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Analyzing the Effect of Host Engagement on Airbnb in London

A Data-Driven Study from 2018 to 2023

Supervisors:
Professor Raguseo Elisabetta
Professor Milone Francesco Luigi

Candidate:
Scivetti Luca (303051)

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ABSTRACT

This study analyzes the correlation between host engagement and performance of listings on Airbnb, across 38 neighborhoods in London from 2018 to 2023. Engagement by hosts, a crucial determinant of success on the platform, is investigated through critical variables: response rate, status of Superhost, and availability for Instantbook. This research places its focus on how these factors have influenced three major performance metrics: occupancy rates, revenue, and number of reservations. This study also assesses the shifting importance of host engagement across diverse market conditions brought on by the pandemic through a division of the study period into pre-COVID, during-COVID, and post-COVID stages.

Results show that the higher level of host engagement—in particular, response rates between 70% and 100%—is strongly correlated to better performance for all measures. Listings that have Instant Book turned on always perform better than those without it, likely because guests prefer easier and smoother booking processes. The Superhost status also impacts significally occupancy rates and revenue, though its effect varies in different competitive neighborhoods as well as marketplace conditions. In non-competitive areas, the same high response rates contribute even more to its performance, which signifies responsiveness in these environments as even more important.

This research fills a gap in the literature by offering data-driven insights into the measurable impact of host engagement on Airbnb listing performance in a major metropolitan city. The findings highlight the importance of optimizing host responsiveness and trust-building features, particularly in varying competitive environments, to maximize listing success in both ordinary and disrupted market conditions.

1. Introduction

1.1 Research background

In recent years, the peer-to-peer accommodation market has skyrocketed and transformed the accommodation sector with the arrival of platforms like Airbnb, where individuals can rent out their homes for a short duration to travelers. Being one of the most recognized sharing economy platforms, millions of hosts and guests have been onboarded to the platform all over the world. In competitive markets such as London and many others, the listing aspects which are very important to the owners who want to maximize their occupancy and overall income generation ability have become of critical importance.

Host engagement is one of the most important predictors regarding success on Airbnb. It is a multi-behavioral term including but not limited to host attentiveness, responsiveness, and hospitality. Past research has shown that host engagement, as observed on listing indicators such as response rate, superhost status, and instantbook feature, have an effect on the performance of a listing. Nevertheless, the extent to which resource use affected listing performance is a subject of further investigation.

1.2 Domestic and International Research Status

A lot of research has been done already regarding the sharing economy, and Airbnb certainly represents one of the key players in such a field. Studies exploring the relationship between host engagement and guest satisfaction have been run worldwide. To name a few, in the U.S. as well as in European markets, a significant correlation has been found between high response rates and better guest experiences (Zervas et al., 2020), which proves to lead to higher listing visibility and number of bookings. In other words, Zervas pointed out that an enhanced level of host engagement can boost listings' performance.

In the UK in particular, especially in London of course, a considerable amount of existing literature deep dives into the relationship between market dynamics and rentals performance. It is proved, for example, that host' who maintain superhost status manage to increase the longevity of their listings (Smith et al., 2019). However, there is not much information about the direct impact of host engagement on metrics like occupancy rate, number of reservations, and revenues, in the context of a large metropolitan city like London. The aim of this research, indeed, is to fill this gap by offering data-driven insights to better understand how host behavior can shape Airbnb's listings' success.

1.3 The choice of the city of London

The UK capital represents one of the most influential cities in the world, under several points of view. London is not only one of the major financial hubs worldwide, but it also stands as one of the largest cultural and touristic melting pot. This makes it a perfect case study for social and economic behaviors, and their impact on entities such as short-term rentals. Airbnb's presence in London is extensive to say the least, and its diverse and rich dataset provides a number of insights to analyze host engagement and the impact it has on the local short-term rental market. The large number of listings and and the city's international and diverse environment make London a fair representative microcosm to study and understand broader trends in this industry. Also, this ensures the robustness of the research and enables an extensive and detailed exploration of the topic.

Nonetheless, the city is divided into unique and particular neighborhoods, which contribute to different levels of competition and market dynamics, more than what the average European city would suggest. Spanning across emerging areas like Stratford to famously luxury ones such as Kensington, there is a nuanced landscape to examine. This represents a key point of this analysis as well, making it possible to deep dive into how different types of neighborhoods are affected by Airbnb dynamics. Also, this helps outlining consumer behavior and market segmentation as a whole.

Another factor that plays a pivotal role in this analysis is the impact of COVID-19 on the market and how it changed the city's dynamics. Without a doubt, the pandemic has had a profound impact on rental markets, and it is the aim of this study to understand how host engagement metrics were perceived before, during, and after the event. This not only expands the existing literature regarding this topic, but also offers new insights into the adaptability and resilience of the Airbnb market in a such a major city.

1.4 Research Scope

This study focuses on Airbnb listings in the city of London, divided into its 38 neighborhoods as follows: Bethnal Green, Bloomsbury, Brixton, Bromley-by-bow, Camden, Chelsea, Chiswick, City of London, Clerkenwell, Covent Garden, Ealing, Fulham, Greenwich, Hackney, Hammersmith, Hampstead, Haringey, Holloway, Isle of Dogs, Islington, Kensington, Maida Vale, Mayfair, North Kensington, Paddington, Peckham, Rotherhithe, Southwark, St John's Wood, Streatham and Dulwich, Sutton, Vauxhall, Waltham Forest, Wandsworth, Wembley, Westminster, Whitechapel, Willesden. The research spans from 2018 to 2023, which represents a symmetrical period in regard to the pandemic, offering equally spanned pre, during, and post-COVID phases. The key metrics involved are listings' performance variables (occupancy rates, revenues, number of reservations), host engagement factors (response rate, superhost status, instantbook feature availability). All these metrics will be explained in detail later on. Also, the study is based on active listings which have been operating throughout the whole period 2018-2023, to ensure consistency of analysis.

1.5 Research Questions

As previously mentioned, then, a clear gap in literature can be seen surrounding the UK capital and the direct impact of host engagement on its listings. Considering its unique attributes, such as economic and cultural diversity, it is interesting to further examine this research topic, to try and fill that gap.

The main aim of this study is to analyze whether an enhanced level of host engagement is correlated to better performance of Airbnb listings. As well as that, is it important to define how host engagement can be measured, and how listing's performance can be assessed, which will be covered in this study too.

Specifically, this research addresses the following key questions:

1. Are higher levels of host engagement positively associated with improved Airbnb listing performance?
2. Which specific engagement metrics have had the most significant impact on listings' performance over the 2018–2023 period?
3. Was host engagement a significant factor during the pandemic?

By focusing on London as a case study, this research will leverage Airbnb data to identify trends and patterns in host engagement that contribute to better listing performance. The study's findings will offer valuable insights to both existing Airbnb hosts and researchers studying the broader sharing economy.

1.6 Structure of the Thesis

This thesis revolves around six main chapters, as follows:

- Introduction – Explanation of the research topic, outline of the research questions and presentation of the structure of the research.

- Literature Review – Outline of the foundational knowledge regarding Airbnb and its growth and development worldwide, host engagement metrics, and listing performance variable. It covers theoretical frameworks and relevant studies that support the research.
- Methodology – Introduction to the methodological approach used, including data collection, data cleaning and data manipulation. This chapter also delves into the analytical framework used to assess performance and host engagement metrics.
- Results – Presentation of the results of the analysis, highlighting key findings and insights. It includes an in-dept overview of different areas of the study and what takeaways are offered by each.
- Conclusion – Summary of key findings and implications, outlining of potential areas for future research.
- Bibliography – List of sources used.

2. Literature Review

2.1 Introduction to the Literature Review

Peer-to-peer platforms have caused significant disruption in most industries, and in the hospitality sector, perhaps the most disruptive is Airbnb. By providing the opportunity for people to rent out their homes or properties to travelers, Airbnb has introduced a new market segment that blends traditional accommodation services with the flexibility and personalization arising from the sharing economy. As the platform continues to grow in major, heavily populated cities such as London, the hosts are then left in an increasingly competitive environment.

As a result, where the engagement of the host has become a serious determinant of listing success, the various activities and behaviors employed by hosts ensuring positive guest experiences involve high response rates, superhost status, and accumulation of guest reviews have gained more and more importance, especially in recent year. In this respect, these factors are not only in developing trust and ensuring smooth communication with potential guests but also in performing well at listings. On the other hand, little has been said with regard to the specific interrelations between the host engagement and occupancy rates, revenues, and number of reservations as key performance metrics of listings' success.

The literature reviewed in this chapter brings together studies undertaken on the sharing economy, platform dynamics, and host engagement that leads to better listing performance on home-sharing platforms, like Airbnb. This will be followed by a general description of the sharing economy and P2P platforms, followed by an in-depth look at the operational model of Airbnb. These sections explore host engagement definition and metrics, with consideration of how such factors may relate to performance indicators. Pertinent studies related to listings in London include changing consumer preferences and COVID-19 influences. The chapter then enumerates an overview of a side-to-side analysis of Airbnb compared with other P2P platforms, centered on trust, reputation, and digital engagement. The chapter concludes by pointing out the lacunars in the existing literature, which the present thesis is supposed to fill.

2.2 The Sharing Economy and Peer-to-Peer Platforms

The sharing economy is the new upcoming economic model in which individuals either share underutilized resources or rent out underutilized resources; this is primarily made possible through digital online platforms. The idea challenges traditional modes of consumption and ownership through the capabilities of the internet in connecting people in a direct manner. This model has allowed various platforms within the hospitality industry, such as Airbnb, to thrive and disrupt conventional hotel businesses with more personalized and cheap options for accommodation. According to Belk (2014) the sharing economy is all about shared consumption where consumers and providers exchange mutual benefits from each other. A technological infrastructure enables such a successful concept that allows users to share assets, like cars or homes, or services, but it has a system for trust enabled through mechanisms of reputation, reviews, and ratings.

The most successful company working on this model is by far Airbnb. It opened a completely new scenery for both hosts and guests, allowing individuals to rent out their homes or spare rooms for short-term rentals. The hosts get an opportunity to monetize their unused spaces, while guests benefit from the authentic homely experience when compared to traditional hotels. In fact, part of the magic of Airbnb lies in a phenomenon that has been identified to foster trust between strangers, an essential characteristic of the sharing economy. The growth of Airbnb thus instigated big debates about its role within the traditional hospitality industry and more so on the urban housing markets. A study from 2017 explains that with the emergence of Airbnb, new competitive dynamics have emerged, in particular in destinations such as London characterized by high levels of tourism and a relatively high cost of living (Zervas et al., 2017). As a result, a greater competition grows within hosts through differentiation in pricing, amenities offered, location of the listing, and last but not least engagement of guests.

2.3 A deep dive into Airbnb

Airbnb was founded in 2008 by Brian Chesky, Joe Gebbia, and Nathan Blecharczyk in San Francisco, California, out of "necessity". Founded in the summer of that year, the idea came about when the three founders rented out air mattresses in their apartment to design enthusiasts who were coming into town for a design conference, as the hotels in the city were all at full capacity at the time. This small experiment would eventually grow into one of the largest peer-to-peer accommodation platforms in the world, featuring millions of properties across more than 220 countries. Its success lies in capitalizing on the rising trend of the previously introduced sharing economy. With its user-friendly interface, Airbnb enables its hosts to create detailed profiles and reviews that help in establishing a trustworthy relationship between guests and hosts, something quite crucial in a model based on sharing out private spaces.

Such sudden growth on the part of Airbnb has to do with a certain correspondence of the service to the interests of both the hosts and guests. For hosts, it represents an opportunity to monetize their underused property, while for guests, it offers a different and most often cheaper option than hotels can. Besides, the platform developed itself, quite literally with an infinite variety of accommodations: spare rooms and apartments, luxury homes, treehouses, boats and so forth. This flexibility has drawn a wide variety of travelers seeking from budget stays to high-end experiences. By 2012, Airbnb had expanded internationally and became well-positioned in Europe and beyond. Its global success has been punctuated by major milestones that include more than 1 billion bookings and the completion of an initial public offering in 2020, placing its value over $100 billion. Yet, the company has also faced regulations in cities such as New York, London, and Paris, concerned about its impact on the respective housing markets, and have taken steps to place restrictions on the number of short-term rentals owners can offer. Meanwhile, the company has continued to innovate. Last year, it unveiled Airbnb Experiences, which offers travelers access to local tours and activities hosted by residents. Today, Airbnb is a competitor not only for hotels but also for major online travel agencies, positioning itself as an all-inclusive platform for accommodations and authentic travel experiences.

2.4 The concept of Host Engagement

In the context of the analysis, "host engagement" means the degree of interaction between hosts and guests – both potential and confirmed – regarding their listings. That means ensuring such interaction is smooth and of quality. The term Engagement refers to a set of behaviors and platform features that signal attentiveness, reliability, and professionalism. In other words, hosts who respond faster, offer more flexibility when booking an accommodation, and generally provide a better experience to the guest are considered more engaged. This turns into a better experience for guests, which positively affects the performance of the listing.

The key metrics identified to measure Host Engagement are Response Rate, Instant book, Superhost Status, and other listing management behaviors, such as cancellation policies. These engagement behaviors are not only important for guest satisfaction but play an important role in the overall reputation and revenue generation of a host, too.

2.4.1 Response Rate and Guest Communication

One of the most critical metrics for host engagement is the response rate. It describes how fast or consistently hosts respond to the inquiries made by guests. For researchers, speed and effectiveness of communication are major determinants for satisfaction – where satisfaction is highly related to the booking rate. In the work of Guttentag (2015), disruptive innovation was discussed in the context of Airbnb. The author points out how host-guest interaction may be one of the most important ways in which guests experience and evaluate the service. Those hosts who answer queries promptly are perceived as more trustworthy than others; this is how the interaction establishes a marked escalation of overall confidence between host and guest. According to another study as well, the response rate of the host is one of the most influencing factors on guest satisfaction. This will make a guest feel valued and reassured with quick responses, hence increasing their intention to book (Liang et al., 2017).

2.4.2 Instantbook and Convenience

Instantbook bypasses the need for hosts to approve every guest booking, enabling guests to book listings instantly, and in the process, reduces friction in the booking process. In essence, enabling Instantbook serves as an indication of how much more a host may interact seamlessly with guests by not introducing unnecessary delay in confirming bookings. Guest trust in hosts is enhanced through the Instantbook feature (Ert et al., 2016). Generally, Instantbook hosts are perceived to be more proactive and efficient hosts, both considered key components of high host engagement. Furthermore, Liang, Choi, & Joppe (2018) explain Instantbook's impacts on guests' behaviors as a “reduced friction” by reducing the number of steps needed for guests to complete their reservation. The study finds that Instantbook hosts report much higher levels of occupancy rates simply because they are allowing the platform to smoothly automate the guest booking process, leading to better guest trust and satisfaction.

2.4.3 Superhost Status and Professionalism

It refers to a badge awarded to Airbnb hosts when meeting certain criteria – explained in detail in the rest of this study – including maintaining a high response rate, not allowing cancellations, and receiving consistently positive reviews. A study shows that Superhosts receive better reviews, which, in turn, allow them to charge higher room prices, justified by their enhance host engagement (Xie et al., 2017). The Superhost status by itself signals professionalism and dependability, qualities very important for securing bookings, especially in competitive markets. Teubner, Hawlitschek, & Dann (2017) reinforce such thesis when presenting evidence that Superhost status is one of the major indicants of trustworthiness in the Airbnb platform. Their study showed that Superhosts were not only more active but also reaped higher revenues because guests would pay a premium price for listings managed by responsible and responsive hosts. In a nutshell, Superhosts depict the highest degree of engagement.

2.5 Airbnb Performance Metrics

Occupancy Rate is one of the key performance indicators for an Airbnb listing. As a function, it can be defined as the time a property was rented out in any given period, supplying a clear indication of a host's success in securing bookings. Xie and Kwok (2017) establish that internal factors such as pricing and host engagement, among others, coupled with external factors of location and seasonality, are great determinants of occupancy. High occupancy often means high returns (Revenues) as hosts can maximize their income from the property. Listings that have higher occupancy also get favored by Airbnb's algorithm; hence, properties that were frequently booked would always come up higher in Airbnb search results: high occupancy provides high visibility, and this in turn would generate more bookings and higher revenues.

Pricing also has a relevant impact on these metrics. A high price for a listing will make it unattractive, while charging too low will attract bookings but will finally reduce revenues. Teubner, Hawlitschek, and Dann (2020) note that this is the point where dynamic pricing – a strategy that allows hosts to adjust their rate based on demand, seasonality, and other competitive factors – is pivotal. Besides being a direct barometer of listings' success, the occupancy rate depends on many external factors too, including market demand, regional economic conditions, and even local regulations. Xie and Kwok (2017) emphasize that in cities like London, which have a high number of listings on Airbnb, a high occupancy rate can be achieved only by constantly adapting the strategy of engaging and manipulating changes in demand. For instance, the COVID-19 pandemic produced unexpected results in the hospitality industry, some factors that greatly altered occupancy rates around the globe. Dolnicar & Zare (2020) mention that comprehending how host engagement can alleviate such external forces will be vital in ensuring consistent output – which is one of the aims of this research.

The relationship between host engagement and listings success is complicated. Overall, faster response times and superhost status tend to be associated with higher occupancy rate (and, consequently, revenues), but guest reviews, pricing strategies, and location all interact to determine overall performance of a listing and need to be actively managed by hosts.

2.6 Other Key Metrics

While the occupancy rate is the leading indicator when analyzing the performance of an Airbnb listing, several other metrics influence the overall performance of any listing, namely: revenues, number of reservations, guest reviews, and listing visibility. Each of these interacts with occupancy rates in a different manner and each requires optimization by the host to ensure overall high performance. This is even more crucial in highly competitive markets such as London. For example, those hosts who have been using dynamic pricing models-that is, adjusting their rates to match current demand-tend to realize higher occupancy rates even in the low season. Indeed, some hosts consistently monitor what occurs in the local market and review their prices accordingly (Teubner et al., 2020). In that way, such hosts always tend to outperform others using static pricing models. This is because, through dynamic pricing, hosts compete while realizing their maximum revenue potential during a high-demand period. Moreover, positive reviews build perceived reliability and quality as well, therefore increasing the likelihood of future bookings.

Also, Airbnb's algorithm for search ranking visibility is based on numerous variables, such as response rate, superhost status, and review scores. According to Zervas, Proserpio, and Byers (2017), listings that appear higher in the search results regularly obtain a competitive advantage because guests are likely to book properties that appear more prominently.

2.7 Key Studies on Airbnb in London

The London market is an unparalleled case for research in Airbnb due to its size, diversity, and high level of competition among hosts. As one of the most popular tourist destinations in the world, it attracts millions of visitors every year, most of whom prefer to book an apartment on Airbnb rather than stay in hotels because such options provide personal and often budget-friendly alternatives. The following section shall review the basic studies investigating different sides of Airbnb performance in London, focusing on how the engagement of hosts, location, and regulatory factors influence listing success.

2.7.1 London's Host Engagement

While focused research based on host engagement is indeed less common in London compared to studies within wider geographic contexts, there are a number of research pieces that enlighten the role of engagement in this fiercely competitive market. A study by Dann and Teubner (2021) explores the impact of host performance on listing performance in London. From a marketing perspective, hosts that responded to inquiries within hours and maintained higher volumes of guest communications were seen to have higher occupancy rates. They also found that the effect of maintaining superhost status was quite pronounced in London, where guests often sought to find reliable and trustworthy hosts from within a sea of options.

Similarly, Li and Srinivasan (2020) noticed that in a highly engaged platform like London, those hosts who had higher response rates and were very present on the platform by frequently updating their listing and messaging consistently with their guests, performed better than less-engaged hosts. These findings hint that in such a saturated market as London, high engagement is not merely a bonus but rather key to successful host differentiation.

2.7.2 Variations in Performance by Location

Location is a great determinant of performance for any listing on Airbnb, and London neighborhoods offer varied demand levels. Different studies, such as that by Oskam and Boswijk (2016), note that listings in central areas like Westminster, Covent Garden, and Kensington will generally realize occupancy rates that are way above what is considered in other areas of the city due to their proximity to major tourist attractions and hubs of transportation. While the listings of outer boroughs, such as Croydon or Barking struggle much more in order to be able to attract more guests, they are cheaper than others in many cases. Besides, according to the previously mentioned study, the activity of the host can reduce the disadvantage linked to the non-central area of the location. For instance, hosts who, in addition to their offerings, can make personalized suggestions about transportation and local facilities, respond to all inquiries of their guests on time, and have high ratings can make their offerings more attractive, even though they are much farther from the city center. This stresses the value of engagement as a great equalizer for less desirable location.

2.7.3 Regulatory Challenges and Their Impact on listings

Airbnb in London has its share of regulatory scrutiny that influences host behaviours and performances of listings. In 2017, London introduced regulations limiting short-term rentals to 90 days per year in a bid to balance the demand for short-term accommodation with the need for long-term housing (Guttentag, 2019). This policy change greatly affected the performance of listings, especially for those hosts who rely on short-term rentals as a primary source of income. Guttentag and Smith (2019) studied how, after the institution of the 90-day limit, most of London's hosts changed their engagement strategy to fit in with the new rule while keeping their occupancy high during the days of allowed renting. Those with high metrics of engagement, such as very high response rates and superhost status, would be able to maximize their bookings within this limited time frame, while others could not. This illustrates that engagement from hosts is relevant not only for occupancy rate improvement but also when dealing with regulatory constraints.

2.8 The impact of the COVID-19 Pandemic

Starting early in 2020, the COVID-19 pandemic really shook the foundations of travel and hospitality worldwide. This probably marked one of the most pivotal moments in the history of Airbnb. With several travel restrictions, lockdowns, and safety concerns bringing international and domestic tourism to an absolute standstill, Airbnb bookings began falling through the floor. By April 2020, global travel through the site had almost completely stopped, and the company found itself needing to make an extremely fast shift in light of the new realities.

2.8.1 Initial Impact and Response

Airbnb saw a significant decline in revenue in the pandemic's early months, laying off 25 percent of its staff, and shelving plans, for the time being, for an initial public offering. It revived plans for a December 2020 IPO. With millions of bookings canceled because of travel bans, the company attempted to navigate the competing needs between hosts and guests by offering flexible cancellation policies that helped guests while attempting to protect host earnings. This created tensions within the community of hosts at Airbnb, as some faced serious financial losses without government support.

As the pandemic wore on, the company began to focus on domestic travel within individual countries and marketed rural and remote listings as ideal for socially distanced vacations. As this approach was quite effective, travels' preference changed due to health concerns. As most of them are avoiding highly concentrated city centers and moving to retreats amidst nature or isolated shelters, there was more demand for rural stays on the Airbnb platform. Indeed, it has been identified that rural Airbnb listings had performed much better during the pandemic than their city counterparts as travelers choose to stay safe, private, and isolated (Dolnicar et al., 2020).

2.8.2 Shifting Guest Preferences During the Pandemic

The pandemic also accelerated changes in consumer preferences for longer-term stays. Working remotely during lockdowns, many used Airbnb not only for vacationing but also started to use the platform for temporary relocations, staying sometimes for months in a rural or suburban house. In response, Airbnb also announced features that would make life easier for long-term guests, including offering monthly discounts and further improving search filters for longer-term stays.

The shift to longer stays helped Airbnb recover more quickly than some of its competitors in the traditional hotel industry that struggled to adapt to the new demands of remote work. In a report, Airbnb said stays over 28 days accounted for a significant share of its bookings during the pandemic in 2021. This reflects Airbnb's adaptability to new trends and means that 'long-term, flexible accommodation' is likely to be kept as part of its core business in the future.

2.8.3 Post-Pandemic Recovery and Long-Term Changes

This means that, with the recovery of the world travel industry, changes in travel behavior caused by the pandemic would continue to help Airbnb. The demand for flexible, decentralized accommodation would persist, and most travelers would still prefer private homes instead of traditional hotels due to health concerns that still linger. The trend was also capitalized on by Airbnb through further expansion of its offerings of unique, remote, socially distanced accommodations. Though it is expected that urban tourism will bounce back, the pandemic has indeed shifted the priorities of travelling for many consumers towards safety, flexibility, and personalisation. The responsiveness of Airbnb during the pandemic-positioning for domestic travel, supporting long-term stays, and encouraging rural tourism-has positioned it well for the future of post-pandemic travel.

2.9 Trust, Reputation, and Digital Platforms

Some of the theoretical underpinnings of such rapid rise are digital platforms like Airbnb, especially those relating to trust, reputation, and behavior in P2P markets. Some sense of security and trust is provided by well-established brands of hotels and other lodging options in more traditional models of hospitality. However, in the sharing economy, trust between the users is mediated mainly through technology, giving way to new dynamics studied with the use of different theoretical lenses.

2.9.1 The Role of Trust and Reputation Systems

Among all these theoretical concepts enabling the environment of fostering trust between the users in a decentralized marketplace lies the hidden reason for Airbnb's success. Trust plays a crucial role in the P2P universe as all the users do not have prior direct experience and must, therefore, rely on indirect signals in order to develop confidence in the other parties. Whereas guests booking traditional hotels interact with a well-recognized brand, an Airbnb transaction generally involves personal spaces and, very often, intimate interaction between the guest and host. Therefore, the platform has to ensure that trust is duly mediated between these two parties for successful transactions to take place.

One of the most implemented mechanisms to build trust in such platforms lies in the reputation system, which provides guests with a channel through which they can review and rate their experiences, helping other potential guests. A host with great reviews or Superhost status in Airbnb is able to send strong signals of reliability, competence, and safety towards potential guests. Indeed, Liang, Schuckert, and Law (2021) have established through their research that listings with more ratings are more likely to receive bookings because such listings create more powerful signals of trustworthiness compared to those with fewer or lower ratings. This dynamic is further supported by the Theory of Planned Behavior (Ajzen, 1991), which suggests that the behavior of individuals is influenced by attitudes, subjective norms, and perceived behavioral control. A guest's attitude to booking on Airbnb is determined through attitude towards the host themselves, shaped through reviews and ratings, among other general norms of trust in the network. This would mean that positive reviews give an attitude that is very conducive towards the host, increasing the rates of booking. For this reason, hosts engage in behaviors that are likely to boost their reputation, such as maintaining a response rate or offering excellent customer service.

