Investigating the relationship between peer-to-peer accommodation and overtourism in European cities

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Submitted to Dr. Jason Stienmetz

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AFFIDAVIT

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ABSTRACT

Overtourism is a term that has been widely promoted over the last years to refer to the phenomenon of an excessive number of tourists overwhelming a destination's capacity and resources, resulting in negative impacts on the environment, infrastructure, local communities, and visitor experiences. Peer-to-peer (P2P) accommodation has grown exponentially over the past few years, revolutionizing the hospitality industry and revolutionizing the way people travel. The relationship between P2P accommodation and overtourism is a complex phenomenon influenced by various factors such as the increased availability of short-term rentals and their impact. This thesis explores this relationship using Airbnb as the reference P2P accommodation platform. It also covers the factors that drive tourists to use P2P accommodation platforms and if these factors can lead to an increase in overtourism in European cities.

The analysis was organized around two data sets, one related to the characteristics of P2P accommodation listings and the tourist density of bednights, and the other related to the characteristics of P2P accommodation listings and the tourist density of arrivals. In total, data regarding the Airbnb listings from 29 Europe cities was gathered for this study. The variables used to measure P2P accommodation were the price, location, variety, and perceived authenticity of listings. Quarterly data regarding the Airbnb listings was gathered on available Inside Airbnb data sets between the years 2021 and 2023 while most of the data for the years 2015 to 2021 was gathered using the Wayback Machine as older data sets were not accessible. The tourist density variable used to measure overtourism was created with quarterly bednights and arrivals data that was gathered on TourMIS.

This study employed a quantitative research design and a linear regression model to find whether there was a relationship between the selected variables using secondary data. Each variable was analyzed separately to test each hypothesis. The results showed that there was no statistical significance between P2P accommodation and overtourism, with all hypotheses rejected. While it was not the expected result, some conclusions can still be drawn from this study. This thesis aims at introducing further research on the relationship between P2P accommodation and overtourism using a wider range of variables and indicators to obtain more accurate results to analyze the selected variables using a multidimensional approach.

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List of Abbreviations

ADR	Average Daily Rate
B&B	Bed-and-breakfast
C2C	Consumer-to-consumer
EU	European Union
IT	Information Technology
P2P	Peer-to-peer
PSR	Peer-to-peer short-term rental
SE	Sharing Economy
TALC	Tourism Area Life Cycle
TCC	Tourism Carrying Capacity
UNWTO	World Tourism Organization
USD	United States Dollar
QOL	Quality of Life

1. INTRODUCTION

Peer-to-peer (P2P) accommodation has known a rapid growth in Europe over the last decades. Relevant studies concluded that this growth is the result of a range of benefits offered both to the tourists (guests) and the service providers (hosts) (Sung et al., 2018). P2P accommodation platforms such as Airbnb have emerged supported by the principles of the sharing economy as new marketplaces and quickly became leaders in the hospitality sector, disrupting the long-held domination of hotels. The emergence of these platforms transformed the tourism sector as it shifted the motivations of tourists for travel. The rise of P2P accommodation can be explained by various factors driving tourists to turn towards alternative forms of lodging while traveling. Accommodation is not viewed only as a place to spend the night but as a part of the whole travel experience. The factors driving the demand for P2P accommodation can be a lower price, the possibility to interact with the local communities (Guttentag, 2015), or the search for a more authentic tourist experience (Bucher et al., 2018; Shuqair et al., 2019). On the other hand, individuals will tend to rent available space in their accommodations mostly to generate income (Stienmetz et al., 2020) or for social interactions (Lutz & Newlands, 2018; Ikkala & Lampinen, 2015).

Despite the numerous positive impacts brought by the rise of peer-to-peer short-term rentals (PSR), concerns have been voiced by different involved parties. Indeed, these sudden changes created in the tourism sector affected the local communities and economies of many European cities, as well as the professionals in the hospitality industry. Challenges arise in cities such as gentrification due to the rise in real estate prices, noise-related problems, seasonality, etc. P2P accommodation platforms are also deeply disrupting the hospitality sector (Sigala, 2015). Every person spending a night in an Airbnb represents a loss for a traditional tourism accommodation establishment, such as a hotel, hostel, or bed-and-breakfast (B&B). These platforms are seen as unfair competition by hoteliers as the taxes and regulations applied to the traditional hotel industry can be avoided due to the lack of regulations (Coyle & Yeung, 2016). This views can be contested nowadays with the rise of regulations in many European countries and cities. P2P accommodations gained popularity with the idea that travelers would rent an accommodation from a local resident and provide "authentic" experiences (Nieuwland & van Melik, 2018, p. 812), and even became the value proposition of different P2P accommodation online platforms, such as Airbnb (Guttentag, 2017). However, the reality is different; more and more owners of P2P accommodations shifted from only renting their property to gain additional income to being a lucrative professional activity. The phenomenon of multi-listings increased exponentially over the years and real estate agencies started to develop and expand into this business. In fact, operators who own multiple units and full-time hosts account for 71% of Airbnb's revenue in its top 12 markets (Dogru et al., 2020).

The UNWTO (World Tourism Organization) defines overtourism as “the impact of tourism on a destination, or parts thereof, that excessively influences the perceived quality of life (QOL) of citizens and/or quality of visitors’ experiences in a negative way” (2018, p.4). Even though the term “overtourism” is quite new to the literature and is now used as a buzz-word, it describes a well-known and existing phenomenon (Capocchi et al., 2019). With the arrival of platforms such as Airbnb or Booking, it has never been easier for tourists to rent an accommodation. Cities have seen an increase in the number of tourists in the span of just a few years, increasing the development of economies, but also causing serious threats to the well-being of their local ecosystems.

1.1. Background of the study

Europe has always been a popular destination for tourism. Comprising 44 countries with 27 of them in the European Union (EU), traveling from one country to another has never been easier for EU residents. The Schengen Agreement (1985) resulting in the border-free Schengen area guarantees free movement for over 425 million EU citizens (European Commission). In 2019, 81% of all tourism arrivals in Europe were EU residents (Eurostat, 2023).

The sharing economy represents one of Europe’s strengths. According to a 2018 survey about Information and Communication Technologies (ICT) in households and by individuals, 21% of individuals aged 16 to 74 in the EU used websites or apps to book accommodation from another individual in the preceding 12-month period (Eurobarometer, 2018). The sharing economy model and P2P accommodation generate opportunities for many European destinations. Some EU countries are more popular than others regarding participation in P2P accommodation. According to a study conducted by Eurostat (2020), the countries with the most individual hosts were Luxemburg (46%), Ireland (34%), and Malta (30%). On the other hand, Czechia (5%), Cyprus (5%), and Latvia (8%) were the countries where the population is the least interested in providing P2P accommodation. Due to its cultural heritage, various landscapes, and beautiful cities, Europe is the leading market worldwide for inbound tourism. There were 744.5 million international tourist arrivals in Europe in 2019. In 2022 and during the bounce back of tourism after the COVID-19 pandemic, Europe remained attractive with 584.9 million international tourist arrivals, making it the region with the highest number of international tourist arrivals worldwide (Statista, 2023). From 2006 to 2019, international tourist arrivals in Europe increased by 64%. In 2019, global tourism expenditure in Europe was USD 643.3 million (Statista, 2022). This constant growth in the number of tourist arrivals in Europe brings economic benefits and numerous growth opportunities for European cities that are using tourism to develop. This phenomenon of mass tourism can cause side effects in European destinations. An increasing number of cities are suffering from problems due to the growth of tourist arrivals. Examples can be capitals such as Berlin, Copenhagen, Amsterdam, Lisbon, and Prague. Smaller cities with a lot of tourism attractivity can be mentioned such as Venice, Dubrovnik, Florence, Bruges, Salzburg, etc. Hospers (2019) described overtourism as being a matter of perception. The negative effects implied by overtourism vary depending on different factors such as the scale of the city, the location of attractions, the felt density, but also the type of travelers.. Overtourism also relates to the resident's perception of the negative impacts implied by the growth of tourism in their residential area.

Led by the growth of the sharing economy and technological advances, online peer-to-peer property rental platforms started appearing (Farmaki et al., 2018). Airbnb shortly became one the biggest and most popular property rental platforms on the P2P accommodation market. It has been recognized that visitors are attracted to using P2P accommodation rather than hotels for a variety of factors, including low prices, location, and a search for authenticity with the feeling of "living like a local". Airbnb has however been heavily criticized for its lack of regulations and faces legal problems (Thompson, 2015; Guttentag, 2015). Some landlords also evacuated tenants in order to empty the property for short-term rental (Jones, 2013). Some researchers identified that the growth of P2P accommodation had negative impacts on local housing markets (Guttiérez et al., 2017). Tourism stakeholders started to take those negative impacts into account and it resulted in some destinations taking action and banning or restricting Airbnb rentals, as the platform failed to cooperate with cities (Cox & Haar, 2020). Many European cities, including Amsterdam and Paris, limited the number of days of rental availability, and others such as Barcelona introduced strict regulations for hosts. The COVID-19 pandemic deeply affected the tourism sector in Europe. Many destinations suffered economic losses with tourism being their main source of revenue, resulting in a loss of jobs for many tourism actors. Even though the pandemic has reduced short-term rental activity (at least for a little while), the local housing units have not returned to long-term rental (Cox & Haar, 2020). P2P accommodation has proven to be somewhat immune to the pandemic, with a significant increase in bookings when the COVID-19 regulations started to get lifted (Statista, 2023).

1.2. Significance & purpose of study

Despite numerous studies published on overtourism in Europe, this phenomenon is still relevant to this day as many cities are affected by an always-increasing flow of tourists. Numerous studies were also conducted on the impacts of P2P accommodation, but the relationship between this relatively new type of accommodation and overtourism is still a relevant subject as there is a lack of research on the topic. With the COVID-19 pandemic, some destinations were able to recover as tourism was stopped in most parts of the world. Now that the tourism sector is recovering, policymakers and governments have taken action against P2P accommodation platforms such as Airbnb in order to limit their impact on cities and their residents, and to avoid the past mistakes that led to those impacts. The effects linked to those new regulations are starting to appear, yet more strategies need to be thought of to find a balance between the development of tourism in Europe and the quality of life of residents.

Thus, this study aims at investigating the relationship between P2P accommodation and overtourism in European cities in order to identify solutions and strategies for a better balance between the development of tourism and the quality of life of residents. A focus is placed on the characteristics making P2P accommodation so popular among tourists and why they prefer to book an Airbnb property rather than a hotel room. To do so, the following research objective has been defined.

Research objective:

- To determine how different characteristics of the P2P accommodation market and tourist behavior influence overtourism in European cities.

1.3. Research questions

To investigate the relationship between P2P accommodation and overtourism and the factors related to the growth of online P2P accommodation platforms, four research questions were developed. Several aspects are being considered, such as the price, the location, and the variety of P2P accommodations, as well as the tourists' search for an authentic experience.

<u>Research Question n°1</u>

RQ1 How does the price of P2P accommodation relate to overtourism in Europe?

<u>Research Question n°2</u>

RQ2 How does the location of P2P accommodation listings influence overtourism in Europe?

<u>Research Question n°3</u>

RQ3 How does the variety of P2P accommodation listings influence overtourism in Europe?

Research Question n°4

RQ4 How does the perceived authenticity of P2P accommodation influence overtourism in Europe?

All four research questions are directly linked as they all refer to some of the characteristics of P2P accommodation and the motivations of tourists to use this type of lodging when traveling. To answer these research questions, the aim is to analyze the guests' perceptions of these different characteristics in relation to traditional accommodations such as hotels. They explore in particular how such motivations can create more overtourism in European cities.

1.4. Structure of the thesis

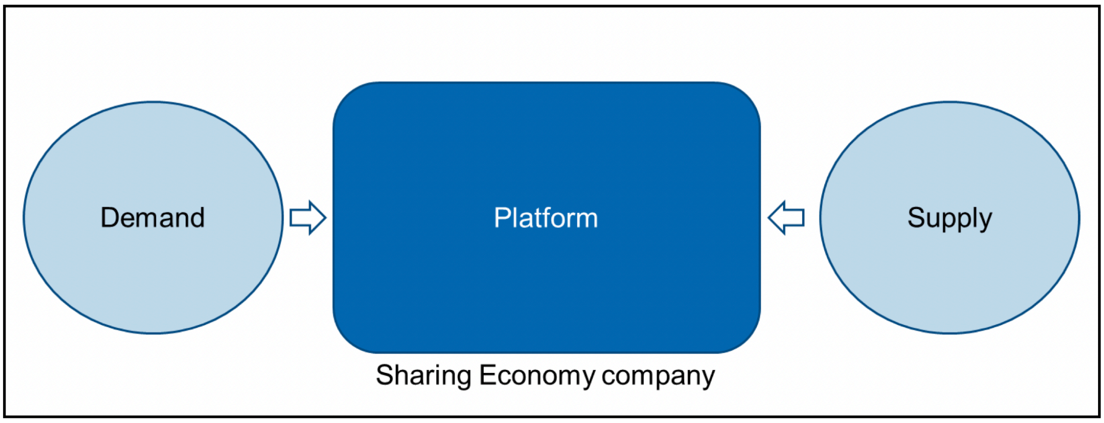
The thesis is organized into five chapters. Chapter one (1) provides a general overview of the topic with an introduction. The significance, purpose of the thesis, and research questions are described in this chapter, as well as the structure of the thesis. Chapter two (2) includes a literature review of past studies on the sharing economy, P2P accommodation, and Airbnb in particular, overtourism, tourists' experience, and behavior. Chapter three (3) covers the methodology of the thesis. It includes the selected methodology, the research design, the variable selection, and the data collection. Chapter four (4) comprises the results of the study including descriptive statistics, hypothesis testing using a linear regression model, and a short discussion on the findings. Finally, chapter five (5) includes a conclusion with a summary of the thesis, the implications for relevant stakeholders, future research, and the limitations of the study.

2. Literature review

2.1. The sharing economy

In order to understand the different terms and concepts of this paper, it is essential to understand the principles of the sharing economy. The sharing economy (SE) refers to the ability of individuals to rent or borrow goods to and from other individuals rather than buy and own them. The term "Sharing Economy" was first mentioned in 2008 and is defined as the "collaborative consumption made by the activities of sharing, exchanging, and rental of resources without owning the goods." (Lessig, 2008, p. 143). Belk (2007, p. 126) argues that sharing involves "the act and process of distributing what is ours to others for their use and/or the act and process of receiving or taking something from others for our use". The sharing economy is often referred to as the consumer-to-consumer (C2C), peer-to-peer (P2P), or collaborative economy. The term "collaborative economy" is often interchangeable with the term "sharing economy", even though it is subject to controversy. There is a debate with regard to the terminology of this term (Polanco-Diges & Debasa, 2020, p. 217). Sigala (2015) points out that the sharing economy is emerging as a global phenomenon and rapidly growing, changing the future of hospitality and tourism. The European Commission, in a Communication, denotes that the sharing economy "refers to business models where activities are facilitated by collaborative platforms that create an open marketplace for the temporary usage of goods or services often provided by private individuals" (2016). They identified three categories of actors: the service providers (private individuals or professionals), the users of the services, and the intermediaries that connect providers with users and that facilitate transactions between them. Hossain (2020) examined the existing literature on SE concepts and synthesized the findings of 219 articles on SE. The study explored the definitional dilemma but also the sharing economy as a phenomenon and key theories related to the topic. The author pointed out that there is a lack of regulations and policies of the SE. Various factors of the sharing economy are researched such as the role of cultural values on individuals' intention to participate in the sharing economy (Gupta et al., 2019). The SE can also be analyzed as a comparison of the "traditional" economy. Dervojeda et al. explain that in traditional markets, consumers buy goods and own them whereas, in the SE, suppliers share their resources temporarily with consumers, either for free or for a fee (2013). The most commonly known sharing economy model is a P2P model (Figure 1). In this model, goods and services are shared between individuals (demand and supply) and the Sharing Economy company (platform) does not contribute to the production of those goods and services, but acts only as an intermediary between demand and supply (Demary, 2015, p. 5).

