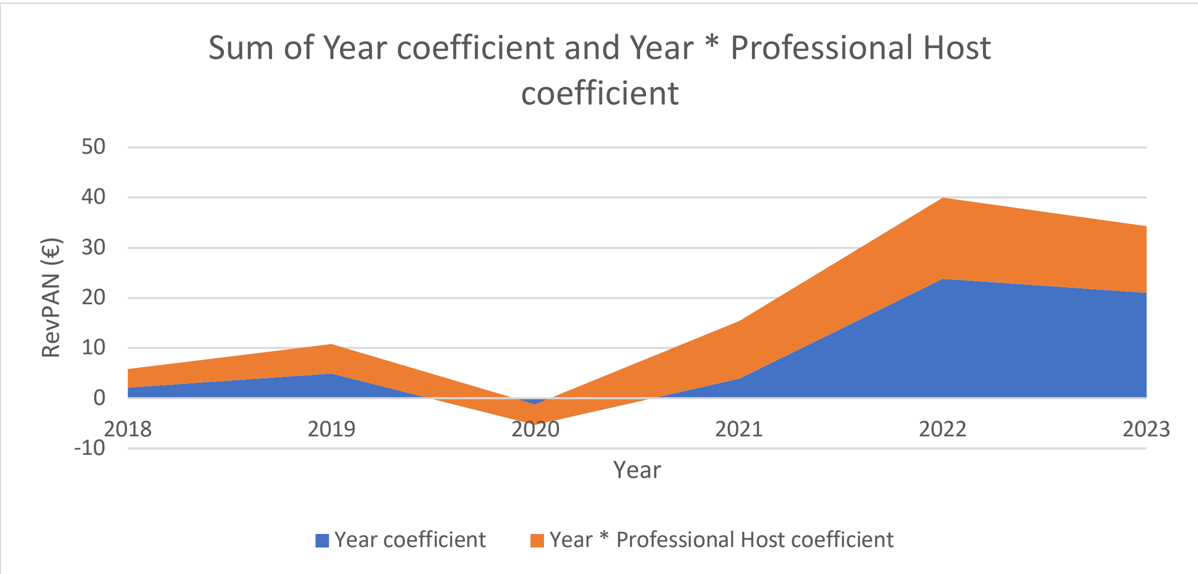
Parella	-9.659633	0.3689915	-26.18	0.0
Pozzo Strada	-8.691106	0.4013363	-21.66	0.0
Regio Parco	-14.22136	0.7671044	-18.54	0.0
San Donato	-8.294619	0.2527228	-32.82	0.0
San Paolo	-7.70476	0.4286073	-17.98	0.0
San Salvario	-6.30796	0.1985153	-31.78	0.0
Santa Rita	-9.464833	0.3504503	-27.01	0.0
Vanchiglia	-6.419545	0.2570467	-24.97	0.0
Month				
Month 2	-.555698	.2946656	-1.89	0.059
Month 3	.0426899	.2926764	0.15	0.884
Month 4	8.116533	.2896655	28.04	0.000
Month 5	7.642743	.285389	26.78	0.000
Month 6	1.117533	.28442	3.93	0.000
Month 7	4.225856	.2812624	15.02	0.000
Month 8	2.12763	.2826627	7.53	0.000
Month 9	7.118767	.2828467	25.17	0.000
Month 10	10.78265	.28575	37.73	0.000
Month 11	13.41026	.2846867	47.11	0.000
Month 12	9.756734	.2822127	34.57	0.000
AirbnbSuperhost	6.813544	.1484194	45.91	0.000
Listing Type				
Hotel room	26.98862	.7643948	35.31	0.000
Private room	-8.808774	.1542858	-57.00	0.000
Shared room	-13.26239	.4348239	-30.50	0.000
Bathrooms	4.898471	.1684426	29.08	0.000
Bedrooms	1.862487	.1210538	15.39	0.000
cons	-3.495372	.3340856	-10.46	0.000

The results for HP3, which examines whether the performance gap between professional and non-professional hosts widens over time as professional hosts gain experience and the market evolves, show a clear increasing trend in the revenue advantage of professional hosts over the years.

The main effects of the year variable indicate overall market fluctuations in RevPAN. The reference year is 2017, the first in the dataset. In the early years, 2018 (€2.00, $p < 0.001$) and 2019 (€4.98, $p < 0.001$) show positive revenue growth. It is noticeable how in 2020 (-€5.30, $p < 0.001$) overall performances are subject to a sharp decline, reflecting the impact of the COVID-19 pandemic on the Airbnb market. From 2021 onwards, the market starts to recover, firstly with a little increase in 2021 (€3.96, $p < 0.001$) as pandemic-related policies such as travel restrictions and lockdowns were still effective in the first months, followed by a clear increase in 2022 (€23.81, $p < 0.001$), and 2023 (€20.96, $p < 0.001$), indicating strong post-pandemic growth and better market conditions compared to the first years of the dataset.