2.9.2 How Trust Evolves on Digital Platforms

As digital platforms, like Airbnb, have grown over time in age and size, the way in which trust has been built and maintained has also constantly changed. The early P2P marketplaces, such as eBay, required some sort of user feedback mechanisms so buyers and sellers could build reputations over time. This simple model has expanded to provide even more advanced ways to build trust. For example, Airbnb's Superhost program provides a higher level of trust by incentivizing hosts through strict requirements that include maintaining a high response rate, continued five-star reviews, and no cancellations.

Social proof theory (Cialdini, 1991) also explains how the trust on Airbnb evolved, stating that potential guests usually used the actions and experiences of others as a heuristic for decision making through reviews and ratings. The more positive reviews there are of the listing, the more likely future guests will perceive that listing as trustworthy. Because of this, trust is built through continuous reinforcement from one community member to another. Apart from trust between users themselves, platforms themselves must work to instill trust in their user base. In this regard, Airbnb has created a number of policies: secure payment systems, guest refund policies, and host assurances of property damage. These measures also resonate with the trust framework by McKnight, Choudhury, and Kacmar (2002), which postulates that in digital environments, people develop trust through structural assurances and feedback systems. In providing these structural mechanisms therefore, Airbnb reduces perceived risk associated with staying in the homes of others, further raising confidence in the site.

2.10 Comparative Analysis: Airbnb vs Other Accommodation Platforms

As the global leader in P2P accommodation, the broader landscape of the sharing economy has been shaped by Airbnb. Yet, it operates in a competitive environment where challenges are emanating from competing platforms such as Vrbo (Vacation Rentals by Owner), Booking.com, and Expedia. The following section provides a comparative analysis of the model of operation and success which Airbnb has built relative to these competitors across key factors including host engagement, user experience, and market penetration.

2.10.1 Airbnb vs. Vrbo

Vrbo, founded in 1995, has existed for more than a decade longer than Airbnb's advent, and works in somewhat the same fashion, allowing property owners to post their homes for short-term rentals. A major difference between the two sites is the philosophy of each in how they approach interaction between guest and host, along with customer service. In Airbnb, for instance, emphasis is placed on interacting well with the hosts as a part of its reputation mechanism. They also want hosts to respond fast to guests, to have high response rates, and to offer experiences that are personalized, as those factors will directly affect the performance of a listing through reviews and ratings. Vrbo, in turn, is more focused on property management than individual host-guest interactions. While reviews and ratings are not irrelevant, Vrbo positioned its value proposition around larger properties available for longer stays with less emphasis on personal interactions with the hosts.

2.10.2 Airbnb vs. Booking

Booking.com was founded as a hotel reservation platform, adding products for vacation rentals and short-term home rentals later on, then directly competing with Airbnb. The main strength of Booking.com involves wide geographical dispersion and high market share in the online travel agency segment, therefore being capable of offering a wide variety of accommodation options beyond P2P rentals. Unlike Airbnb, which caters most of its services to leisure travelers, Booking.com is popularly used by leisure and business travelers due to its massive supply of hotels and professionally managed properties. A key difference in the sites can be seen through the interaction required or expected between the hosts and guests. For example, Airbnb allows for a high degree of interaction between guests and hosts since this helps build trust and is likely to enhance the experience of guests. On the other hand, the Booking.com model is more like a travel agency, with less attention to personal touches or, importantly, the host's engagement. Moreover, property profiles in Booking.com are more professionally managed, especially the vacation rental sectors, which means there is more coherence on the platform compared to the usually more personalized stays with Airbnb.

2.10.3 Airbnb vs. Expedia

Another key player in the Online Travel Agents market is Expedia. Like Booking.com, it offers a wide range of products: from traditional hotels to vacation rentals. Expedia owns Vrbo, meaning that it has a presence in the traditional hotel market and in the vacation rental market. Still, Expedia's business model is oriented mainly toward professional managed accommodations, without strong exposure to the P2P element that characterizes Airbnb. One of the biggest differences between the two sites is their target markets and how the company draws in and engages customers. Airbnb has successfully appealed to a segment wanting something unique, very local, with a focus on direct interaction between the host and guest at the same time. While Expedia offers a broader range of travel services, including flights, car rentals, and vacation packages, Airbnb's more niche focus on P2P accommodation has allowed the company to create a rich community of both hosts and guests focused first on authentic travel experiences rather than the conveniences offered by traditional hotels.

2.11 Gaps in Literature

While there is a growing body of research on Airbnb and its impact on the accommodation industry, significant gaps remain, particularly in understanding the direct link between host engagement and occupancy rates. Many studies have focused on guest satisfaction, pricing strategies, or the general performance of Airbnb as a disruptive platform, but fewer have examined how specific engagement metrics—such as response rates, superhost status, and instantbook—affect the day-to-day success of listings, especially in competitive urban markets like London. Moreover, much of the existing research on Airbnb's performance metrics tends to focus on global trends rather than localized case studies. While certain studies have begun to address location-specific dynamics in London, there is still a need for deeper analysis of how host engagement interacts with external factors such as local regulations, market saturation, and seasonal demand fluctuations.

Few studies have explored how engagement levels evolve over time, particularly in response to external shocks like the COVID-19 pandemic, which dramatically altered travel patterns and guest expectations. This gap presents an opportunity for further research to investigate how London hosts adapted their engagement strategies during the pandemic and whether these changes led to long-term shifts in occupancy rates. This thesis aims to fill some of these gaps by providing a comprehensive analysis of how host engagement metrics influence listings performance in London's Airbnb market between 2018 and 2023. The findings will offer insights into which aspects of engagement are most critical for maintaining high performance in a competitive, heavily regulated market, particularly in the wake of recent global disruptions.

3. Methodology

3.1 Introduction

The aim of this chapter is to outline the research methodology used in the study on the role played by host engagement regarding listing performance on Airbnb in London between 2018 and 2023. A mixed-methods approach was be applied, bringing together quantitative and qualitative views on how the research question can be addressed from both a managerial and an engineering perspective. Quantitative analysis of data is central in this study, where tools such as Excel, Python and Stata were used in approaches such as descriptive statistics, regression analysis, multivariate analysis, time series analysis, and data visualization, to look into the trends and relationships within the dataset. These techniques allow for a robust analysis of how different variables such as host response rate, Superhost status, and instantbook feature influence occupancy rates, revenues, and number of reservations.

Moreover, the study also intends to provide qualitative insights into interpreting the findings from a business and managerial perspective in order to obtain actionable recommendations for the hosts and other stakeholders at Airbnb. The methodology therein adopts a complementary approach, hence allowing for comprehensive results that are data-driven and appropriate for practical business application.

3.2 Research Design

This study adopts an exploratory research design that helps in establishing and analyzing various host engagement factors that relate to the performance of an Airbnb listing. Given the depth of the platform itself and the array of variables affecting the performance of any one given listing on Airbnb, it requires this type of approach to deep dive into the correlations between a variety of host behaviors, such as response rate, Superhost status, and Instant Book, among others, with primary performance indicators such as occupancy rate and revenues.

The mixed-method approach in place, although relying heavily on quantitative analysis, through regression analysis and time series analysis, also focuses on a qualitative part, that helps complement the managerial implications for business based on the findings and places results into perspective, providing recommendations to hosts and other stakeholders alike on the Airbnb platform.

3.3 Data Sources

This study's dataset was sourced from a third-party provider through Politecnico di Torino university in a comprehensive dataset format. The dataset covers the city of London, ranging from

2017 to 2023, on a monthly breakdown of variables. However, this study will focus on a yearly analysis from 2018 to 2023, to allow a proper year-on-year comparison and to make the data symmetric about the pre- and post-pandemic periods.

The dataset contains a wide range of variables that allow the granular analysis of the degree of host engagement and listing performance. Key variables in this regard include:

- Occupancy Rate (calculated as the ratio of booked nights to available nights)
- Response Rate (percentage of inquiries responded to by hosts within 24 hours)
- Superhost status (whether or not the host has Superhost designation)
- Instant Book availability (whether guests can book instantly without prior host approval)
- Maximum Guest Capacity (the number of guests the listing can accommodate)
- Price Tier (categorizing listings into budget, economy, midscale, upscale, and luxury)

On top of this comes additional listing-specific data, such as property type, amenities, reviews, cancellation policies, and real-time listing updates that give context to the analysis. The substantial data gathered allows for deep exploration of the associations of host activity with performance measures such as occupancy rate. While extra data was reviewed from other sources for the literature review, the dataset provided by the third party remains the primary source of the analysis conducted in this study.

3.4 Data Collection

The data collection process for this study involved a thorough and systematic approach to ensure the quality and reliability of the dataset. The initial dataset provided by the third party, covering Airbnb listings from 2017 to 2023, contained a wide array of variables, many of which were not directly relevant to the focus of this analysis. As a first step, data from 2017 was removed to maintain symmetry and balance in the year-over-year comparison, ensuring that the pre- and post-pandemic periods were equally represented. This decision was made to align the analysis with the study's objective of examining trends from 2018 onward. A comprehensive data cleaning process was then undertaken to address any inconsistencies and ensure the integrity of the dataset. Missing values were identified and removed, but since these represented only a small fraction of the total data points, their exclusion did not significantly impact the overall analysis. This process was essential to eliminate potential biases or inaccuracies and to ensure that the findings were based on complete and reliable data.

In terms of data preparation, several key variables were categorized into ranges. Given the sheer volume of the data—spanning millions of records—this step was crucial for simplifying the analysis and enhancing the interpretability of the results. Variables such as price tiers, guest capacities, and response rates were grouped into ranges to make comparative analysis more feasible. For example, price tiers were categorized into budget, economy, midscale, upscale, and luxury segments, and response rates were classified into specific percentage intervals. This approach enabled clearer identification of trends and patterns within the dataset while allowing for a more efficient exploration of correlations between host engagement variables and occupancy rates. The data was then organized by year to facilitate year-over-year comparisons. This temporal structuring of the data made it possible to analyze shifts in listing performance across time, including pre-pandemic, pandemic, and post-pandemic periods. Additionally, this approach provided a clearer view of trends, enabling the identification of key shifts in occupancy rates and other performance metrics over time.

To enrich the analysis, a new variable was created based on available data: average occupancy rate. This derived metric expresses the share of days being booked by a listing relative to its total availability and, hence, immediately joined the core variables of interest in this study. By providing variables and categorizing them in this way, the analysis would better support the research question through the insight it would give into how host response rate and Superhost status, among others, relate to listing success. To summarize, data collection and preparation included very careful cleaning, categorizing, and transformation of variables so that the analysis was methodologically sound but could also provide meaningful results.

3.5 Variables and Measures

This study incorporates a range of variables to investigate the relationship between host engagement and Airbnb listing performance, with a focus on key factors influencing occupancy rates, revenues, and number of reservations. The variables are grouped into three categories: dependent variables, independent variables, and control variables.

3.5.1 Independent Variables

The independent variables in this study represent factors related to host engagement and listing characteristics. These variables are expected to influence the performance of Airbnb listings:

- **Response rate**: The percentage of inquiries a host responds to within 24 hours.
- **Superhost status**: Whether a host holds the Superhost designation.

- **Instant Book availability**: Whether a listing offers the option for guests to book instantly without prior host approval.
- **Price tier**: A categorization of listings into budget, economy, midscale, upscale, and luxury.
- **Neighborhood**: The 38 different neighborhoods of the city.
- **Reporting Year**: The reference year, from 2018 to 2023.
- **Reporting Month**: The reference month.

These variables capture different aspects of host engagement and listing features that are likely to impact a listing's performance.

To ensure that the analysis isolates the effect of host engagement on the listing performance, several control variables are included. These control for external factors that might influence occupancy rates independently of host engagement: Price Tier, Neighborhood, Reporting Year, and Reporting Month.

3.5.2 Dependent Variables

The dependent variable in this study measures listing performance and is the key outcome of interest:

- **Occupancy rate**: Calculated as the proportion of reserved days to available days for each listing. This metric reflects how often a listing is booked and serves as the primary indicator of its success.
- **Revenue (USD)**: listing revenue in US Dollars ($). Includes cleaning fees but no other additional fees.
- **Number of Reservations**: number of reservations made to a specific listing.

3.6 Analytical Methods

The analysis in this study employs a range of statistical techniques to explore the relationship between host engagement factors and the performance of Airbnb listings. The following methods were used:

1. **Descriptive Statistics**: To summarize the dataset, including measures such as mean, median, and standard deviation for variables like response rate, occupancy rate, and price tier. This provided a general understanding of the data distribution and key trends.
2. **Correlation Analysis**: Used to assess the strength and direction of the relationship between independent variables (e.g., response rate, Superhost status) and the dependent variable (occupancy rate). Pearson's correlation coefficient was used to identify significant correlations.

3. **Regression Analysis**: A multiple regression model was applied to quantify the impact of multiple independent variables on occupancy rates, allowing for the isolation of the effect of each factor (e.g., host engagement) while controlling for other variables (e.g., neighborhood, property type).
4. **Multivariate Analysis**: This was used to explore how combinations of variables (such as price tier and response rate) influence occupancy rates, providing a more complex understanding of interactions between host engagement factors.
5. **Time Series Analysis**: Applied to assess changes in occupancy rates and host engagement metrics over time, particularly before and after the pandemic. This analysis allowed for the identification of trends and shifts in guest behavior and host strategies.
6. **Data Visualization**: Graphical methods, including line charts, scatter plots, and bar graphs, were used to illustrate the results and trends, making the findings more interpretable and accessible.

4. Results

This chapter presents the results of the study conducted on Airbnb listings in the city of London from 2018 to 2023. The goal of the analysis is to evaluate the relationship between host engagement variables, such as response rate, superhost status and instantbook availability, and the performance of Airbnb listings, measured through revenues, occupancy rate and number of reservations. Results are structured according to the research questions outlined in the earlier chapters. Statistical methods such as correlation analysis, regression analysis, and time series analysis were applied to the dataset, and the key results from each method are detailed in the following sections.

4.1 Occupancy Rate

4.1.1 Introduction

An initial descriptive analysis was conducted to understand the overall average occupancy rate of the listings under review from 2018 to 2023. The study results indicate a clear fluctuation in the average occupancy rate of Airbnb listings in London between 2018 and 2023. Starting in 2018, the occupancy rate increased steadily, peaking in 2019, when more than 50 percent of available listings were occupied. However, this upward trend came to an abrupt halt in 2020, when the occupancy rate dropped sharply to about 30 percent in 2021. This decline was closely linked to the outbreak of the COVID-19 pandemic and related travel restrictions, which had a significant impact on short-term rental markets. After this low point, a remarkable recovery began in 2022, with the occupancy rate returning to above 50 percent, reflecting a recovery in travel and rental demand. In 2023, although the recovery was sustained, the occupancy rate declined slightly from its 2022 peak, stabilizing at around 48 percent. These results demonstrate a cyclical trend in occupancy rates, strongly influenced by external factors such as the pandemic.

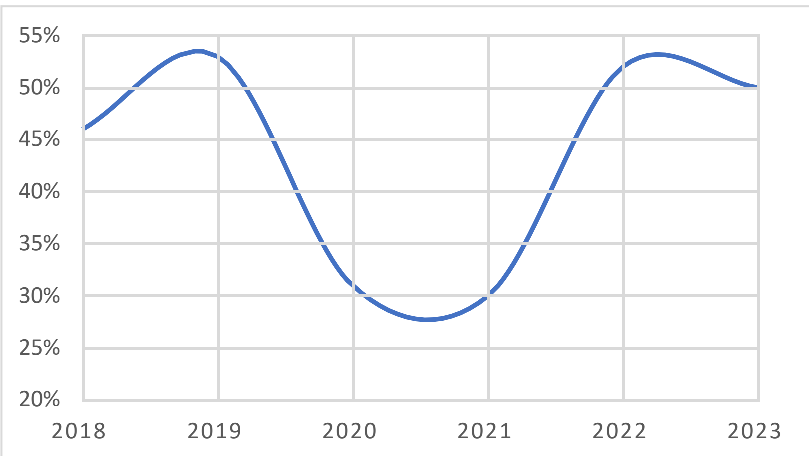

Figure 1. Average Occupancy Rate for all listings, from 2018 to 2023.

4.1.2 Analysis by Price Tier

The study also reveals insights into the average occupancy rate of Airbnb listings in London between 2018 and 2023 based on different price tiers. The aim of this analysis is to explore how different price tiers have responded to both internal market trends and external shocks, such as global travel restrictions and economic downturns caused by the pandemic. By examining the average occupancy rates within each price category, we can identify which segments were most resilient or vulnerable during these challenging times. For instance, budget and economy listings are often seen as more resilient due to their appeal to cost-conscious travelers, while luxury and upscale listings might be more susceptible to fluctuations in discretionary spending and international travel restrictions. This study seeks to validate or challenge these assumptions by providing empirical data on the occupancy trends of these segments.

Listings in the budget category consistently achieved the highest occupancy rates, averaging close to 50%. This indicates that more affordable listings maintained higher demand during this period. The economy and midscale tiers followed closely, with occupancy rates slightly below 50%, suggesting that these mid-range price tiers also performed well in attracting consistent bookings. In contrast, the luxury and upscale tiers experienced lower average occupancy rates, with both categories hovering around 40%. These findings suggest that while higher-priced listings did attract some demand, they were less frequently booked compared to more budget-friendly options, highlighting the stronger performance of lower-priced accommodations across the five-year period.

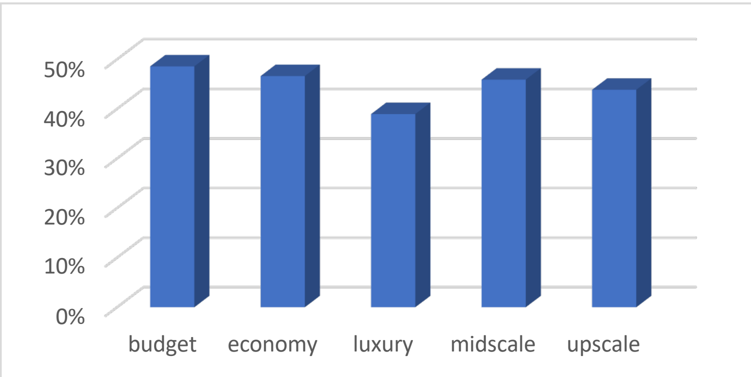

Figure 2. Average Occupancy Rate by Price Tier, from 2018 to 2023.

4.1.3 Analysis by Price Tier over the years

The study also highlights how price bands influenced the average occupancy rate for each year. The budget and economy categories showed steady demand, maintaining the highest occupancy rates over the period. The midscale segment also performed well, albeit slightly lower than the economy categories. In contrast, the luxury and upscale categories reported lower occupancy rates, indicating lower demand for the high-end options. These results reinforce the trend already observed, whereby the more affordable options benefited from stronger demand, particularly during periods of economic uncertainty, while the more expensive listings experienced lower occupancy.

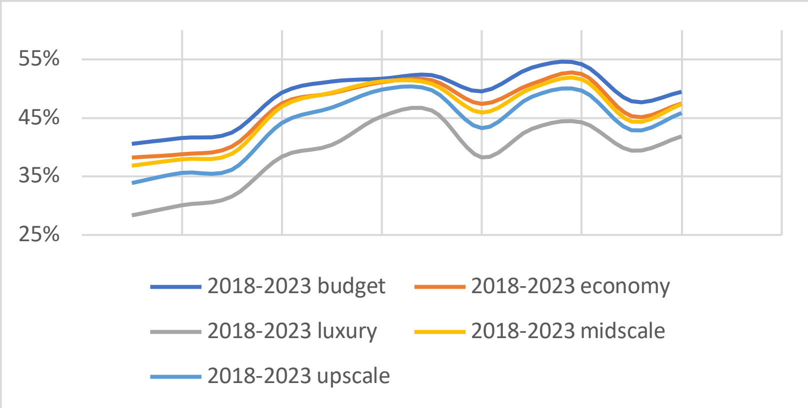

Figure 3. Average Occupancy Rate by Price Tier by Year.

4.1.4 Seasonality trends

Within the same analysis, a further insight into the impact of seasonality on the average occupancy rate of Airbnb listings by price range is provided. The results show that listings in the budget and economy categories maintain higher occupancy rates than those in the luxury and upscale categories in all quarters analyzed. During January-March, occupancy rates are generally lower for all categories, but the gap between the economy and luxury categories is already evident. In the April-September period, the peak in occupancy is observed for all categories, with the cheaper bands continuing to outperform the high-end ones, creating an even wider gap. Finally, in the October-December quarter, occupancy rates tend to decline again, but the trend remains constant: the cheapest options are booked more than the most expensive ones, suggesting that demand for the lower price ranges is less affected by seasonality than for the high-end listings.

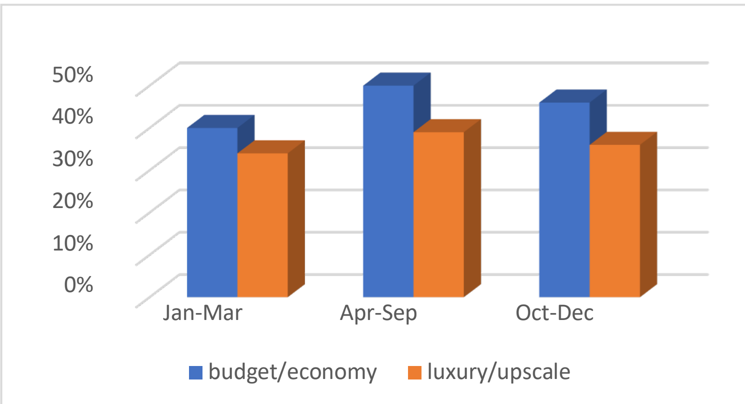

Figure 4. Average Occupancy Rate by seasonality, in different Price Tiers.

4.1.5 Regression Analysis: Host Engagement vs. Occupancy Rate

Having established a clear understanding of the general trends and patterns of Airbnb occupancy rates in different price ranges and over time, it is now important to delve into the factors influencing these variations. While price and seasonality provide a broad insight, the role of host engagement, a critical aspect in guest decision-making, deserves a more in-depth examination. The following section presents the results of a regression analysis designed to assess the impact of host engagement - as measured by response rate, super-host status and instantbook availability - on occupancy rates. By analyzing these variables, we aim to quantify their influence and understand how host practices contribute to occupancy performance.

4.1.6 Model Fit

The regression model shows an R-square of 0.1284, which indicates that approximately 12.84% of the variance in the employment rate is explained by the model. Although this is not a particularly high value, it is not unusual in business contexts, where many other factors could influence the dependent variable. Furthermore, the value of the F-statistic is 541.50 with a p-value equal to 0.000, which makes the model highly significant overall. This implies that at least one of the independent variables is contributing to the explanation of the variance of the employment rate.

Source	SS	df	MS			
				Number of obs	=	227,966
				F(62, 227903)	=	541.50
Model	4418.41383	62	71.2647392	Prob > F	=	0.0000
Residual	29993.5546	227,903	.131606669	R-squared	=	0.1284
				Adj R-squared	=	0.1282
Total	34411.9684	227,965	.150952859	Root MSE	=	.36278

Table 1. Overall Regression on Occupancy Rate.

4.1.7 Overall Significance

Turning to the results of the host involvement variables, we see that the response rate has a positive and significant impact on the occupancy rate. For example, a response rate between 20% and 50% is associated with an increase in occupancy rate of 5.56%, with a p-value of 0.000, indicating high statistical significance. A response rate between 50% and 70% produces an increase in the employment rate of 11.17%, while the highest response rate, between 70% and 100%, results in an increase in the employment rate of 17.9%. These results show a strong positive correlation between the fastest and most frequent response rate and the occupancy rate. In other words, hosts that respond more promptly achieve significantly higher occupancy rates, suggesting that speed of response is a critical factor for success on Airbnb. The Instantbook function, on the other hand, presents a coefficient of 0.0487 with a p-value of 0.000, suggesting that listings offering this option have a higher occupancy rate of 4.87%. This result indicates that the ability to book immediately without having to wait for host approval improves trust and convenience for guests, contributing positively to the occupancy rate. Finally, Superhost status also positively influences the occupancy rate, with a coefficient of 0.0706 and a p-value of 0.000, showing that listings managed by Superhost have a higher occupancy rate of 7.06%. This result underlines how such status is a symbol of reliability and quality and provides significant competitive advantage.

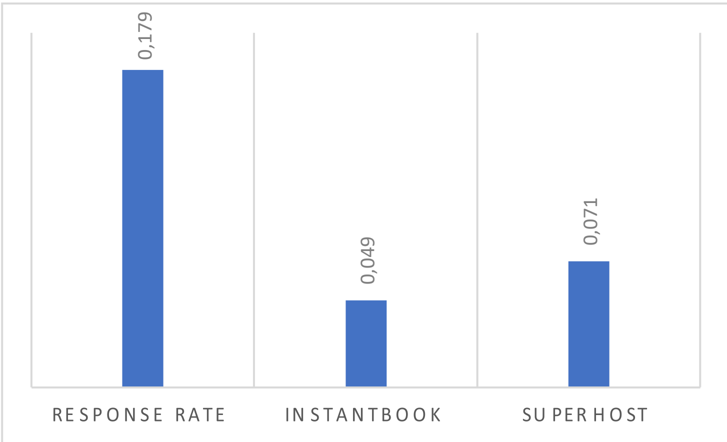

Figure 5. Impact of Host Engagement on Occupancy Rate.