FIGURE 1: STRUCTURE OF A PEER-TO-PEER MODEL



Source: Demary (2015, p. 5)

Even though sharing goods and services is not new, technological advances such as the development of the internet facilitated the growth of the sharing economy, with the creation of online platforms that made sharing easier than it was before (European Parliament, 2017). These technological advances as well as the low prices associated with P2P rental allowed the sharing economy to gain popularity over the years. In the context of tourism, the sharing economy refers to the growing number of individuals sharing temporarily what they own (accommodation), or what they do (meals & excursions) with tourists (European Parliament, 2017). The growth of the sharing economy can be explained by a so-called "win-win" situation for both supply and demand, meaning it brings financial benefits to both providers and users. The sharing economy has revolutionized tourism, providing new options for travelers in their choice of accommodation and allowing them to no longer be tied to traditional accommodation. For example, online P2P paid accommodation, including P2P rental platforms and vacation rental platforms represent the largest sector of the sharing economy in terms of transaction value (PwC, 2016). Sovani and Jayawardena (2017) argue that the sharing economy is a phenomenon that is here to stay for a while in the industry and that destinations should embrace the disruption it caused in order to ensure it brings benefits to the different stakeholders.

2.2. Peer-to-peer accommodation

2.2.1. Introduction to P2P accommodation

Supported by the principles of the SE and enabled by technological advances, a growing number of individuals started renting their accommodation to tourists for economic and social benefits. P2P accommodation is a segment of the sharing economy with several aspects making it a unique and distinct sector inside the sharing economy (Belarmino & Koh, 2020). It is defined as online networking platforms that allow people to lease out parts of their property or their entire property for a short period of time (Belk, 2014). This resulted in platforms such as Airbnb being created and overtaking the hospitality market in less than a decade. Individuals started renting unused spare bedrooms for a small fee (e.g. Airbnb), or for free (e.g. Couchsurfing) (Karlsson & Dolnicar, 2016). The rise of P2P accommodation is due to the fact it provides benefits for both the users and suppliers (Sung et al., 2018). Hawlitschek et al. found that enjoyment, income, and social experiences are motivators for P2P rental participation on the supplier side (2016). Similarly, Karlsson and Dolnicar (2016) identified three reasons why hosts rent their property on short-term rental. The most important ones are income generation, social interaction, and sharing experiences.

Short-term rental only started as a way for individuals to earn additional income or as a way to meet people, but it shifted towards a professionalization of the sector. The growth of P2P short-term rental quickly attracted micro-entrepreneurs looking at this phenomenon not only as a way to earn additional revenues but as a lucrative activity. Operators who own multiple units and full-time hosts account for 71% of Airbnb's revenue in its top 12 markets (Dogru et al., 2020). Multi-listing hosts refer to individuals who list more than one property of P2P accommodation online platforms and constitute one type of professional host (Gunter & Önder, 2018). For example, 69.1% of all listings in Venice are multi-listings (Inside Airbnb, 2023). Out of the 7.286 active listings in Venice, 1.652 are owned by hosts owning more than 10 listings in the city. Hosts with multiple listings are more likely to use P2P accommodation platforms to not only earn extra revenue but as a professional activity and are unlikely to live in the property. Such activities are violating most local short-term rental laws designed to protect residential housing. The other type of professional hosts is full-time hosts, renting their property monthly or yearly (O'Neil & Ouyang, 2016). Multi-listing hosts and full-time hosts have been scarcely researched over the last few years. The research principally focuses on performance differences with non-professional hosts (O'Neil & Ouyang, 2016; Xie & Mao, 2017; Xie et al., 2021). Companies also started to focus on the short-term rental business and to professionalize the area due to the large economic benefits possible. Such companies specializing in the business of renting apartments for short-term rental take on P2P accommodation online platforms such as Airbnb and dominate certain regions (Gil & Sequera, 2020). These companies mainly operate in key areas of destinations where the demand and the prices are the highest and some companies can even use pseudonyms to hide their identity from users, thus completely violating the principles of the sharing economy.

2.2.2. Disruption in the hospitality industry

P2P accommodation is seen as a disruptor in the lodging industry (Sovani & Jayawardena, 2017). This disruption in the traditional hospitality sector is caused by P2P accommodation taking a large share of the accommodation market. The growth of P2P accommodation in historic centers compared to hotels is facilitated by the availability of supply in existing apartment buildings (Gutiérrez et al., 2017). Forgacs and Dolnicar (2017) showed that the emergence of P2P accommodation platforms such as Airbnb significantly impacts negatively the hospitality industry. It was shown that the demand for traditional accommodation decreased, therefore threatening the jobs of many tourism professionals working in the traditional hospitality sector. The lack of regulations and the indulgence of policymakers towards P2P accommodation online platforms has also been pointed out by hoteliers. Coyle and Yeung (2016) argue that P2P online platforms are seen as unfair competition by traditional hospitality professionals as they can avoid tax regulations and profit from illegal listings, while hotels have to follow strict regulations. In an article published by The Guardian, John O'Neil, director of the Centre for Hospitality Real Estate Strategy at Pennsylvania State University, estimate that "most hoteliers I speak with have accepted Airbnb's existence and growth. Their concerns have more to do with leveling the playing field between hotels and Airbnb operators because Airbnb has so many unfair competitive advantages relative to hotels" (Hickey & Cookney, 2016). The professionalization of hosts also causes concerns among hoteliers as it is seen as unfair competition as they turn housing units into quasi-hotels, and therefore seen as threatening the hotel industry (Somerville & Levine, 2017).

Other research has shown that P2P accommodation had a negative effect on occupancy and average daily rates of hotels (Zervas et al., 2017). Xie and Kwok (2017) examined the price positioning of Airbnb accommodations when they were first implanted in Austin, Texas. The aim of their study was to analyze the impacts of P2P accommodation on hotels. The research found that Airbnb did have a negative impact on hotel performance when entering the market; however, the results showed also that the impacts are mitigated as there is a high range of prices on Airbnb and the platform has a statistically significant higher average daily rate (ADR) than hotels. Therefore, even though P2P accommodation disrupts the traditional hospitality sector when entering a market, its pricing inconsistency and the higher-priced properties were cited as the reason why P2P accommodation did not cause a more significant impact (Xie and Kwok, 2017). Similarly, Quattrone et al. (2016) conducted a comprehensive study on Airbnb data in London. The results revealed that P2P lodging spread into residential areas and grew into areas with few hotels, if any.

2.3. Airbnb

Airbnb is one of the most successful companies in the global sharing economy. It was founded in 2008 by two entrepreneurs seeking to offset their high rental costs. Airbnb was developed as a short-term rental platform that hosts could use to rent their entire properties or unused spare bedrooms online. It now competes with other online travel booking websites such as Expedia and Booking.com. Since its founding in 2008, Airbnb became one of the most used travel and tourism websites and serves as a representative P2P accommodation platform. In 2021, Airbnb had 12.7 million listings with 8.5 million active listings overall and 356.9 million nights booked (Airbnb Statistics, 2022). The platform expanded overseas in 2011, opening its first office abroad in Hambourg, Germany. Even though the company started as a privately owned business, it went public in 2020. Airbnb generates profit through service fees to hosts and guests but does not own the rented properties on its website (Statista, 2023). In 2021, the company value of Airbnb was 113 billion USD.

Airbnb can be seen as a disruptive innovation (Guttentag, 2015) due to its unique company's business model and tourist appeal. Disruptive innovation is defined as "the process by which a product or service initially takes root in simple applications at the bottom of a market—typically by being less expensive and more accessible—and then relentlessly moves upmarket, eventually displacing established competitors." (Christensen & Raynor, 2003). The disrupting factor of Airbnb causes disturbances in the traditional tourism accommodation sector, but the rise of Airbnb is also of great significance for destinations as it poses a dilemma on whether they should respond or not to the illegality of some Airbnb rentals with its benefits and costs. Airbnb hosts engage in collaborative consumption as a supplement in income or to establish new relationships with guests (Dillahunt & Malone, 2015). Guttentag (2015) argues that the rise of Airbnb is due to an offer of initially cheaper and a simpler product supported by Internet technologies.

The COVID-19 pandemic impacted all actors in the tourism sector, Airbnb included. In 2020, the number of nights and experiences booked with Airbnb dropped to under 200 million (Statista, 2022), in comparison to the previous year when the platform accounted for approximately 327 million bookings. However, the platform quickly recovered from the pandemic as by 2022, approximately 393 million nights were booked on Airbnb (Statista, 2023), representing an increase from the previous year, but also an increase from the pre-pandemic numbers. Airbnb managed not only to recover from the pandemic but even to increase the previous numbers. With the exception of the United States, Airbnb is most present in Europe. As of September 10, 2022, the European cities with the highest number of listings are London and Paris, with respectively 69,351 and 61,365 rooms and apartments for rental (Statista, 2022). In the past, both cities have ranked among the most popular Airbnb destinations in Europe. Other popular European destinations for Airbnb rental are Rome (24,782 listings), Madrid (20,681 listings, and Mallorca (19,049 listings). In comparison to the pre-COVID-19 era, London had approximately 64,000 listings from July 2016 to July 2017, and 75,700 active listings in the following year, from July 2017 to July 2018 (Statista, 2020). It can be concluded that even though the activity of P2P short-term rentals has been impacted by the COVID-19 pandemic, it quickly recovered in major tourism hotspots. In London, the number of active listings in 2022 is larger than the number of listings from 2016 to 2017, and with the end of most regulations related to the pandemic, this number is expected to grow again.

2.3.1. Issues and limitations

The rapid growth of P2P accommodation and Airbnb in particular raised concerns and critics regarding its potential impacts. Residents of tourism hotspots such as Barcelona or Venice criticized Airbnb for its lack of regulations and for enabling an increase in home rents, making it harder for local residents to afford housing (Thompson, 2015). The illegal activity of many Airbnb-type rentals has been the subject of different concerns (Gottlieb, 2013). Guttentag (2015) discusses the legality issues of Airbnb, as well as the critics linked to the lack of tax regulations surrounding the platform. Airbnb has also been criticized for being the opposite of the concept of the sharing economy. Cadwalladr, in an article for The Guardian, denotes “Airbnb is about making money, not about sharing: money for its founders and investors, money for the people who open up their homes. It would be more accurately described as a "capitalist economy” (2013). Cox and Haar, in a report for Inside Airbnb, mention that P2P rental platforms such as Airbnb fail to cooperate with cities in order to reduce their negative impacts on destinations and residents and insist on the need for strong regulations to protect housing (2020). In their report, the authors found that Airbnb has caused several issues such as an increase in rents, damage to urban communities, and ruined affordable social housing programs. Other negative impacts can directly come from the hosts of Airbnb accommodations. Some landlords evicted tenants in order to use the empty properties for short-term rental, often without ever returning to long-term rental (Jones, 2013). Moreover, online P2P short-term rental platforms, Airbnb included, failed to cooperate with cities for a long time and profit from illegal listings (Cox & Haar, 2020). The authors argue that Airbnb has failed to cooperate in many ways: Hiding the identities of hosts and locations of illegal listings, refusing to provide data for enforcement, failing to disclose activity for taxes collected, using taxes to avoid housing regulations, proposing ineffective regulations to delay and block better regulations, etc. With the appearance of the COVID-19 pandemic, researchers try to identify whether the pandemic would slow the rise of P2P accommodation, or if the sector would be immune. Studies have shown that even though the pandemic has reduced short-term rental activity, the units that were lost to short-term rental didn’t return to long-term rental (Cox & Haar, 2020).

As a result of the multiple critics against the platform over the years, Airbnb started to become heavily regulated in 2019 and was even made illegal in some cities where it was popular (IPropertyManagement, 2022). For example, hosts wanting to list their property for short-term rental on Airbnb in Barcelona must have a city-approved license. In Paris, hosts must have a registration number to rent their property on Airbnb, and apartments can only be rented out for 120 days per year. These regulations slowed the growth of the platform in many cities in Europe. Since Airbnb regulations started to be analyzed, the number of studies on regulations has considerably increased as pointed out by Guttentag (2019). Hübscher and Kallert (2022) identified that cities follow highly individual approaches regarding the regulation of Airbnb. The authors found that the growth of Airbnb in European cities depends highly on the strictness of regulations. Following the example of Paris, other French cities took action to regulate Airbnb. Lyon also put a limit on short-term rentals and hosts can rent their property only for 120 days per year. Hosts are also required to request a registration number from the city hall and to declare the tourist tax collected (Petitprez, 2023). Following these regulations, the number of listings in cities such as Bordeaux was reduced by half (From 8,000-10,000 in 2018 to 4,668 in 2021). However, the introduction of licenses for P2P short-term rentals is still largely not applied by most hosts. In Lyon in the first quarter of 2023, only 8 listings out of the 9.575 total listings in the city were licensed for short-term rental, meaning that 99.9% of listings are considered illegal (Inside Airbnb, 2023). A similar phenomenon appears in other European destinations such as Florence where 98.1% of all active listings in the first quarter of 2023 are unlicensed (Inside Airbnb, 2023). This shows that even though regulations are appearing in many destinations in order to limit the negative impacts caused by P2P accommodation platforms, it will take a long time for them to be applied by all actors participating in P2P short-term rental.

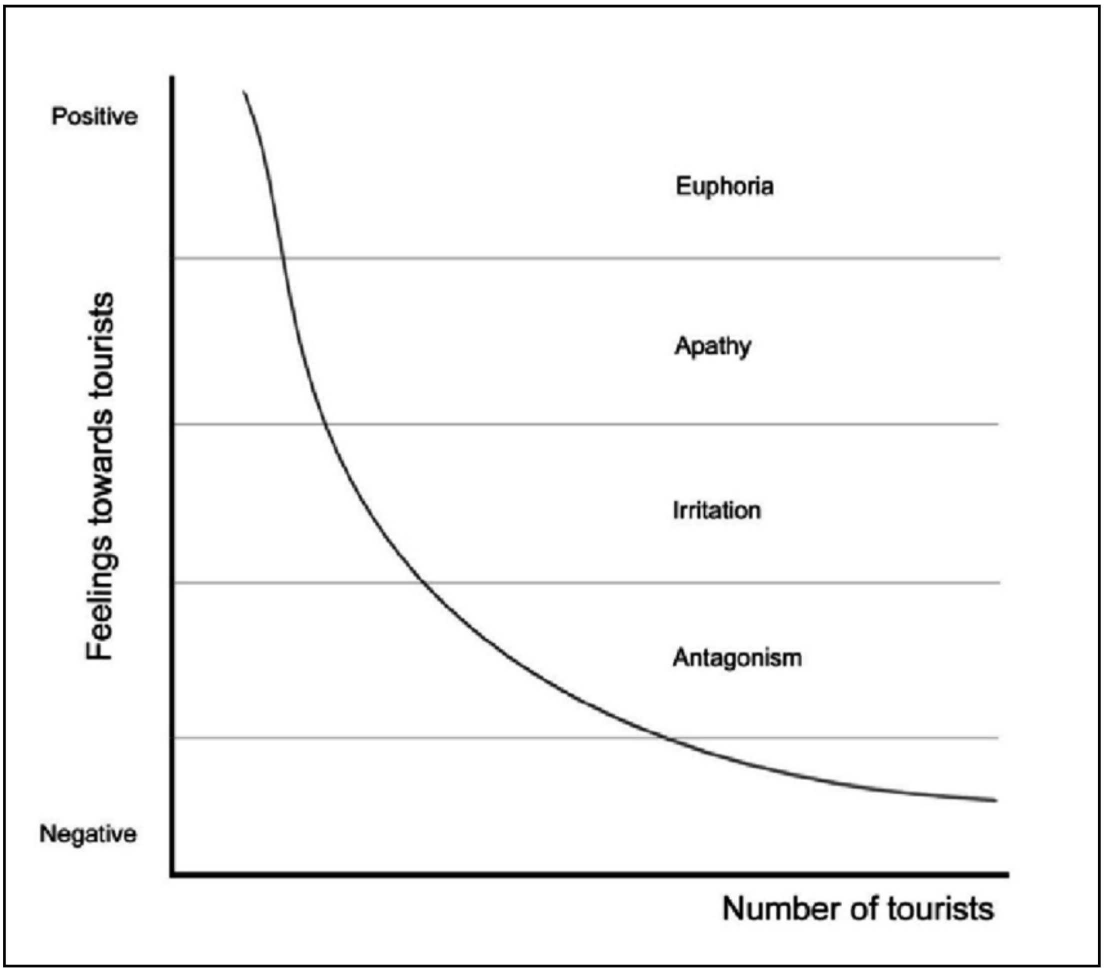
2.4. Overtourism

2.4.1. Definition and history

Overtourism has been a growing concern in Europe due to the increase in tourism arrivals faced by many destinations. This increase in the flow of tourists can negatively affect the livelihoods of the local communities and residents of those cities, as well as the necessary resources to sustain tourism (Milano et al., 2019). Goodwin (2019, p. 111) claims that "overtourism is the opposite of responsible tourism which is about using tourism to make better places to live in and to visit". According to the same author, destinations experience overtourism when "hosts or guests, locals or visitors, feel that there are too many visitors and that the quality of life in the area or the quality of the experience has deteriorated unacceptably" (2017, p. 1). However, overtourism is considered a new term that is being used to describe an already-existing phenomenon. This complex phenomenon is related to the balance between optimal and excessive development in the tourism planning of a destination. It is also strongly linked to the impacts of tourism growth on residents and the destinations carrying capacities. Even though the term overtourism wasn't mentioned, the impacts of tourism on local residents and destinations' carrying capacity have been widely studied for decades (Milano et al., 2022).