The key focus of the regression is on the interaction term Year, in order to investigate if the revenue advantage of professional hosts has changed over time as the market improves. The interaction coefficients are positive and increasing year-by-year, which suggests how the growing market has been better exploited by professional hosts to increase the performance gap with their non-professional counterparts. In 2018 (€3.78, $p < 0.001$) and 2019 (€5.82, $p < 0.001$), professional hosts already had a revenue premium, but this advantage remains stable in 2020 (€4.11, $p < 0.001$) despite the overall market decline. From 2021 (€11.43, $p < 0.001$) onwards, the revenue gap between professional and non-professional hosts widens significantly, reaching its highest levels in 2022 (€16.18, $p < 0.001$) and 2023 (€13.27, $p < 0.001$).

The results provide a strong support for HP3, validating the proposition that professional hosts leverage their growing experience in an evolving market to widen the performance gap with non-professional hosts. Specifically, the RevPAN gap shows a high increase in post-pandemic years, showing how professional hosts have adapted more effectively to the new market conditions by implementing better pricing strategies to maximize their revenues.



The fourth Model translates into the following regression:

RevPAN = β0 + β1 COVID * β2 Professionalhost + β3 MaxGuests + β4 OverallRating + β5 NumberofReviews + β6 NumberofPhotos + β7 Month + β8 Neighborhood +β9 AirbnbSuperhost + β10 ListingType + β10 Bathrooms + β10 Bedrooms + ε

	Coef.	**Std. Err.**	**t**	**P>|t|**
COVID	-10.59946	.213999	-49.53	0.000
Professionalhost	8.045572	.1530404	52.57	0.000
COVID#Professionalhost	-4.045545	.3810647	-10.62	0.000
MaxGuests	3.75807	.0546882	68.72	0.000
OverallRating	.2239783	.0015907	140.80	0.000
NumberofReviews	.0632456	.0011024	57.37	0.000
NumberofPhotos	.0526474	.0020864	25.23	0.000
Month				
Month 2	-.4629626	.3192777	-1.45	0.147
Month 3	1.778092	.3180077	5.59	0.000
Month 4	10.58032	.3141908	33.67	0.000
Month 5	10.09977	.3089249	32.69	0.000
Month 6	1.6796	.3073969	5.46	0.000
Month 7	4.913581	.3038873	16.17	0.000
Month 8	2.622885	.3052481	8.59	0.000
Month 9	7.803888	.305133	25.58	0.000
Month 10	12.04129	.3086396	39.01	0.000
Month 11	14.68343	.3074042	47.77	0.000
Month 12	10.73567	.3050901	35.19	0.000
Neighborhood				
Aurora	-8.851108	.2311125	-38.30	0.000
Barriera di Milano	-15.56622	.4442632	-35.04	0.000
Borgata Vittoria	-14.54225	.6263033	-23.22	0.000
Borgo Po e Cavoretto	-7.298762	.3735197	-19.54	0.000
Cenisia	-5.356829	.3305483	-16.21	0.000
Crocetta	-2.522644	.2907935	-8.68	0.000
Falchera	-18.37583	.9900981	-18.56	0.000
Le Valette	-15.287	.7081946	-21.59	0.000
Madonna del Pilone	-9.546563	.4541596	-21.02	0.000

Madonna di Campagna	-14.49031	.6062585	-24.04	0.000
Mercati generali	-9.75216	.4333157	-22.51	0.000
Mirafiori Nord	-11.67246	.6137214	-19.02	0.000
Mirafiori Sud	-17.57353	.6839934	-25.69	0.000
Nizza millefonti	-9.674006	.3611133	-26.79	0.000
Parella	-10.38749	.4020046	-25.84	0.000
Pozzo Strada	-9.546236	.4398275	-21.70	0.000
Regio Parco	-15.54323	.8476325	-18.34	0.000
San Donato	-9.224768	.2701926	-34.14	0.000
San Paolo	-8.732853	.4739893	-18.04	0.000
San Salvario	-6.974246	.2124565	-32.83	0.000
Santa Rita	-10.01631	.377534	-26.53	0.000
Vanchiglia	-7.261533	.2756238	-26.35	0.000
AirbnbSuperhost	5.702074	.1516634	37.60	0.000
Listing Type				
Hotel room	19.06434	.8817715	21.62	0.000
Private room	-10.14176	.1697938	-59.73	0.000
Shared room	-15.17497	.4993257	-30.39	0.000
Bathrooms	6.444175	.1878835	34.30	0.000
Bedrooms	2.650033	.1332056	19.89	0.000
cons	-2.655621	.3275958	-8.11	0.000

The results for HP4, which examines whether professional hosts suffered greater revenue losses during the COVID-19 period compared to non-professional hosts, provide strong evidence that professional hosts were more negatively affected during the market downturn.