Examining the control variables, the results indicate that the different price bands significantly influence the occupancy rate. Ads in the ‘economy’ bracket show a 4.17% lower occupancy rate than the ‘budget’ ads used as a reference group. Ads in the ‘luxury’ bracket show a decrease in occupancy rate of 18.82%, followed by the ‘midscale’ and ‘upscale’ ads, which show decreases of 7.65% and 11.03% respectively. These results suggest that the higher price bands tend to have lower occupancy rates, probably due to lower affordability. Budget' listings therefore appear more competitive in terms of occupancy. Regarding the year-related variables, there is an increase in the employment rate of 4.03% in 2019 compared to 2018, which serves as the reference year. However, 2020 shows a sharp decrease in the employment rate, with a decrease of 22.53%, most likely due to the COVID-19 pandemic. In 2021, a reduction in the employment rate is also observed, at 19.03%, although the impact of the pandemic seems to have been less severe than in the previous year. In 2022, the employment rate rose again by 3.45%, indicating a gradual recovery. However, in 2023, there is a slight decline of 1.91%, probably related to post-pandemic readjustment factors. Finally, the analysis of the variable ‘reference month’ reveals a significant seasonality in the employment rate. For example, the employment rate in August is 3.17% lower than in April, which was chosen as the reference month. December also shows a drop in the employment rate, with a decrease of 2.33%. January and February show the most significant reductions, with declines of 13.18% and 11.50% respectively. These results highlight the importance of seasonality, with the winter months recording significantly lower occupancy rates than the spring or summer months.

4.1.8 Deep dive on the Superhost Status

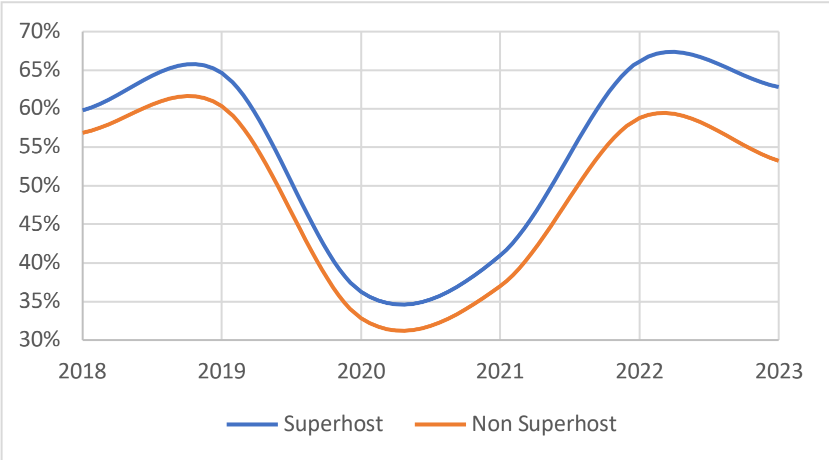

Figure 6. Gap between Superhosts and not over the years.

The graph illustrates the average occupancy rate between Superhosts and Non-Superhosts from 2018 to 2023, showing a clear and growing disparity over the years. Initially, in 2018, the difference between Superhosts and Non-Superhosts is relatively small, with Superhosts slightly ahead in occupancy rates. However, as the years pass, particularly after the COVID-19 pandemic in 2020, the gap between these two categories begins to widen significantly. In 2022, Superhosts show a substantial advantage over non-Superhosts, with occupancy rates above 65%, while non-Superhosts struggle to exceed 55%. This widening gap suggests that Superhosts have become increasingly competitive in attracting bookings, potentially due to their enhanced reputation, reliability, and quality of service. Superhosts' ability to maintain higher occupancy rates, even during periods of market recovery, indicates that guests increasingly prioritize listings run by more experienced and reliable hosts. In contrast, non-superhosts face greater difficulties in achieving similar occupancy levels, implying that the benefits of holding superhost status have become more pronounced over time. This trend emphasizes the growing importance of host commitment and professionalism to ensure lasting success on platforms such as Airbnb.

The increasing gap in occupancy rates between Superhosts and non-Superhosts can be attributed to several key factors:

1. **Increased guest awareness and trust**: As the Airbnb platform and Superhost program has matured, guests have become more aware of the Superhost badge, associating it with a higher likelihood of a positive experience. This awareness may have prompted more guests to choose Superhosts over non-Superhosts, especially in times of uncertainty.
2. **Promotion of the platform**: Airbnb's promotion of the Superhost program, whether through search algorithm prioritization or marketing initiatives, has likely increased the visibility of Superhost listings. This may have provided an additional competitive advantage, helping to increase Superhost occupancy rates.
3. **Travelers' cautious behavior during the uncertainty**: The pandemic increased travelers' caution when choosing accommodation. Superhosts' advertisements were considered more reliable, and guests perceived them as safer choices during periods of uncertainty.
4. **Competitive advantage in a growing market**: As the short-term rental market became more competitive, achieving Superhost status gave hosts a clear advantage. Guests increasingly see Superhosts as a more advantageous proposition, further increasing the occupancy rate gap between Superhosts and non-Superhosts.

4.1.9 Deep dive on the Response Rate

Understanding this correlation is vital for hosts looking to optimize their listings and for the platform to enhance overall guest satisfaction and competitiveness in the market. The analysis covers both the pre-pandemic and post-pandemic periods, allowing us to observe how these dynamics shifted during a time of unprecedented global travel restrictions and economic uncertainty caused by the COVID-19 pandemic. We examine data spanning four categories of response rates to determine which levels of host engagement are most effective in maintaining high occupancy rates, even during market disruptions.

- **Low Responsive (0–20%)**: This category indicates low engagement, where hosts respond to less than 20% of guest inquiries. Listings in this category often struggle with guest communication, which can negatively impact guest satisfaction and booking rates.
- **Moderately Responsive (20–50%)**: Hosts in this category show moderate levels of engagement, responding to between 20% and 50% of inquiries. While these hosts maintain some level of communication, there is considerable room for improvement in responsiveness.
- **Highly Responsive (50–70%)**: This category reflects a high degree of responsiveness, with hosts replying to more than half of guest inquiries. Listings in this category demonstrate a solid commitment to guest communication, which positively influences occupancy rates.

- **Very Highly Responsive (70–100%)**: Representing the most engaged hosts, this category includes hosts who respond to over 70% of inquiries. These hosts exhibit very high engagement and are most likely to maintain high occupancy rates due to their prompt communication with potential guests.

An analysis of average occupancy rates by host response rate category reveals a clear correlation between host responsiveness and ad occupancy. Ads with low responsiveness show an average occupancy rate of 26.58%, while those with moderate responsiveness reach an average rate of 31.70%. Ads with high responsiveness see a further increase, with an average rate of 35.88%. Finally, ads with very high responsiveness register the highest average occupancy rate, at 46.93%. Overall, considering all categories, the overall average occupancy rate is 44.64%, indicating that higher host responsiveness is closely associated with higher ad occupancy.

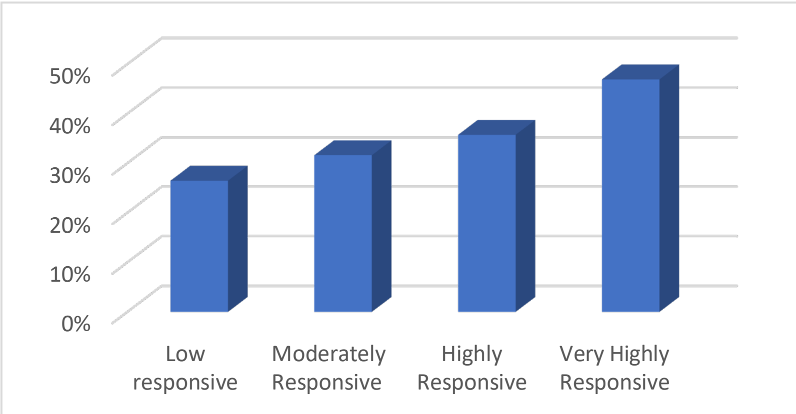

Figure 7. Average Occupancy Rate by Response Rate Category.

Another result shows the average occupancy rate in 2021 for offers categorized as low responsiveness and very high responsiveness. A growing gap between the two categories can be seen over the course of the year. Offers with low responsiveness consistently show significantly lower occupancy rates, which fluctuate slightly but remain below 20%. In contrast, offers with very high responsiveness show a steady and significant increase in occupancy, which rises sharply in the middle of the year and peaks at over 50%. This growing gap underlines the crucial role of host engagement in increasing occupancy rates. Listings managed by highly responsive hosts consistently perform better and attract more guests throughout the year, while listings with less responsive hosts struggle to keep up. This suggests that responsiveness is becoming an increasingly important factor in guest decision-making, with highly responsive hosts receiving more bookings over time.

Figure 8. Average Occupancy Rate Gap by Response Rate in 2021.

4.1.10 Key Takeaways

In summary, the regression results clearly show that host involvement, measured mainly in terms of response rate, but also in terms of Instantbook availability and Superhost status, has a significant and positive impact on the occupancy rate. At the same time, it can be observed that higher price ranges, pandemic years and winter months generally represent factors that reduce the occupancy rate, for which host engagement might play an even more crucial role.

Overall, the findings from this analysis highlight the growing importance of host responsiveness in the Airbnb market. As consumer expectations continue to evolve, particularly in a post-pandemic world, hosts who prioritize timely and effective communication are likely to outperform their less responsive counterparts. For Airbnb as a platform, these insights emphasize the need to encourage and support host engagement practices that enhance guest satisfaction and drive occupancy. This analysis provides a valuable contribution to the literature on short-term rentals, offering new perspectives on the role of host behavior in shaping market outcomes.

Future research could explore additional factors that influence occupancy rates, such as pricing strategies, guest reviews, and the impact of location-specific events. Understanding these dynamics will be crucial for hosts and platforms alike to adapt to an increasingly competitive and unpredictable market environment.

4.2 Revenues

4.2.1 Introduction

Another important metric in the context of Airbnb listings performance is, of course, revenue. This section of the study therefore lays out the main results of analyses exploring the impact of host engagement on this variable. Specifically, a regression analysis was conducted with revenue as the dependent variable, studying the effect of the independent variables themselves, including the control variables. The goal is to understand if and how a higher level of host engagement can be correlated with positive economic outcomes.

4.2.2 Regression Analysis: Host Engagement vs. Revenues

In order to fully understand the effect of host engagement not only on occupancy rates, but also on the revenue generated by Airbnb listings, it is necessary to further explore the analysis with a broader economic perspective. While the previous section focused on the impact of response dynamics, Instantbook availability and Superhost status on bookings, it is equally crucial to assess how these same factors directly influence host revenues. Host engagement, defined by responsiveness and the adoption of tools that simplify the guest experience, is an important lever for maximizing revenue. In the next section, through a detailed regression, I will analyze how the main indicators of host engagement contribute to the growth or contraction of revenues, providing a comprehensive view not only on the operational efficiency of hosts, but also on their financial performance. This analysis will provide insight into the extent to which active host engagement affects the economic success of listings, highlighting differences according to variables such as price ranges, seasonality, and geographical location.

4.2.3 Model Fit

The regression model to explain variations in revenue (RevenueUSD) has an R-square of 0.2174, indicating that about 21.74% of the variability in revenue is explained by the independent variables. Again, this R-square is not particularly high because revenues are influenced by many external factors that cannot all be included in the model. The Prob > F statistic of 0.0000 shows that the overall model is highly statistically significant, meaning that the independent variables collectively explain the variation in revenues better than a model without predictors.

Source	SS	df	MS			
				Number of obs	=	227,966
				F(63, 227902)	=	1004.78
Model	6.9498e+11	63	1.1031e+10	Prob > F	=	0.0000
Residual	2.5021e+12	227,902	10978960.8	R-squared	=	0.2174
				Adj R-squared	=	0.2172
Total	3.1971e+12	227,965	14024570.9	Root MSE	=	3313.5

Table 2. Overall Regression on Revenues

4.2.4 Overall Significance

Analyzing the host engagement variables, the response rate reveals a significant impact on revenue. Ads with a response rate between 20% and 50% show a coefficient of 305.25 ($p < 0.001$), meaning that these ads earn about \$305 more than the reference group, which has a response rate between 0% and 20%, holding other variables constant. Ads with a response rate between 50% and 70% earn an average of \$776 more, while those with the highest response rate (between 70% and 100%) earn an average increase in revenue of \$855.64. These results clearly indicate that a higher response rate is associated with a significant increase in revenue, confirming the idea that more responsive hosts attract more bookings and, consequently, generate more revenue.

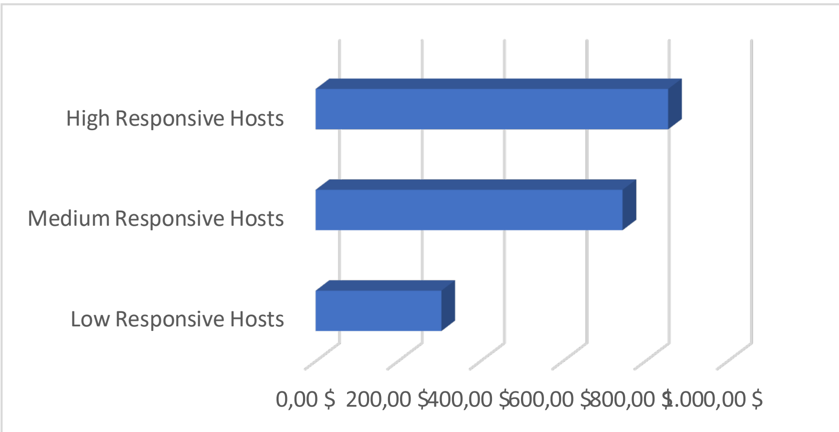

Figure 9. Increase in Listing Revenue by Host Responsiveness.

The Instantbook option has an equally important effect on revenue, with a coefficient of 691.16 ($p < 0.001$), suggesting that listings with Instantbook enabled earn on average \$691 more than those without this option. This result underscores how enabling Instantbook, which facilitates immediate booking by guests, leads to significant economic benefits for hosts. Superhost status also has a considerable positive impact, with a coefficient of 546.75 ($p < 0.001$), showing that Superhost hosts earn on average \$546 more than non-Superhost hosts. These results reinforce the importance of host engagement, highlighting that becoming a Superhost and improving booking speed and accessibility are key factors in increasing revenue.

Examining the control variables, it is observed that, not surprisingly, the highest price ranges generate significantly higher revenues than the reference group ("budget" ads). In particular, listings in the "luxury" range show the greatest positive effect on revenues, with an average increase of $199.73. On the other hand, the type of listing has a negative impact on revenue if it is private or shared rooms. Ads offering a private room experience an average decrease of $1886.29, while shared rooms experience an even greater decrease of $2374.07 than ads offering the entire property. These results could indicate that listings offering a whole house are much more profitable than those offering only part of the property.

Regarding location, the neighborhood variables reveal interesting trends. Some neighborhoods, such as Covent Garden (neighborhood_10), are associated with a substantial increase in revenues, with an average increase of $2077.73. In contrast, neighborhoods such as Bromley-by-Bow (neighborhood_4) and Brixton (neighborhood_3) are associated with a significant decrease in revenues, highlighting how the geographic location of Airbnb listings plays a crucial role in determining revenues. The years 2020 (year_3) and 2021 (year_4) had a strongly negative impact on revenues, with decreases of $1142.11 and $732.82, respectively, likely due to the effects of the COVID-19 pandemic on Airbnb bookings. However, subsequent years show signs of recovery: in 2022 (year_5), revenues increased by $583.50, and in 2023 (year_6) there was a further increase of $562.14, indicating a recovery in bookings after the decline suffered during the pandemic.

Finally, the months of the year significantly influence revenues. Months such as July (month_6) and June (month_7) are associated with increases in revenues, with increases of $699.79 and $523.71, respectively, likely reflecting higher seasonal demand during the summer months. In contrast, months such as February (month_4) and January (month_5) have a significant negative impact, with decreases of $731.19 and $740.09, respectively, in revenues, underscoring low demand during the winter months.

4.2.5 Key Takeaway

From the analysis on the impact of host engagement on revenue, clear and significant results emerge. Response rate has the most significant influence: ads with a response rate between 70% and 100% earn on average $855.64 more than less responsive ads. This highlights how a high level of host responsiveness is a key factor in attracting more bookings and generating higher revenue. Enabling the Instantbook feature also leads to a notable increase in revenue: ads that enable instant booking to earn an average of $691.16 more than those without this option, suggesting that ease of booking plays a crucial role in guests' choices. Finally, Superhost status has a significant impact, with an average revenue increase of $546.75 compared to non-Superhost hosts. This shows that the reputation and trustworthiness associated with Superhost status provide an important competitive advantage, contributing tangibly to the financial success of hosts on Airbnb.

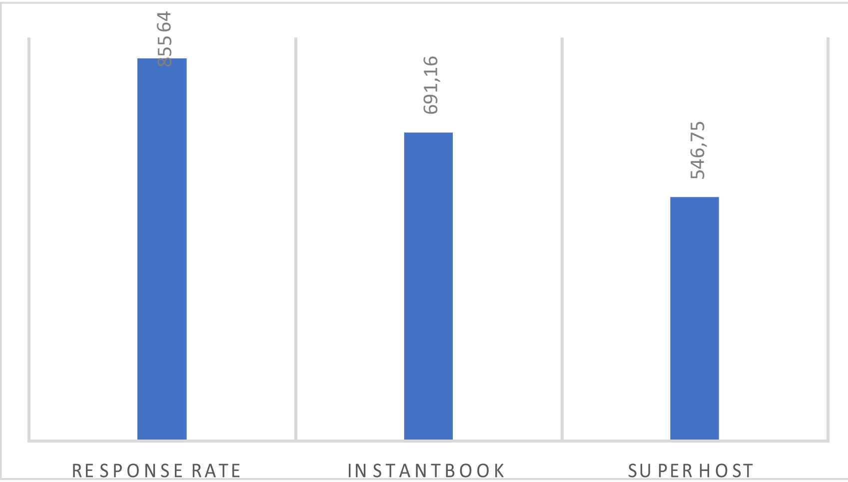

Figure 10. Impact of Host Engagement on Revenues

4.3 Number of Reservations

4.3.1 Introduction

The third important metric to analyze in the context of the impact of host engagement on Airbnb performance is the number of individual bookings that are made on the platform. This metric offers additional perspective on listing success, allowing one to study not only how long the listing has been rented, but also how many different times. This metric is useful in understanding whether the listing is performing well, assuming that a high number of distinct bookings means that guests have liked and probably the reviews and rating of the listing are positively impacting the listing's performance.

4.3.2 Regression Analysis: Host Engagement vs. Number of Reservations

To fully understand the impact of host engagement not only on revenue but also on the number of bookings received from Airbnb listings, it is critical to expand the analysis with a more operational perspective. The previous section explored how dynamics such as response rate, Instantbook availability, and Superhost status influence revenue; however, it is equally important to assess how these same factors directly influence the number of bookings. Host engagement, measured in terms of responsiveness in responses and adoption of tools that simplify the booking process, can be instrumental in attracting more guests. In the next section, through a detailed regression, I will analyze how the main indicators of host engagement affect the growth or contraction of the number of bookings, offering an overall view not only on the effectiveness of hosts in securing a high booking rate, but also on their competitive positioning. This analysis will provide insight into the extent to which active host engagement affects the success of listings, highlighting any differences related to variables such as price ranges, seasonality, and geographic location.

4.3.3 Model Fit

The regression model has an R-square of 0.1066, meaning that the model explains about 10.66 percent of the variation in the number of bookings. Although this may seem a relatively low value, this is common in models that analyze complex behaviors such as those related to Airbnb bookings, which are influenced by multiple external factors. As well as that, this value aligns with the previous ones, regarding Occupancy Rate and Revenues. The F-statistic is 438.73 with a p-value of 0.000, showing that the overall model is statistically significant, that is, the independent variables analyzed collectively explain the variation in the number of bookings better than a model without predictors.

Source	SS	df	MS			
				Number of obs	=	227,966
				F(62, 227903)	=	438.73
Model	300997.513	62	4854.7986	Prob > F	=	0.0000
Residual	2521900.43	227,903	11.0656746	R-squared	=	0.1066
				Adj R-squared	=	0.1064
Total	2822897.95	227,965	12.3830323	Root MSE	=	3.3265

Table 3. Overall Regression on Number of Reservations.

4.3.4 Overall Significance

Analyzing the host engagement variables, interesting results emerge. Ads with a response rate between 20% and 50% receive, on average, 0.24 more bookings than the reference group (i.e., ads with a response rate between 0% and 20%), holding other variables constant. When the response rate rises to 50%-70%, the effect becomes more pronounced, with an average increase of 0.47 bookings. Finally, ads with a response rate between 70% and 100% see a significant increase of 1.10 more bookings than the reference group. These results suggest a strong positive correlation between host response rate and the number of bookings, showing that greater responsiveness leads to more bookings.

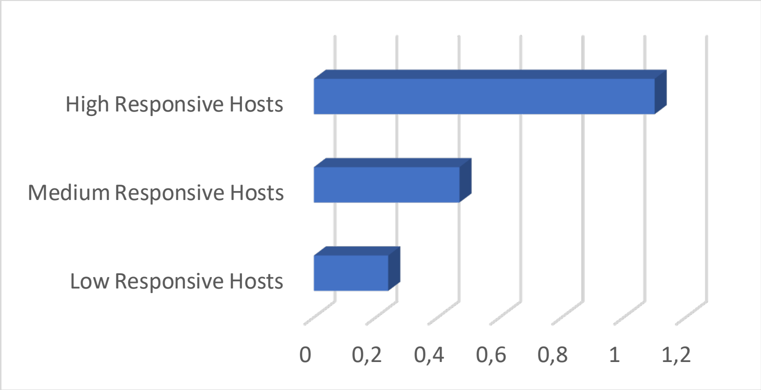

Figure 11. Increase in Number of Reservations by Host Responsiveness.

The Instantbook option has an equally significant impact: such listings get an average of 1.24 more bookings than those that do not, with a p-value of 0.000, indicating clear statistical significance. This result suggests that the ability to book immediately without waiting for host approval significantly increases the likelihood of receiving bookings. Superhost status also has a positive impact, with an average increase of 0.42 bookings compared to hosts not holding this status, confirming the importance of a good reputation and perceived professionalism in attracting more guests.

Control variables related to price ranges show that all price levels above the "budget" range have negative coefficients, indicating that they receive fewer bookings than the latter. For example, ads in the "economy" range show a coefficient of -0.15, while those in the "luxury" range experience an even greater decline, with a coefficient of -0.62, highlighting how more expensive ads tend to be less successful in terms of bookings than cheaper ones. Location also plays a crucial role. Some neighborhoods, such as Covent Garden, show a very positive impact on the results, with a coefficient of 1.22 and a p-value of 0.000, suggesting that this area attracts significantly more bookings. In contrast, other areas such as Westminster have negative coefficients, indicating fewer bookings than other areas. Analyzing monthly trends, the months of July and June show a significant increase in the number of bookings, with coefficients of 0.48 and 0.53, respectively, demonstrating greater demand during the summer months. In contrast, the winter months, such as January and February, show a negative impact, with a reduction in the number of bookings during these periods.

Finally, pandemic years, such as 2020 and 2021, had a significant negative impact on results, with coefficients of -1.53 and -1.42, respectively, demonstrating the dramatic effect of the health crisis on bookings. However, as recovery begins in 2022 and 2023, a recovery in bookings is observed, although not yet to pre-pandemic levels.

4.3.5 Key Takeaway

Analysis of the impact of host engagement on the number of bookings shows that, of all the variables examined, Instantbook has the greatest impact, with an average increase of 1.24 bookings compared to listings that do not offer this option. This result can be explained by the fact that Instantbook simplifies the booking process, eliminating the wait for host approval and making the guest experience more immediate and convenient. It seems to play a crucial role in determining the number of bookings, probably because guests prefer to avoid potential delays or rejections and opt for an immediate confirmation. Response rate also remains an important factor, with the most responsive listings seeing an average increase of 1.1 bookings, showing that the host's readiness in interacting with potential guests positively affects the success of the listing. Finally, Superhost status also contributes an average increase of 0.42 bookings, a sign that the host's reputation and perceived professionalism continue to be a competitive advantage, although less impactful than the speed of the booking process.

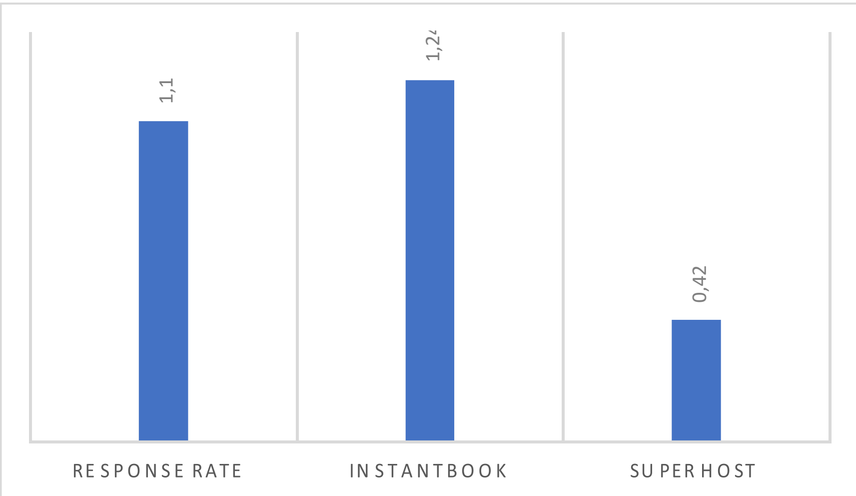

Figure 12. Impact of Host Engagement on Number of Reservations.

4.4 Host Engagement Impact – Pre, During, and Post COVID-19

4.4.1 Introduction

In this new phase of the study, an in-depth analysis of the impact of host engagement on Airbnb listings performance is conducted, evaluated in three distinct periods: pre-covid, during the pandemic, and post-covid. The objective of this analysis is to examine how key host engagement variables, such as response rate, Instantbook availability, and Superhost status, affected bookings and revenue at very different market moments characterized by unique external conditions. The pre-covid period includes all data collected through March 2020, which is a period characterized by relatively stable market demand. The period during the covid covers data from April 2020 to December 2021, a phase when the pandemic introduced dramatic changes in guest behavior patterns, with travel restrictions and high uncertainty. Finally, the post-covid period includes data from January 2022 onward, representing a phase of gradual market recovery, with increasing demand and new behavioral dynamics from both guests and hosts.