For example, Doxey (1975) proposed an irritation index (or "irridex") (Figure 1) that measures how the residents' perception changes towards visitors in a specific area but is also based on the understanding of tourism development in different stages of a destination's life cycle (Pavlić & Portolan, 2016). Doxey identified four stages of local perception toward tourists: euphoria, apathy, irritation, and antagonism. At first, tourism creates enthusiasm due to the economic benefits generated (euphoria). It is followed by a change of attitudes with the growth of visitors. Locals then become used to tourists and indifferent (apathy). The excess of tourists leads to concerns and resentment from the residents (irritation), and can even lead to hostile feelings towards tourists (antagonism). The last two stages are relevant for overtourism as they relate to residents' hostile attitudes rising from the negative impacts due to a surplus of tourists in destinations.

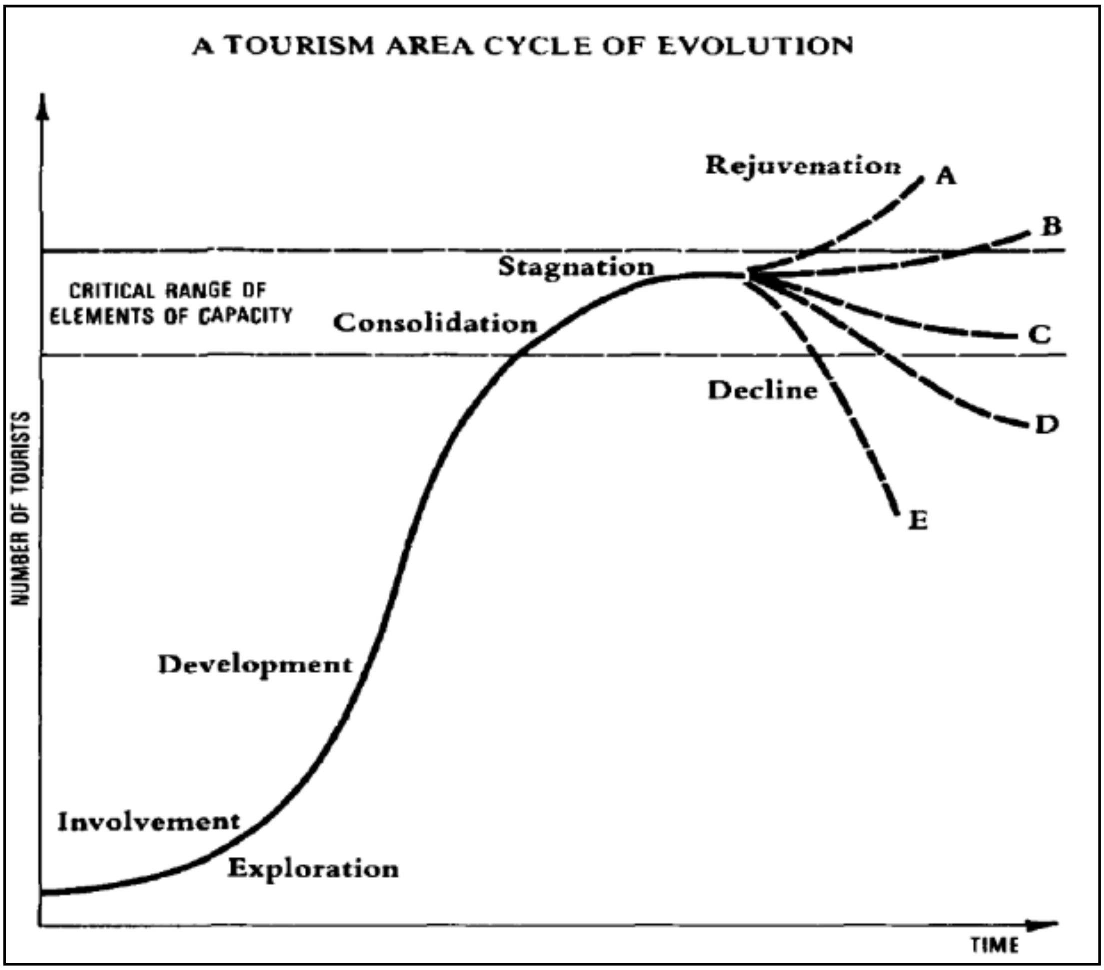
FIGURE 2: DOXEY'S IRRITATION INDEX



Source: Doxey (1975)

Similarly, Pizam (1978) conducted a study in order to examine the existence of the negative impacts of tourism. He then drew comparisons between local residents' perception of tourism and their dependence on tourism for a livelihood. He found that residents employed in non-tourism enterprises had negative attitudes toward tourists. The residents' perception of overtourism will be further discussed in subchapter 2.4.3 Residents' perception. Butler (1980) developed a model of the tourism product lifecycle and destination decline (Figure 2). Butler's Tourism Area Life Cycle (TALC) is a widely used model to study the evolution of a particular destination and discusses tourism carrying capacity and sustainability. Butler wrote about the evolution of a tourism cycle in six stages: exploration, involvement, development, consolidation, stagnation, and decline or rejuvenation. In each stage of the life cycle, the destination undergoes several changes. In the fifth stage "stagnation", the carrying capacity of the destination has been reached or exceeded. In the final stage of his model, Butler identifies a range of five possible scenarios that fit between the rejuvenation or total decline of the destination. The continued use of resources and a failure in managing effectively tourism growth can lead to the decline of a destination.

Figure 3: Butler's tourism area life cycle (TALC) model



Source: Butler (1980)

The way that tourism negatively affected destinations has been studied as early as the 1960s. A common point between these studies was that an excess of tourists in certain destinations led to harm to the local environment and negative attitudes from the local residents towards tourists. It shows that even though overtourism is seen as a growing concern, the question of effectively managing tourism destinations is not new.

2.4.2. Tourism carrying capacity

The wording "Overtourism" first appeared in a Skift article on Iceland ()has only been frequently used since 2015, and it has become the most commonly used expression to describe the negative impacts of tourism (Koens et al., 2018). Before this term became popular, discussions regarding the carrying capacity of a destination were put forward by researchers in the 1980s. The purpose was to find the limit in terms of the number of tourists that could visit a destination without harming the local environment and residents, and the quality of experience of other visitors. The term tourism carrying capacity (TCC) was introduced by the UNWTO in a work report in 1978-1979 and is defined as "The maximum number of people that may visit a tourist destination at the same time, without causing destruction of the physical, economic, socio-cultural environment and an unacceptable decrease in the quality of visitors' satisfaction" (2018, p. 3). Later on, Hovinen (1982) defined carrying capacity as the maximum number of tourists that can be accommodated without causing excessive environmental degradation and without leading to a decrease in tourist satisfaction. Mathieson and Wall (1982) defined carrying capacity by considering the impact of tourism on a destination in terms of environmental and experiential aspects, such as the maximum number of tourists a destination can accept without endangering its natural and recreational resources. The tourism carrying capacity has been further studied by O'Reilly (1986). The author drew the conclusion that the lack of control regarding the carrying capacity of a destination can lead to overcapacity, especially in developing countries, resulting in the destruction or near-destruction of historical landmarks and natural resources. O'Reilly points out the fact that it is necessary for the concept of tourism carrying capacity to be included in the planning for tourism of a destination.

Despite being a useful tool for managing visitors in vulnerable areas, the concept of tourism carrying capacity is imperfect (Zekan et al., 2022). Its limitations have been discussed by several researchers, and the main issue is that it is focused on tourism numbers, meaning the negative effects of tourism are resulting from mass tourism and an increase in visitor numbers (McCool & Lime, 2001). However the reality is more complex and it is part of the reason why overtourism is now being more used, as it englobes a broader vision.

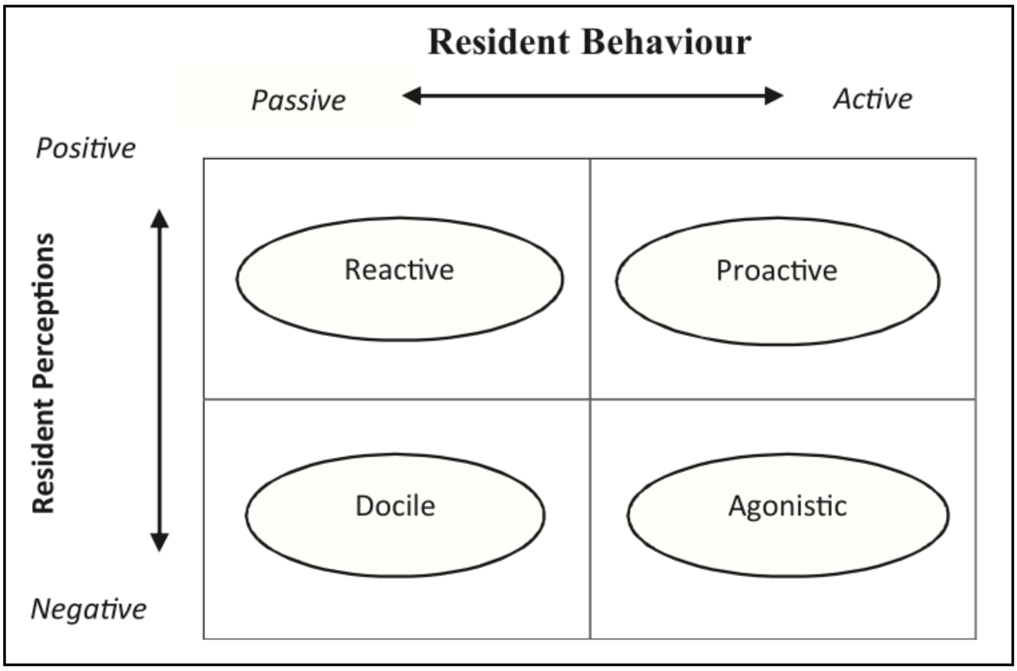
2.4.3. Residents' perception

As mentioned previously, overtourism is in part a matter of perception. The definition of overtourism by the UNWTO given in the "Chapter 1 Introduction" notes "the impact of tourism [...] that excessively influences the perceived quality of life of citizens [...]". Destinations and residents do not perceive the negative effects of tourism equally. It is also important to make the distinction between overcrowding and overtourism (Dodds & Butler, 2019). According to the author, overtourism "represents a situation where numbers of visitors overload the services and facilities available and become a serious inconvenience for permanent residents of such locations." Likewise, Singh (2018, p. 2) insists on the difference between overtourism and mass tourism, stating that overtourism is not confined to the concepts of crowding, but more a matter of perception of different actors, whether they are hosts, guests, locals, or visitors.

The negative impacts of tourism have been known and studied for decades, and yet overtourism is still considered a growing concern. As the number of tourists keeps increasing in popular European destinations, concerns from local residents as well as negative attitudes towards tourists arise. The concept of tourismphobia emerged at the same time as overtourism and is also associated with the rapid growth of tourism in the past years (Milano et al., 2019). According to Milano et al. (2019, p.1), tourismphobia is "a feeling of rejection towards tourism that manifests in the form of assaults to restaurants, businesses, and yachts; attacks on tourist buses, bikes damaged in tourist spots, and other acts of vandalism". Those phenomena can mainly be observed in top European destinations such as Barcelona, Venice, Dubrovnik, etc. However, those destinations have almost always been known for having a large flow of tourists. For example, local residents of Venice complained about overcrowding at the end of the 19th century (Hospers, 2019). Twain, in his travel book "A Tramp Abroad" (1880), depicts his own view as a tourist rather than a sensitive traveler and his awareness of some of the impacts linked to mass tourism, such as how it affects and promotes a false version of a destination.

The perceived negative impacts of tourism depend on the implication of residents in tourism. For example, a study by Milman and Pizam (1988) undertaken in Central Florida found that residents who were employed in the tourism industry expressed the most positive attitudes toward tourism impacts. Local residents and officials will tend to tolerate the negative effects of tourism if it brings positive economic benefits. The example of the island of Amorgos represents this principle (Tribe, 2011, p. 411). Tourism developed quickly over the last 20 years on the island, changing the economy and allowing locals to make more money in two months with tourism than they could have made in a year. Even though there is overcrowding and a phenomenon of mass tourism, it is not considered overtourism if the locals perceive tourism as a whole as positive. Stergiou and Farmaki studied the residents' perception of the impact of P2P accommodation through fifty-one structured interviews (2020). The authors revealed that there is a dominance of negative perceptions of socio-economic and environmental impacts among local residents. This study also came up with a typology of residents based on their perceptions and behaviors toward the impacts of P2P accommodation (Figure 4). This typology categorizes residents into four categories: the re-active, the proactive, the docile, and the agonistic. Regarding the perception of P2P ac-commodation, some residents wish to take this growth as an opportunity to participate ac-tively in P2P accommodation (proactive), whereas some residents remain passive and do not wish to take an active role regarding this phenomenon (reactive). As to the behavior of residents regarding the growth of P2P accommodation, some residents accept this new re-ality and the changes occurring in their neighborhoods, considering that there isn't much they can do (docile). On the other hand, some residents show actively their dissatisfaction regarding P2P accommodation (agonistic). These residents can have aggressive behavior toward guests or hosts of rental accommodations, striving the limit the negative impacts by taking the situation into their hands. The impacts of P2P accommodation are further dis-cussed later in this paper.

FIGURE 4: TYPOLOGY OF RESIDENTS



Source: Stergiou & Farmaki (2020, p. 8)

2.4.4. COVID-19 and overtourism

Since its appearance, overtourism was one of the most used expressions to describe the negative impacts of tourism on destinations and local residents. However, it all came to change when a global health crisis hit the world and completely changed the face of tourism. Destinations that were flooded with tourists quickly started emptying. After overtourism, a phenomenon known as “undertourism” appeared (Milano et al., 2022). It is defined as the “reduction in the number of visitors to a minimum level” (Coronel et al., 2022). Destinations suffered terrible economic losses due to the COVID-19 pandemic, as well as the tourism sector in general. Undertourism was an already existing phenomenon before the COVID-19 pandemic, affecting destinations linked with terrorism (Bassil et al., 2017), and Miftarević (2023) points out that there is a lack of research on the concept of undertourism. As tourism was at a stop during COVID-19, overtourism no longer became a concern and the negative impacts of tourism slowly disappeared. One of the negative impacts linked with overtourism is the use of natural resources by tourists. The COVID-19 pandemic allowed destinations to rest, and their natural resources to grow. Local residents also generally perceived the break from overtourism as positive (Wendt et al., 2022). The COVID-19 pandemic also made destinations rethink tourism development and planning to avoid a sudden resurge of overtourism. Calls for degrowth in the sector have been launched in order to develop tourism more sustainably in the future. For example, demarketing is presented as a potential solution for the post-COVID-19 period. Demarketing is defined as “that aspect of marketing that deals with discouraging customers in general or a certain class of customers in particular on either a temporary or permanent basis” (Kotler & Levy, 1971). During the pandemic, tourism stakeholders implemented different measures to limit and mitigate the impacts of the crisis on the tourism sector. The tourism sector had to evolve and innovative services were promoted such as the development of digital tourism (Liutikas, 2023). Sustainable tourism also became a major goal of tourism worldwide to counter the effects of mass tourism in the pre-COVID-19 period on destinations. Introducing measures related to sustainable tourism promotes a different kind of tourism in compliance with the carrying capacity of destinations (Seabra & Bhatt, 2022). On the other hand, some tourism experiences contrasted with undertourism and suffered from overtourism during the COVID-19 pandemic due to staycations and domestic tourism. Such experiences can include hiking and nature tourism for example.