The main effect of COVID is -€10.60 ($p < 0.001$**)**, indicating that RevPAN was significantly lower during the pandemic compared to non-COVID periods. This confirms that the market as a whole experienced a major decline, which is expected given the travel restrictions and reduced demand for short-term rentals during that time.

The key interaction term COVID × Professional Host is -€4.05 ($p < 0.001$), which indicates that professional hosts saw an additional revenue decline of €4.05 per available night compared to non-professional hosts during the COVID-19 period. The coefficient is statistically significant; therefore, it can be concluded that the results are accurate and that professional hosts suffered higher revenue losses, and the performance gap narrowed, supporting the hypothesis that professional hosts are more sensitive to market downturns.

The results highlight how professional hosts that typically base their successful performance on the understanding of market dynamics to implement winning strategies such as dynamic pricing and price positioning, were highly impacted by the unexpected and sudden drop in demand the COVID pandemic brought. Non-professional hosts, on the other hand were less impacted. This may be due to the greater flexibility in compromising the asking price for their listings and higher proportion of long-term stays.

Overall, the results provide strong evidence supporting HP4, by highlighting that even if professional hosts achieve better performances in normal market conditions (as found in the previous hypotheses), they adopt a business model that is more vulnerable during market downturns, such as the COVID-19 pandemic. This reinforces the findings that professional hosts are subject to unexpected fluctuations as they normally implement strategies to outperform non-professional hosts based on the understanding of the market trends.

The fifth Model translates into the following regression:

RevPAN = β0 + β1 Range * β2 Professionalhost + β3 MaxGuests + β4 OverallRating + β5 NumberofReviews + β6 NumberofPhotos + β7 Month + β8 Year +β9 AirbnbSuperhost + β11 ListingType + β12 Bathrooms + β13 Bedrooms + β14 Neighborhood + ε

	Coef.	Std. Err.	t	P>|t|
Range				
Luxury	92.25801	.4981397	185.21	0.000
Mid-level	25.91621	.1404335	184.54	0.000
Professionalhost	-2.168643	.185644	-11.68	0.000
Range#Professionalhost				
Luxury#1	19.87908	.708732	28.05	0.000
Mid-level#1	11.36528	.2458676	46.23	0.000
MaxGuests	1.351551	.0478151	28.27	0.000
OverallRating	.131775	.0112636	11.70	0.000
NumberofReviews	.0631078	.0009562	66.00	0.000
NumberofPhotos	.0524242	.0018592	28.20	0.000
Month				
Month 2	1.626626	.2754121	5.91	0.000
Month 3	1.563379	.2733496	5.72	0.000
Month 4	8.544981	.2700822	31.64	0.000
Month 5	6.92019	.265726	26.04	0.000
Month 6	2.085435	.2650848	7.87	0.000
Month 7	4.518148	.2620538	17.24	0.000
Month 8	4.516078	.2633444	17.15	0.000
Month 9	8.224789	.263139	31.26	0.000
Month 10	10.98791	.2661522	41.28	0.000
Month 11	11.31715	.2652533	42.67	0.000
Month 12	7.509966	.2632619	28.53	0.000
Year				
Year 2018	1.778938	.2001961	8.89	0.000
Year 2019	4.218644	.1983106	21.27	0.000
Year 2020	-4.908265	.2089619	-23.49	0.000
Year 2021	4.156615	.2171536	19.14	0.000
Year 2022	3.810716	1.024383	3.72	0.000
Year 2023	-.2372582	1.024681	-0.23	0.817