The analysis aims to understand how the impact of host engagement variables changed between these phases, highlighting whether and how the pandemic context changed the effectiveness of measures such as Instantbook, host responsiveness, and Superhost's status in ensuring ad performance in terms of bookings and revenue.

4.4.2 Impact on Occupancy Rate

4.4.2.1 Model Fit

The regression model for the pre-covid period has an R-squared of 0.0973, meaning that about 9.73 percent of the variation in occupancy rate is explained by the independent variables included in the model. Although this value seems relatively low, it is in line with expectations for models that analyze complex behaviors influenced by multiple external factors, such as Airbnb bookings. The F-statistic is 95.80 with a p-value of 0.000, showing that the overall model is highly significant. This indicates that the independent variables analyzed contribute significantly to explaining the variation in occupancy rate.

Source	SS	df	MS			
				Number of obs	=	**50,694**
				F(57, 50636)	=	**95.80**
Model	**686.728134**	**57**	**12.047862**	Prob > F	=	**0.0000**
Residual	**6368.14958**	**50,636**	**.125763283**	R-squared	=	**0.0973**
				Adj R-squared	=	**0.0963**
Total	**7054.87772**	**50,693**	**.139168676**	Root MSE	=	**.35463**

Table 4. Regression on Occupancy Rate in the Pre-Pandemic phase.

In the period during the pandemic, the R-squared drops to 0.0446, indicating that only 4.46% of the variation in occupancy rate is explained by the model. This drop in R-squared probably reflects the uncertainty and rapid changes introduced by the pandemic, which made it more difficult to predict host behavior. Although the explained variability is smaller than in the pre-covid phase, the F-statistic is 41.85 with a p-value of 0.000, showing that the model still remains significant. Even during a period of uncertainty, the host engagement variables retain some predictive ability with respect to the occupancy rate.

Source	SS	df	MS			
				Number of obs	=	51,186
				F(57, 51128)	=	41.85
Model	329.936032	57	5.78835144	Prob > F	=	0.0000
Residual	7072.11865	51,128	.138321833	R-squared	=	0.0446
				Adj R-squared	=	0.0435
Total	7402.05468	51,185	.144613748	Root MSE	=	.37192

Table 5. Regression on Occupancy Rate during the Pandemic.

In the post-pandemic period, the R-squared returns to higher values, reaching 0.0972, very similar to the pre-covid period. This value suggests that the model explains about 9.72% of the variation in the occupancy rate. The F-statistic is significantly high, with a value of 238.13 and a p-value of 0.000, indicating that the overall model is highly significant in this period as well. This return to greater predictive ability of the model may reflect the fact that the market has stabilized after the pandemic crisis, with more predictable dynamics similar to those observed in the pre-covid period.

Source	SS	df	MS			
				Number of obs	=	126,086
				F(57, 126028)	=	238.13
Model	1750.74498	57	30.7148241	Prob > F	=	0.0000
Residual	16255.473	126,028	.128983028	R-squared	=	0.0972
				Adj R-squared	=	0.0968
Total	18006.218	126,085	.142810152	Root MSE	=	.35914

Table 6. Regression on Occupancy Rate in the Post-Pandemic phase.

In summary, the model's ability to explain variation in occupancy rate is highest in the pre-covid and post-covid periods, while during the pandemic, uncertainty and drastic changes led to a reduction in the model's explanation of variability. However, in all three phases, the model remains statistically significant, showing that host engagement variables still have a significant impact on the performance of Airbnb listings.

4.4.2.2 Overall Significance

During the COVID phase, i.e., the period between April 2020 and December 2021, host engagement maintained a crucial role in determining occupancy rate, but with some changes in key factors compared to the pre-pandemic period. The highest response rate of 70% to 100% continued to be decisive, with a positive effect of 0.13, although slightly lower than in the pre-pandemic period. This suggests that even in a situation of great uncertainty, the ability of hosts to maintain quick and effective communication remained essential to ensure guest confidence. Also of interest is the fact that the response rate of 50% to 70% became significant, with an increase of 0.06, probably because, in a highly unstable environment, the ability to respond appropriately gained more value than before.

The Instantbook option maintained a positive impact on the occupancy rate, with an increase of 0.07, indicating that despite travel-related restrictions and uncertainty, guests still preferred the convenience of instant and secure booking. However, Superhost status had a more modest impact, with an increase of 0.04, similar to the pre-pandemic period, suggesting stability in the importance of this variable during the crisis.

In the post-COVID period from January 2022, the importance of host involvement changed again, with some significant variations. The higher response rate of 70 percent to 100 percent saw an even greater impact, with a positive effect of 0.23, indicating that as travel recovered, host communication and reliability became crucial aspects of attracting bookings. This suggests that, in a market that was recovering from pandemic uncertainty, guests attached increasing importance to host responsiveness as a sign of reliability and safety. On the other hand, the effect of Instantbook decreased slightly from previous phases, with an increase of 0.03. Although it remains significant, this decrease may reflect a change in the priorities of hosts, who may have preferred to focus more on aspects related to communication and host reliability rather than just the convenience of instant booking after the pandemic. Finally, Superhost status saw a large increase in its impact, with a positive effect of 0.09. This increase suggests that as travel resumed, guests placed greater importance on host reputation and reliability, likely due to the increased focus on service quality after a period of uncertainty.

4.4.2.3 Key Takeaway

Analysis of the three phases - pre-covid, during covid and post-covid - reveals some key dynamics regarding host engagement and its impact on occupancy rate. In the pre-covid period, response rate proved to be the most important variable, maintaining a central role even during the pandemic. However, with the post-covid upswing, its effect became even more pronounced, indicating that host communication and responsiveness became critical for guests. Instantbook had a consistent positive impact in all phases, although in the post-covid period it saw a slight reduction in its weight, suggesting that the convenience of instant booking was gradually overtaken by other factors such as trust and responsiveness. Superhost status, which was initially of lesser importance, became more important post-covid, highlighting an increasing preference of guests for reliable hosts of recognized quality. These results indicate how context influenced guests' priorities, with increasing value placed on host responsiveness and reputation during the recovery period.

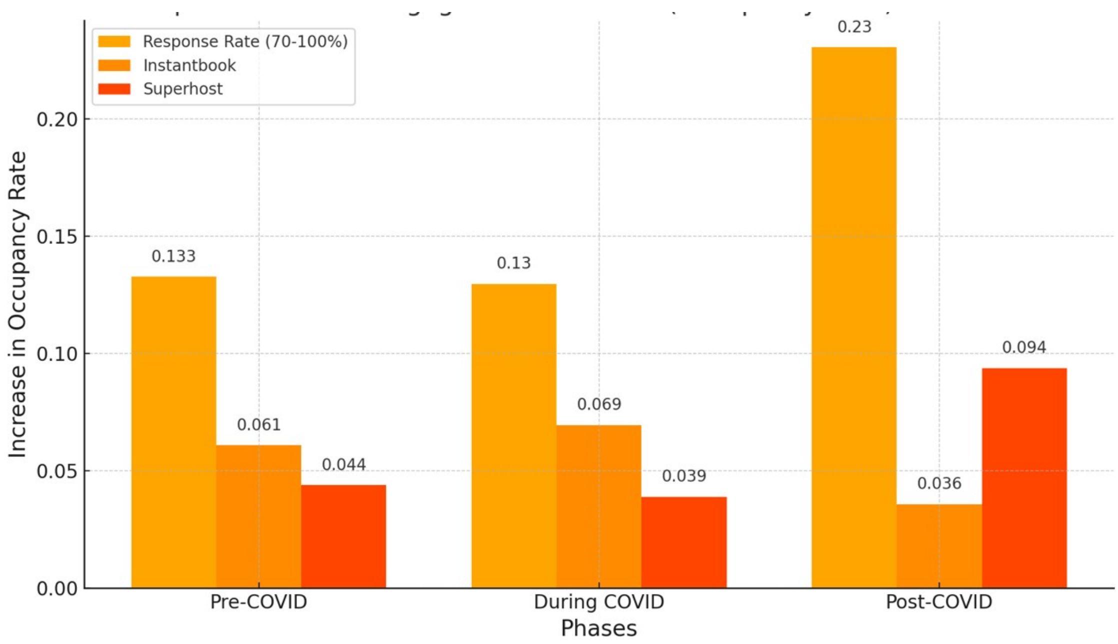

Figure 13. Impact of Host Engagement Metrics on Occupancy Rate before, during and after the Pandemic.

4.4.3 Impact on Revenues

4.4.3.1 Model Fit

The regression model for the pre-covid period has an R-squared of 0.1361, indicating that about 13.61% of the variation in revenues is explained by the independent variables included in the model. This value is quite common for models that deal with complex behaviors, where multiple external factors influence the results. The F-statistic is 139.91, with a p-value of 0.0000, showing that the model is highly significant, and that the independent variables in the model contribute significantly to explaining the variation in revenues.

Source	SS	df	MS			
				Number of obs	=	50,694
				F(57, 50636)	=	139.91
Model	5.6041e+10	57	983167237	Prob > F	=	0.0000
Residual	3.5582e+11	50,636	7027099.07	R-squared	=	0.1361
				Adj R-squared	=	0.1351
Total	4.1186e+11	50,693	8124686.27	Root MSE	=	2650.9

Table 7. Regression on Revenues in the Pre-Pandemic phase.

During the pandemic, the R-squared drops to 0.0773, indicating that the model explains about 7.73 percent of the variation in revenues. This value probably reflects the greater market volatility and uncertainty during the pandemic period, where external and unforeseen factors may have had a greater impact. Nevertheless, the F-statistic is 75.11, with a p-value of 0.0000, showing that the model remains significant even during this phase.

Source	SS	df	MS			
				Number of obs	=	51,186
				F(57, 51128)	=	75.11
Model	2.6140e+10	57	458593998	Prob > F	=	0.0000
Residual	3.1218e+11	51,128	6105933.88	R-squared	=	0.0773
				Adj R-squared	=	0.0762
Total	3.3832e+11	51,185	6609827.98	Root MSE	=	2471

Table 8. Regression on Revenues during the Pandemic.

In the post-pandemic period, the R-squared rises to 0.1643, the highest value among the three phases. This means that about 16.43% of the variation in revenues is explained by the model in this period. The F-statistic is particularly high, with a value of 434.74, accompanied by a p-value of 0.0000, indicating that the model is highly significant in the post-pandemic context. This increase in R-squared suggests that the market has stabilized, and revenue dynamics have returned to a more predictable state than during the pandemic period.

Source	SS	df	MS			
				Number of obs	=	126,086
				F(57, 126028)	=	434.74
Model	3.8172e+11	57	6.6968e+09	Prob > F	=	0.0000
Residual	1.9414e+12	126,028	15404287.2	R-squared	=	0.1643
				Adj R-squared	=	0.1639
Total	2.3231e+12	126,085	18424796.5	Root MSE	=	3924.8

Table 9. Regression on Revenues in the Post-Pandemic phase.

In summary, the model exhibits relatively stable predictive ability in the pre-covid and post-covid periods, with a reduction in predictive ability during the pandemic phase, likely due to increased uncertainty and unpredictable market fluctuations. However, in all three phases, the model remains significant, suggesting that host engagement variables continue to influence revenues, even in highly variable market environments.

4.4.3.2 Overall Significance

During the pre-COVID phase, the analysis shows that two main factors had a significant impact on Airbnb ad revenues: the availability of Instantbook and Superhost status. Ads with Instantbook enabled generated an average of $401 more, a sign that the ability to book immediately was highly valued by guests, who preferred greater convenience in the booking process. Similarly, Superhost status had a positive impact on revenue, bringing in an increase of $401, highlighting the trust placed by travelers in hosts with a consistently good and high level of service. However, the response rate effect proved significant only for hosts with a very high response rate, between 70 percent and 100 percent, who saw an increase in revenues of $546. Groups with lower response rates did not show a statistically significant impact. This suggests that, before the pandemic, guests tended to prefer hosts they could trust, such as Superhosts, and those who offered convenience through the Instantbook option, while immediate host communication was only relevant when the response rate was particularly high.

During the COVID phase, the effect of Instantbook remained important, leading to an increase in revenues of $465, demonstrating that, even during the pandemic, the convenience of being able to book immediately remained a determining factor for guests. However, Superhost status lost some of its relevance, with the average increase in revenue reduced to only $113, suggesting that during the period of COVID-related uncertainty, confidence in Superhost status was less crucial than during the previous phase. A significant change occurred with response rate: all response ranges became statistically significant. Hosts with a response rate between 70 percent and 100 percent saw a $652 increase in revenue, while lower response bands, such as those between 20 percent and 50 percent, also saw a positive impact, contributing an increase of $218. This change reflects the increasing role of communication during the pandemic, when guests needed more reassurance and responsiveness from hosts.

In the post-COVID period, the effect of Instantbook became even more prominent, with a revenue impact of $767, the highest value recorded among the three phases. This suggests that, after the pandemic, guests increasingly valued the ability to book quickly and without complications. Superhost status also regained some of its importance, with an increase in revenue of $451, a sign that trust in highly qualified hosts was again a key factor for guests resuming travel. Response rate retained its relevance across all bands, with the most responsive hosts (response rate between 70 percent and 100 percent) seeing a significant increase in revenue of $1,412, a notable increase from previous phases. Even the lowest response bands continued to positively influence revenues, demonstrating that good communication has become a key element in maximizing earnings, regardless of the host's level of responsiveness. These results reflect the evolution of guest priorities during and after the pandemic, with an increasing emphasis on booking convenience and trust in responsive and reliable hosts.

4.4.3.3 Key Takeaway

Analysis of the impact of host engagement variables on revenue in the three phases - pre-covid, during covid, and post-covid - shows how these factors variably affected host earnings. In the pre-pandemic period, Instantbook and Superhost status played a central role, significantly impacting revenues, while response rate was relevant only when very high (70-100%). During the pandemic, communication became increasingly important, with all response rate ranges contributing to revenues, demonstrating how crucial it was to maintain good communication in a period of uncertainty. Despite this, Instantbook retained its relevance, but Superhost status lost some of its weight. In the post-pandemic period, however, the response rate saw a sharp increase in importance, with the higher levels leading to significant increases in revenues. Instantbook also continued to be a relevant factor, while Superhost status regained ground, indicating that trust in hosts has become a key element again. The chart below clearly visualizes these dynamics, highlighting how host priorities have changed over time, adapting to different market contexts.

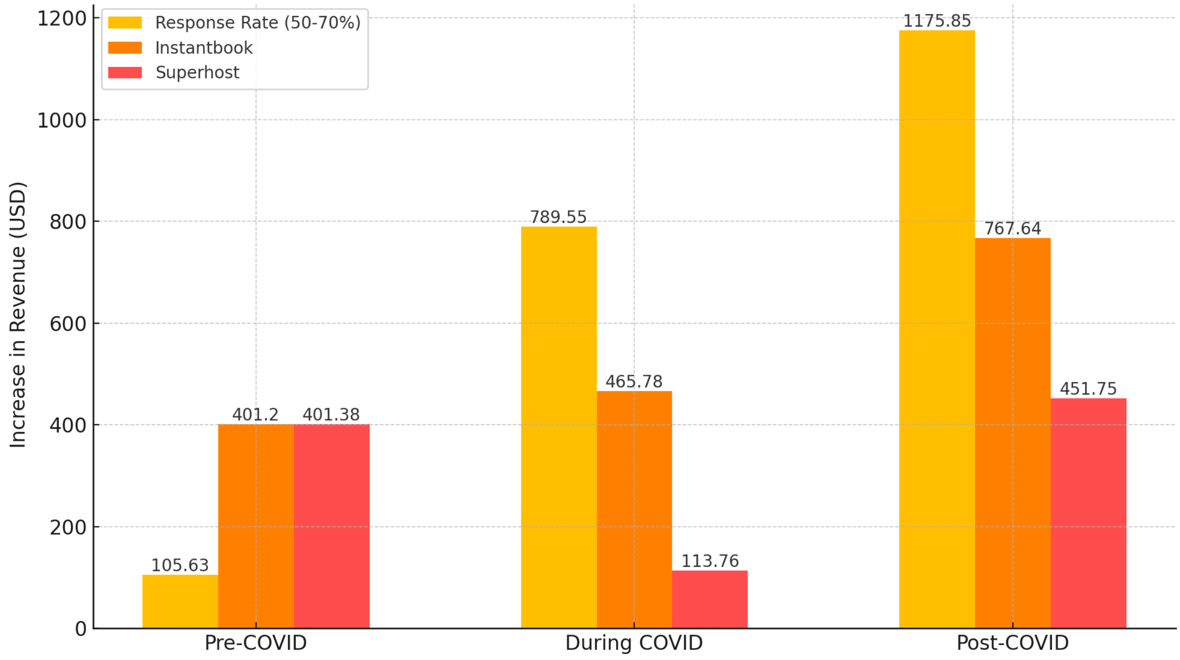

Figure 14. Impact of Host Engagement Metrics on Revenues before, during and after the Pandemic.

4.4.4 Impact on Number of Reservations

4.4.4.1 Model Fit

The regression model for the pre-covid period has an R-squared of 0.1178, indicating that about 11.78 percent of the variation in the number of bookings is explained by the independent variables included in the model. Although not high, this value is typical for models dealing with complex behaviors such as Airbnb bookings, which are influenced by many external factors. The F-statistic is 134.45, with a p-value of 0.0000, showing that the model is highly significant. This suggests that the independent variables in the model contribute significantly to explaining the variation in bookings at this stage.

Source	SS	df	MS			
				Number of obs	=	**59,467**
				F(59, 59407)	=	**134.45**
Model	**83535.7523**	**59**	**1415.86021**	Prob > F	=	**0.0000**
Residual	**625617.124**	**59,407**	**10.5310338**	R-squared	=	**0.1178**
				Adj R-squared	=	**0.1169**
Total	**709152.877**	**59,466**	**11.9253502**	Root MSE	=	**3.2452**

Table 10. Regression on Number of Reservations in the Pre-Pandemic phase.

During the pandemic, the R-squared decreased slightly to 0.1096, indicating that the model explains about 10.96% of the variation in bookings. This slight decrease in R-squared may reflect the uncertainty and volatility in the market during the pandemic period, when unforeseen external factors had a stronger impact on bookings. However, the F-statistic is 78.75, with a p-value of 0.0000, indicating that the model remains significant, showing that host engagement variables continue to influence bookings during this phase of uncertainty.

Source	SS	df	MS			
				Number of obs	=	**37,157**
				F(58, 37098)	=	**78.75**
Model	**36189.6242**	**58**	**623.959037**	Prob > F	=	**0.0000**
Residual	**293948.483**	**37,098**	**7.92356685**	R-squared	=	**0.1096**
				Adj R-squared	=	**0.1082**
Total	**330138.107**	**37,156**	**8.88518967**	Root MSE	=	**2.8149**

Table 11. Regression on Number of Reservations during the Pandemic.

Nel periodo post-pandemia, l'R-squared scende ulteriormente a 0,0885, suggerendo che circa l'8,85% della variazione nelle prenotazioni è spiegata dal modello. Questo rappresenta il valore più basso tra le tre fasi, il che potrebbe riflettere una maggiore complessità del mercato post-pandemico, con una varietà di fattori che influenzano le decisioni degli ospiti. La F-statistic è pari a 210,84, con un p-value di 0,0000, indicando che il modello rimane altamente significativo anche nel periodo post-pandemico. Nonostante la diminuzione dell'R-squared, il modello mantiene la capacità di spiegare una parte significativa della variazione nel numero di prenotazioni.

Source	SS	df	MS			
				Number of obs	=	**126,086**
				F(58, 126027)	=	**210.84**
Model	**146952.85**	**58**	**2533.66984**	Prob > F	=	**0.0000**
Residual	**1514438.69**	**126,027**	**12.0167796**	R-squared	=	**0.0885**
				Adj R-squared	=	**0.0880**
Total	**1661391.54**	**126,085**	**13.176758**	Root MSE	=	**3.4665**

Table 12. Regression on Number of Reservations in the Post-Pandemic phase.

4.4.4.2 Overall Significance

During the pre-COVID phase, host engagement variables showed different impacts on bookings. The response rate between 70% and 100% had a significantly positive effect, with an increase of 0.70 bookings per listing. In contrast, lower response rates, in the 20-50% and 50-70% ranges, did not show statistically significant effects. This indicates that before the pandemic, only very high response rates made a difference in terms of the number of bookings. The effect of Instantbook was particularly significant, with an increase of 1.10 bookings per listing, showing that guests clearly preferred options that allowed immediate booking. Superhost status also had a positive impact, with an increase of 0.63 bookings per listing, suggesting that even before the pandemic, guests were already placing trust in these hosts. In summary, before the pandemic, Instantbook emerged as the factor with the strongest impact on bookings, followed by response rates above 70 percent. Superhost status had a moderate but still important impact, indicating that trust and efficiency were already key factors for Airbnb hosts. Interestingly, the non-significance of some variables at this stage does not necessarily represent a negative result: it simply suggests that prior to the pandemic, host involvement was not yet as crucial as it would be later, when the market evolved, making responsiveness and trust building increasingly critical aspects, especially during the uncertainty of the pandemic.

During the COVID phase, the importance of response rate increased. The response rate between 50% and 70% also became significant, contributing to 0.35 more bookings, while the higher response rate (70-100%) continued to show an even stronger effect, with an increase of 0.83 bookings. This reflects the fact that communication became a crucial factor during the pandemic, when guests sought more reassurance and promptness in responses from hosts. The Instantbook effect, while remaining high, slightly decreased in importance compared to the pre-COVID period, still contributing 0.97 more bookings per listing. This shows that, despite the pandemic, the convenience of instant booking remained a key determinant for guests. Superhost status, on the other hand, saw a significant decline in its impact, with an increase of only 0.08 bookings, suggesting that during the pandemic, reliance on Superhost status became less relevant, likely due to the general uncertainty regarding travel during that period. In summary, during COVID, communication became a much more critical factor, with response rates becoming more prominent, while Superhost status lost some of its influence, probably due to uncertain travel conditions.

In the post-COVID phase, the highest response rate (70-100%) continued to show a very strong effect, with an increase of 1.46 bookings per listing. Lower response rates also showed positive and significant effects, indicating a continued emphasis on communication and host responsiveness. Instantbook remained the factor with the strongest impact, with an increase of 1.33 bookings, which was slightly higher than the pre-COVID rate. This suggests that post-COVID hosts continued to place high importance on the ability to book quickly and without complications. Superhost status regained importance, with an increase of 0.43 bookings per listing, reflecting a renewed interest in trusting reliable hosts as pandemic-related uncertainty diminished. In conclusion, in the post-COVID phase, Instantbook retained its primacy as a determinant of bookings, while high response rates had an even greater influence. Superhost status regained relevance, suggesting that travelers resumed their search for reliable and quality hosts as tourism returned to normal.

4.4.4.3 Key Takeaway

Analysis of the impact of host engagement variables on the number of bookings across the three phases - pre-covid, during covid and post-covid - shows how guest priorities changed over time. In the pre-pandemic period, Instantbook emerged as the determining factor, with a strong impact on the number of bookings, while high response rate (70-100%) and Superhost status had a less pronounced but still significant effect. During the pandemic, communication became an even more critical factor, with an increase in the weight of response rates, especially in the higher ranges, at the expense of the importance of Superhost status, which saw a drastic decrease in its relevance. However, Instantbook continued to maintain a significant impact. In the post-pandemic period, Instantbook reconfirmed its dominant role in increasing bookings, but the highest response rate also experienced significant growth, demonstrating that host responsiveness has become critical to guests resuming travel. Superhost status, although it has not fully recovered to its pre-COVID level of importance, has nonetheless seen an improvement, suggesting that trust in qualified hosts has once again become a key element in guest decision making. The graph at the bottom clearly visualizes these dynamics and confirms the changes in the importance of host engagement variables over time.

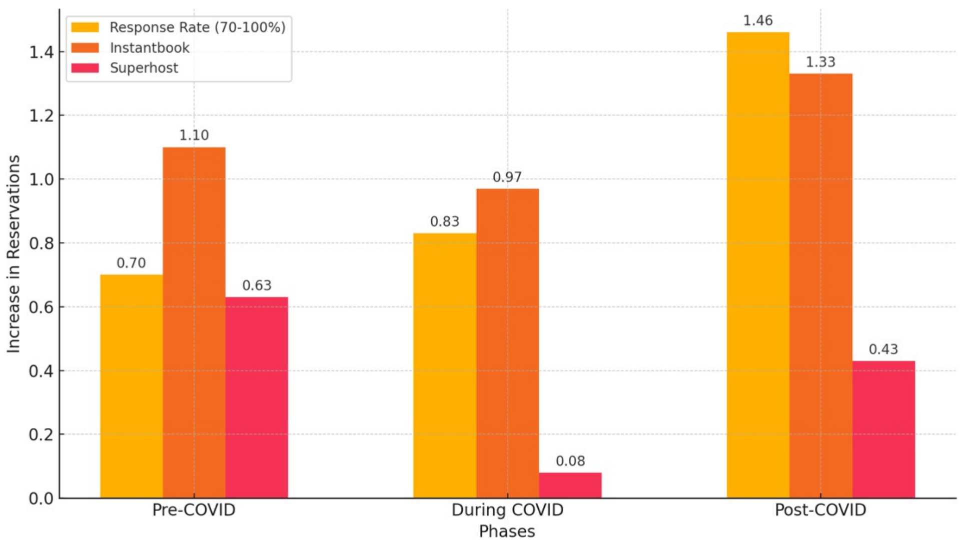

Figure 15. Impact of Host Engagement Metrics on Number of Reservations before, during and after the Pandemic.