The reality of the post-COVID-19 period is mitigated. As soon as the pandemic started to slow down and the travel restrictions were lifted, tourism came back to life. Tourism in Europe has known a strong rebound since the pandemic. According to Eurostat, there was a 27% rise in nights spent at EU tourist accommodation establishments in 2021 compared to 2020, totaling 1.8 billion on overnight stays (2022). As the post-COVID-19 period is still ongoing, it is difficult to draw conclusions yet on whether overtourism will return to its original state or if the evolution in the tourism planning and development of destinations will prevent it from happening. Both solutions are possible, however sustainable tourism has been widely promoted since the pandemic, and destinations are acting toward maintaining a balance between tourism growth and the three pillars of sustainability (Mihalic, 2021).

2.5. Characteristics of peer-to-peer accommodation

The factors explaining the shift of tourists from the traditional accommodation sector to P2P short-term rental have been studied for some time. Indeed, P2P short-term rentals and traditional accommodation providers are not identical, they provide different services for tourists with different needs (Guttentag et al., 2017). This new accommodation sector also started to attract new customers as they provide different characteristics such as a large variety of supply (Dolnicar, 2018), immersive experiences driven by a search for authenticity (Paulauskaite et al. 2017), but also social interactions (Tussyadiah, 2014). As tourists are now faced with a large variety of choices regarding short-term property rental, the decision-making part is crucial in pre-trip planning as they are making choices regarding different factors. Cheung (2019) argues that the rise of P2P accommodation over hotels has been motivated by location, house feeling, and low cost. Guttentag et al. (2017) identified six dimensions related to the motivation of travelers to use Airbnb instead of traditional accommodations. Those dimensions are price, functional attributes, unique and local authenticity, novelty, travel bragging and sharing economy ethos. From these six dimensions, the authors divided the respondents of the study into five segments: Money Savers, Home Seekers, Collaborative Consumers, Pragmatic Novelty Seekers, and Interactive Novelty Seekers. Another key component linked to the success of P2P accommodation is the trust built with the consumers. Platforms such as Airbnb create online communities when users rely on other user-generated content to verify the trustworthiness of the hosts renting their property (Murillo et al., 2017). This trustworthiness on the Airbnb platform is built through online reviews where guests can provide information on the quality of the hosts and accommodation to other guests. Online reviews are also useful for hosts that can assess the trustworthiness of guests from other hosts' reviews (Murillo et al., 2017). The characteristics of P2P accommodation and more precisely Airbnb are discussed in more detail in the chapters below.

2.5.1. The price factor

One of the characteristics influencing the decision-making of travelers when booking accommodation is the price. Hamari, Sjöklint, and Ukkonen (2015) found that economic benefits were a significant motivator for individuals to use P2P accommodation services. A study by Martin-Fuentes et al. (2019) shows that Airbnb prices are significantly lower than those of hotels and that they fluctuate very little, whereas hotels tend to adjust prices using yield or revenue management depending on the season. Guttentag et al. (2017) identified the category of tourists staying in P2P accommodation listings rather than hotels for its low costs as the “Money Savers”. The authors argue that this type of tourist uses P2P rentals as a way to save money and is usually not motivated by other factors. They are also often young and without children, with 62.9% of them being under 30. The prices of Airbnb listings can largely vary depending on various factors. Gibbs et al. (2017) identified that physical characteristics, location, and host characteristics significantly influence the prices of listings. In an environment as competitive as short-term property rental, prices play a huge factor in the decision-making of tourists. Tourists that are motivated to save money when booking accommodation tend to turn towards the cheapest alternative. Suárez-Vega et al. (2022) identified that the substitution of Airbnb with hotels is price-elastic, meaning that the demand for Airbnb increases as the price of listings decreases. If prices were to increase, the demand for hotels would increase, showing that the rise of P2P accommodation is in part due to the fact it is generally cheaper than hotels. Numerous researchers have indicated that P2P accommodation tends to be less expensive than hotels, even though they are often more expensive than hostels (Guttentag, 2015).

However, in some cases, P2P accommodation is not cheaper than hotels. A study by US personal finance company NerdWallet analyzed a thousand Airbnb reservations between 2022 and 2023 (French & Kemmis, 2023). Even though it can be difficult to compare the prices of Airbnb listings due to their variety, some key indicators can provide useful information as to whether such rentals are better are worse than hotels regarding prices. The study concluded that Airbnb accommodation is rarely cheaper for short-stays mostly due to discounts and cleaning fees, but more cost-effective for larger groups. Indeed, the study looked at six-person accommodations on Airbnb and three hotel rooms, assuming two adults per room, and the average Airbnb for six was 33 percent cheaper than three hotel rooms. However, the study also showed that the average hotel room was 29 percent cheaper than an Airbnb for two. Similarly, Lane and Woodworth (2016) examined U.S. Airbnb data and compared average rates of different types of Airbnb accommodation with average hotel rates and it was found that Airbnb's entire homes cost more on average than hotels, including when only looking at listings with one bedroom. The popularity of P2P accommodation therefore can’t only be established by its low prices as it has been proven that Airbnb rentals are not always cheaper than hotels. The popularity comes from a combination of factors including the experience, the location, and the variety of these listings, all of which are detailed later in the paper. It has been proven that Airbnb can be considered a substitute for hotels in some cases, but not always.

As the COVID-19 pandemic affected the tourism sector, it also affected the prices of P2P property rentals. Milone et al. (2023) identified that the surge of the COVID-19 pandemic caused a significant decline in Airbnb demand, resulting in a rise in Airbnb prices. The authors also argue that pricing strategies substantially differ between commercial and private hosts. Based on economic principles, an increase in the demand for Airbnb lowers the prices as the competition between hosts forces them to offer a better price than their competitors in order to remain attractive to guests. Owens (2023) argue that since the pandemic outbreak, Airbnb prices have increased by 35%. The increase in prices benefited neither the guests nor the hosts as guests have voiced unhappiness regarding this increase in prices as it comes with additional fees with their bookings, and hosts claimed declining business.

Overall, the price of P2P accommodation can impact overtourism in various ways. Affordable P2P accommodation can make travel more accessible to budget-conscious travelers, leading to an increase in the number of tourists visiting a destination. On the other hand, high prices for P2P accommodation can limit the number of visitors who can afford to stay in a destination, potentially reducing overtourism. However, high prices can also contribute to the gentrification and displacement of local residents. The increasing supply of affordable accommodation led by the growth of P2P short-term rental can also potentially contribute to overtourism by making it easier for people to visit, therefore increasing the number of visitors in a specific location.

H_1: The difference in price between P2P accommodation and hotels have a significant positive effect on overtourism in Europe

2.5.2. The location factor

Nowadays, there are Airbnb listings in almost every possible location on the planet. One of the advantages that P2P accommodation has over hotels is that there are not bound to buy and build new properties in order to expand, as they very often use already existing buildings. This advantage allows Airbnb to be located in many city centers in Europe, gaining a huge competitive advantage over traditional accommodation providers. This advantage that is offered through P2P accommodation can satisfy the needs of upper-level customers that would possibly choose hotels without this feature. While several researchers argue that P2P accommodation is a substitute for hotels (Dogru et al., 2020), some studies do not find a substitution effect between P2P accommodation and hotels, claiming that P2P accommodation had no influence on the revenues generated by hotels (Blab et al., 2018). One of the reasons used as a justification for the absence of a relationship between P2P accommodation and hotels is the location. Indeed, some studies have shown that in major cities such as Paris, the competition between Airbnb listings and hotels is not significant (Heo et al., 2019). However, large tourist hotspots such as Paris have plenty of hotels located in key areas of the city and still benefiting from tourism even though there's new competition with property rental platforms. Smaller cities with historical city centers such as Dubrovnik are not saturated with hotels. Therefore, the growth of P2P accommodation in those centers completely changed the offer of short-term property rentals. When before travelers needed to walk from their hotels to the center, they are now directly located in the key hotspot in the city. Jia and Bai (2020) argue that Airbnb rentals were more likely to be located in neighborhoods with good transit, close to the city center, and with a high median house value and household income. Tussyadiah and Zach (2015) found that both hotel guests and P2P short-term rentals emphasized the importance of location, even though hotel guest reviews tended to emphasize convenience and short-term rental reviews emphasized the general appeal. Another way of looking at the location factor of P2P short-term rentals is that the importance of that motivation for tourists can be seen as unexpected (Guttentag, 2017). The author argues that P2P listings tend to be located in residential neighborhoods rather than clustered in city centers like hotels, and that location should therefore represent more of a drawback than a reason to choose it. This view might have been accurate some time ago when P2P listings were mostly located in residential areas but this is not the case anymore as many P2P listings are nowadays located in many city centers of European destinations.

The location of P2P accommodation can affect overtourism in European destinations in various ways. Firstly, P2P accommodation platforms often concentrate their listings in popular tourist areas, which can contribute to overcrowding and put pressure on local resources (Slee, 2015). It has also been proven that the popularity of P2P accommodation in certain areas can contribute to gentrification, with local residents being priced out of their neighborhoods or facing pressure to sell their homes to investors (Cocola-Grant & Gago, 2019). P2P accommodation can also lead to an increase in demand for services such as restaurants, transportation, and entertainment, leading to overcrowding and negative impacts on the local environment. Similarly, P2P accommodation can encourage unsustainable tourist behavior, such as visiting popular sites during peak hours or participating in low-quality, low-cost tours. Finally, P2P accommodation depending on the location can have a negative impact on local culture by promoting a homogenized experience for tourists and reducing opportunities for interaction with local residents.

H_2: The location of P2P accommodation listings have a significant positive effect on overtourism in Europe

2.5.3. The variety factor

"Variety is one of the consumer's greatest concerns." (Fortune Magazine, 1991). With the rise of new technologies, consumers are always faced with a variety of choices in various areas of their life, such as food, activities, accommodations, etc. When facing different choices of selectable products, individuals often choose products in different categories even though they can repeatedly select their favorite products; it is regarded as variety-seeking behavior (Kahn & Louie, 1990). Variety-seeking buyer behavior is defined as "the buying tendencies of those consumers that do not have a high involvement with a product when there is a significant difference between brands" (Variety-Seeking Buying Behavior: Definition & Marketing Strategies, 2018). A variety-seeking behavior refers to consumers switching between different products or categories to avoid diminishing utility due to repetitive purchases or consumption (Ratner et al., 1999). A basic assumption regarding the variety of a certain category of products is that offering more options is superior to offering fewer options as a greater variety of options can satisfy a wider range of tastes (Lancaster, 1990). However, this assumption has been challenged by more recent research doubting the effectiveness of consumers having too many choices (Schwartz, 2004). Other research has shown that offering more options sometimes disserves the consumer as it leads to decision conflict and uncertainty (Greenleads & Lehmann, 1995).

2.5.3.1. Variety in P2P accommodation

The variety of listings on P2P accommodation platforms influences the decision-making of customers. There are four main types of places on Airbnb: entire places, private rooms, hotel rooms, and shared rooms (Airbnb, 2023). Apartments and private houses represent most of the current Airbnb listings. As Airbnb regroups millions of different listings, the platform offers a large variety of choices for travelers, depending on their needs. Listings can vary from villas by the ocean to small wooden cabins in the mountain, from tree houses in the forest to yurts, domes, troglodyte houses, or even windmills. That variety of choices changes the perspective of thinking of an accommodation only as a place to sleep. The accommodation now becomes part of the experience, or in some cases, it becomes the experience in itself. The market for those "unusual" accommodations has been booming for more than ten years led by the search of tourists for authenticity. Its popularity comes from the experience it provides to its customers (Hospitality On, 2022). Tourists book these types of accommodation in order to create a different experience from their everyday life. The rise of social media platforms such as Instagram also promotes such accommodations as the customers can share their experience with their network (friends & family). Airbnb even dedicated a category on its website to these unusual accommodations. This phenomenon is nowadays not only limited to online platforms specialized in P2P short-term rentals such as Airbnb as hospitality professionals are beginning to show interest in this market as they can make significant revenue.

Whereas before consumers had little choice regarding the variety of their accommodations being mostly hotel rooms or hostels, P2P accommodation opened a wide range of different listings to choose from. The variety in the choices of hotels consists of the different ranges of hotels that guests can book from: budget hotels/motels, mid-range hotels, and upscale hotels. The variety in P2P accommodation can also represent the functional attributes of such accommodations compared to hotel rooms. It is first important to emphasize the difference between hotels' functional attributes such as the staff availability, check-in/out process, and the different facilities and P2P accommodation's unique functional attributes (Guttentag et al., 2017). The existing literature has emphasized the benefits for guests to have access to household amenities and larger space available inside the accommodation (Guttentag, 2015). It has also been proven that staying in a private property instead of a generic traditional accommodation such as a hotel room provides guests with a more "homely" atmosphere (McIntosh & Siggs, 2005). These functional attributes can also be used to emphasize the general experience of a guest as the "homely" atmosphere these attributes can generate contributes to the local experience a guest can feel; whereas guests staying in hotel rooms are conditioned as tourists with their choice of accommodation.

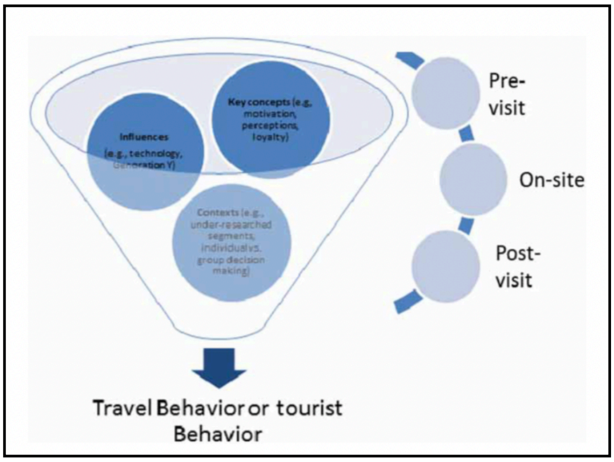
H_3: The variety of P2P accommodation listings have a significant positive effect on over-tourism in Europe

2.5.4. The experience factor

2.5.4.1. Tourist behavior

When it comes to booking accommodation, travelers never had more choices. They are faced with an overwhelming number of trade-offs, resulting in an overload in their decision-making process (Vriens et al. 2020). An analysis of tourist behavior is important in order to understand the changes in the behavior of travelers when deciding on the booking of accommodation. Cohen et al. (2013) provide a highly structured review of the literature on travel behavior. There is a lack of comprehensive reviews on consumer behavior concepts and models in tourism. Part of the reason why is that travel behavior can be considered a continuous process that includes inter-correlated stages and concepts that can't always be analyzed. However, concepts, influences, and research contexts can be studied for a specific

FIGURE 5: FACTORS SHAPING TRAVEL BEHAVIOR



Source: Cohen et al. (2013)

travel stage in the visitation process. The impact or role that various factors play in shaping travel behavior differs substantially depending upon the nature of the trip, the stage of the trip (trip planning, during the trip, or after the trip) as well as the trip goal (reason for the trip such as business or pleasure) (Figure 5). The authors also showed that tourism decision-making and consumption are often highly interpersonal and emotional.

Decision-making in tourism consumer behavior has often been studied considering that humans are rational (Engel et al. 1968), however, more recent studies have proven that it is not always the case (Hyde & Lawson, 2003), arguing that those former studies were unable to capture the complexity of decision-making in tourism. The emergence of new technologies changed the way individuals make decisions. Gretzel (2010) discusses the role of information technology and argues that technology will fundamentally restructure the nature of the tourism experience. Thaler and Tucker (2013) discuss the changing environment regarding the availability of information about the different aspects of a consumer's life, including how they make decisions. The authors argue that the availability of new data enables travelers to make better decisions as they are faced with more alternatives when booking a flight, restaurant, accommodation, etc. The development of information technology (IT) and the changes in the values and lifestyles of individuals induced changes in consumer behavior and led to a "new" kind of traveler. Benckendorff et al. (2019) discuss the importance of information technology in the travel and tourism industry and how technological innovations change the industry. New technologies allow tourists to be better informed, more independent, and more realistic.