Neighborhood				
Aurora	-2.897304	0.2005077	-14.45	0.000
Barriera di Milano	-6.525348	0.3847545	-16.96	0.000
Borgata Vittoria	-5.496509	0.5411272	-10.16	0.000
Borgo Po e Cavoretto	-4.691577	0.3222586	-14.56	0.000
Cenisia	-1.383103	0.2853098	-4.85	0.000
Crocetta	-1.405841	0.250833	-5.60	0.000
Falchera	-8.153204	0.8545285	-9.54	0.000
Le Valette	-7.959843	0.6111247	-13.02	0.000
Madonna del Pilone	-5.549039	0.3919499	-14.16	0.000
Madonna di Campagna	-6.521423	0.5203387	-12.53	0.000
Mercati generali	-4.39174	0.3739845	-11.74	0.000
Mirafiori Nord	-4.350545	0.5298086	-8.21	0.000
Mirafiori Sud	-7.702593	0.5909034	-13.04	0.000
Nizza millefonti	-4.881162	0.3119309	-15.65	0.000
Parella	-2.999985	0.3475781	-8.63	0.000
Pozzo Strada	-3.308486	0.3798591	-8.71	0.000
Regio Parco	-7.813806	0.7314744	-10.68	0.000
San Donato	-3.97704	0.2336638	-17.02	0.000
San Paolo	-3.299725	0.4091821	-8.06	0.000
San Salvario	-2.695613	0.1837337	-14.67	0.000
Santa Rita	-4.157624	0.3261405	-12.75	0.000
Vanchiglia	-2.837213	0.2381249	-11.91	0.000
AirbnbSuperhost	4.274581	.1342587	31.84	0.000
Listing Type				
Hotel room	13.17824	.7606923	17.32	0.000
Private room	-2.441587	.1506169	-16.21	0.000
Shared room	-2.168405	.434308	-4.99	0.000
Bathrooms	4.037358	.1632727	24.73	0.000
Bedrooms	1.601538	.1151502	13.91	0.000
cons	-9.534598	.3197691	-29.82	0.000

The results of the regression used to test HP5, which has the objective to identify if the revenue advantage of professional hosts increases with the listing's market segment, strongly support the hypothesis that professional host gain a clear competitive advantage in terms of performance in higher-end listing.

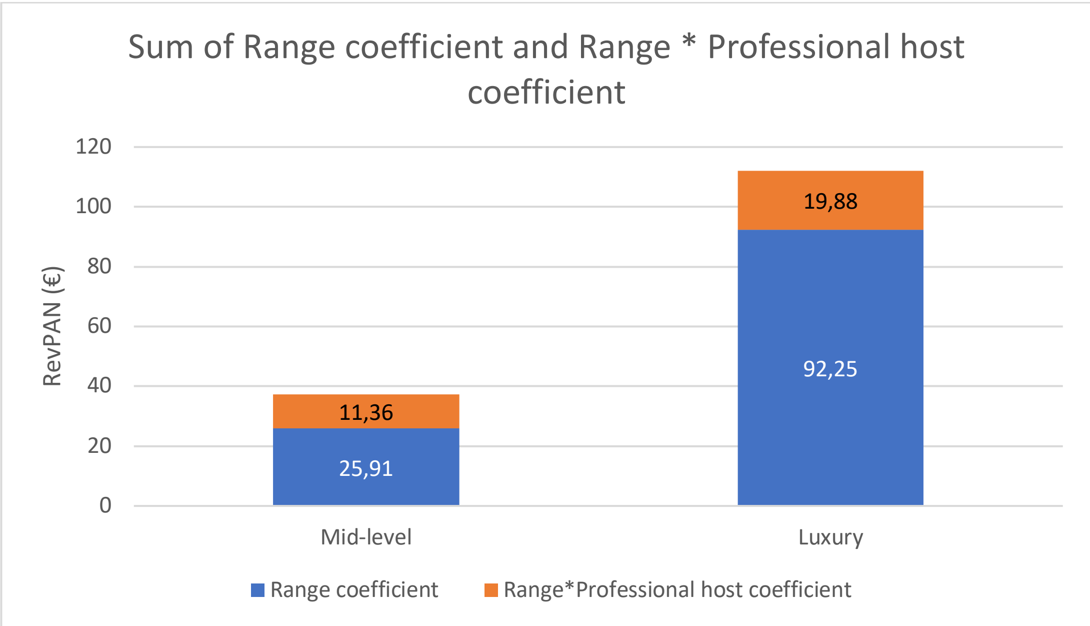
The effect of market segment categories on RevPAN is clear. Compared to Economy properties, which is the baseline used in the regression, Mid-level listings exhibit higher level (€25.92, $p < 0.001$), with Luxury listings distinctly outperforming the other categories with a higher RevPAN of (€92.26, $p < 0.001$) compared to Economy listings. This confirms that higher-end listings generate more revenues on average compared to other accomodations.