4.5 Host Engagement Impact – By Neighborhood Competitiveness

4.5.1 Introduction

The last section of this chapter is devoted to an in-depth analysis aimed at assessing how host engagement, as measured by the usual metrics of response rate, Instantbook, and Superhost status, affects the performance of listings on Airbnb. Even at this stage of the analysis, the variables used to measure listings performance remain consistent with those analyzed in previous sections. However, the uniqueness of this investigation lies in the division of the market according to the competitiveness of neighborhoods. To conduct this analysis, I developed a new variable that represents the density of listings per square kilometer within each neighborhood. This approach reflects the complexity of the market in which hosts operate, as a higher density of listings is indicative of more intense competition among listings in the same geographic area.

The calculation of the density median allowed a clear threshold to distinguish "competitive" from "non-competitive" neighborhoods. Neighborhoods were classified as "competitive" if their density of listings exceeded the median, while they were defined as "non-competitive" if they were below this threshold. This classification provides insight into whether the complexity of the local market, as expressed through competition among listings, affects the importance of host engagement and, ultimately, the performance of listings.

The main objective of this analysis is to understand how the level of competitiveness affects the role of host engagement. In a highly competitive market, factors such as speed of response, Instantbook availability, and Superhost status are expected to have a greater impact on the ability to attract reservations and increase revenue, as guests can more easily make comparisons between listings in the same area. On the other hand, in less competitive neighborhoods, where the density of listings is lower, the effect of host engagement may be less relevant, as choice for guests is more limited, and other variables may take on greater importance. This subdivision allows for a detailed examination of whether and how the market context changes the weight of host engagement in determining the success of listings on Airbnb.

4.5.2 Impact on Occupancy Rate

4.5.2.1 Model Fit

For competitive neighborhoods, the model has an R-squared of 0.1294, indicating that about 12.94 percent of the variation in the employment rate is explained by the independent variables included in the analysis. This suggests a moderate ability of the model to represent the phenomenon analyzed in a highly competitive environment. The F-statistic, equal to 427.10 with a p-value of 0.0000, confirms the strong statistical significance of the model, showing that host engagement variables have a significant influence on the occupancy rate in neighborhoods with higher competition.

Source	SS	df	MS			
				Number of obs	=	114,932
				F(40, 114891)	=	427.10
Model	2210.42492	40	55.2606229	Prob > F	=	0.0000
Residual	14865.1668	114,891	.129384955	R-squared	=	0.1294
				Adj R-squared	=	0.1291
Total	17075.5917	114,931	.14857255	Root MSE	=	.3597

Table 13. Regression on Occupancy Rate in Competitive Neighborhoods.

As for non-competitive neighborhoods, the model shows a slightly lower R-squared of 0.1276, indicating that 12.76 percent of the variation in occupancy rate is explained by the included variables. Again, the R-squared value suggests a moderate predictive ability of the model. However, the F-statistic of 359.30, with a p-value of 0.0000, shows high statistical significance, demonstrating that even in less competitive neighborhoods, host engagement variables have an important impact on the occupancy rate.

Source	SS	df	MS			
				Number of obs	=	113,034
				F(46, 112987)	=	359.30
Model	2208.12673	46	48.0027549	Prob > F	=	0.0000
Residual	15095.0881	112,987	.13360022	R-squared	=	0.1276
				Adj R-squared	=	0.1273
Total	17303.2148	113,033	.153081089	Root MSE	=	.36551

Table 14. Regression on Occupancy Rate in Non-Competitive Neighborhoods.

4.5.2.2 Overall Significance

The analysis of competitive neighborhoods shows that the response rate between 20 percent and 50 percent has a coefficient of 0.0567 and is statistically significant ($p < 0.001$). This indicates that, although less significant than higher response rates, even this lower level of host responsiveness has a positive impact on occupancy rates in highly competitive neighborhoods. However, the 50% to 70% response rate shows a stronger effect, with a coefficient of 0.1105 ($p < 0.001$), suggesting that listings in this response range have a more substantial impact on occupancy rates. This range of responsiveness seems particularly effective in competitive neighborhoods. The highest response rate, between 70% and 100%, has the highest coefficient of 0.1706 ($p < 0.001$), demonstrating a significant positive effect on occupancy rates. High host responsiveness is crucial for better performance in these areas with high competition. In addition, the Instantbook variable exhibits a positive coefficient of

0.0482 ($p < 0.001$), indicating that listings with Instantbook enabled experience a significant increase in occupancy rates, further underscoring guests' preference for ease of booking in these areas. Superhost status also has a positive impact, with a coefficient of 0.0614 ($p < 0.001$), reflecting the strong trust guests place in Superhost-managed listings, which translates into higher occupancy rates in competitive neighborhoods.

Turning to non-competitive neighborhoods, the response rate between 20 percent and 50 percent shows a coefficient of 0.0502 ($p < 0.001$), signaling a similar positive impact on occupancy rates compared to competitive neighborhoods, although the effect is slightly smaller. The response rate between 50 percent and 70 percent also has a positive impact, with a coefficient of 0.1070 ($p < 0.001$), similar to that observed in competitive neighborhoods, although the effect remains slightly weaker. However, the response rate between 70% and 100% has a very high coefficient of 0.1820 ($p < 0.001$), suggesting that in non-competitive neighborhoods, higher response rates have an even stronger impact on employment rates than in competitive areas. Instantbook also maintains a significant impact, with a coefficient of 0.0482 ($p < 0.001$), similar to its effect in competitive neighborhoods, confirming the value of instant booking options in both types of areas. Finally, Superhost status has a coefficient of 0.0799 ($p < 0.001$), showing a stronger impact in non-competitive than competitive neighborhoods, reflecting how trust in Superhosts becomes an even more decisive factor in areas with less competition.

4.5.2.3 Key Takeaway

In summary, the analysis shows that in competitive districts, the highest response rates (70-100%) have a significant impact on occupancy rates, followed by response rates in the middle range (50-70%), which still show a significant effect. The lower response rates (20-50%) are also significant, although their impact is less than in the higher ranges. This indicates that in neighborhoods with high competition, the importance of host responsiveness is crucial for improving listing performance. Instantbook is confirmed as a factor that significantly improves occupancy rates, reflecting guests' preference for faster and more convenient booking options, while Superhost status further boosts guest confidence, also contributing positively to occupancy rates.

In non-competitive neighborhoods, however, higher response rates (70-100%) are observed to have an even greater impact than in competitive neighborhoods. This suggests that, in areas with less competition, host responsiveness plays an even greater role in determining booking success. In addition, Instantbook maintains a positive impact on both types of neighborhoods, while Superhost status becomes even more relevant in less competitive areas, where trust in hosts carries more weight in guest decision making.

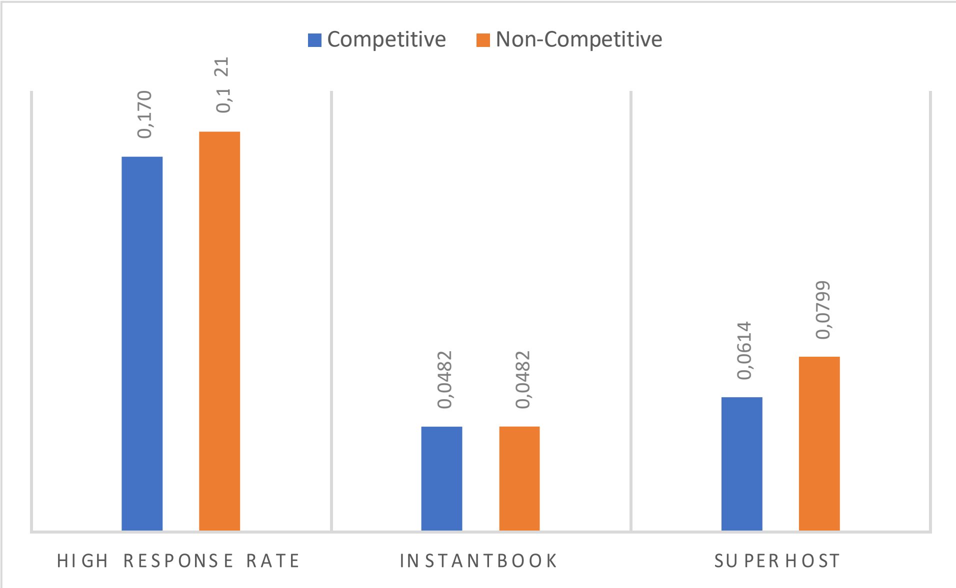

Figure 16. Impact of Host Engagement on Occupancy Rate by Neighborhood Competitiveness.

4.5.3 Impact on Revenues

4.5.3.1 Model Fit

As for competitive neighborhoods, the model fit analysis shows an R-squared value of 0.1686, indicating that about 16.86 percent of the variation in revenues can be explained by the independent variables included in the model. The F-statistic of 582.41 confirms that the model is highly significant, indicating a strong correlation between the variables considered and revenues in the highly competitive neighborhoods.

Source	SS	df	MS			
				Number of obs	=	114,932
				F(40, 114891)	=	582.41
Model	3.2822e+11	40	8.2054e+09	Prob > F	=	0.0000
Residual	1.6187e+12	114,891	14088810	R-squared	=	0.1686
				Adj R-squared	=	0.1683
Total	1.9469e+12	114,931	16939676.9	Root MSE	=	3753.5

Table 15. Regression on Revenues in Competitive Neighborhoods.

In the case of non-competitive neighborhoods, the R-squared value is 0.1431, showing that about 14.31% of the variation in revenues can be explained by the model variables. Again, the F-statistic, with a value of 410.28, demonstrates strong statistical significance, indicating that the model variables have a significant impact on revenues in the low-competitive neighborhoods.

Source	SS	df	MS			
				Number of obs	=	113,034
				F(46, 112987)	=	410.28
Model	1.7376e+11	46	3.7773e+09	Prob > F	=	0.0000
Residual	1.0402e+12	112,987	9206632.73	R-squared	=	0.1431
				Adj R-squared	=	0.1428
Total	1.2140e+12	113,033	10740097	Root MSE	=	3034.2

Table 16. Regression on Revenues in Non-Competitive Neighborhoods.

4.5.3.2 Overall Significance

In the analysis conducted on competitive neighborhoods, the response rate between 20 percent and 50 percent shows a coefficient of 167.38 but is not found to be statistically significant ($p = 0.107$). This indicates that, for listings located in neighborhoods with a high density of competition, a response rate in this range does not have a significant impact on revenues. In contrast, listings with a response rate between 50 percent and 70 percent show a highly significant coefficient of 1326.88 ($p < 0.001$), suggesting a strong increase in revenue for listings within this response range. The highest response rate, i.e., between 70% and 100%, is also highly significant with a coefficient of 943.38 ($p < 0.001$), although its impact, while substantial, is less than in the 50-70% range. In addition, the Instantbook variable shows a coefficient of 639.57 ($p < 0.001$), indicating a significant increase in revenue for listings that offer instant booking. Superhost status also has a positive and significant impact, with a coefficient of 466.45 ($p < 0.001$), showing that, in competitive quarters, being Superhost contributes to significantly increased revenues.

In non-competitive neighborhoods, on the other hand, the response rate between 20 percent and 50 percent has a coefficient of 358.58, which is significant ($p < 0.001$). This shows a positive impact on revenues, which is even more pronounced than that observed in competitive neighborhoods for the same response rate range. As for the response rate range between 50 percent and 70 percent, the coefficient is 187.86 ($p = 0.016$), showing a positive but weaker effect than in competitive neighborhoods. The highest response rate, i.e., between 70% and 100%, is highly significant with a coefficient of 1037.43 ($p < 0.001$), and shows a stronger positive impact than competitive neighborhoods, suggesting that in less competitive areas the effectiveness of high host responsiveness is even more pronounced. Again, Instantbook confirms its importance with a slightly higher coefficient than competitive neighborhoods, at 647.16 ($p < 0.001$), consolidating the positive effect on revenues. Finally, Superhost status has a coefficient of 259.31 ($p < 0.001$), indicating a positive impact on revenues in non-competitive quarters, although less than observed in competitive quarters.

4.5.3.3 Key Takeaway

Analysis of competitive neighborhoods shows that, even with lower response rates, host responsiveness has a positive effect on revenue, but it is with higher response rates that a greater impact is observed. Instantbook functionality continues to be a relevant factor in increasing revenue, suggesting that, in competitive neighborhoods, hosts favor ease and speed of booking. Superhost status positively affects revenues, indicating that guest trust in established hosts is instrumental in improving economic performance in areas with high competition.

In non-competitive neighborhoods, on the other hand, high response rates are even more effective in increasing revenues, highlighting the importance of quick and constant communication with potential guests in these areas. Here again, Instantbook confirms its value as a tool for generating more revenue. Superhost status appears to have a less significant impact than competitive neighborhoods, indicating that, in more saturated markets, the trust generated by Superhost status becomes a crucial element in maximizing earnings.

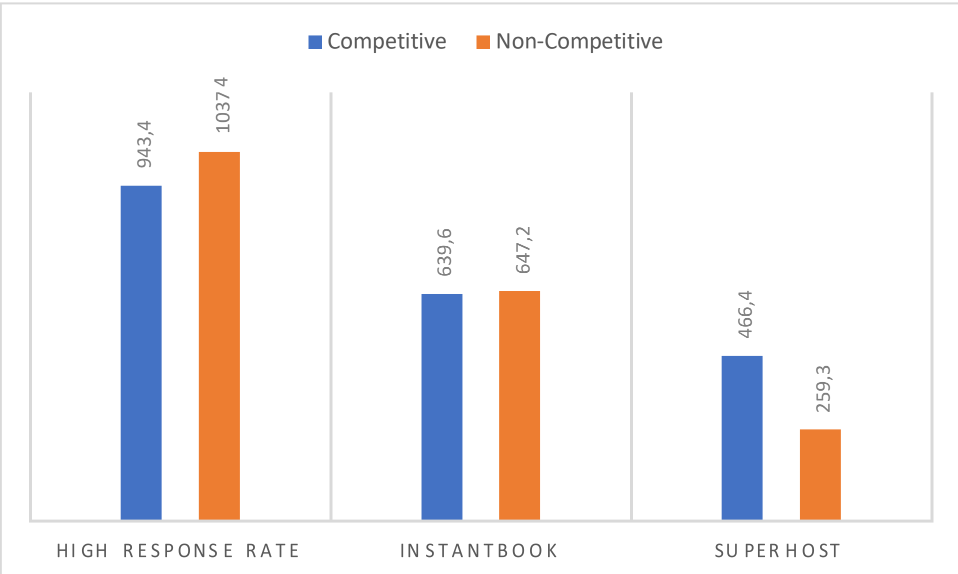

Figure 17. Impact of Host Engagement on Revenues by Neighborhood Competitiveness.

5. Conclusions

5.1 Introduction

The objective of this thesis has been to examine the multifaceted impact of host engagement on the performance of Airbnb listings in 38 neighborhoods of London, analyzing a dataset spanning from 2018 to 2023. The analysis was framed around key indicators of host engagement, specifically response rate, Instantbook availability, and Superhost status, all of which were evaluated for their influence on three critical metrics: occupancy rates, revenues and number of reservations. The study aimed not only at understanding the overall trends during this period but also to deep dive into specific time periods—pre-COVID, during COVID, and post-COVID—to uncover how the dynamics of host engagement evolved through these distinct phases. Furthermore, the investigation included a comparison between competitive and non-competitive neighborhoods, defined by the density of listings per square kilometer, in order to gauge whether the level of market competition alters the role of host engagement in driving listing performance.

The motivation for this research lies in the increasingly competitive landscape of the short-term rental market, particularly in major metropolitan areas such as London, where Airbnb has become a dominant player. Hosts looking to maximize their performance must continuously refine their strategies, particularly with regard to guest engagement. By leveraging host engagement data, this study aimed at identifying the specific behaviors that yield the highest returns, offering practical recommendations for hosts aiming to improve their occupancy rates, revenues and number of reservations.

To achieve this, the study employed a combination of regression analyses, where host engagement variables were modeled against occupancy, revenue and number of reservations outcomes. Control variables, including neighborhood, price tier, year, and month, were incorporated to ensure that the analyses isolated the effects of host engagement from other potentially confounding factors. This approach allowed for a detailed understanding of how each host engagement variable interacts with listing performance over time and across market conditions.

As the results of the analyses show, host engagement plays a significant role in Airbnb listing performance, though its impact varies depending on market conditions and external disruptions, such as the COVID-19 pandemic. In particular, response rate, Instantbook, and Superhost status were found to be key drivers of performance, though the degree to which each contributed varied across the studied phases and neighborhood competitiveness levels. This chapter will synthesize the findings from the various analyses, drawing out the main conclusions regarding host engagement and its role in shaping Airbnb listing success, while also offering practical implications for hosts and suggestions for future research in this field.

5.2 Summary of Key Findings

5.2.1 Host Engagement vs Occupancy Rate

This analysis explores how host engagement variables, including response rate, Superhost status, and Instantbook availability, impact the occupancy rates of Airbnb listings. The data span from 2018 to 2023, highlighting both general occupancy trends and the influence of host behaviors.

Higher host engagement, particularly response rates between 70% and 100%, has a strong and statistically significant positive impact on occupancy rates. Listings with Superhost status and Instantbook availability also show higher occupancy, underscoring the importance of trust and booking ease for guests.

5.2.2 Host Engagement vs Revenue

This regression analysis examines the relationship between host engagement metrics and the revenue generated by Airbnb listings. By focusing on the revenue impacts of response rates, Superhost status, and Instantbook, this analysis measures the financial performance associated with higher host engagement.

Listings with Instantbook enabled and high response rates (70-100%) generate significantly more revenue, with Instantbook having the most substantial impact. Superhost status also positively affects revenue, indicating that reliability and responsiveness lead to higher income for hosts.

5.2.3 Host Engagement vs Number of Reservations

This section evaluates the effect of host engagement on the number of reservations secured by listings, providing insights into the frequency of bookings rather than just the occupancy rate or total revenue.

Listings with a very high response rate (70-100%) and Instantbook see the highest increase in the number of reservations. Superhost status also contributes positively, but Instantbook remains the strongest driver of frequent bookings, showing guests' preference for ease and speed of booking.

5.2.4 Host Engagement Pre, During, and Post COVID

This analysis investigates how the impact of host engagement variables changed across three periods: pre-COVID, during COVID, and post-COVID. The goal was to understand how external market shocks, such as the pandemic, influenced the relative importance of host engagement factors.

During COVID, communication became significantly more critical, with response rates playing a bigger role than before. Instantbook remained important, but Superhost status saw a decline during the pandemic. Post-COVID, however, both high response rates and Superhost status regained importance, as guests resumed travel and sought reliable hosts.

5.2.5 Host Engagement by Neighborhood Competitiveness

This analysis examines how host engagement impacts listings' performance in competitive versus non-competitive neighborhoods. Neighborhood competitiveness was determined by the density of listings per square kilometer, with performance metrics such as occupancy, revenue, and reservations evaluated accordingly.

In competitive neighborhoods, high response rates (50-70% and 70-100%) significantly improve performance, but in non-competitive areas, response rates in the highest range (70-100%) show even greater effectiveness. Instantbook remains a crucial factor in both competitive and non-competitive areas, though Superhost status is more impactful in competitive neighborhoods.

5.3 Key Takeaways

Based on the key findings from the study, here are the answers to the questions outlined in the Introduction:

1. *Are higher levels of host engagement positively associated with improved Airbnb listing performance?*

   Yes, higher levels of host engagement are strongly associated with improved Airbnb listing performance across all metrics studied: occupancy rate, revenue, and number of reservations. Listings with higher response rates (especially between 70-100%), Instantbook enabled, and Superhost status consistently outperformed those with lower engagement. The analyses show that engaged hosts, who communicate promptly and simplify the booking process, significantly increase their listing's performance, highlighting the value of strong host engagement in the Airbnb market.

2. *Which specific engagement metrics have had the most significant impact on listings' performance over the 2018–2023 period?*

   Instantbook and high response rates (70-100%) have proven to be the most significant engagement metrics for listings' performance across the 2018–2023 period. Instantbook, in particular, showed a significant impact on increasing both revenue and the number of reservations, as guests favor the convenience of immediate bookings. Response rates, especially in the 70-100% range, were another strong predictor of improved occupancy and revenue. Superhost status also positively influenced performance but was slightly less impactful compared to Instantbook and response rate.

3. *Was host engagement a significant factor during the pandemic?*

   Host engagement was a crucial factor during the pandemic, though the dynamics shifted slightly. During COVID, response rates became even more critical as communication and reliability gained importance during uncertain times. Instantbook remained a strong factor, reflecting guests' continued preference for booking convenience. However, Superhost status saw a decline in importance during the pandemic, likely due to the reduced travel demand and uncertainty. Post-COVID, both high response rates and Superhost status regained their significance as travel resumed and guests sought trustworthy hosts.

5.4 Limitations

One limitation arises from the specific market constraints, in particular the impact of the COVID-19 pandemic, which led to abnormal market conditions. While the analysis attempts to account for this by dividing the data into phases before, during and after the pandemic, the uniqueness of the pandemic’s impact on travel behavior could mean that the results from this period do not apply to more typical market conditions. This could impact the general applicability of the results, particularly when looking at long-term trends.

In addition, several assumptions were made in the modeling. For example, the competitive intensity of neighborhoods was derived using a proxy variable (supply density per square kilometer) which, while indicative, may not fully capture the complexity of competition in different areas. Other factors, such as local regulations or economic conditions, were not directly controlled for, which may have influenced performance in ways that were not fully accounted for in the regression models.

Finally, there is the issue of measurement consistency for some engagement metrics such as response rate and superhost status. While these metrics are useful indicators, they may not capture the full scope of host behavior or the subtleties of guest interactions. For example, hosts with similar response rates may differ in the quality of their interactions, which is not quantifiable in the dataset.

These limitations should be considered when interpreting the results. They highlight the importance of cautious generalization. Future research could address some of these limitations by using larger data sets, including additional variables, or applying the analysis to other regions and contexts.

5.5 Future Research

Future research could dive deeper into several areas that were not fully explored in this study. For instance, a more granular analysis of seasonality effects on Airbnb listings could uncover specific periods where host engagement has a greater or lower impact on performance, potentially offering hosts strategic insights to optimize their listings throughout the year. Moreover, the growing role of emerging technologies like AI-powered booking systems or personalized guest experiences could be studied to determine their impact on both host engagement and listing performance. Another significant area for future exploration is the long-term effect of the COVID-19 pandemic on short-term rental platforms, particularly regarding shifts in traveler preferences, changes in host engagement strategies, and how the pandemic has permanently altered the dynamics of competitive and non-competitive neighborhoods. Finally, examining how Airbnb listings adapt to ongoing market changes, such as increasing regulation or shifts in travel trends, could provide valuable insights for hosts aiming to stay competitive in a post-pandemic market.

5.6 Concluding Remarks

In conclusion, this research offers valuable contributions to the growing body of literature on Airbnb host engagement and its impact on listing performance. By providing a comprehensive analysis of how different aspects of host engagement—such as response rate, Instantbook availability, and Superhost status—affect occupancy rates, revenues, and reservation numbers across various market conditions, this study fills a gap in understanding the nuanced role of host behavior in influencing guest decisions. The research also sheds light on the evolving dynamics of the Airbnb platform, particularly during and after the COVID-19 pandemic, highlighting how host engagement strategies adapted to changing market realities. Moreover, the differentiation between competitive and non-competitive neighborhoods provides a more targeted understanding of how market complexity shapes the effectiveness of host engagement. Overall, this research not only reinforces the importance of active host participation in driving success on short-term rental platforms but also adds depth to existing knowledge by examining the effects of external factors such as market competition and global crises like the pandemic.