2.5.4.2. Generations and motives for travel

It has long been recognized that age is an important factor affecting travel behavior and that people from different generations travel for different motives. Gursoy et al. (2008) define generations as a "proposed group of individuals who were born during the same time period and who experienced the same key historical or social life events". The authors also argue that these similar experiences greatly influence individuals' values and behaviors. It is first important to understand the different generations currently involved in tourism in order to analyze the different motivations for travel. The five major generations are known in chronological order as the "Silent Generation", "Baby Boomers", "Generation X", "Generation Y", and "Generation Z". Each generation is usually 20-25 years, so the motivations between generations change regularly. For example, a young adult will not look for the same experience as an older person. Technology plays a large part in the inter-generational differences related to decision-making. Several studies have been conducted to investigate the generational characteristics of online tourist information sources and processing (Reisenwitz

& Fowler, 2019). Studies show that the use of the internet has increased in all generations, but the older generations are less likely to use the internet for information search. The rise of P2P accommodation therefore benefited younger generations that are used to the internet in their daily lives, making it easier to book accommodations on online platforms.

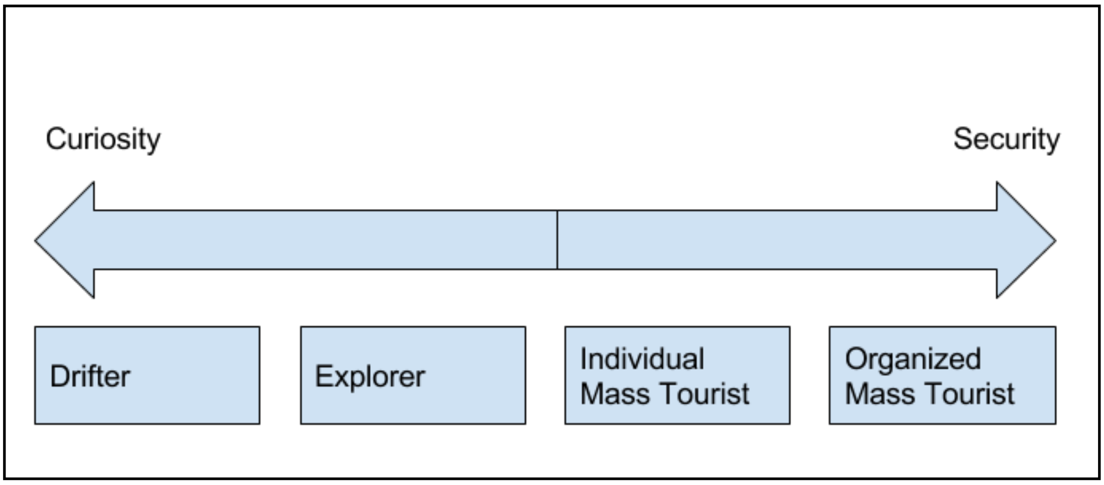
A 2016 report by Airbnb states that "millennials are the largest generation in history, and by 2025, millennials and younger generations will account for 75% of all consumers and travelers" (Airbnb, 2016, p. 2). Millennials are defined as individuals born between 1980 and the early 2000s and surpassed the baby boomers generation in terms of numbers. They represent roughly 60% of all guests who have ever booked accommodation on Airbnb. It is also said that Millenials would rather travel than buy a house or pay off debts. Due to this fact, and the fact that it is a generation familiar with the use of the internet for information search, millennials are the perfect category to target for P2P accommodation platforms. Millennials are also linked with the search for authenticity. The Airbnb report states "Over 80% of millennials seek unique travel experiences and say that the best way to learn about a place is to live like the locals do" (p. 2). Airbnb has long been seen as a platform providing authentic and local experiences due to its listings located in key areas of destinations and the experience it provides to guests by sharing the life of a local. Therefore, it attracts new kinds of customers that would not be able to access that authenticity through traditional accommodations.

Through a quantitative survey conducted on 1.285 residents of Tenerife, Spain, Garau-Vadell et al. showed that millennial residents are more supportive of P2P accommodations than any other generation (2023). The authors argue that their support is based on a greater perception of the positive economic benefits, as well as the social and environmental impacts than previous generations. This shows that when individuals are involved in using P2P accommodations, they are also more tolerant towards P2P accommodations in their home cities. Millennials are considered to display a great commitment to local communities (Hira, 2007). This generation is also said to appreciate true connections with local populations and the creation of authentic local experiences (Ketter, 2021). Based on often wrong beliefs about the positive benefits the rise of P2P accommodation brought to local communities, millennials can overestimate the positive social impacts of P2P accommodation and underestimate the negative ones (Garau-Vadell et al., 2023).

2.5.4.3. Quest for authenticity

Understanding the tourist experience is crucial in analyzing tourist behavior. Early studies of the tourist experience emphasize its distinctiveness from everyday life. Smith defines the tourist as "a temporarily leisured person who visits a place away from home for the purpose of experiencing change" (1978, p. 1). Similarly, Turner and Ash (1975) argue that individuals leave their regular environments for the purpose of tourism to suspend the norms and values governing their lives. The authors argue that tourism allows individuals to think about their daily lives from a different perspective. MacCannell (1973) portrays tourism as a quest for authenticity. He argues that individuals perceive their daily lives as inauthentic as opposed to the search for authentic experiences when traveling and breaking the bonds of their everyday experiences. The notion of differentiating the tourism experience from the routine of everyday life has been challenged since the 90s. Lash and Urry (1994) argue that nowadays many aspects of experiences that were once confined to tourism are now accessible in various contexts of everyday life. They argue that many tourist-related experiences are currently reachable without the necessity for travel to separate destinations. In that context, Uriely (2005) identified four conceptual developments in the study of the tourist experience: de-differentiating the experience, pluralizing the experience, the role of subjectivity, and toward relative interpretations. The author argues that early conceptualizations of the tourist experience are not relevant anymore and that the experience is subjective and shaped by various factors such as class, ethnicity, or gender. Uriely also argues that "as part of an attempt to capture the essence of tourism, early conceptualizations were not concerned with the variety of meanings and motivations" (2005, p. 204). The author describes the necessity of pluralizing the tourist experience instead of the generalization introduced by early conceptualizations. In that context, Cohen developed a typology of four tourist types, one of the first major typologies to be introduced in the travel and tourism industry (1972) (Figure 6). The notion of plurality introduced by the author set the beginning of different categorizations aiming to capture the variety of the tourist experience.

FIGURE 6: COHEN'S TOURIST TYPOLOGY



Source: Cohen (1972)

The four types of tourists identified by Cohen are the Drifter, the Explorer, the Individual mass tourist, and the Organized mass tourist. The first two types of tourists (the Drifter and the Explorer) are deemed noninstitutionalized tourists and the latter two (The Individual mass tourist and the Organised mass tourist) are examples of institutionalized tourists. The Drifter and the Explorer are represented as searching for a low familiarity and high novelty. The Drifter is considered a highly adventurous tourist searching for an authentic experience by living in the local community. The Explorer is a tourist that often travels alone and seeks comfortable accommodation and reliable transportation. Those two types of tourists are the ones that are the most active in P2P accommodation rentals as it often allows them to live closer to local communities. The Individual mass tourist and the Organized mass tourist are represented as searching for a high familiarity and low novelty, often seeking for similar experiences over the years. The Individual mass tourist is not controlled by a group and has a somewhat controlled time and itinerary. The Organized mass tourist often follows a tour guide with a fixed itinerary in advance. Cohen's tourist typology is important as it helps understand the kinds of tourists that are interested in participating in P2P accommodation rental to "differentiate" from mass tourists.

In order to understand the tourist experience, it is important to understand how the customer experience is relevant for most businesses, and how P2P accommodation platforms benefit from providing a memorable experience for their guests. For Meyer and Schwager, "Customer experience encompasses every aspect of a company's offering – the quality of customer care, of course, but also advertising, packaging, product and service features, ease of use and reliability" (2007, p. 118). The authors argue that customer experience should be the central focus of every travel-related business. They indicate that the owners/leaders of most companies don't really understand why the customer experience is so important, or they fail to incorporate measures that can then be used to provide insight into ways that might guide the development of new strategies for customer management. Tourism contrasts with the "normal" consumption of goods regarding the stages of consumption. The travel experiences often happen in the pre and post-consumption stages in addition to the actual trip.

Since its foundation, Airbnb has often been considered a platform providing "authentic accommodation" (Nieuwland & van Melik, 2018, p. 812), and its popularity among tourists comes in part from this belief. In fact, the potential for a more unique and authentic local experience became the value proposition of P2P accommodation online platforms, including Airbnb (Guttentag et al., 2017). It has however been proven that the sustainable attributes that made the popularity of Airbnb are not relevant anymore (Oskam, 2019). Cinar et al. argue that one of the main elements encouraging individuals to travel is their quest for authenticity, lacking in their everyday life (2022). That search for authentic experiences means that tourists are more likely to experience authenticity through subjective experiences rather than viewed objects (Cinar et al., 2022). The authors argue that the quest for authenticity begins in the pre-travel stage and that there is only a little literature on authenticity in the pre-travel phase. The search for authenticity made Airbnb popular due to its various listings in several European city centers. The variety of Airbnb listings also includes atypical forms of accommodation such as tree houses, glass bubbles, or even yurts, that would otherwise not be accessible to tourists without P2P. Derived from the previously stated research question, a hypothesis is developed that can help us understand the relationship between the search for authentic experiences and overtourism in Europe. NOUTUR (standing for New Perspectives for Tourism and Leisure) studying the impacts of P2P online platforms such as Airbnb on the cities they advertise. NOUTUR concluded that tourists "take advantage of the identities of destinations and their communities, and commodify them, without taking into account the needs of the inhabitants of the neighborhoods they advertise". The search for authenticity and local experience damages the cities in which P2P accommodation is the most present. Consequently, such tourists contribute to further overcrowding in already saturated tourist destinations.

The professionalization of the hosts on P2P accommodation platforms contrasts with the perceived authenticity of such platforms. The phenomenon of multi-listings in the same destinations is not compatible with creating a local and authentic experience. Many of the hosts do not live in the apartment they rent as it is used only for short-term rental and not as a way of earning extra revenues from time to time. Most of the listings are also rented by companies in the business of P2P short-term rental. The perceived authenticity of those listings can be contested as they are considered as "quasi-hotels", therefore not providing a more local experience than what hotels can provide. For example, research on P2P short-term rentals has put forward the benefits of accessing a local resident host who can provide the guest with tips and advice on local and authentic restaurants or activities (Guttentag et al, 2017; Belarmino et al., 2019). However, it can be concluded that there isn't much difference between the local tips of a supposedly "local" host and those of a hotel concierge. This perceived authenticity can be explained in a combination of other different factors such as host-guest interactions and the co-creation of the experience. The relationship between guests and hosts in the P2P short-term rental sector has been the topic of much research. Belarmino et al. (2019) argue that guests in P2P emphasize their relationship with the hosts while hotel guests place more value on room attributes.

The notion of trust plays an important role in the host-guest relationship and in the authenticity perceived by guests booking a P2P listing. Trust in the sharing economy is referred as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis, & Schoorman, 1995, p. 712). The trust in P2P accommodation is twofold: the user's trust towards providers (hosts) and the user's trust towards the platform (e.g. Airbnb). Pelgander et al. (2022) argue that user trust in providers is based on emotional traits while user trust in the platform is based on functional components. It can be concluded that the provider and the platform complement each other in ensuring the trust created for the guest. User trust can however be perceived as a weakness of P2P accommodation when it can't be ensured. In contrast to relying upon an established formal enterprise associated with a familiar global brand, guests must entrust a (generally unlicensed) stranger with ensuring the quality, cleanliness, and security of their sleeping area (Guttentag et al., 2017). However, it was shown with time that it did not constitute an issue as the growth of P2P accommodation was phenomenal, and online short-term rental platforms became incredibly popular.

H_4: The perceived authenticity of P2P accommodations leads to an increase in overtourism in European destinations

2.6. Research model

Based on the literature review and on the hypotheses derived from the research questions, the research model below has been created (Figure 7). The research model shows the potential influence of the four selected independent variables on the dependent variable of this study. The next part of this study focuses on analyzing this relationship by the testing and verification of the derived hypotheses.

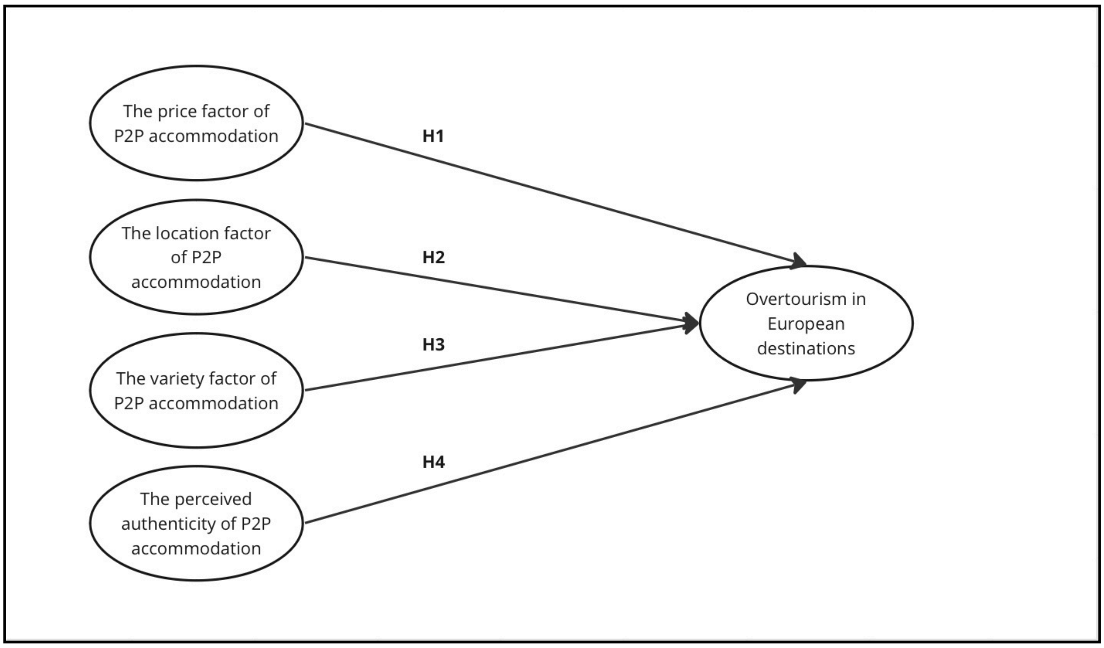


FIGURE 7: RESEARCH MODEL

Source: Author

3. METHODOLOGY

This chapter of the paper emphasizes a thorough understanding of the applied research methods used to address the general objective of this thesis, which is to determine how different characteristics of the P2P accommodation market and tourist behavior influence overtourism in European destinations. This chapter provides a detailed explanation of the selected data acquisition method, research approach, and methodology as the most suitable methods provide more precise research outcomes, resulting in more accurate and useful results, predictions, and added value. The first part of this chapter provides general information regarding the selection of methodology and research design. It is followed by an explanation of the process of variable selection and data collection.

3.1. Selection of methodology

The purpose of this chapter is to provide an overview of the research methods used in this paper in order to better understand them. The correct choice of methodology is crucial in research as the process of collecting information, analyzing it, and drawing conclusions based on this collected data provides more accurate results and accomplishes the goal of the study. According to Creswell (2014), three different approaches can be used when conducting research: a qualitative, quantitative, or mixed-methods approach. Qualitative research involves collecting and analyzing non-numerical data to gain a deeper understanding of concepts, opinions, or experiences, whereas quantitative research involves collecting and analyzing numerical data for statistical analysis. The mixed-methods approach combines both quantitative and qualitative methods of collecting data.

The most appropriate research method that can be used to address the research questions of this paper is a quantitative secondary data analysis. A quantitative research method is the most efficient way of analyzing and quantifying the specific variables related to the different characteristics of P2P accommodation related to overtourism (See Chapter 2.6. Research model). Quantitative research focuses on the testing of hypotheses by identifying statistical relationships between two or more variables (Hair et al., 2012). An explanatory research is conducted in order to provide a better understanding of the cause-and-effect relationship between the independent and dependent variables. In the proposed research model, the independent variables are the price, location, variety, and perceived experience of P2P accommodation while the dependent variable is overtourism in European destinations. Further details regarding the selected variables for this study are provided later in Chapter 3.3. Variable selection.