The key results that emerge from this regression is the interaction term between professional host status and market segment. They reveal that professional hosts gain a significant performance advantage in higher-end properties. The interaction coefficient for Luxury × Professional hosts is 19.87 ($p < 0.001$), signaling that professional hosts earn €19.87 per available night in the luxury segment compared to non-professional hosts. Similarly of what seen in the RevPAN of Mid-level listings, the interaction coefficient for Mid-level × Professional Host is 11.36 ($p < 0.001$), meaning that professional hosts earn €11.36 more per night. Both values are statistically significant, meaning that the results successfully describe the mixed effect of professional hosts and the economic level of the listing.

The findings confirm that professional hosts see an increase of their revenue advantage with the property market segment, reaching the bigger performance gap in the luxury categories. This validates the hypothesis, by showing that professional hosts can better implement the successful strategies that justify higher rates in premium listings without making the property lose appeal and ultimately achieving significantly better performances than non-professional hosts.

On the other hand, the identified smaller performance gap in economy listings shows how professional hosts are not able to successfully outperform non-professional hosts in lower-end properties. This may be due to the lack of flexibility and the price sensitivity for guests looking to stay in cheaper listings.

To sum up, the results from the regression strongly support HP5, validating the proposition that professional hosts are able to achieve significant revenue advantage in premium listings over non-professional hosts. This can be explained by their ability to leverage on their expertise to successfully implement the strategies that are found in the literature to bring higher revenues on average, such as price positioning, to maximize their premium properties value.



CONCLUSION

This study had the objective to analyze the differences in performance between listings managed by professional and non-professional Airbnb hosts in Turin, focusing on how factors such as location, seasonality, market fluctuations, and economic range differently influence revenue outcomes. Through comparative analysis and regression models, the research provided key insights into whether professional hosts revenue advantage is consistent across market segments and conditions.

As already identified in previous research, professional hosts, on average, achieve higher revenues per available night (RevPAN) than non-professional hosts. However, this advantage is not uniform across all market conditions. Location plays a critical role, with centrally located listings exhibiting stronger performance for professional hosts who can capitalize on dynamic pricing and sustained demand, with performances showing a higher difference on average in central and tourist attractive locations. In contrast, listings in peripheral areas show a smaller gap between professional and non-professional host performance, with the latter even showing higher revenues on average in some peripheral neighborhoods, suggesting that location is a key determinant in amplifying the revenue advantage of experienced operators.

Seasonality also has a noticeable impact, with professional hosts benefiting more from peak demand periods. The ability to implement strategic pricing and maximize occupancy during high-season months results in a more pronounced revenue gap during these periods. These findings are coherent with previous research on the ability to effectively implement price positioning strategies, with professional hosts that are found to systematically outperform non-professional hosts when it comes to setting the right price to maximize revenues. This research uses these previous findings to investigate if this advantage was gained homogenously during the year of if professional hosts capitalized better peak demand periods, further widening their advantage. The hypothesis was validated, finding that professional hosts use high-demand periods as a competitive advantage to consistently outperform non-professional hosts in terms of performance.

However, unexpected market fluctuations, including economic downturns or changes in demand patterns, appear to affect professional hosts more significantly than non-professionals. This is the case during the COVID-19 pandemic, where professional hosts suffered more in terms of revenues than their non-professional counterparts. This suggests that while professional hosts excel in predictable markets, their reliance on high occupancy rates and revenue optimization techniques makes them more vulnerable when demand suddenly decreases. The findings indicate that during low-demand periods, the revenue difference between professional and non-professional hosts diminishes, highlighting the risks associated with a strategy that heavily depends on market conditions.

The economic range of listings also plays a crucial role in shaping revenue outcomes. As price positioning was found to be the main strategy that largely impacted professional hosts performances more than non-professional hosts (Kwok, Xie 2018), it is plausible to assume that their advantage is even more pronounced in listings of higher-end segment, thanks to the fact that they can set the price more flexibly than for economic listings. The thesis indeed shows a strong revenue advantage achieved by professional hosts in the luxury and mid-level segments. This is likely due to the fact that they better leverage their expertise in price positioning to achieve higher profitability. On the other hand, the gap has been observed to narrow in properties belonging to the economy segment, where a higher price sensitivity among guests limits the flexibility of professional hosts to dynamically adjust the price to outperform the market. This finding aligns with the observed shift in professional host investments, with a growing focus on mid-level and luxury properties over time.

To sum up, the study provides a detailed examination of the gap in performances between professional and non-professional hosts, and how it varies across different market conditions. The results focus on the importance of key factors such as location, seasonality, market dynamics and economic segment of the listing and examines how the gap in performance varies according to these factors. The results could be useful to guide property managers at identifying the key success factors of professional hosts that are shown to outperform non-professional hosts.

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