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Appendix

Source	SS	df	MS
Model	218.628009	44	4.96881839
Residual	3169.17887	23,271	.136185762
Total	3387.80688	23,315	.145305892

Number of obs	=	23,316
F(44, 23271)	=	36.49
Prob > F	=	0.0000
R-squared	=	0.0645
Adj R-squared	=	0.0628
Root MSE	=	.36903

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.0490072	.0036569	13.40	0.000	.0418394	.0561751
AirbnbSuperhost	.0384524	.0057456	6.69	0.000	.0271908	.0497141
Instantbook	.0696884	.0062061	11.23	0.000	.0575241	.0818527
PriceTier_num						
economy	-.047044	.0075778	-6.21	0.000	-.0618971	-.0321909
luxury	-.2377696	.0089356	-26.61	0.000	-.255284	-.2202552
midscale	-.0705866	.0078401	-9.00	0.000	-.0859537	-.0552195
upscale	-.1096795	.0080768	-13.58	0.000	-.1255106	-.0938484
Neighborhood_num						
Bloomsbury	-.0006258	.017597	-0.04	0.972	-.035117	.0338654
Brixton	-.0846655	.0181944	-4.65	0.000	-.1203277	-.0490032
Bromley-by-bow	-.0798106	.0266195	-3.00	0.003	-.1319865	-.0276347
Camden	.0579591	.0194641	2.98	0.003	.0198082	.09611
Chelsea	-.0516738	.0195492	-2.64	0.008	-.0899916	-.013356
Chiswick	-.020073	.0279729	-0.72	0.473	-.0749017	.0347557
City of London	.0928641	.0342551	2.71	0.007	.0257218	.1600063
Clerkenwell	.0911636	.0218728	4.17	0.000	.0482916	.1340357
Covent Garden	.1281433	.022731	5.64	0.000	.0835891	.1726975
Ealing	-.0693993	.0226377	-3.07	0.002	-.1137706	-.0250279
Fulham	-.0675398	.0223858	-3.02	0.003	-.1114175	-.0236621
Greenwich	-.1190429	.0187891	-6.34	0.000	-.1558707	-.0822151
Hackney	-.0510017	.0167203	-3.05	0.002	-.0837745	-.0182288
Hammersmith	.0178033	.0207226	0.86	0.390	-.0228145	.058421
Hampstead	-.0294525	.0210199	-1.40	0.161	-.0706529	.0117479
Haringey	-.06816	.0177863	-3.83	0.000	-.1030223	-.0332978
Holloway	-.0409906	.0224241	-1.83	0.068	-.0849434	.0029621
Isle of Dogs	-.0211163	.0233274	-0.91	0.365	-.0668395	.0246069
Islington	.0767418	.0173946	4.41	0.000	.0426472	.1108364
Kensington	.0157403	.0182991	0.86	0.390	-.0201272	.0516079
Maida Vale	.01505	.0238607	0.63	0.528	-.0317186	.0618186
Mayfair	.0593269	.020528	2.89	0.004	.0190906	.0995631
North Kensington	.0116204	.0214995	0.54	0.589	-.03052	.0537608
Paddington	.0404823	.0190023	2.13	0.033	.0032365	.0777281
Peckham	-.0253105	.0204533	-1.24	0.216	-.0654004	.0147794
Rotherhithe	-.0031832	.025871	-0.12	0.902	-.0538921	.0475257
Southwark	.0763127	.0187186	4.08	0.000	.039623	.1130024
St Johnss Wood	.0773599	.0358061	2.16	0.031	.0071775	.1475422
Streatham and Dulwich	-.0738951	.0267491	-2.76	0.006	-.1263251	-.0214651
Sutton	-.1702033	.0370064	-4.60	0.000	-.2427382	-.0976684
Vauxhall	.0793867	.0203535	3.90	0.000	.0394926	.1192808
Waltham Forest	-.1256543	.0206332	-6.09	0.000	-.1660968	-.0852119
Wandsworth	-.0733645	.0173881	-4.22	0.000	-.1074463	-.0392828
Wembley	-.0500676	.0365064	-1.37	0.170	-.1216225	.0214873
Westminster	.0867511	.0221474	3.92	0.000	.0433407	.1301614
Whitechapel	.0559872	.017831	3.14	0.002	.0210373	.0909371
Willensden	-.0679839	.0196805	-3.45	0.001	-.1065589	-.0294089
_cons	.4608343	.0196465	23.46	0.000	.4223259	.4993427

Results for Year: 2018

Regression 1 – Host Engagement vs Occupancy Rate (2018)

Source	SS	df	MS
Model	246.084821	44	5.59283683
Residual	3402.6801	27,333	.124489815
Total	3648.76492	27,377	.133278479

Number of obs	=	27,378
F(44, 27333)	=	44.93
Prob > F	=	0.0000
R-squared	=	0.0674
Adj R-squared	=	0.0659
Root MSE	=	.35283

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.0577428	.0032778	17.62	0.000	.0513181	.0641675
AirbnbSuperhost	.0501331	.0050454	9.94	0.000	.0402438	.0600224
Instantbook	.0573928	.0053377	10.75	0.000	.0469307	.0678549
PriceTier_num						
economy	-.0441874	.0067978	-6.50	0.000	-.0575115	-.0308633
luxury	-.2181812	.0077619	-28.11	0.000	-.233395	-.2029675
midscale	-.0783102	.0070489	-11.11	0.000	-.0921264	-.0644941
upscale	-.1117599	.0071701	-15.59	0.000	-.1258138	-.0977061
Neighborhood_num						
Bloomsbury	-.0318907	.0163843	-1.95	0.052	-.0640047	.0002234
Brixton	-.0596263	.017191	-3.47	0.001	-.0933215	-.0259311
Bromley-by-bow	-.0554115	.0239358	-2.31	0.021	-.1023269	-.008496
Camden	.0298877	.0177768	1.68	0.093	-.0049557	.0647311
Chelsea	-.07421	.0186058	-3.99	0.000	-.1106784	-.0377416
Chiswick	-.0548352	.0244446	-2.24	0.025	-.1027479	-.0069226
City of London	-.0697354	.0292855	-2.38	0.017	-.1271366	-.0123343
Clerkenwell	-.0153306	.0203263	-0.75	0.451	-.0551711	.0245099
Covent Garden	-.0171749	.02102	-0.82	0.414	-.0583752	.0240255
Ealing	-.0811871	.0216548	-3.75	0.000	-.1236316	-.0387425
Fulham	-.1376161	.0200175	-6.87	0.000	-.1768515	-.0983806
Greenwich	-.1681125	.0174562	-9.63	0.000	-.2023275	-.1338975
Hackney	-.0817925	.0161915	-5.05	0.000	-.1135287	-.0500563
Hammersmith	-.0567269	.0189227	-3.00	0.003	-.0938164	-.0196373
Hampstead	-.0585129	.0197219	-2.97	0.003	-.0971689	-.0198569
Haringey	-.10443	.016662	-6.27	0.000	-.1370884	-.0717716
Holloway	-.02893	.0205778	-1.41	0.160	-.0692636	.0114035
Isle of Dogs	-.0908574	.0205357	-4.42	0.000	-.1311083	-.0506065
Islington	.0186817	.0161018	1.16	0.246	-.0128786	.050242
Kensington	-.0339035	.0166459	-2.04	0.042	-.0665302	-.0012767
Maida Vale	-.011905	.0229371	-0.52	0.604	-.0568629	.033053
Mayfair	-.0390723	.0176827	-2.21	0.027	-.0737312	-.0044134
North Kensington	-.046668	.0197008	-2.37	0.018	-.0852824	-.0080535
Paddington	-.0280975	.0173961	-1.62	0.106	-.0621947	.0059997
Peckham	-.0755541	.0189059	-4.00	0.000	-.1126106	-.0384975
Rotherhithe	-.0248387	.023437	-1.06	0.289	-.0707764	.021099
Southwark	-.0069929	.0175197	-0.40	0.690	-.0413324	.0273465
St Johnss Wood	.0297919	.0323149	0.92	0.357	-.0335468	.0931307
Streatham and Dulwich	-.1207035	.0240654	-5.02	0.000	-.1678729	-.0735341
Sutton	-.2162372	.034923	-6.19	0.000	-.284688	-.1477864
Vauxhall	.0562047	.0192865	2.91	0.004	.0184022	.0940071
Waltham Forest	-.1275646	.0193767	-6.58	0.000	-.1655439	-.0895852
Wandsworth	-.1104363	.01623	-6.80	0.000	-.1422479	-.0786248
Wembley	-.1045086	.029305	-3.57	0.000	-.161948	-.0470693
Westminster	.0654772	.0193829	3.38	0.001	.0274858	.1034686
Whitechapel	.0145062	.0165193	0.88	0.380	-.0178725	.046885
Willensden	-.079836	.0184465	-4.33	0.000	-.115992	-.04368
_cons	.5062574	.0185287	27.32	0.000	.4699403	.5425746

Results for Year: 2019

Regression 2 – Host Engagement vs Occupancy Rate (2019)

Source	SS	df	MS			
				Number of obs	=	23,896
				F(44, 23851)	=	19.70
Model	120.104075	44	2.72963807	Prob > F	=	0.0000
Residual	3304.36197	23,851	.138541863	R-squared	=	0.0351
				Adj R-squared	=	0.0333
Total	3424.46605	23,895	.14331308	Root MSE	=	.37221

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.0434998	.0036578	11.89	0.000	.0363302	.0506693
AirbnbSuperhost	.0369959	.0056277	6.57	0.000	.0259652	.0480266
Instantbook	.0651452	.0059262	10.99	0.000	.0535294	.076761
PriceTier_num						
economy	-.0424666	.0078566	-5.41	0.000	-.057866	-.0270672
luxury	-.1463705	.0087693	-16.69	0.000	-.1635589	-.1291822
midscale	-.0449817	.0079847	-5.63	0.000	-.0606321	-.0293312
upscale	-.0884055	.0080523	-10.98	0.000	-.1041886	-.0726225
Neighborhood_num						
Bloomsbury	-.0414401	.019211	-2.16	0.031	-.0790948	-.0037854
Brixton	-.0467175	.0209455	-2.23	0.026	-.0877721	-.0056629
Bromley-by-bow	-.0152114	.0295858	-0.51	0.607	-.0732015	.0427787
Camden	.0121567	.0208302	0.58	0.559	-.0286718	.0529851
Chelsea	-.1117392	.0218226	-5.12	0.000	-.1545129	-.0689656
Chiswick	.0196733	.0290759	0.68	0.499	-.0373173	.0766639
City of London	-.0419479	.0337412	-1.24	0.214	-.1080828	.0241871
Clerkenwell	-.0385381	.0237732	-1.62	0.105	-.085135	.0080589
Covent Garden	.015129	.0240735	0.63	0.530	-.0320566	.0623146
Ealing	-.0810287	.023929	-3.39	0.001	-.1279312	-.0341263
Fulham	-.0510329	.0228241	-2.24	0.025	-.0957696	-.0062962
Greenwich	-.0512469	.0206694	-2.48	0.013	-.0917603	-.0107336
Hackney	-.0473091	.0197712	-2.39	0.017	-.086062	-.0085562
Hammersmith	-.0453543	.0222747	-2.04	0.042	-.0890141	-.0016945
Hampstead	-.0816951	.0229746	-3.56	0.000	-.1267268	-.0366634
Haringey	-.0295746	.0203361	-1.45	0.146	-.0694347	.0102855
Holloway	-.02965	.0242208	-1.22	0.221	-.0771243	.0178242
Isle of Dogs	-.0655267	.0232493	-2.82	0.005	-.1110969	-.0199565
Islington	-.0029004	.0197994	-0.15	0.884	-.0417084	.0359076
Kensington	-.0252256	.0194568	-1.30	0.195	-.0633621	.0129108
Maida Vale	-.080982	.0259958	-3.12	0.002	-.1319354	-.0300286
Mayfair	-.0647316	.0209452	-3.09	0.002	-.1057854	-.0236777
North Kensington	-.0734623	.0240159	-3.06	0.002	-.1205351	-.0263896
Paddington	-.0512196	.0198899	-2.58	0.010	-.090205	-.0122341
Peckham	-.0605923	.0222626	-2.72	0.006	-.1042284	-.0169562
Rotherhithe	-.0742346	.0278448	-2.67	0.008	-.1288122	-.019657
Southwark	-.0205081	.0207405	-0.99	0.323	-.0611608	.0201446
St Johnss Wood	-.0617095	.0366723	-1.68	0.092	-.1335896	.0101706
Streatham and Dulwich	-.0707505	.0283598	-2.49	0.013	-.1263376	-.0151635
Sutton	.0266061	.0434382	0.61	0.540	-.0585355	.1117478
Vauxhall	.0451956	.0227408	1.99	0.047	.0006222	.089769
Waltham Forest	-.0469467	.0233586	-2.01	0.044	-.092731	-.0011624
Wandsworth	-.0584271	.0196061	-2.98	0.003	-.0968564	-.0199979
Wembley	-.0455862	.0320527	-1.42	0.155	-.1084115	.0172391
Westminster	.0556448	.0224927	2.47	0.013	.0115578	.0997318
Whitechapel	.003174	.0197738	0.16	0.872	-.0355838	.0419318
Willensden	-.0808254	.0222924	-3.63	0.000	-.12452	-.0371308
_cons	.2489895	.0219468	11.35	0.000	.2059723	.2920067

Results for Year: 2020

Regression 3 – Host Engagement vs Occupancy Rate (2020)

Source	SS	df	MS			
Model	150.959471	44	3.43089707	Number of obs	=	27,290
Residual	3802.30614	27,245	.139559778	F(44, 27245)	=	24.58
				Prob > F	=	0.0000
Total	3953.26561	27,289	.144866635	R-squared	=	0.0382
				Adj R-squared	=	0.0366
				Root MSE	=	.37358

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.0504511	.0035061	14.39	0.000	.0435791	.0573232
AirbnbSuperhost	.0410414	.0052311	7.85	0.000	.0307883	.0512946
Instantbook	.0724977	.0054537	13.29	0.000	.0618082	.0831872
PriceTier_num						
economy	-.0082141	.0074852	-1.10	0.272	-.0228855	.0064572
luxury	-.114566	.008052	-14.23	0.000	-.1303484	-.0987836
midscale	-.0274901	.0076501	-3.59	0.000	-.0424846	-.0124955
upscale	-.0640784	.0076384	-8.39	0.000	-.0790501	-.0491067
Neighborhood_num						
Bloomsbury	-.0152078	.0202991	-0.75	0.454	-.054995	.0245795
Brixton	-.0576659	.0219245	-2.63	0.009	-.1006391	-.0146927
Bromley-by-bow	-.0491476	.029171	-1.68	0.092	-.1063243	.0080291
Camden	.038004	.0216427	1.76	0.079	-.0044169	.0804249
Chelsea	-.0668063	.0227303	-2.94	0.003	-.1113588	-.0222538
Chiswick	.0478433	.0286936	1.67	0.095	-.0083976	.1040842
City of London	-.0601058	.0282156	-2.13	0.033	-.1154099	-.0048017
Clerkenwell	-.0138977	.0240214	-0.58	0.563	-.0609808	.0331854
Covent Garden	.1187462	.0236088	5.03	0.000	.0724717	.1650208
Ealing	-.0339776	.0241391	-1.41	0.159	-.0812913	.0133362
Fulham	.0317882	.0235207	1.35	0.177	-.0143136	.0778899
Greenwich	-.1082155	.0212057	-5.10	0.000	-.1497797	-.0666513
Hackney	.0049963	.0206593	0.24	0.809	-.035497	.0454897
Hammersmith	-.0275132	.022992	-1.20	0.231	-.0725787	.0175523
Hampstead	-.0621386	.023346	-2.66	0.008	-.1078979	-.0163793
Haringey	-.0400917	.0211909	-1.89	0.059	-.081627	.0014436
Holloway	.0208774	.0246661	0.85	0.397	-.0274694	.0692242
Isle of Dogs	-.0606113	.0237344	-2.55	0.011	-.1071318	-.0140907
Islington	.0392724	.0210709	1.86	0.062	-.0020276	.0805724
Kensington	-.0221584	.0202603	-1.09	0.274	-.0618697	.0175528
Maida Vale	.0510975	.0268382	1.90	0.057	-.0015068	.1037018
Mayfair	-.025241	.0213428	-1.18	0.237	-.067074	.0165919
North Kensington	-.0221946	.0235211	-0.94	0.345	-.0682972	.023908
Paddington	-.0006585	.0205041	-0.03	0.974	-.0408476	.0395305
Peckham	-.0704795	.0228728	-3.08	0.002	-.1153114	-.0256476
Rotherhithe	.0167754	.0301124	0.56	0.577	-.0422465	.0757973
Southwark	-.0206158	.021474	-0.96	0.337	-.0627059	.0214744
St Johnss Wood	-.0917863	.0333651	-2.75	0.006	-.1571837	-.026389
Streatham and Dulwich	-.0648516	.0291268	-2.23	0.026	-.1219416	-.0077616
Sutton	-.0260189	.0383408	-0.68	0.497	-.1011688	.049131
Vauxhall	.0027921	.0234825	0.12	0.905	-.0432348	.048819
Waltham Forest	-.0607073	.0236616	-2.57	0.010	-.1070852	-.0143294
Wandsworth	.0043821	.0206831	0.21	0.832	-.036158	.0449221
Wembley	-.0926888	.031776	-2.92	0.004	-.1549714	-.0304062
Westminster	.0393859	.0228279	1.73	0.084	-.005358	.0841297
Whitechapel	-.0302594	.0207673	-1.46	0.145	-.0709644	.0104457
Willensden	-.0355531	.0229011	-1.55	0.121	-.0804405	.0093344
_cons	.2223032	.0225239	9.87	0.000	.1781553	.2664511

Results for Year: 2021

Regression 4 – Host Engagement vs Occupancy Rate (2021)

Source	SS	df	MS			
Model	304.926366	44	6.93014468	Number of obs	=	43,510
Residual	5786.17139	43,465	.133122544	F(44, 43465)	=	52.06
				Prob > F	=	0.0000
				R-squared	=	0.0501
				Adj R-squared	=	0.0491
Total	6091.09776	43,509	.139996271	Root MSE	=	.36486

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.058676	.0029092	20.17	0.000	.052974	.064378
AirbnbSuperhost	.0754573	.004054	18.61	0.000	.0675114	.0834033
Instantbook	.0257933	.0039728	6.49	0.000	.0180066	.03358
PriceTier_num						
economy	-.0350943	.0061958	-5.66	0.000	-.0472382	-.0229504
luxury	-.1716203	.006335	-27.09	0.000	-.1840371	-.1592035
midscale	-.0723776	.006093	-11.88	0.000	-.08432	-.0604352
upscale	-.0975874	.0061181	-15.95	0.000	-.109579	-.0855958
Neighborhood_num						
Bloomsbury	-.030008	.0153075	-1.96	0.050	-.0600109	-5.06e-06
Brixton	-.1223359	.0166735	-7.34	0.000	-.1550163	-.0896554
Bromley-by-bow	-.0669798	.0215246	-3.11	0.002	-.1091685	-.0247912
Camden	.0123902	.016081	0.77	0.441	-.0191289	.0439093
Chelsea	-.055937	.0169878	-3.29	0.001	-.0892334	-.0226407
Chiswick	-.0974422	.0215742	-4.52	0.000	-.1397281	-.0551564
City of London	-.0634434	.0204094	-3.11	0.002	-.1034463	-.0234405
Clerkenwell	-.0119191	.0183743	-0.65	0.517	-.0479331	.0240949
Covent Garden	.0654601	.0177742	3.68	0.000	.0306223	.1002978
Ealing	-.1528172	.0184062	-8.30	0.000	-.1888938	-.1167406
Fulham	-.0720485	.0176286	-4.09	0.000	-.1066008	-.0374961
Greenwich	-.1895169	.0162418	-11.67	0.000	-.2213511	-.1576826
Hackney	-.048107	.0154372	-3.12	0.002	-.0783643	-.0178498
Hammersmith	-.0506586	.017907	-2.83	0.005	-.0857567	-.0155604
Hampstead	-.0814434	.0180148	-4.52	0.000	-.1167528	-.046134
Haringey	-.0989433	.0158619	-6.24	0.000	-.130033	-.0678537
Holloway	-.0454347	.0193368	-2.35	0.019	-.0833353	-.0075342
Isle of Dogs	-.0810927	.0170365	-4.76	0.000	-.1144845	-.0477009
Islington	-.0029211	.0158802	-0.18	0.854	-.0340465	.0282044
Kensington	-.0306741	.0152461	-2.01	0.044	-.0605566	-.0007915
Maida Vale	-.1063277	.0205036	-5.19	0.000	-.1465152	-.0661402
Mayfair	-.0330425	.0159244	-2.07	0.038	-.0642545	-.0018304
North Kensington	-.035302	.0174523	-2.02	0.043	-.0695088	-.0010953
Paddington	-.0510847	.0151283	-3.38	0.001	-.0807365	-.021433
Peckham	-.1310701	.0179071	-7.32	0.000	-.1661684	-.0959718
Rotherhithe	-.0209732	.0221918	-0.95	0.345	-.0644695	.0225231
Southwark	-.0000962	.0162772	-0.01	0.995	-.0319998	.0318073
St Johnss Wood	-.0808171	.0250263	-3.23	0.001	-.1298692	-.0317651
Streatham and Dulwich	-.1913345	.0224045	-8.54	0.000	-.2352478	-.1474212
Sutton	-.2833181	.0302464	-9.37	0.000	-.3426015	-.2240347
Vauxhall	-.0090337	.0176347	-0.51	0.608	-.0435981	.0255306
Waltham Forest	-.1199897	.0179432	-6.69	0.000	-.1551588	-.0848206
Wandsworth	-.0739642	.015562	-4.75	0.000	-.104466	-.0434625
Wembley	-.1283064	.0237507	-5.40	0.000	-.1748583	-.0817546
Westminster	-.0523039	.0173237	-3.02	0.003	-.0862587	-.0183491
Whitechapel	-.0310679	.0158662	-1.96	0.050	-.0621658	.0000301
Willensden	-.0606557	.0174141	-3.48	0.000	-.0947876	-.0265239
_cons	.4970191	.0176168	28.21	0.000	.46249	.5315483

Results for Year: 2022

Regression 5 – Host Engagement vs Occupancy Rate (2022)

Source	SS	df	MS			
				Number of obs	=	82,576
				F(44, 82531)	=	144.07
Model	844.706465	44	19.1978742	Prob > F	=	0.0000
Residual	10997.2095	82,531	.133249439	R-squared	=	0.0713
				Adj R-squared	=	0.0708
Total	11841.9159	82,575	.143408004	Root MSE	=	.36503

OccupancyRate	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.0796759	.0022439	35.51	0.000	.0752778	.0840739
AirbnbSuperhost	.1015667	.0029772	34.11	0.000	.0957314	.1074019
Instantbook	.0448405	.0027589	16.25	0.000	.0394331	.0502478
PriceTier_num						
economy	-.0560007	.0046222	-12.12	0.000	-.0650601	-.0469413
luxury	-.2163935	.0048652	-44.48	0.000	-.2259293	-.2068577
midscale	-.1062949	.0045488	-23.37	0.000	-.1152106	-.0973792
upscale	-.1390651	.0046004	-30.23	0.000	-.1480818	-.1300484
Neighborhood_num						
Bloomsbury	-.0144187	.0110758	-1.30	0.193	-.0361272	.0072898
Brixton	-.0789067	.0120951	-6.52	0.000	-.102613	-.0552004
Bromley-by-bow	-.0743018	.014983	-4.96	0.000	-.1036683	-.0449353
Camden	-.006282	.0114532	-0.55	0.583	-.0287303	.0161662
Chelsea	-.0151061	.0121707	-1.24	0.215	-.0389605	.0087484
Chiswick	-.1385406	.016072	-8.62	0.000	-.1700416	-.1070397
City of London	.0430354	.0152769	2.82	0.005	.0130927	.072978
Clerkenwell	.0382423	.0128735	2.97	0.003	.0130103	.0634742
Covent Garden	.0681507	.0136886	4.98	0.000	.0413212	.0949801
Ealing	-.204541	.0129633	-15.78	0.000	-.2299489	-.179133
Fulham	-.0877438	.0127107	-6.90	0.000	-.1126566	-.062831
Greenwich	-.2022199	.0117853	-17.16	0.000	-.225319	-.1791207
Hackney	-.0473988	.0111686	-4.24	0.000	-.0692892	-.0255083
Hammersmith	-.054005	.0128464	-4.20	0.000	-.0791839	-.0288261
Hampstead	-.023024	.0132761	-1.73	0.083	-.0490451	.0029971
Haringey	-.0970756	.0115983	-8.37	0.000	-.1198082	-.0743431
Holloway	-.0462655	.0137361	-3.37	0.001	-.0731883	-.0193428
Isle of Dogs	-.0974769	.0120411	-8.10	0.000	-.1210773	-.0738764
Islington	-.000653	.0114625	-0.06	0.955	-.0231195	.0218134
Kensington	-.0016197	.011013	-0.15	0.883	-.023205	.0199656
Maida Vale	-.1000823	.0139188	-7.19	0.000	-.1273631	-.0728015
Mayfair	.0122387	.0113387	1.08	0.280	-.0099851	.0344625
North Kensington	-.0126108	.0129489	-0.97	0.330	-.0379905	.0127688
Paddington	-.0055282	.0109111	-0.51	0.612	-.0269139	.0158575
Peckham	-.1107213	.0132392	-8.36	0.000	-.13667	-.0847726
Rotherhithe	-.077193	.0157151	-4.91	0.000	-.1079945	-.0463915
Southwark	-.0036729	.0116187	-0.32	0.752	-.0264456	.0190997
St Johnss Wood	-.0380886	.0178246	-2.14	0.033	-.0730248	-.0031525
Streatham and Dulwich	-.1476823	.0153542	-9.62	0.000	-.1777763	-.1175882
Sutton	-.2761615	.0209497	-13.18	0.000	-.3172228	-.2351001
Vauxhall	-.0032551	.0124345	-0.26	0.793	-.0276266	.0211163
Waltham Forest	-.1269404	.013185	-9.63	0.000	-.1527829	-.1010978
Wandsworth	-.0798881	.0112081	-7.13	0.000	-.101856	-.0579202
Wembley	-.1854436	.0164379	-11.28	0.000	-.2176619	-.1532254
Westminster	-.0096424	.012625	-0.76	0.445	-.0343873	.0151025
Whitechapel	-.0118649	.0113171	-1.05	0.294	-.0340463	.0103165
Willensden	-.1079973	.0124017	-8.71	0.000	-.1323044	-.0836901
_cons	.3708015	.0131364	28.23	0.000	.3450543	.3965487

Results for Year: 2023

Regression 6 – Host Engagement vs Occupancy Rate (2023)

Source	SS	df	MS			
				Number of obs	=	23,316
				F(44, 23271)	=	79.65
Model	2.2823e+10	44	518702927	Prob > F	=	0.0000
Residual	1.5155e+11	23,271	6512390.6	R-squared	=	0.1309
				Adj R-squared	=	0.1292
Total	1.7437e+11	23,315	7478995.09	Root MSE	=	2551.9