3.2. Research design

An organized plan for conducting research toward a defined goal is referred to as a research design (Kumar et al., 2019). This chapter presents the research design employed in the study to investigate the relationship between P2P short-term rental platforms and overtourism. The research questions of the study guided the research design. The specific research questions were:

1. How does the price of P2P accommodation relate to overtourism in Europe?
2. How does the location of P2P accommodation listings influence overtourism in Europe?
3. How does the variety of P2P accommodation listings influence overtourism in Europe?
4. How does the perceived authenticity of P2P accommodation influence overtourism in Europe?

A quantitative research approach was adopted to examine the relationship between P2P short-term rental platforms and overtourism. By using this approach, numerical data could be collected and analyzed statistically to draw objective conclusions.

According to Fritz and Morgan, the process of sampling is used by researchers to examine a portion or sample of a larger group of potential participants for the purpose of making statements that are generalizable to the entire group or population (2010). The target population of this study is European cities. Due to limited available data, the sampling procedure consists of a selection of 29 European cities analyzed quarterly over a period of eight years, from approximately 2015 to 2023. The selected cities are located in various European countries in order to respect variety that will provide more accurate results of the impact of P2P short-term rentals in European cities. Only European tourism cities are considered in this study and not whole destinations. Gaps in the quarterly data represent the lack of available information for a specific city and time period. Further limitations are discussed in Chapter 5.3. Limitations.

3.3. Variable selection

The following chapter contains information on the selection choice of the different variables of the study. Dependent and independent variables are variables in mathematical modeling, statistical modeling, and experimental sciences (Rutherford, 1994). The independent variable is the variable the experimenter manipulates or changes and is assumed to directly affect the dependent variable, while the dependent variable is the variable being tested and measured in an experiment and is “dependent” on the independent variable (Mcleod, 2023). Of the two, it is always the dependent variable whose variation is being studied, by altering inputs, also known as regressors in a statistical context.

3.3.1. Dependent variable

In this subsection, we will focus on the dependent variable of the study, which is overtourism. Overtourism is a complex concept that encompasses various dimensions and indicators. Different dimensions must be taken into account in order to operationalize overtourism, such as tourist density, infrastructure strain, environmental degradation, and socio-cultural disruption, such as the residents’ perception of tourism in their local area. As overtourism can increase or decrease depending on various factors, it is the dependent variable of this study.

However, in this study, a unidimensional approach is used to operationalize overtourism: tourist density. This dimension captures the overcrowding and congestion experienced by residents and tourists in the destination. It is measured with two distinct variables: the number of tourism bednights per inhabitant, and the number of tourism arrivals per inhabitant. Two tourist density values are then gathered: the tourist density of bednights, and the tourist density of arrivals. To measure overtourism across this dimension, secondary data was used. The main secondary data source used is the TourMIS database, displaying information on the number of bednights and arrivals for the selected cities.

For more precision, the term "bednights" refers to the number of nights spent by guests in a particular accommodation facility, such as a hotel, resort, or guesthouse. Bednights are calculated by multiplying the number of occupied rooms by the number of nights stayed. The term “arrivals” refers to the number of visitors who arrive in a particular destination, whether it be a country, city, or specific tourism site, during a specific period of time. It represents the count of individuals who have completed their journey and have arrived at the destination for tourism purposes.

3.3.2. Independent variables

In this subsection, we will focus on the independent variables of the study, which include price, location, variety, and perceived authenticity of P2P short-term rentals. These variables are crucial in understanding the factors that contribute to overtourism and its relationship with the growing popularity of P2P accommodation platforms.

- <u>Price</u>: Price refers to the cost of renting a P2P short-term accommodation unit. It is an important factor that influences tourists' decision-making process and has the potential to affect destination choices and travel behaviors. In this study, the price of P2P rentals will be assessed based on the average rental rate per night

- Location: Location represents the geographical position of P2P short-term rentals within the destination. It plays a significant role in attracting tourists, as it determines accessibility to tourist attractions, amenities, and transportation networks. Location is measured through neighborhood density.

- Variety: Variety refers to the range and diversity of P2P short-term rental options available in a destination. It encompasses different types of accommodations, such as apartments, houses, villas, or unique properties, offering tourists a wide selection of choices. Variety is measured through the number of listings and the percentage of entire accommodations among the analyzed Airbnb listings.

- Perceived Authenticity: Perceived authenticity captures the extent to which P2P short-term rentals are perceived as providing an authentic local experience for tourists. It reflects the authenticity and uniqueness of the accommodation and its alignment with the local culture, heritage, and community. In this study, perceived authenticity is measured through the percentage of multi-listings and the number of reviews.

It is important to mention that these four variables were chosen subjectively. They do not objectively represent the entirety of the P2P accommodation factors that can have an impact on overtourism.

3.4. Data collection

The data collected for this study is secondary, meaning that the data has already been collected and is readily available from other sources. The data collected needs to be homogeneous for every selected variable as the relationship between the variables must be systematic and temporal (Dudovskiy, 2016). The data collected mostly comes from two sources: Inside Airbnb for the independent variables and TourMIS for the dependent variables. The population for each study comes from various sources, including TourMIS and national statistical offices.

The data collected related to the independent variables of this study has been gathered freely on Inside Airbnb data sets. Inside Airbnb is a website that provides access to data and visualizations related to Airbnb listings in various cities around the world. It is an independent project that aims to promote transparency and facilitate the analysis of the impact of short-term rentals on housing markets and communities. Those data sets provide various and valuable information over the last four quarters of each selected destination. The data gathered from the pre-COVID-19 era also comes from Inside Airbnb data sets but is recovered using the Wayback Machine as they are not accessible anymore on their website.

The data collected and used to measure the dependent variable of this study as well as the general tourism information regarding the selected destinations has been collected on TourMIS, such as the quarterly bednights and arrivals. TourMIS stands for Tourism Management Information System. This digital platform is used to collect, store, analyze, and disseminate tourism-related information and data. The TourMIS system manages tourism information in a comprehensive and integrated way to support tourism decision-making processes.

The quarterly bednights and arrivals have been gathered in four different categories. The abbreviation "NAS" represents the number of bednights in all forms of paid accommodation in the greater city area, while the abbreviation "NA" represents the number of bednights in all forms of paid accommodation in the city area only. Similarly, the abbreviation "NGS" represents the number of bednights in hotels and similar establishments in the greater city area, while the abbreviation "NG" represents the number of bednights in hotels and similar establishments in the city area only. The same process is applied to the number of arrivals with the abbreviations "AAS", "AA", "AGS", and "AG". The yearly population has also been gathered according to two categories. The abbreviation "POP" represents the municipal population of a city while the abbreviation "POPS" represents the population in the greater city area. Every abbreviation is used with the corresponding one, meaning that if a variable for a city contains data related to the greater city area, then the corresponding variable contains a similar type of data.

4. RESULTS AND DISCUSSION

In this chapter, the results of the analysis are presented. Firstly, descriptive statistics are provided to give an overview and comparison between the two dimensions used to measure overtourism, the tourist density of bednights, and the tourist density of arrivals. The next part presents the linear regression model performed on the two data sets. It is followed by the testing of the presented hypotheses. Finally, this chapter concludes with a summary of the findings.

4.1. Descriptive statistics

Descriptive statistics of the study were computed in Jamovi to have a rough overview of the two ways used to measure the dependent variable of this study, overtourism. The data was segmented by city, with one variable being the tourist density of bednights (Table 1), and the other being the tourist density of arrivals (Table 2). The results are summarized in the two tables below.

Out of the selected cities, on average, Lisbon is the city with the highest tourist density with a mean of respectively 5.87 for the tourist density of bednights and 2.46 for the tourist density of arrivals. It is followed by Copenhagen with a tourist density of bednights of 5.57 and another Portuguese city, Porto, with a tourist density of arrivals of 2.13. It is due to the fact that these cities are relatively small regarding the number of tourists they welcome every year. By analyzing the standard deviation of each table, it can be seen that Lisbon and Copenhagen are clear outliers in the tourist density of bednights' data set as their standard deviation are largely superior to the other selected cities with respective values of 2.20 and 1.43. These outliers have a high standard deviation as they have more variability compared to the other cities. For example, the minimum tourist density of bednights for the city of Lisbon is 1.60 and its maximum is 7.82, showing a large variance over the quarters and years. Similarly, the minimum tourist density of bednights for the city of Copenhagen is 1.84 and its maximum is 5.57.

TABLE 1: DESCRIPTIVE STATISTICS OF TOURIST DENSITY OF BEDNIGHTS PER CITY

Cities	N	Minimum	Maximum	Mean	Median	Standard dev.
Amsterdam	11	1.05	2.32	1.75	1.90	.492
Antwerp	7	.359	1.30	.943	1.03	.324
Barcelona	10	1.40	3.70	2.74	2.91	.786
Berlin	8	.917	2.34	1.89	2.07	.482

Bologna	3	.983	1.00	.995	.999	.0112
Bordeaux	2	1.06	1.14	1.10	1.10	.0618
Brusels	5	1.28	1.55	1.42	1.44	.109
Copenhagen	6	1.84	5.57	3.58	3.75	1.43
Ghent	3	1.38	1.66	1.50	1.45	.147
Lisbon	6	1.60	7.82	5.87	6.50	2.20
Madrid	8	.823	1.60	1.37	1.43	.236
Malaga	1	.723	.723	.723	.723	NaN
Munich	5	2.17	3.42	2.70	2.66	.488
Oslo	4	1.46	2.30	1.82	1.76	.356
Paris	10	.759	1.18	1.04	1.09	.123
Prague	4	1.32	3.34	2.41	2.48	.865
Rotterdam	4	.739	1.02	.876	.872	.123
Seville	5	1.47	2.67	2.21	2.49	.510
Stockholm	5	.881	1.94	1.41	1.42	.411
The Hague	4	.756	1.41	1.06	1.04	.287
Valencia	4	1.43	2.08	1.73	1.71	.287
Vienna	6	.468	2.58	1.99	2.24	.782

Table 2: Descriptive statistics of tourist density of arrivals per city

Cities	**N**	**Minimum**	**Maximum**	**Mean**	**Median**	**Standard dev.**
Amsterdam	11	.526	1.21	.873	.944	.244
Antwerp	7	.196	.679	.521	.594	.171
Barcelona	10	.718	1.57	1.22	1.30	.290
Berlin	8	.351	.969	.766	.809	.204
Bordeaux	2	.666	.722	.694	.694	.0394
Brusels	5	.683	.830	.733	.731	.0595
Ghent	3	.764	.870	.800	.766	.0608
Lisbon	6	.694	3.22	2.46	2.73	.901
Madrid	8	.410	.782	.671	.697	.112

Munich	5	1.01	1.49	1.22	1.18	.178
Oslo	4	.845	1.23	1.02	1.00	.158
Paris	10	.380	.517	.478	.494	.0414
Porto	6	1.29	3.23	2.13	2.01	.743
Prague	3	.993	1.45	1.23	1.26	.228
Rotterdam	4	.444	.543	.494	.494	.0454
Seville	4	.694	1.23	1.06	1.16	.248
The Hague	4	.405	.686	.556	.566	.120
Valencia	4	.649	.792	.719	.717	.0632
Vienna	6	.200	1.17	.884	.972	.361

4.2. Linear regression

The linear regression method analyzes and models the relationship between a dependent variable and an independent variable. It assumes that there is a linear relationship between the variables, meaning that the change in the dependent variable is directly proportional to the change in the independent variable. In order to make the data more suitable for our study, the natural logarithm of the "tourist density" variables was taken. It is used to make data conform more closely to assumptions of normality.

Three types of indicators, or dummy variables:

- <u>Cities</u>: There are 22 cities selected in the tourist density of bednights data set and 19 cities selected in the tourist density of arrivals data set. When looking at the model coefficients later on in the next chapters, Amsterdam always serves as the reference city.

- <u>Quarters</u>: Q1 is the dummy variable for quarter one, Q2 is the dummy variable for quarter two, Q3 is the dummy variable for quarter three, and Q4 is the dummy variable for quarter four. Regarding the model coefficients and the different indicators, Q1 serves as the reference for the other quarters

- <u>Years</u>: The selected years range from 2015 to 2023, with 2015 always serving as the reference year. The only exception is regarding the influence of variety on overtourism with the neighborhood density variable as it uses a different data set with years ranging from 2021 to 2023. In that case, 2021 serves as the reference year.

The next part of this study focuses on the testing of hypotheses with a linear regression model.

4.3. Hypothesis testing

In order to test the research hypotheses of this study, the coefficients of the linear regression model were considered. The results of all hypothesis tests are summarized in Table 19. The following chapters focus on the relationship between each of the selected independent variables including the price, location, variety, and perceived authenticity on the dependent variable that is overtourism, measured with the natural logarithm of bednights and arrivals.

4.3.1. Influence of Price on Overtourism (H1)

This chapter focuses on the testing of H_1, which relates to the influence of price on overtourism. Below is an overview of the coefficients used in this chapter:

- α is the intercept - it is the value of the natural log of tourist density of bednights or arrivals when the natural log of price is set to zero.
- $LP_{B_{it}}$ is the natural logarithm of the average price of Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.
- $LP_{A_{it}}$ is the natural logarithm of the average price of Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.

When computing the price variable into the Jamovi software, the assumption of normality was not respected and the data did not follow a normal distribution. The natural logarithm of price was taken in order to test for significance. In order to check for assumptions of the regression model, residual plots were created with the natural logarithm of price. The histogram of the residuals created showed a normal distribution with a few outliers. Using Cook's distance to identify influential observations that may disproportionately affect the regression analysis, two rows of data were deleted in order to obtain more appropriate regression coefficients. The R^2 and adjusted R^2 in the model fit measures (See Table 5) indicate that the proportion of variance in the natural logarithm of overtourism explained by the natural logarithm of price is a good fit for the selected model with respective values of .941 and .919 for the bednights variable and .942 and .921 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05.

Looking at the model coefficients, the intercept α = .242 for the tourist density of bednights and the intercept α = .618 for the tourist density of arrivals is not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant with p-value =

<.001 at alpha = .05, with Q1 as the reference. Regarding the tourist density of arrivals, the difference in price between Antwerp and Amsterdam is statistically significant with a p-value = <.001 at alpha = .05. The difference in the listings' prices of the cities of Barcelona, Lisbon, Munich, Paris, Porto, Rotterdam, and The Hague are also all statistically significant from Amsterdam with a p-value = <.001. In total, the listings' price difference in 13 out of 18 cities is statistically significant from the listings' prices in Amsterdam. Regarding the tourist density of bednights, the difference in the listings' prices of 17 out of the 21 selected cities is statistically significant from Amsterdam. A summary of the regression coefficients regarding the effect of price on overtourism can be found in Appendix 1 and Appendix 2.

H_1 stated that the difference in price between P2P accommodation platforms and hotels would have a significant positive impact on overtourism in Europe. The estimated coefficient $LP_{B_{it}}$ = .480, p <.001, and $LP_{A_{it}}$ = .912, p <.001 indicates that the effect of price is not statistically significant at alpha = .05 (See Table 4). Therefore, H_1 is not supported.

TABLE 3: MODEL FIT MEASURES OF PRICE ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.970	.941	.919	43.1	32	86	<.001
Arrivals	2	.971	.942	.921	44.1	29	78	<.001

TABLE 4: MODEL COEFFICIENTS OF PRICE ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Log price	-.0900	.1267	-.710	.480
Arrivals		-.0135	.1216	-.1113	.912

4.3.2. Influence of Location on Overtourism (H2)

This chapter focuses on the testing of H_2, which relates to the influence of neighborhood density on overtourism. Below is an overview of the coefficients used in this chapter:

- α is the intercept - it is the value of the natural log of tourist density of bednights or arrivals when the neighborhood density variable is set to zero.

- $N_{B_{it}}$ is the neighborhood density of Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.
- $N_{A_{it}}$ is the neighborhood density of Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.