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	181.2762	25.28843	7.17	0.000	131.7092	230.8432
AirbnbSuperhost	350.9783	39.73165	8.83	0.000	273.1017	428.855
Instantbook	373.8298	42.91614	8.71	0.000	289.7113	457.9482
PriceTier_num						
economy	110.3993	52.40229	2.11	0.035	7.687323	213.1112
luxury	984.2866	61.79163	15.93	0.000	863.1709	1105.402
midscale	277.3293	54.21579	5.12	0.000	171.0628	383.5959
upscale	459.0241	55.85277	8.22	0.000	349.549	568.4992
Neighborhood_num						
Bloomsbury	537.5064	121.6865	4.42	0.000	298.9928	776.0199
Brixton	-411.8288	125.8179	-3.27	0.001	-658.4402	-165.2174
Bromley-by-bow	-204.0814	184.0788	-1.11	0.268	-564.8879	156.7251
Camden	698.3469	134.5978	5.19	0.000	434.5263	962.1675
Chelsea	1280.204	135.1868	9.47	0.000	1015.229	1545.179
Chiswick	-303.5202	193.438	-1.57	0.117	-682.6714	75.63102
City of London	1511.5	236.8805	6.38	0.000	1047.199	1975.802
Clerkenwell	1200.867	151.2544	7.94	0.000	904.3981	1497.335
Covent Garden	2806.157	157.1891	17.85	0.000	2498.057	3114.258
Ealing	-457.8154	156.5439	-2.92	0.003	-764.6517	-150.9791
Fulham	139.1478	154.8023	0.90	0.369	-164.275	442.5705
Greenwich	-439.6159	129.9301	-3.38	0.001	-694.2874	-184.9443
Hackney	-156.0066	115.624	-1.35	0.177	-382.6373	70.62408
Hammersmith	329.8698	143.3011	2.30	0.021	48.99012	610.7495
Hampstead	283.3618	145.3568	1.95	0.051	-1.547168	568.2707
Hampstead	283.3618	145.3568	1.95	0.051	-1.547168	568.2707
Haringey	-605.4121	122.9954	-4.92	0.000	-846.4913	-364.3329
Holloway	-7.058136	155.0671	-0.05	0.964	-310.9998	296.8835
Isle of Dogs	-386.5415	161.3133	-2.40	0.017	-702.7263	-70.35678
Islington	318.7762	120.2872	2.65	0.008	83.00527	554.5471
Kensington	835.4171	126.5421	6.60	0.000	587.3862	1083.448
Maida Vale	560.9528	165.0015	3.40	0.001	237.539	884.3666
Mayfair	2204.723	141.9551	15.53	0.000	1926.482	2482.964
North Kensington	629.1127	148.673	4.23	0.000	337.7038	920.5215
Paddington	1611.517	131.4046	12.26	0.000	1353.955	1869.078
Peckham	8.494347	141.4388	0.06	0.952	-268.735	285.7237
Rotherhithe	-111.7368	178.9031	-0.62	0.532	-462.3986	238.9251
Southwark	848.066	129.4427	6.55	0.000	594.3497	1101.782
St Johnss Wood	1042.238	247.6061	4.21	0.000	556.9133	1527.562
Streatham and Dulwich	-610.8173	184.9753	-3.30	0.001	-973.381	-248.2536
Sutton	-891.9697	255.9061	-3.49	0.000	-1393.563	-390.3769
Vauxhall	790.0226	140.7481	5.61	0.000	514.1471	1065.898
Waltham Forest	-413.79	142.6827	-2.90	0.004	-693.4574	-134.1225
Wandsworth	-209.3134	120.2418	-1.74	0.082	-444.9952	26.36849
Wembley	-891.9622	252.4486	-3.53	0.000	-1386.778	-397.1464
Westminster	865.0906	153.1537	5.65	0.000	564.8994	1165.282
Whitechapel	223.0924	123.3046	1.81	0.070	-18.59266	464.7775
Willensden	2.042451	136.0942	0.02	0.988	-264.7111	268.796
_cons	588.7858	135.8592	4.33	0.000	322.4928	855.0789

Results for Year: 2018

Regression 7 – Host Engagement vs Revenue (2018)

Source	SS	df	MS			
Model	2.7369e+10	44	622017546	Number of obs	=	27,378
Residual	2.0959e+11	27,333	7667894.85	F(44, 27333)	=	81.12
				Prob > F	=	0.0000
				R-squared	=	0.1155
				Adj R-squared	=	0.1141
Total	2.3696e+11	27,377	8655270.55	Root MSE	=	2769.1

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	246.1555	25.72508	9.57	0.000	195.733	296.578
AirbnbSuperhost	445.7673	39.59779	11.26	0.000	368.1536	523.381
Instantbook	441.2427	41.89132	10.53	0.000	359.1336	523.3518
PriceTier_num						
economy	179.6665	53.3509	3.37	0.001	75.09605	284.237
luxury	1144.16	60.91732	18.78	0.000	1024.759	1263.562
midscale	278.4484	55.32116	5.03	0.000	170.0161	386.8807
upscale	492.1109	56.27277	8.75	0.000	381.8134	602.4084
Neighborhood_num						
Bloomsbury	673.5646	128.5875	5.24	0.000	421.5265	925.6027
Brixton	95.40087	134.9185	0.71	0.480	-169.0462	359.8479
Bromley-by-bow	-291.0934	187.8538	-1.55	0.121	-659.2964	77.10951
Camden	720.2904	139.5161	5.16	0.000	446.8318	993.749
Chelsea	1608.536	146.0227	11.02	0.000	1322.324	1894.748
Chiswick	-160.4579	191.8466	-0.84	0.403	-536.4869	215.5712
City of London	868.3313	229.8394	3.78	0.000	417.8344	1318.828
Clerkenwell	1043.465	159.525	6.54	0.000	730.7883	1356.142
Covent Garden	1828.077	164.9699	11.08	0.000	1504.727	2151.426
Ealing	44.35474	169.9516	0.26	0.794	-288.7591	377.4686
Fulham	219.2867	157.1021	1.40	0.163	-88.64139	527.2148
Greenwich	-373.8483	137.0001	-2.73	0.006	-642.3754	-105.3212
Hackney	-141.6797	127.0747	-1.11	0.265	-390.7525	107.3932
Hammersmith	272.9934	148.5098	1.84	0.066	-18.09328	564.08
Hampstead	410.9665	154.7821	2.66	0.008	107.5859	714.3472
Haringey	-401.1924	130.7671	-3.07	0.002	-657.5026	-144.8822
Holloway	291.3252	161.4991	1.80	0.071	-25.22135	607.8717
Isle of Dogs	4.877614	161.1683	0.03	0.976	-311.0205	320.7757
Islington	325.0527	126.3704	2.57	0.010	77.36023	572.7451
Kensington	1065.215	130.6406	8.15	0.000	809.153	1321.277
Maida Vale	504.6684	180.0157	2.80	0.005	151.8285	857.5083
Mayfair	2419.066	138.7774	17.43	0.000	2147.055	2691.076
North Kensington	708.5689	154.6158	4.58	0.000	405.514	1011.624
Paddington	1171.127	136.5283	8.58	0.000	903.5248	1438.73
Peckham	53.63431	148.3778	0.36	0.718	-237.1938	344.4624
Rotherhithe	155.1168	183.9388	0.84	0.399	-205.4126	515.6461
Southwark	738.5327	137.4982	5.37	0.000	469.0293	1008.036
St Johnss Wood	769.5995	253.6141	3.03	0.002	272.503	1266.696
Streatham and Dulwich	-323.0568	188.8705	-1.71	0.087	-693.2526	47.13909
Sutton	-1056.131	274.0832	-3.85	0.000	-1593.349	-518.9144
Vauxhall	1030.301	151.3645	6.81	0.000	733.6192	1326.983
Waltham Forest	-359.0065	152.0728	-2.36	0.018	-657.0768	-60.93616
Wandsworth	-76.94876	127.3763	-0.60	0.546	-326.6128	172.7152
Wembley	-706.7213	229.9923	-3.07	0.002	-1157.518	-255.9248
Westminster	1566.959	152.1211	10.30	0.000	1268.794	1865.125
Whitechapel	262.1328	129.6474	2.02	0.043	8.017303	516.2483
Willensden	132.1872	144.7718	0.91	0.361	-151.573	415.9473
_cons	313.2679	145.4171	2.15	0.031	28.24301	598.2928

Results for Year: 2019

Regression 8 – Host Engagement vs Revenue (2019)

Source	SS	df	MS
Model	4.4907e+09	44	102060372
Residual	8.6109e+10	23,851	3610279.38
Total	9.0599e+10	23,895	3791564.34

Number of obs	=	23,896
F(44, 23851)	=	28.27
Prob > F	=	0.0000
R-squared	=	0.0496
Adj R-squared	=	0.0478
Root MSE	=	1900.1

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	140.2861	18.6725	7.51	0.000	103.6869	176.8854
AirbnbSuperhost	141.6743	28.72844	4.93	0.000	85.36471	197.9839
Instantbook	319.8391	30.25232	10.57	0.000	260.5426	379.1355
PriceTier_num						
economy	154.2244	40.10639	3.85	0.000	75.61334	232.8355
luxury	573.4493	44.76565	12.81	0.000	485.7058	661.1928
midscale	233.2822	40.76018	5.72	0.000	153.3897	313.1747
upscale	336.8969	41.10562	8.20	0.000	256.3273	417.4665
Neighborhood_num						
Bloomsbury	225.798	98.06839	2.30	0.021	33.57772	418.0182
Brixton	-29.29878	106.923	-0.27	0.784	-238.8747	180.2772
Bromley-by-bow	-136.9549	151.0301	-0.91	0.365	-432.9835	159.0737
Camden	294.2565	106.3342	2.77	0.006	85.83476	502.6782
Chelsea	296.3837	111.4002	2.66	0.008	78.03238	514.7351
Chiswick	196.3125	148.427	1.32	0.186	-94.6139	487.2389
City of London	91.18243	172.2426	0.53	0.597	-246.424	428.7889
Clerkenwell	125.4467	121.3577	1.03	0.301	-112.4221	363.3154
Covent Garden	1130.849	122.8908	9.20	0.000	889.9752	1371.723
Ealing	14.75239	122.1533	0.12	0.904	-224.6759	254.1807
Fulham	273.2303	116.5128	2.35	0.019	44.85781	501.6028
Greenwich	-29.16806	105.5135	-0.28	0.782	-235.9812	177.645
Hackney	32.04545	100.9285	0.32	0.751	-165.7809	229.8718
Hammersmith	257.7828	113.7081	2.27	0.023	34.90773	480.6579
Hampstead	290.3686	117.2811	2.48	0.013	60.49028	520.2469
Haringey	-36.26727	103.812	-0.35	0.727	-239.7454	167.2109
Holloway	172.6057	123.6425	1.40	0.163	-69.74147	414.9529
Isle of Dogs	263.5137	118.6835	2.22	0.026	30.88646	496.1409
Islington	139.2359	101.072	1.38	0.168	-58.8716	337.3435
Kensington	357.3503	99.3231	3.60	0.000	162.6708	552.0299
Maida Vale	-6.603574	132.7036	-0.05	0.960	-266.711	253.5038
Mayfair	784.1861	106.9211	7.33	0.000	574.6139	993.7583
North Kensington	-6.134926	122.5968	-0.05	0.960	-246.4324	234.1625
Paddington	326.4282	101.5341	3.21	0.001	127.4149	525.4415
Peckham	298.4565	113.6465	2.63	0.009	75.70219	521.2107
Rotherhithe	-21.67106	142.1427	-0.15	0.879	-300.2797	256.9376
Southwark	447.1135	105.8764	4.22	0.000	239.5891	654.6379
St Johnss Wood	28.2496	187.2054	0.15	0.880	-338.6849	395.1841
Streatham and Dulwich	-113.149	144.7716	-0.78	0.434	-396.9106	170.6126
Sutton	-156.501	221.744	-0.71	0.480	-591.1333	278.1313
Vauxhall	535.1439	116.0876	4.61	0.000	307.6049	762.6829
Waltham Forest	-20.25111	119.2412	-0.17	0.865	-253.9714	213.4692
Wandsworth	-5.343384	100.0856	-0.05	0.957	-201.5174	190.8307
Wembley	-266.5507	163.6229	-1.63	0.103	-587.262	54.1606
Westminster	861.032	114.8208	7.50	0.000	635.9759	1086.088
Whitechapel	90.61438	100.9414	0.90	0.369	-107.2371	288.4658
Willensden	208.1478	113.7987	1.83	0.067	-14.90482	431.2004
_cons	-61.08001	112.0346	-0.55	0.586	-280.6749	158.5149

Results for Year: 2020

Regression 9 – Host Engagement vs Revenue (2020)

Source	SS	df	MS
Model	1.8915e+10	44	429885908
Residual	2.2453e+11	27,245	8241251.97
Total	2.4345e+11	27,289	8921099.7

Number of obs	=	27,290
F(44, 27245)	=	52.16
Prob > F	=	0.0000
R-squared	=	0.0777
Adj R-squared	=	0.0762
Root MSE	=	2870.8

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	257.355	26.94239	9.55	0.000	204.5465	310.1635
AirbnbSuperhost	83.49548	40.19808	2.08	0.038	4.705189	162.2858
Instantbook	568.4977	41.90888	13.57	0.000	486.3541	650.6412
PriceTier_num						
economy	336.835	57.51998	5.86	0.000	224.0929	449.5771
luxury	1566.439	61.87599	25.32	0.000	1445.159	1687.72
midscale	574.5618	58.78711	9.77	0.000	459.3361	689.7876
upscale	842.2235	58.69752	14.35	0.000	727.1734	957.2737
Neighborhood_num						
Bloomsbury	78.00569	155.9885	0.50	0.617	-227.7398	383.7512
Brixton	216.2592	168.4794	1.28	0.199	-113.969	546.4875
Bromley-by-bow	-69.65415	224.1652	-0.31	0.756	-509.0293	369.721
Camden	278.8825	166.3139	1.68	0.094	-47.10133	604.8663
Chelsea	468.7449	174.6712	2.68	0.007	126.3804	811.1094
Chiswick	248.1657	220.4965	1.13	0.260	-184.0186	680.35
City of London	-359.7431	216.8234	-1.66	0.097	-784.728	65.24187
Clerkenwell	424.4274	184.5927	2.30	0.021	62.6163	786.2384
Covent Garden	2024.641	181.4225	11.16	0.000	1669.043	2380.238
Ealing	217.119	185.4969	1.17	0.242	-146.4645	580.7024
Fulham	658.1947	180.7449	3.64	0.000	303.9255	1012.464
Greenwich	40.95112	162.9554	0.25	0.802	-278.4497	360.352
Hackney	290.1018	158.7569	1.83	0.068	-21.0699	601.2735
Hammersmith	159.261	176.6823	0.90	0.367	-187.0454	505.5674
Hampstead	343.5988	179.4024	1.92	0.055	-8.03903	695.2366
Haringey	244.2589	162.8419	1.50	0.134	-74.91949	563.4372
Holloway	765.5681	189.5468	4.04	0.000	394.0467	1137.089
Isle of Dogs	594.6237	182.387	3.26	0.001	237.1358	952.1116
Islington	203.5511	161.9196	1.26	0.209	-113.8197	520.9218
Kensington	217.7989	155.6906	1.40	0.162	-87.36267	522.9605
Maida Vale	244.1855	206.2387	1.18	0.236	-160.053	648.4239
Mayfair	1072.284	164.0089	6.54	0.000	750.8181	1393.75
North Kensington	420.1471	180.7484	2.32	0.020	65.87101	774.4231
Paddington	236.6107	157.5641	1.50	0.133	-72.22303	545.4444
Peckham	257.7939	175.7664	1.47	0.142	-86.71727	602.3051
Rotherhithe	290.9478	231.3993	1.26	0.209	-162.6067	744.5023
Southwark	304.3432	165.0174	1.84	0.065	-19.09944	627.7858
St Johnss Wood	71.39848	256.3949	0.28	0.781	-431.1486	573.9456
Streatham and Dulwich	230.7231	223.8254	1.03	0.303	-207.9861	669.4324
Sutton	-441.8577	294.6305	-1.50	0.134	-1019.349	135.6332
Vauxhall	200.0015	180.4517	1.11	0.268	-153.693	553.6961
Waltham Forest	40.98474	181.8277	0.23	0.822	-315.4069	397.3764
Wandsworth	615.4978	158.9399	3.87	0.000	303.9674	927.0282
Wembley	-242.7087	244.1832	-0.99	0.320	-721.3203	235.9028
Westminster	835.0214	175.4214	4.76	0.000	491.1865	1178.856
Whitechapel	63.02307	159.5868	0.39	0.693	-249.7752	375.8214
Willensden	688.9122	175.9842	3.91	0.000	343.9742	1033.85
_cons	-563.4404	173.085	-3.26	0.001	-902.6958	-224.185

Results for Year: 2021

Regression 10 – Host Engagement vs Revenue (2021)

Source	SS	df	MS
Model	2.1868e+11	44	4.9700e+09
Residual	1.2558e+12	82,531	15215552.6
Total	1.4744e+12	82,575	17855725.6

Number of obs	=	82,576
F(44, 82531)	=	326.64
Prob > F	=	0.0000
R-squared	=	0.1483
Adj R-squared	=	0.1479
Root MSE	=	3900.7

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	541.9955	23.97803	22.60	0.000	494.9987	588.9922
AirbnbSuperhost	571.7427	31.81402	17.97	0.000	509.3875	634.098
Instantbook	794.0403	29.4809	26.93	0.000	736.2579	851.8226
PriceTier_num						
economy	386.6756	49.39193	7.83	0.000	289.8678	483.4835
luxury	2283.498	51.98931	43.92	0.000	2181.599	2385.397
midscale	584.2353	48.60851	12.02	0.000	488.963	679.5077
upscale	980.3039	49.15891	19.94	0.000	883.9528	1076.655
Neighborhood_num						
Bloomsbury	557.2536	118.3551	4.71	0.000	325.2786	789.2287
Brixton	-64.72041	129.2469	-0.50	0.617	-318.0433	188.6025
Bromley-by-bow	-304.2193	160.1066	-1.90	0.057	-618.027	9.588419
Camden	556.2155	122.388	4.54	0.000	316.3359	796.0952
Chelsea	1869.512	130.0549	14.37	0.000	1614.606	2124.419
Chiswick	-329.7896	171.7437	-1.92	0.055	-666.406	6.826784
City of London	1345.946	163.2478	8.24	0.000	1025.981	1665.91
Clerkenwell	1375.382	137.565	10.00	0.000	1105.756	1645.009
Covent Garden	3626.568	146.2745	24.79	0.000	3339.871	3913.265
Ealing	-519.0143	138.5244	-3.75	0.000	-790.521	-247.5075
Fulham	493.5544	135.8248	3.63	0.000	227.3387	759.77
Greenwich	-413.9576	125.9366	-3.29	0.001	-660.7923	-167.1228
Hackney	-112.9881	119.3469	-0.95	0.344	-346.9071	120.931
Hammersmith	228.3924	137.2755	1.66	0.096	-40.6665	497.4513
Hampstead	500.9218	202.2258	2.48	0.013	104.5555	897.2882
Haringey	-38.0635	178.0582	-0.21	0.831	-387.0608	310.9338
Holloway	402.0208	217.0662	1.85	0.064	-23.43289	827.4746
Isle of Dogs	404.6898	191.2433	2.12	0.034	29.84926	779.5302
Islington	567.489	178.2634	3.18	0.001	218.0894	916.8887
Kensington	1152.629	171.145	6.73	0.000	817.1818	1488.076
Maida Vale	-75.46148	230.1642	-0.33	0.743	-526.5875	375.6646
Mayfair	2998.446	178.7594	16.77	0.000	2648.074	3348.818
North Kensington	1003.662	195.9109	5.12	0.000	619.6729	1387.651
Paddington	1087.877	169.8232	6.41	0.000	755.0206	1420.734
Peckham	-94.45642	201.017	-0.47	0.638	-488.4536	299.5407
Rotherhithe	459.5313	249.1142	1.84	0.065	-28.73719	947.7998
Southwark	875.1293	182.72	4.79	0.000	516.9947	1233.264
St Johnss Wood	581.106	280.9335	2.07	0.039	30.47108	1131.741
Streatham and Dulwich	-452.3449	251.5025	-1.80	0.072	-945.2944	40.6046
Sutton	-1242.568	339.5313	-3.66	0.000	-1908.056	-577.0809
Vauxhall	591.3977	197.9589	2.99	0.003	203.3947	979.4008
Waltham Forest	-413.8554	201.4224	-2.05	0.040	-808.6471	-19.06373
Wandsworth	258.6776	174.6913	1.48	0.139	-83.72069	601.0758
Wembley	-33.29735	266.6142	-0.12	0.901	-555.8662	489.2715
Westminster	1710.711	194.468	8.80	0.000	1329.551	2091.872
Whitechapel	364.6711	178.106	2.05	0.041	15.58013	713.7621
Willensden	355.1585	195.4819	1.82	0.069	-27.98969	738.3066
_cons	-273.8921	197.7573	-1.38	0.166	-661.5001	113.716

Results for Year: 2022

Regression 11 – Host Engagement vs Revenue (2022)

Source	SS	df	MS
Model	2.1868e+11	44	4.9700e+09
Residual	1.2558e+12	82,531	15215552.6
Total	1.4744e+12	82,575	17855725.6

Number of obs	=	82,576
F(44, 82531)	=	326.64
Prob > F	=	0.0000
R-squared	=	0.1483
Adj R-squared	=	0.1479
Root MSE	=	3900.7

RevenueUSD	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	541.9955	23.97803	22.60	0.000	494.9987	588.9922
AirbnbSuperhost	571.7427	31.81402	17.97	0.000	509.3875	634.098
Instantbook	794.0403	29.4809	26.93	0.000	736.2579	851.8226
PriceTier_num						
economy	386.6756	49.39193	7.83	0.000	289.8678	483.4835
luxury	2283.498	51.98931	43.92	0.000	2181.599	2385.397
midscale	584.2353	48.60851	12.02	0.000	488.963	679.5077
upscale	980.3039	49.15891	19.94	0.000	883.9528	1076.655
Neighborhood_num						
Bloomsbury	557.2536	118.3551	4.71	0.000	325.2786	789.2287
Brixton	-64.72041	129.2469	-0.50	0.617	-318.0433	188.6025
Bromley-by-bow	-304.2193	160.1066	-1.90	0.057	-618.027	9.588419
Camden	556.2155	122.388	4.54	0.000	316.3359	796.0952
Chelsea	1869.512	130.0549	14.37	0.000	1614.606	2124.419
Chiswick	-329.7896	171.7437	-1.92	0.055	-666.406	6.826784
City of London	1345.946	163.2478	8.24	0.000	1025.981	1665.91
Clerkenwell	1375.382	137.565	10.00	0.000	1105.756	1645.009
Covent Garden	3626.568	146.2745	24.79	0.000	3339.871	3913.265
Ealing	-519.0143	138.5244	-3.75	0.000	-790.521	-247.5075
Fulham	493.5544	135.8248	3.63	0.000	227.3387	759.77
Greenwich	-413.9576	125.9366	-3.29	0.001	-660.7923	-167.1228
Hackney	-112.9881	119.3469	-0.95	0.344	-346.9071	120.931
Hammersmith	228.3924	137.2755	1.66	0.096	-40.6665	497.4513
Hampstead	323.3729	141.8673	2.28	0.023	45.31398	601.4318
Haringey	-243.117	123.9384	-1.96	0.050	-486.0353	-.1987096
Holloway	164.8101	146.783	1.12	0.262	-122.8835	452.5036
Isle of Dogs	-110.0364	128.6701	-0.86	0.392	-362.2289	142.1561
Islington	298.6382	122.4874	2.44	0.015	58.56381	538.7125
Kensington	1318.067	117.6834	11.20	0.000	1087.408	1548.725
Maida Vale	57.11689	148.7351	0.38	0.701	-234.4029	348.6367
Mayfair	2650.188	121.1643	21.87	0.000	2412.707	2887.669
North Kensington	930.5146	138.3702	6.72	0.000	659.31	1201.719
Paddington	1258.956	116.5951	10.80	0.000	1030.431	1487.482
Peckham	-143.3037	141.4725	-1.01	0.311	-420.5888	133.9814
Rotherhithe	-19.86509	167.93	-0.12	0.906	-349.0067	309.2765
Southwark	609.5331	124.1567	4.91	0.000	366.187	852.8793
St Johnss Wood	836.0965	190.4722	4.39	0.000	462.7724	1209.421
Streatham and Dulwich	-568.3715	164.0731	-3.46	0.001	-889.9535	-246.7894
Sutton	-1195.344	223.8668	-5.34	0.000	-1634.122	-756.567
Vauxhall	587.0737	132.8734	4.42	0.000	326.6428	847.5045
Waltham Forest	-386.8414	140.8937	-2.75	0.006	-662.992	-110.6908
Wandsworth	73.46583	119.7692	0.61	0.540	-161.2809	308.2125
Wembley	-441.8177	175.6541	-2.52	0.012	-786.0985	-97.53697
Westminster	1788.904	134.9096	13.26	0.000	1524.482	2053.326
Whitechapel	187.6577	120.9331	1.55	0.121	-49.37035	424.6857
Willensden	-201.2279	132.5229	-1.52	0.129	-460.9719	58.51603
_cons	-868.448	140.374	-6.19	0.000	-1143.58	-593.316

Results for Year: 2023

Regression 12 – Host Engagement vs Revenue (2023)

Source	SS	df	MS			
				Number of obs	=	23,316
				F(44, 23271)	=	45.63
Model	21655.4184	44	492.168599	Prob > F	=	0.0000
Residual	250989.578	23,271	10.7855089	R-squared	=	0.0794
				Adj R-squared	=	0.0777
Total	272644.997	23,315	11.6939737	Root MSE	=	3.2841