When collecting data regarding the Airbnb listings, the neighborhoods variable was empty in some rows as it had to be calculated manually from each data set available on the Inside Airbnb website and could not be retrieved using the Wayback Machine. Therefore, the available data for this variable ranges from the year 2021 to 2023 as they are the only years with an available access to data sets depending on the city and the quarters. In order to analyze this variable, a separate dataset had to be created only with the rows with available data on neighborhood density. In order to check for assumptions of the regression model, residual plots were created with the natural logarithm of price. The histogram of the residuals created as well as the scatterplot showed a normal distribution. The R^2 and adjusted R^2 in the model fit measures (See Table 7) indicate that the proportion of variance in the natural logarithm of overtourism explained by the percentage of neighborhood density is a good fit for the selected model with respective values of .960 and .940 for the bednights variable and 0.962 and 0.944 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05.

Looking at the model coefficients, the intercept α = .027 for the tourist density of bednights and the intercept α = <.001 for the tourist density of arrivals is statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant with p-value = <.001 at alpha = .05, with Q1 as the reference. Similarly, the two dummy variables for years are statistically significant with p-value = <.001 at alpha = .05, with 2021 as the reference. When looking at the regression coefficients of the difference in neighborhood density between the different cities, we can see that The difference in neighborhood density is statistically significant for 14 out of the 20 selected cities with Amsterdam as the reference city regarding the tourist density of bednights and is statistically significant for 10 out of the 17 selected cities with Amsterdam as the reference city regarding the tourist density of arrivals. A summary of the regression coefficients regarding the effect of neighborhood density on overtourism can be found in Appendix 3 and Appendix 4.

H_2 stated that the location of P2P short-term rental listings would have a significant positive impact on overtourism in Europe. The estimated coefficient $N_{B_{it}}$ = .476, p <.001 and $N_{A_{it}}$ =

.157, p <.001 indicates that the effect of clustered neighborhoods is not statistically significant at alpha = .05 (See Table 6). Therefore, H_2 is not supported.

TABLE 5: MODEL FIT MEASURES OF NEIGHBORHOODS ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.980	.960	.940	48.4	26	53	<.001
Arrivals	2	.981	.962	.944	54.9	23	50	<.001

TABLE 6: MODEL COEFFICIENTS OF NEIGHBORHOODS ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Neighborhoods	.7964	1.1098	.718	.476
Arrivals		1.51100	1.0512	1.4374	.157

4.3.3. Influence of Variety on Overtourism (H3)

This chapter focuses on the testing of H_3, which relates to the influence of listings' variety on overtourism. Below is an overview of the coefficients used in this chapter:

- α is the intercept - it is the value of the natural log of tourist density of bednights or arrivals when the natural logarithm of listings or the entire accommodation variable is set to zero, depending on which one is analyzed.
- $LNL_{B_{it}}$ is the natural logarithm of the number of Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.
- $LNL_{A_{it}}$ is the natural logarithm of the number of Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.
- $EA_{B_{it}}$ is the percentage of entire accommodations among Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.

- $EA_{A_{it}}$ is the percentage of entire accommodations among Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.

The variety variable was analyzed using two indicators: the number of Airbnb listings and the percentage of entire accommodations among those listings. The number of listings can provide an indication of the variety or diversity of accommodation options available in a given location. A higher number of listings typically suggests a greater variety of choices in terms of property types, amenities, and styles of accommodation. Also, by examining the distribution of entire accommodations, the range of choices available to travelers can be assessed.

When computing the listings variable into the Jamovi software and using the residual plots, the normality assumptions were not respected and the data was not following a normal distribution. The natural logarithm of the listings variable was taken in order to continue with the linear regression model. The residuals plots and scatterplot showed that the natural logarithm of the number of listings was closer to the normality assumptions. When analyzing the histogram of the residuals, the same outliers mentioned in the previous chapters were removed from the data set using Cook's distance.

Looking at the model coefficients, the intercept α = .038 for the tourist density of bednights is statistically significant at alpha = .05, and the intercept α = <.383 for the tourist density of arrivals is not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant with p-value = <.001 at alpha = .05, with Q1 as the reference. When looking at the regression coefficients of the difference in the number of listings between the different cities, we can see that 16 out of the 21 selected have a p-value superior to the alpha of .05 and is therefore statistically significant for the tourist density of bednights. Regarding the difference in the number of listings related to the tourist density of arrivals, 13 out of the 18 selected cities are statistically significant to the reference city of Amsterdam. A summary of the regression coefficients regarding the effect of the number of listings on overtourism can be found in Appendix 5 and Appendix 6.

H_3 stated that the variety of P2P short-term rental listings would have a significant positive effect on overtourism in Europe. The estimated coefficient $LNL_{B_{it}}$ = .089, p <.001 indicates that the effect of the number of listings is not statistically significant on the tourist density of bednights at alpha =.05. The estimated coefficient $LNL_{A_{it}}$ = .158, p <.001 indicates that the effect of variety is also not statistically significant on the tourist density of arrivals at alpha = .05 (See Table 8).

TABLE 7: MODEL FIT MEASURES OF LISTINGS ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.971	.943	.922	44.4	32	86	<.001
Arrivals	2	.972	.944	.923	45.3	29	78	<.001

TABLE 8: MODEL COEFFICIENTS OF LISTINGS ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Log listings	-.14467	.0842	-1.7176	.089
Arrivals		-.11306	.0794	-1.4240	.158

The second indicator used to measure the variety variable is the percentage of entire accommodations in the Airbnb listings analyzed. The data seemed to follow the normality assumptions and to be approximately normally distributed by looking at the residual plots and the scatterplot. The same outliers mentioned previously have been deleted from the data set using Cook's distance in order to perform the same analysis as for the previous variables.

Looking at the model coefficients, the intercept α = .049 for the tourist density of bednights is statistically significant at alpha = .05, and the intercept α = .036 for the tourist density of arrivals is also statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant for both the tourist density of bednights and arrivals, with Q1 as the reference. Only the difference in the percentage of entire accommodation between the years 2019 and 2015 is statistically significant with a p-value = <.001 at alpha = .05. The difference in the percentage of accommodation between Amsterdam and 17 of the 21 selected cities is statistically significant with a p-value superior to alpha = .05 for the tourist density of bednights, and 17 of the 18 selected for the tourist density of arrivals. A summary of the regression coefficients regarding the effect of the percentage of entire accommodation on overtourism can be found in Appendix 7 and Appendix 8.

The estimated coefficient $EA_{B_{it}}$ = .028, p <.001 indicates that the effect of entire accommodation is statistically significant on the tourist density of bednights at alpha =.05. The estimated coefficient $EA_{A_{it}}$ = .370, p <.001 indicates that the effect of entire accommodation is not statistically significant on the tourist density of arrivals at alpha = .05 (See Table 10). These results indicate that H_3 is partially supported in relation to the effect of the percentage of entire accommodation on the tourist density of bednights, but rejected in the three other tests. As the effect of variety on overtourism is not statistically significant, H_3 is therefore rejected.

TABLE 9: MODEL FIT MEASURES OF ENTIRE ACC. ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.972	.944	.923	45.5	32	86	<.001
Arrivals	2	.985	.969	.958	82.0	29	75	<.001

TABLE 10: MODEL COEFFICIENTS OF ENTIRE ACC. ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Entire acc.	.00454	.00203	2.2392	.028
Arrivals		.00129	.00143	.901	.370

After analyzing the two indicators separately, the natural logarithm of listings and the percentage of accommodations were analyzed together to test the effect of both indicators on the variety variable. The R^2 and adjusted R^2 in the model fit measures (See Table 11) indicate that the proportion of variance in the natural logarithm of overtourism explained by the natural logarithm of listings and the percentage of entire accommodation is a good fit for the selected model with respective values of .945 and .924 for the bednights variable and .945 and .924 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05. A summary of the results is shown in Appendix 9 and Appendix 10.

Looking at the model coefficients, the intercept α = .144 for the tourist density of bednights is not statistically significant at alpha = .05, and the intercept α = .692 for the tourist density of arrivals is also not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant for both the tourist density of bednights and arrivals, with Q1 as the reference.

With all regression coefficients superior to the alpha level (<.05) (See Table 12), it indicates that the effect of the correlation between the two indicators and overtourism is not statistically significant. Therefore, H_3 stays rejected.

TABLE 11: MODEL FIT MEASURES OF LISTINGS AND ENTIRE ACC. ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.972	.945	.924	44.3	33	85	<.001
Arrivals	2	.972	.945	.924	44.2	30	77	<.001

TABLE 12: MODEL COEFFICIENTS OF LISTINGS AND ENTIRE ACC. ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Log Listings	-.10272	.08610	-1.1931	.236
Bednights	Entire acc.	.00388	.00210	1.8516	.068
Arrivals	Log Listings	-.08297	.08237	-1.0073	.317
Arrivals	Entire acc.	.00265	.00204	1.2989	.198

4.3.4. Influence of Perceived Authenticity on Overtourism (H4)

This chapter focuses on the testing of H_4, which relates to the influence of the perceived authenticity of Airbnb listings on overtourism. Below is an overview of the coefficients used in this chapter:

- α is the intercept - it is the value of the natural log of tourist density of bednights or arrivals when the natural logarithm of reviews or the multi-listings variable is set to zero, depending on which one is analyzed.
- $LR_{B_{it}}$ is the natural logarithm of the number of reviews of Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.
- $LR_{A_{it}}$ is the natural logarithm of the number of reviews of Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.

- $ML_{B_{it}}$ is the percentage of multi-listings among Airbnb listings related to the natural logarithm of the tourist density of bednights for destination i during time period t.
- $ML_{A_{it}}$ is the percentage of multi-listings among Airbnb listings related to the natural logarithm of the tourist density of arrivals for destination i during time period t.

The first indicator used to measure the perceived authenticity variable is the number of reviews. The rationale for using the number of reviews as an indicator of a perceived authenticity is that a higher number of reviews generally suggests a larger pool of past guests who have shared their experiences and opinions about a particular listing. As the data did not follow normality assumptions, the natural logarithm of the number of reviews was taken. The natural logarithm of the number of reviews made the data more normally distributed and therefore the linear regression analysis was possible. The R^2 and adjusted R^2 in the model fit measures (See Table 13) indicate that the proportion of variance in the natural logarithm of overtourism explained by the natural logarithm of reviews is a good fit for the selected model with respective values of .950 and .931 for the bednights variable and .944 and .923 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05. A summary of the results is shown in Appendix 11 and Appendix 12.

Looking at the regression coefficients, the intercept α = .078 for the tourist density of bednights is statistically significant at alpha = .05, and the intercept α = .327 for the tourist density of arrivals is not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant for both the tourist density of bednights and arrivals, with Q1 as the reference. Looking at the regression coefficients regarding the difference between the selected, 16 out of the 21 selected cities have statistically significant results regarding the reference city of Amsterdam for the tourist density of bednights and 14 out of the 18 selected are statistically significant for the tourist density of arrivals at alpha = .05.

H_4 stated that the perceived authenticity of P2P accommodations would have a significant positive effect on overtourism in Europe. The estimated coefficient $LR_{B_{it}}$ = .159, p <.001 and $LR_{A_{it}}$ =.196, p <.001 indicates that the effect of the number of reviews on the tourist density of bednights and arrivals is not statistically significant at alpha = .05 (See Table 14).

Table 13: Model fit measures of reviews on tourist density

Model Fit Measures

Variable	Model	R	R^2	Adjusted R^2	Overall Model Test F	df1	df2	p
Bednights	1	.975	.950	.931	48.8	32	82	<.001
Arrivals	2	.971	.944	.923	45.1	29	78	<.001

TABLE 14: MODEL COEFFICIENTS OF REVIEWS ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Log Reviews	-.14671	-.1032	-1.4221	.159
Arrivals		-.1333	.1021	-1.3049	.196

The second indicator used to measure the perceived authenticity variable is the percentage of multi-listings. The rationale for using the percentage of multi-listings as an indicator of perceived authenticity is that a higher percentage of multi-listings equates to a loss of authenticity. Indeed, it was previously mentioned that P2P online platforms such as Airbnb were known for providing authentic experiences to guests with a local host. Multi-listings suggest that a host owns more than one listing and that it is more likely that such hosts are professionals rather than simple locals renting their accommodation for a small income surplus. The data followed a rather normal distribution, and therefore the linear regression analysis was possible. The R^2 and adjusted R^2 in the model fit measures (See Table 15) indicate that the proportion of variance in the natural logarithm of overtourism explained by the percentage of multi-listings is a good fit for the selected model with respective values of .942 and .920 for the bednights variable and .945 and .924 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05. A summary of the results is shown in Appendix 13 and Appendix 14.

Looking at the model coefficients, the intercept α = .005 for the tourist density of bednights is statistically significant at alpha = .05, and the intercept α = .201 for the tourist density of arrivals is not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant for both the tourist density of bednights and arrivals, with Q1 as the reference.

The estimated coefficient $ML_{B_{it}}$ = .223, p <.001 and $ML_{A_{it}}$ = .064, p <.001 indicates that the effect of multi-listings on the tourist density of bednights and arrivals is also not statistically significant at alpha = .05 (See Table 16). Due to the fact that both the reviews and the multi-listings variable are not statistically significant, it can be concluded that H_4 is not supported and that the effect of perceived authenticity on overtourism is not statistically significant.

TABLE 15: MODEL FIT MEASURES OF MULTI-LISTINGS ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.971	.942	.920	43.6	32	86	<.001
Arrivals	2	.972	.945	.924	46.2	29	78	<.001

TABLE 16: MODEL COEFFICIENTS OF MULTI-LISTINGS ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Multi-listings	-.78851	.6428	-1.2268	.223
Arrivals		-1.1400	.6075	-1.876	.064

After analyzing the two indicators separately, the natural logarithm of reviews and the percentage of multi-listings were analyzed together to test the effect of both indicators on the perceived authenticity variable. The R^2 and adjusted R^2 in the model fit measures (See Table 17) indicate that the proportion of variance in the natural logarithm of overtourism explained by the natural logarithm of reviews and percentage of multi-listings is a good fit for the selected model with respective values of .951 and .930 for the bednights variable and .946 and .924 for the arrivals variable. Results of the F-test show that the model fit is statistically significant for both tourist density of bednights and arrivals with p = <.001 at alpha = .05. A summary of the results is shown in Appendix 15 and Appendix 16.

Looking at the model coefficients, the intercept α = .102 for the tourist density of bednights is not statistically significant at alpha = .05, and the intercept α = .430 for the tourist density of arrivals is also not statistically significant at alpha = .05. All three dummy variables for quarters are statistically significant for both the tourist density of bednights and arrivals, with Q1 as the reference.

With all regression coefficients superior to the alpha level (<.05) (See Table 18), it indicates that the effect of the correlation between the two indicators and overtourism is not statistically significant. Therefore, H_4 stays rejected.

TABLE 17: MODEL FIT MEASURES OF REVIEWS AND MULTI-LISTINGS ON TOURIST DENSITY

Model Fit Measures								
					Overall Model Test			
Variable	Model	R	R^2	Adjusted R^2	F	df1	df2	p
Bednights	1	.975	.951	.930	47.2	33	81	<.001
Arrivals	2	.972	.946	.924	44.6	30	77	<.001

TABLE 18: MODEL COEFFICIENTS OF REVIEWS AND MULTI-LISTINGS ON TOURIST DENSITY

Model Coefficients - Natural log density of bednights & arrivals					
Variable	Predictor	Estimate	SE	t	p
Bednights	Log Reviews	-.1276	.1056	-1.208	.230
Bednights	Multi-listings	-.5448	.6245	-.872	.386
Arrivals	Log Reviews	-.09893	.1032	-.9589	.341
Arrivals	Multi-listings	-1.01934	.6207	-1.6422	.105

4.3.5. Results of Hypotheses Testing

Based on the results of this study, none of the selected hypotheses proved to be statistically significant, therefore, all hypotheses are rejected.

TABLE 19: RESULTS OF HYPOTHESES TESTING

H_1: The difference in price between P2P accommodation and hotels has a significant positive effect on overtourism in Europe	Not supported
H_2: The location of P2P short-term rental listings has a significant positive effect on overtourism in Europe	Not supported
H_3: The variety of P2P short-term rental listings has a significant positive effect on overtourism in Europe	Not supported
H_4: The perceived authenticity of P2P accommodationshas a significant positive effect on overtourism in Europe	Not supported

4.4. Discussion of Findings

In relation to the dependent variable overtourism, measured by the tourist density of bednights and the tourist density of arrivals, none of the independent variables were statistically significant, based on the analysis of price, location, variety, and perceived authenticity of P2P accommodation listings.