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.2280664	.0325441	7.01	0.000	.1642779	.291855
AirbnbSuperhost	.6872802	.0511313	13.44	0.000	.5870595	.7875009
Instantbook	1.0698	.0552295	19.37	0.000	.9615467	1.178053
PriceTier_num						
economy	-.1687509	.0674373	-2.50	0.012	-.3009325	-.0365693
luxury	-1.062806	.0795206	-13.37	0.000	-1.218672	-.9069407
midscale	-.0750719	.0697711	-1.08	0.282	-.211828	.0616841
upscale	-.3351774	.0718778	-4.66	0.000	-.4760626	-.1942921
Neighborhood_num						
Bloomsbury	-.1922073	.1566003	-1.23	0.220	-.4991542	.1147396
Brixton	-.8994842	.161917	-5.56	0.000	-1.216852	-.5821161
Bromley-by-bow	-.6484894	.2368938	-2.74	0.006	-1.112817	-.1841619
Camden	1.696359	.173216	9.79	0.000	1.356844	2.035874
Chelsea	-.3268694	.173974	-1.88	0.060	-.6678699	.014131
Chiswick	.4106664	.2489384	1.65	0.099	-.0772693	.898602
City of London	.8610401	.3048453	2.82	0.005	.2635233	1.458557
Clerkenwell	.9035792	.1946517	4.64	0.000	.522049	1.285109
Covent Garden	1.869031	.2022891	9.24	0.000	1.472531	2.26553
Ealing	-.3118726	.2014588	-1.55	0.122	-.7067451	.0829998
Fulham	-.8543138	.1992175	-4.29	0.000	-1.244793	-.4638343
Greenwich	-.8513097	.1672091	-5.09	0.000	-1.179051	-.5235689
Hackney	-.8755108	.1487984	-5.88	0.000	-1.167165	-.5838562
Hammersmith	-.3282534	.1844165	-1.78	0.075	-.6897218	.0332151
Hampstead	-.203615	.187062	-1.09	0.276	-.5702688	.1630388
Haringey	-.6791542	.1582848	-4.29	0.000	-.9894027	-.3689056
Holloway	-.66661	.1995582	-3.34	0.001	-1.057757	-.2754627
Isle of Dogs	.2263487	.2075967	1.09	0.276	-.1805545	.6332518
Islington	.0853143	.1547995	0.55	0.582	-.2181031	.3887316
Kensington	-.0505194	.162849	-0.31	0.756	-.3697143	.2686754
Maida Vale	-.0527146	.212343	-0.25	0.804	-.4689209	.3634917
Mayfair	.3334797	.1826843	1.83	0.068	-.0245935	.6915528
North Kensington	-.25305	.1913296	-1.32	0.186	-.6280686	.1219686
Paddington	.5703904	.1691067	3.37	0.001	.2389302	.9018506
Peckham	-.3512142	.1820198	-1.93	0.054	-.7079851	.0055566
Rotherhithe	.6065832	.2302332	2.63	0.008	.1553109	1.057855
Southwark	.8397293	.1665819	5.04	0.000	.5132179	1.166241
St Johnss Wood	-.3898701	.3186482	-1.22	0.221	-1.014442	.2347013
Streatham and Dulwich	-1.215499	.2380476	-5.11	0.000	-1.682088	-.7489097
Sutton	-1.090432	.3293296	-3.31	0.001	-1.73594	-.4449242
Vauxhall	1.289473	.1811309	7.12	0.000	.9344444	1.644501
Waltham Forest	-1.166276	.1836206	-6.35	0.000	-1.526185	-.806368
Wandsworth	-.5473105	.1547411	-3.54	0.000	-.8506132	-.2440079
Wembley	.3672575	.32488	1.13	0.258	-.2695288	1.004044
Westminster	1.722961	.1970958	8.74	0.000	1.33664	2.109282
Whitechapel	.8408794	.1586826	5.30	0.000	.5298511	1.151908
Willensden	-.5886545	.1751417	-3.36	0.001	-.9319438	-.2453651
_cons	2.585954	.1748394	14.79	0.000	2.243257	2.928651

Results for Year: 2018

Regression 13 – Host Engagement vs Number of Reservations (2018)

Source	SS	df	MS			
				Number of obs	=	27,378
				F(44, 27333)	=	51.18
Model	26427.3389	44	600.621339	Prob > F	=	0.0000
Residual	320743.883	27,333	11.7346754	R-squared	=	0.0761
				Adj R-squared	=	0.0746
Total	347171.222	27,377	12.6811273	Root MSE	=	3.4256

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.3404567	.031824	10.70	0.000	.2780801	.4028333
AirbnbSuperhost	.7702014	.0489856	15.72	0.000	.6741871	.8662156
Instantbook	1.264986	.0518229	24.41	0.000	1.16341	1.366561
PriceTier_num						
economy	-.1495854	.0659993	-2.27	0.023	-.2789473	-.0202235
luxury	-.8866536	.0753595	-11.77	0.000	-1.034362	-.738945
midscale	.0343958	.0684366	0.50	0.615	-.0997435	.1685351
upscale	-.2829704	.0696139	-4.06	0.000	-.4194171	-.1465237
Neighborhood_num						
Bloomsbury	.2862325	.159073	1.80	0.072	-.0255586	.5980235
Brixton	-.1780475	.1669048	-1.07	0.286	-.5051894	.1490944
Bromley-by-bow	-.4613811	.23239	-1.99	0.047	-.9168773	-.005885
Camden	1.388362	.1725924	8.04	0.000	1.050072	1.726652
Chelsea	-.233293	.1806417	-1.29	0.197	-.5873598	.1207739
Chiswick	1.07242	.2373294	4.52	0.000	.6072419	1.537597
City of London	.3707604	.2843295	1.30	0.192	-.1865398	.9280607
Clerkenwell	.9225059	.197345	4.67	0.000	.5356997	1.309312
Covent Garden	1.332185	.2040808	6.53	0.000	.9321762	1.732194
Ealing	-.0691864	.2102436	-0.33	0.742	-.4812746	.3429017
Fulham	-1.145593	.1943477	-5.89	0.000	-1.526524	-.7646613
Greenwich	-.6235501	.1694799	-3.68	0.000	-.9557393	-.2913609
Hackney	-.906371	.1572014	-5.77	0.000	-1.214494	-.5982482
Hammersmith	-.3352418	.1837183	-1.82	0.068	-.695339	.0248554
Hampstead	.1883969	.1914776	0.98	0.325	-.186909	.5637028
Haringey	-.4438264	.1617693	-2.74	0.006	-.7609024	-.1267504
Holloway	-.0400359	.1997872	-0.20	0.841	-.431629	.3515572
Isle of Dogs	-.0889728	.199378	-0.45	0.655	-.4797637	.3018181
Islington	.2070939	.1563302	1.32	0.185	-.0993213	.5135091
Kensington	.2785667	.1616127	1.72	0.085	-.0382024	.5953358
Maida Vale	-.2406424	.2226936	-1.08	0.280	-.6771333	.1958484
Mayfair	.2176209	.1716786	1.27	0.205	-.1188778	.5541196
North Kensington	-.4987625	.191272	-2.61	0.009	-.8736654	-.1238597
Paddington	.3701867	.1688964	2.19	0.028	.0391413	.7012321
Peckham	-.6486762	.1835551	-3.53	0.000	-1.008454	-.2888988
Rotherhithe	.5564818	.2275468	2.45	0.014	.1104785	1.002485
Southwark	.6415159	.1700961	3.77	0.000	.3081188	.9749129
St Johnss Wood	.5489385	.3137407	1.75	0.080	-.0660091	1.163886
Streatham and Dulwich	-1.256294	.2336478	-5.38	0.000	-1.714255	-.798332
Sutton	-1.024492	.3390626	-3.02	0.003	-1.689072	-.3599118
Vauxhall	1.390807	.1872499	7.43	0.000	1.023788	1.757827
Waltham Forest	-.8340229	.188126	-4.43	0.000	-1.202759	-.4652864
Wandsworth	-.4409372	.1575745	-2.80	0.005	-.7497913	-.1320831
Wembley	.0914391	.2845186	0.32	0.748	-.4662319	.64911
Westminster	1.753574	.1881858	9.32	0.000	1.38472	2.122428
Whitechapel	.9557102	.1603841	5.96	0.000	.6413492	1.270071
Willensden	-.2354031	.1790942	-1.31	0.189	-.5864368	.1156306
_cons	2.372393	.1798924	13.19	0.000	2.019795	2.724991

Results for Year: 2019

Regression 14 – Host Engagement vs Number of Reservations (2019)

Source	SS	df	MS			
				Number of obs	=	23,896
				F(44, 23851)	=	22.88
Model	6753.24834	44	153.482917	Prob > F	=	0.0000
Residual	159988.788	23,851	6.70784402	R-squared	=	0.0405
				Adj R-squared	=	0.0387
Total	166742.036	23,895	6.97811409	Root MSE	=	2.59

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.2443997	.0254521	9.60	0.000	.194512	.2942874
AirbnbSuperhost	.1328131	.0391591	3.39	0.001	.0560587	.2095675
Instantbook	.8099566	.0412363	19.64	0.000	.7291308	.8907823
PriceTier_num						
economy	-.0835887	.0546682	-1.53	0.126	-.1907418	.0235644
luxury	-.483299	.0610191	-7.92	0.000	-.6029003	-.3636976
midscale	-.0382038	.0555593	-0.69	0.492	-.1471036	.0706961
upscale	-.208567	.0560302	-3.72	0.000	-.3183898	-.0987442
Neighborhood_num						
Bloomsbury	-.0060887	.133675	-0.05	0.964	-.2681001	.2559227
Brixton	-.335245	.1457446	-2.30	0.021	-.6209136	-.0495764
Bromley-by-bow	-.7339819	.205866	-3.57	0.000	-1.137492	-.3304714
Camden	.4230109	.1449419	2.92	0.004	.1389156	.7071062
Chelsea	-.6198556	.1518472	-4.08	0.000	-.9174858	-.3222254
Chiswick	.5125342	.2023178	2.53	0.011	.1159785	.9090899
City of London	-.1609916	.2347803	-0.69	0.493	-.6211759	.2991927
Clerkenwell	.1725998	.1654201	1.04	0.297	-.1516341	.4968337
Covent Garden	.8658801	.1675099	5.17	0.000	.53755	1.19421
Ealing	-.3975608	.1665047	-2.39	0.017	-.7239206	-.0712011
Fulham	-.3923609	.1588162	-2.47	0.013	-.7036506	-.0810711
Greenwich	-.4058674	.1438232	-2.82	0.005	-.68777	-.1239648
Hackney	-.5980596	.1375736	-4.35	0.000	-.8677126	-.3284067
Hammersmith	-.3990001	.1549931	-2.57	0.010	-.7027965	-.0952037
Hampstead	-.5296278	.1598634	-3.31	0.001	-.8429701	-.2162855
Haringey	-.3399891	.141504	-2.40	0.016	-.617346	-.0626323
Holloway	-.2656049	.1685346	-1.58	0.115	-.5959433	.0647336
Isle of Dogs	-.4549902	.161775	-2.81	0.005	-.7720795	-.1379009
Islington	-.0837374	.1377691	-0.61	0.543	-.3537736	.1862989
Kensington	-.0509471	.1353852	-0.38	0.707	-.3163107	.2144166
Maida Vale	-.6422138	.1808854	-3.55	0.000	-.9967608	-.2876668
Mayfair	-.2839079	.145742	-1.95	0.051	-.5695714	.0017556
North Kensington	-.5910791	.1671091	-3.54	0.000	-.9186235	-.2635346
Paddington	-.041234	.1383991	-0.30	0.766	-.3125049	.2300369
Peckham	-.3948333	.1549091	-2.55	0.011	-.698465	-.0912016
Rotherhithe	-.4551124	.1937517	-2.35	0.019	-.8348781	-.0753468
Southwark	-.0443173	.1443179	-0.31	0.759	-.3271895	.2385549
St Johnss Wood	-.450186	.2551758	-1.76	0.078	-.9503468	.0499747
Streatham and Dulwich	-.6664079	.1973352	-3.38	0.001	-1.053197	-.2796184
Sutton	-.3335487	.3022546	-1.10	0.270	-.9259869	.2588894
Vauxhall	.2018213	.1582365	1.28	0.202	-.1083324	.5119749
Waltham Forest	-.4312216	.1625352	-2.65	0.008	-.7498008	-.1126424
Wandsworth	-.5446623	.1364245	-3.99	0.000	-.8120631	-.2772615
Wembley	-.557932	.223031	-2.50	0.012	-.9950869	-.1207771
Westminster	.4740052	.1565098	3.03	0.002	.167236	.7807744
Whitechapel	.1299185	.137591	0.94	0.345	-.1397687	.3996057
Willensden	-.3623085	.1551166	-2.34	0.020	-.6663468	-.0582701
_cons	1.165948	.152712	7.63	0.000	.8666231	1.465273

Results for Year: 2020

Regression 15 – Host Engagement vs Number of Reservations (2020)

Source	SS	df	MS			
Model	14530.7031	44	330.243253	Number of obs	=	27,290
Residual	251797.729	27,245	9.24197941	F(44, 27245)	=	35.73
				Prob > F	=	0.0000
Total	266328.432	27,289	9.75955265	R-squared	=	0.0546
				Adj R-squared	=	0.0530
				Root MSE	=	3.0401

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.3364824	.0285313	11.79	0.000	.2805596	.3924053
AirbnbSuperhost	.0759631	.0425688	1.78	0.074	-.0074739	.1594
Instantbook	1.101383	.0443805	24.82	0.000	1.014395	1.188371
PriceTier_num						
economy	-.0362817	.0609122	-0.60	0.551	-.1556729	.0831094
luxury	-.0028219	.0655252	-0.04	0.966	-.1312545	.1256108
midscale	.127713	.0622541	2.05	0.040	.0056917	.2497342
upscale	-.0301925	.0621592	-0.49	0.627	-.1520278	.0916428
Neighborhood_num						
Bloomsbury	.0953207	.165188	0.58	0.564	-.2284562	.4190977
Brixton	-.0880968	.1784156	-0.49	0.621	-.4378004	.2616068
Bromley-by-bow	-.4002209	.2373854	-1.69	0.092	-.8655084	.0650666
Camden	.3459772	.1761224	1.96	0.049	.0007684	.6911861
Chelsea	-.570033	.1849725	-3.08	0.002	-.9325885	-.2074774
Chiswick	.4238938	.2335003	1.82	0.069	-.0337788	.8815664
City of London	-.4615602	.2296107	-2.01	0.044	-.9116088	-.0115115
Clerkenwell	.4591224	.1954791	2.35	0.019	.0759734	.8422715
Covent Garden	1.923649	.192122	10.01	0.000	1.54708	2.300218
Ealing	-.0973715	.1964367	-0.50	0.620	-.4823974	.2876545
Fulham	-.1507697	.1914044	-0.79	0.431	-.5259321	.2243928
Greenwich	-.4935164	.1725657	-2.86	0.004	-.831754	-.1552788
Hackney	-.3015146	.1681197	-1.79	0.073	-.6310378	.0280086
Hammersmith	-.4208993	.1871023	-2.25	0.024	-.7876292	-.0541693
Hampstead	-.201404	.1899827	-1.06	0.289	-.5737798	.1709718
Haringey	-.0312435	.1724455	-0.18	0.856	-.3692455	.3067586
Holloway	.3630876	.2007254	1.81	0.070	-.0303444	.7565196
Isle of Dogs	-.1391543	.1931434	-0.72	0.471	-.5177253	.2394166
Islington	.1493837	.1714689	0.87	0.384	-.1867042	.4854715
Kensington	-.2447337	.1648726	-1.48	0.138	-.5678923	.078425
Maida Vale	-.4218424	.2184018	-1.93	0.053	-.849921	.0062362
Mayfair	-.2182568	.1736814	-1.26	0.209	-.5586811	.1221675
North Kensington	-.3365285	.1914081	-1.76	0.079	-.7116981	.0386411
Paddington	.1895909	.1668565	1.14	0.256	-.1374564	.5166383
Peckham	-.5252023	.1861324	-2.82	0.005	-.8900312	-.1603734
Rotherhithe	.4707003	.2450462	1.92	0.055	-.0096027	.9510034
Southwark	-.0931923	.1747494	-0.53	0.594	-.4357101	.2493255
St Johnss Wood	-.6190396	.2715159	-2.28	0.023	-1.151225	-.0868546
Streatham and Dulwich	-.2691962	.2370256	-1.14	0.256	-.7337785	.1953862
Sutton	-.8752356	.3120065	-2.81	0.005	-1.486784	-.263687
Vauxhall	.0273743	.1910939	0.14	0.886	-.3471796	.4019281
Waltham Forest	-.4819294	.1925511	-2.50	0.012	-.8593394	-.1045194
Wandsworth	-.0812863	.1683135	-0.48	0.629	-.4111893	.2486167
Wembley	-.5523092	.258584	-2.14	0.033	-1.059147	-.0454713
Westminster	.59381	.185767	3.20	0.001	.2296972	.9579227
Whitechapel	.0031586	.1689985	0.02	0.985	-.3280871	.3344043
Willensden	.0042861	.186363	0.02	0.982	-.3609949	.369567
_cons	.9563297	.1832927	5.22	0.000	.5970665	1.315593

Results for Year: 2021

Regression 16 – Host Engagement vs Number of Reservations (2021)

Source	SS	df	MS			
				Number of obs	=	43,510
				F(44, 43465)	=	71.97
Model	42526.7871	44	966.517888	Prob > F	=	0.0000
Residual	583699.092	43,465	13.429175	R-squared	=	0.0679
				Adj R-squared	=	0.0670
Total	626225.879	43,509	14.3930194	Root MSE	=	3.6646

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	.460669	.0292191	15.77	0.000	.403399	.517939
AirbnbSuperhost	.2716151	.0407179	6.67	0.000	.1918073	.3514229
Instantbook	1.441165	.0399017	36.12	0.000	1.362957	1.519373
PriceTier_num						
economy	-.1942938	.0622298	-3.12	0.002	-.3162654	-.0723222
luxury	-.4811856	.0636279	-7.56	0.000	-.6058975	-.3564737
midscale	-.2661265	.061197	-4.35	0.000	-.3860737	-.1461792
upscale	-.2250432	.0614492	-3.66	0.000	-.3454848	-.1046017
Neighborhood_num						
Bloomsbury	1.126939	.1537455	7.33	0.000	.8255945	1.428283
Brixton	-.374794	.1674659	-2.24	0.025	-.7030302	-.0465577
Bromley-by-bow	-.4215667	.2161893	-1.95	0.051	-.8453017	.0021684
Camden	.7167167	.1615148	4.44	0.000	.4001447	1.033289
Chelsea	-.7300068	.1706222	-4.28	0.000	-1.064429	-.3955841
Chiswick	-.0575604	.2166875	-0.27	0.791	-.4822719	.367151
City of London	-.4256478	.2049886	-2.08	0.038	-.8274293	-.0238663
Clerkenwell	.34393	.1845484	1.86	0.062	-.0177883	.7056483
Covent Garden	1.475948	.1785208	8.27	0.000	1.126044	1.825852
Ealing	-.4579586	.184869	-2.48	0.013	-.8203054	-.0956119
Fulham	-.4423998	.1770585	-2.50	0.012	-.7894379	-.0953618
Greenwich	-.7496302	.1631299	-4.60	0.000	-1.069368	-.4298926
Hackney	-.5034541	.1550487	-3.25	0.001	-.8073525	-.1995557
Hammersmith	-.1414067	.179855	-0.79	0.432	-.4939259	.2111125
Hampstead	-.2086049	.1809376	-1.15	0.249	-.563246	.1460361
Haringey	-.0552376	.1593141	-0.35	0.729	-.3674961	.2570209
Holloway	.351932	.1942157	1.81	0.070	-.0287344	.7325984
Isle of Dogs	-.3081159	.1711112	-1.80	0.072	-.6434971	.0272653
Islington	.5275413	.1594977	3.31	0.001	.2149228	.8401598
Kensington	-.0777831	.1531286	-0.51	0.611	-.377918	.2223519
Maida Vale	-.6693107	.2059349	-3.25	0.001	-1.072947	-.2656745
Mayfair	.0302851	.1599415	0.19	0.850	-.2832032	.3437734
North Kensington	-.1736113	.1752874	-0.99	0.322	-.517178	.1699553
Paddington	.5954183	.151946	3.92	0.000	.2976014	.8932352
Peckham	-.8204397	.1798561	-4.56	0.000	-1.172961	-.4679185
Rotherhithe	.7009092	.2228901	3.14	0.002	.2640405	1.137778
Southwark	.591203	.1634851	3.62	0.000	.270769	.9116369
St Johnss Wood	-.5382013	.2513597	-2.14	0.032	-1.030871	-.0455315
Streatham and Dulwich	-1.062764	.2250269	-4.72	0.000	-1.503821	-.6217072
Sutton	-2.200181	.3037889	-7.24	0.000	-2.795613	-1.604749
Vauxhall	.2270195	.1771198	1.28	0.200	-.1201387	.5741776
Waltham Forest	-.7114208	.1802187	-3.95	0.000	-1.064653	-.3581887
Wandsworth	-.477275	.1563016	-3.05	0.002	-.7836291	-.1709208
Wembley	.4042002	.2385479	1.69	0.090	-.0633581	.8717584
Westminster	.4883671	.1739964	2.81	0.005	.1473309	.8294032
Whitechapel	.4551354	.1593568	2.86	0.004	.142793	.7674777
Willensden	-.0473596	.1749036	-0.27	0.787	-.3901739	.2954547
_cons	2.0377	.1769395	11.52	0.000	1.690895	2.384505

Results for Year: 2022

Regression 17 – Host Engagement vs Number of Reservations (2022)

Source	SS	df	MS			
Model	**74240.2537**	**44**	**1687.27849**	Number of obs	=	**82,576**
Residual	**957790.144**	**82,531**	**11.6052168**	F(44, 82531)	=	**145.39**
				Prob > F	=	**0.0000**
Total	**1032030.4**	**82,575**	**12.4980975**	R-squared	=	**0.0719**
				Adj R-squared	=	**0.0714**
				Root MSE	=	**3.4066**

NumberofReservations	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ResponseRateCategory	**.5240155**	**.0209409**	**25.02**	**0.000**	**.4829714**	**.5650596**
AirbnbSuperhost	**.5220797**	**.0277844**	**18.79**	**0.000**	**.4676224**	**.5765369**
Instantbook	**1.286309**	**.0257468**	**49.96**	**0.000**	**1.235845**	**1.336772**
PriceTier_num						
economy	**-.2242934**	**.0431359**	**-5.20**	**0.000**	**-.3088394**	**-.1397473**
luxury	**-.7898482**	**.0454043**	**-17.40**	**0.000**	**-.8788402**	**-.7008561**
midscale	**-.4216459**	**.0424517**	**-9.93**	**0.000**	**-.504851**	**-.3384409**
upscale	**-.4612854**	**.0429324**	**-10.74**	**0.000**	**-.5454325**	**-.3771382**
Neighborhood_num						
Bloomsbury	**.7453822**	**.1033641**	**7.21**	**0.000**	**.5427894**	**.947975**
Brixton	**-.425899**	**.1128763**	**-3.77**	**0.000**	**-.6471357**	**-.2046623**
Bromley-by-bow	**-.3439114**	**.1398273**	**-2.46**	**0.014**	**-.6179719**	**-.069851**
Camden	**.6081213**	**.1068862**	**5.69**	**0.000**	**.398625**	**.8176175**
Chelsea	**-.7078681**	**.113582**	**-6.23**	**0.000**	**-.9304879**	**-.4852483**
Chiswick	**-.4887437**	**.1499904**	**-3.26**	**0.001**	**-.7827238**	**-.1947635**
City of London	**.1900068**	**.1425706**	**1.33**	**0.183**	**-.0894306**	**.4694441**
Clerkenwell	**.478425**	**.1201408**	**3.98**	**0.000**	**.2429498**	**.7139001**
Covent Garden	**.6161612**	**.1277472**	**4.82**	**0.000**	**.3657776**	**.8665449**
Ealing	**-1.311365**	**.1209787**	**-10.84**	**0.000**	**-1.548482**	**-1.074248**
Fulham	**-.769917**	**.1186211**	**-6.49**	**0.000**	**-1.002413**	**-.5374205**
Greenwich	**-1.052434**	**.1099853**	**-9.57**	**0.000**	**-1.268005**	**-.8368638**
Hackney	**-.6452336**	**.1042303**	**-6.19**	**0.000**	**-.8495242**	**-.4409429**
Hammersmith	**-.2763424**	**.119888**	**-2.31**	**0.021**	**-.511322**	**-.0413628**
Hampstead	**-.2127639**	**.1238982**	**-1.72**	**0.086**	**-.4556035**	**.0300758**
Haringey	**-.2296159**	**.1082402**	**-2.12**	**0.034**	**-.4417659**	**-.017466**
Holloway	**-.0694193**	**.1281913**	**-0.54**	**0.588**	**-.3206733**	**.1818346**
Isle of Dogs	**-.5394735**	**.1123726**	**-4.80**	**0.000**	**-.759723**	**-.319224**
Islington	**.0145245**	**.106973**	**0.14**	**0.892**	**-.1951417**	**.2241907**
Kensington	**-.2709253**	**.1027775**	**-2.64**	**0.008**	**-.4723684**	**-.0694822**
Maida Vale	**-.7401142**	**.1298962**	**-5.70**	**0.000**	**-.9947097**	**-.4855187**
Mayfair	**-.0404116**	**.1058175**	**-0.38**	**0.703**	**-.2478131**	**.1669899**
North Kensington	**-.2910983**	**.1208441**	**-2.41**	**0.016**	**-.5279517**	**-.0542448**
Paddington	**.5237837**	**.101827**	**5.14**	**0.000**	**.3242035**	**.7233639**
Peckham	**-.8525722**	**.1235534**	**-6.90**	**0.000**	**-1.094736**	**-.6104083**
Rotherhithe	**-.1194025**	**.1466598**	**-0.81**	**0.416**	**-.4068546**	**.1680497**
Southwark	**.6311049**	**.1084308**	**5.82**	**0.000**	**.4185813**	**.8436285**
St Johnss Wood	**.1668564**	**.1663468**	**1.00**	**0.316**	**-.159182**	**.4928948**
Streatham and Dulwich	**-1.079725**	**.1432914**	**-7.54**	**0.000**	**-1.360575**	**-.7988753**
Sutton	**-2.063687**	**.1955116**	**-10.56**	**0.000**	**-2.446889**	**-1.680486**
Vauxhall	**.0169995**	**.1160435**	**0.15**	**0.884**	**-.2104449**	**.2444439**
Waltham Forest	**-.9784786**	**.1230479**	**-7.95**	**0.000**	**-1.219652**	**-.7373056**
Wandsworth	**-.7537818**	**.1045991**	**-7.21**	**0.000**	**-.9587952**	**-.5487684**
Wembley	**-.4641127**	**.1534055**	**-3.03**	**0.002**	**-.7647865**	**-.163439**
Westminster	**.1216841**	**.1178218**	**1.03**	**0.302**	**-.1092458**	**.3526139**
Whitechapel	**.3923546**	**.1056156**	**3.71**	**0.000**	**.1853488**	**.5993604**
Willensden	**-.7925648**	**.1157374**	**-6.85**	**0.000**	**-1.019409**	**-.5657203**
_cons	**1.750535**	**.1225941**	**14.28**	**0.000**	**1.510251**	**1.990818**

Results for Year: 2023

Regression 18 – Host Engagement vs Number of Reservations (2023)