The variable “price” did not demonstrate a significant impact on overtourism. This implies that variations in the average price of the selected listings within the studied context did not have a discernable influence on the level of overtourism, measured by tourist density of bednights and arrivals. Similarly, the variable "location" did not exhibit a significant relationship with overtourism. This suggests that the “neighborhood density” indicator did not have a substantial impact on the level of overtourism. The variable "variety" also did not yield statistically significant results. This indicates that the diversity or range of P2P accommodation options available within the study measured with the number of listings and percentage of entire accommodation variables did not have a noticeable effect on overtourism. However, is worth mentioning that the effect of the percentage of entire accommodation is statistically significant on the tourist density of bednights. Lastly, the variable "perceived authenticity" did not show significant results. This implies that the number of reviews and the percentage of multi-listings of P2P accommodation did not play a significant role in influencing the level of overtourism. A statistically significant relationship was not observed between any of the examined independent variables (price, location, variety, and perceived authenticity) and overtourism, as measured by tourist density metrics. According to these findings, other factors outside the scope of this study may be more influential in driving overtourism. The results of this study can potentially be explained due to a few factors:

- Sample size: The sample size was relatively small to efficiently assess the impact of P2P short-term rentals on overtourism, therefore resulting in limited statistical power. Although significant relationships between variables can exist, it is more challenging to detect them with a small sample.

- Range of indicators: The four variables measured are complex and relying on only one or two indicators is insufficient to fully measure those variables. Relying on only one or two indicators may oversimplify or overlook important aspects of the variable being measured.

- Outliers: When conducting the analysis before removing the different outliers that were mentioned in the previous chapters, some of the analyzed variables were significant at alpha =.05. Removing the outliers increased the p-value of almost all indicators, making them not significant.

- Time period: Most of the data collected for the study relates to the post-COVID-19 pandemic. As the COVID-19 pandemic completely changed the tourism and hospitality sector, P2P accommodation also suffered from the consequences of these years when the tourism industry was at its lowest point. Therefore, the data collected for this study might not be relevant for the pre-pandemic years, and the results of the study might just apply to the last few years after the beginning of the pandemic.

5. Conclusion

After providing the results of the study in the previous chapters, this chapter aims at concluding this thesis by comparing the results of the analysis with the existing literature on the topic. Therefore, the research objective, the research questions, and the selected hypotheses are summarized in order to introduce further research on the topic. The limitations of this study are also discussed.

5.1. Summary

The research objective of this thesis was to determine how different characteristics of the P2P accommodation market and tourist behavior influence overtourism in European cities. Based on the existing literature, four different characteristics of the P2P accommodation market and tourist behavior were chosen to be analyzed, respectively the price, location, variety, and perceived authenticity of Airbnb listings. It was later shown that none of these variables were statistically significant and that none of them had a positive effect on overtourism in the selected cities. Based on these characteristics, four research questions were developed.

The first research question was "How does the price of P2P accommodation relate to overtourism in Europe?" Price plays an important role in the tourists' decision-making process regarding the choice of accommodation. Several studies showed that the prices of P2P short-term rentals are often lower than those of hotels (Martin-Fuentes et al., 2019; Guttentag, 2015). Guttentag et al. (2017) identified the category of tourists staying in P2P accommodation listings rather than hotels for its low costs as the "Money Savers". However, it was shown that P2P short-term rentals are not always cheaper than hotels, mostly depending on the unit's capacity. An Airbnb property is on average cheaper to rent for 6 people than 3 hotel rooms fitting two people each, whereas a hotel room is on average cheaper to rent for two people than an Airbnb (French & Kemmis, 2023). The results of the study showed that the average price of Airbnb listings had no statistical significance on overtourism in the selected cities. As mentioned previously, this result can be explained by a few factors. When looking at the data sets, this result can be explained due to the fact that the prices of Airbnb listings have increased exponentially over the last few years. Therefore, the argument stating that the popularity of Airbnb compared to hotels came from its low prices may be outdated.

The second research question was "How does the location of P2P accommodation listings influence overtourism in Europe?" Location was also found to play an important role in the tourists' decision-making process regarding their choice of accommodation. It was shown that the location of P2P short-term rentals can often be concentrated in popular tourist areas such as city centers, which can contribute to overcrowding (Slee, 2015). The study used a neighborhood density indicator to measure the location variable by taking the listings in the three most popular neighborhoods for each selected city and comparing them to the whole city. The results showed that there was no statistical significance between the neighborhood density and an increased overtourism in the selected cities. This can be explained by the fact that Airbnb listings, although located in many city centers, are also located in a lot of residential areas. Guttentag (2017), argues that the motivation of travelers to book P2P short-term rentals due to their location can be seen as unexpected as P2P listings tend to be located in residential neighborhoods rather than clustered in city centers like hotels, and that location should therefore represent more of a drawback than a reason to choose it.

The third research question was "How does the variety of P2P accommodation listings influence overtourism in Europe?" The variety of P2P rentals was also found to be an important motivator for some travelers when booking their accommodations. Those travelers are regarded as variety-seeking consumers (Kahn & Louie, 1990). This behavior can be applied to the decision-making of tourists while looking for accommodation if they would rather choose a different type of accommodation every time they travel than always stay with the same type of accommodation. For those travelers, Airbnb offers more variety than hotels. In this study, the variety variable was measured using the number of listings, and the percentage of entire accommodation among those listings. The results of the study showed that the relationship between variety and overtourism was statistically not significant with the selected indicators. More indicators could have provided more accurate results. Those indicators could have been the listings' amenities, comparing the differences between those amenities and those of hotels, a geographical distribution of listings to analyze the variety of locations, etc.

The fourth research question was "How does the perceived authenticity of P2P accommodation influence overtourism in Europe?" Airbnb has long been perceived as a platform providing authentic experiences (Nieuwland & van Melik, 2018, p. 812), and the potential for a more unique and authentic local experience became the value proposition of P2P accommodation online platforms, including Airbnb (Guttentag et al., 2017). However, according to Oskam (2019), the sustainable attributes that made the popularity of Airbnb are no longer relevant. In this study, the perceived authenticity of Airbnb listings was measured with the number of reviews and the percentage of multi-listings. The results showed that the relationship between perceived authenticity and an increased overtourism was statistically not significant with the selected indicators. As mentioned previously, the attributes that made Airbnb perceived as authentic are not as relevant nowadays as they were before.

5.2. Implications for relevant stakeholders

One of the main goals of this paper was to understand how P2P accommodation could lead to an increase in overtourism in European cities. The findings obtained through this investigation could potentially benefit different stakeholders involved in destination management such as destination management organizations. Based on these findings, or on more accurate findings coming from further research, decisions can be taken to limit the impact of P2P accommodation if needed, or on the contrary, these findings could be used to explain that overtourism may not necessarily be increased by the rise of P2P accommodation platforms.

5.3. Future Research & Limitations

Continuing with the subject of this thesis, future research can be conducted using different variables and indicators than those used to conduct this study. For example, the overtourism variable was only measured with a single dimension, tourist density, whereas it could be interesting to look at the other indicators mentioned earlier such as the resident's perception. A combination of multiple indicators could provide better results regarding the relationship between P2P short-term rental platforms and overtourism in European cities. Also, this study focused exclusively on the Airbnb platform. It could be interesting if further research would focus on other platforms that are specialized in P2P short-term rentals to compare these providers and Airbnb directly. Such platforms could be Booking.com, Expedia, or HomeAway. Another axis for future research could be the focus on single European cities or destinations with an in-depth analysis of the P2P accommodation market with several variables and several indicators per variable. Using a wide range of cities only allowed scrapping the surface of this topic and not conducting an analysis using every P2P accommodation factor that could influence overtourism.

It is essential to acknowledge certain limitations associated with this study. Firstly, overtourism is a complex phenomenon and there are still some debates among researchers as to the nature of the indicators used to measure this phenomenon. Choosing the right dimensions and indicators is a subjective process and can vary depending on the nature of the research. Therefore, measuring overtourism with a single dimension can lead to misinterpretations and a failure to capture the full complexity and nuances of this phenomenon. It can lead to a wrong generalization of the results and an oversimplified understanding of the issue. This limitation can be extended to the indicators and variables used to measure the four independent variables of the study. As mentioned previously, only using a few indicators to capture the complexity of each variable may be insufficient and provide results that may not be generalizable to the entirety of the variables.

Furthermore, one of the major limitations of this study is the lack of available data regarding the different features of P2P short-term rental platforms over the years and related to different cities. One of the first goals of this study was to use a few numbers of selected cities and to analyze the growth of Airbnb in those cities over a larger period of time (~10-15 years). After researching for available secondary data, this goal had to be changed as there was no available data for that time period, with Inside Airbnb only sharing data for the last four quarters (June 2022 to March 2023). This low availability of data clearly represents one of the main limitations of this study as the results that were found may have differed if the data sets used included more data. The absence of relevant data limited the scope and depth of the study and led to gaps in the findings.

The COVID-19 pandemic might have also caused some limitations in this study. Indeed, this pandemic represents a significant external factor that can influence the findings and interpretations of the results. The pandemic disrupted travel patterns, impacted tourist behavior, and shifted P2P accommodation markets. The study's conclusions may not be applicable to non-pandemic conditions, since the data collected during and after the pandemic may not accurately reflect pre-pandemic trends and dynamics. Therefore, future research should focus on finding available and relevant data for the pre-pandemic period in order to obtain more accurate results.

Finally, it is important to denote the difference between P2P accommodation and P2P accommodation platforms like Airbnb. Indeed, the focus on this thesis was the impact of P2P accommodation on overtourism. However, the data collected regarding P2P accommodations was only gathered on Airbnb listings. Listings that are on Airbnb are not only P2P, some of them are also professional businesses, therefore they are not technically a part of this thesis' topic. Moreover, Airbnb does not regroup the entirety of all P2P accommodation listings in the selected cities and does not consitute the only reference in terms of P2P accommodation online platform, but more of an indication of the overall trend in the cities studied. The results of this thesis therefore contain listings that do not take part in the sharing economy and P2P accommodation phenomenon. Further research could investigate this limitation in depth and only focus on listings that are part of the P2P accommodation rental, but also investigate more P2P online platforms to analyze and compare the results.

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APPENDICES

Appendix 1: Price variable on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	0.7185	0.6093	1.179	0.242
log price	-0.0900	0.1267	-0.710	0.480
City:				
Antwerp – Amsterdam	-0.5645	0.0965	-5.853	<.001
Barcelona – Amsterdam	0.4208	0.0825	5.098	<.001
Berlin – Amsterdam	-0.0904	0.1310	-0.690	0.492
Bologna – Amsterdam	-0.7271	0.1111	-6.545	<.001
Bordeaux – Amsterdam	-0.6828	0.1426	-4.786	<.001
Brussels – Amsterdam	-0.4060	0.1263	-3.213	0.002
Copenhagen – Amsterdam	0.6331	0.0881	7.185	<.001
Ghent – Amsterdam	-0.3384	0.1205	-2.809	0.006
Lisbon – Amsterdam	1.1502	0.1055	10.900	<.001
Madrid – Amsterdam	-0.3213	0.1011	-3.177	0.002
Malaga – Amsterdam	-0.6708	0.1691	-3.967	<.001
Munich – Amsterdam	0.3916	0.0926	4.229	<.001
Oslo – Amsterdam	-0.0470	0.1024	-0.459	0.648
Paris – Amsterdam	-0.6119	0.0791	-7.736	<.001
Prague – Amsterdam	0.2692	0.1099	2.451	0.016
Rotterdam – Amsterdam	-0.7827	0.1084	-7.221	<.001
Seville – Amsterdam	0.2127	0.0917	2.319	0.023
Stockholm – Amsterdam	-0.2743	0.1051	-2.610	0.011
The Hague – Amsterdam	-0.5991	0.1021	-5.867	<.001
Valencia – Amsterdam	-0.0977	0.1052	-0.929	0.355
Vienna – Amsterdam	0.0436	0.1263	0.345	0.731
Quarter:				
2 – 1	0.3939	0.0579	6.802	<.001
3 – 1	0.5080	0.0608	8.353	<.001
4 – 1	0.3836	0.0647	5.933	<.001
Year:				
2016 – 2015	-0.1181	0.0955	-1.237	0.220
2017 – 2015	0.1434	0.1153	1.244	0.217
2018 – 2015	0.0704	0.0788	0.893	0.374
2019 – 2015	0.1467	0.1275	1.150	0.253
2021 – 2015	-0.7026	0.1008	-6.968	<.001
2022 – 2015	0.0339	0.0989	0.343	0.733
2023 – 2015	0.1055	0.1361	0.775	0.440

[a] Represents reference level

Appendix 2: Price variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	-0.2923	0.5837	-0.5008	0.618
log price	-0.0135	0.1216	-0.1113	0.912
City:				
Antwerp – Amsterdam	-0.4226	0.0914	-4.6238	<.001
Barcelona – Amsterdam	0.3455	0.0778	4.4385	<.001
Berlin – Amsterdam	-0.2095	0.1240	-1.6897	0.095
Bordeaux – Amsterdam	-0.4116	0.1343	-3.0655	0.003
Brussels – Amsterdam	-0.2781	0.1190	-2.3362	0.022
Ghent – Amsterdam	-0.1497	0.1131	-1.3234	0.190
Lisbon – Amsterdam	1.0597	0.0993	10.6748	<.001
Madrid – Amsterdam	-0.2900	0.0954	-3.0411	0.003
Munich – Amsterdam	0.3419	0.0869	3.9327	<.001
Oslo – Amsterdam	0.1565	0.0959	1.6316	0.107
Paris – Amsterdam	-0.6511	0.0742	-8.7780	<.001
Porto – Amsterdam	1.0148	0.1114	9.1059	<.001
Prague – Amsterdam	0.3576	0.1130	3.1649	0.002
Rotterdam – Amsterdam	-0.5649	0.1017	-5.5543	<.001
Seville – Amsterdam	0.1820	0.0903	2.0146	0.047
The Hague – Amsterdam	-0.4608	0.0956	-4.8178	<.001
Valencia – Amsterdam	-0.1882	0.0986	-1.9082	0.060
Vienna – Amsterdam	0.0311	0.1194	0.2601	0.795
Quarter:				
2 – 1	0.3163	0.0651	4.8596	<.001
3 – 1	0.4113	0.0667	6.1695	<.001
4 – 1	0.3342	0.0685	4.8792	<.001
Year:				
2016 – 2015	-0.0984	0.0957	-1.0278	0.307
2017 – 2015	0.1741	0.1085	1.6048	0.113
2018 – 2015	0.0724	0.0742	0.9763	0.332
2019 – 2015	0.1887	0.1203	1.5680	0.121
2021 – 2015	-0.6336	0.0903	-7.0193	<.001
2022 – 2015	-0.0702	0.0936	-0.7508	0.455
2023 – 2015	0.0120	0.1364	0.0878	0.930

[a] Represents reference level

Appendix 3: Neighborhood density variable on tourist density of bed-nights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	-1.0703	0.4716	-2.269	0.027
Neighborhoods	0.7964	1.1098	0.718	0.476
City:				
Antwerp – Amsterdam	-0.4907	0.1280	-3.832	<.001
Barcelona – Amsterdam	0.4355	0.1676	2.598	0.012
Berlin – Amsterdam	0.0818	0.2734	0.299	0.766
Bologna – Amsterdam	-1.1388	0.4604	-2.473	0.017
Brussels – Amsterdam	-0.6140	0.2096	-2.929	0.005
Copenhagen – Amsterdam	0.5041	0.1371	3.675	<.001
Ghent – Amsterdam	-0.4144	0.1036	-3.999	<.001
Lisbon – Amsterdam	1.1344	0.1022	11.105	<.001
Madrid – Amsterdam	-0.4106	0.1440	-2.852	0.006
Malaga – Amsterdam	-1.1547	0.5214	-2.214	0.031
Munich – Amsterdam	0.3912	0.1612	2.428	0.019
Oslo – Amsterdam	-0.2426	0.1776	-1.366	0.178
Paris – Amsterdam	-0.5905	0.1722	-3.429	0.001
Prague – Amsterdam	0.0820	0.3136	0.261	0.795
Rotterdam – Amsterdam	-1.0375	0.2202	-4.711	<.001
Seville – Amsterdam	0.1821	0.1618	1.125	0.266
Stockholm – Amsterdam	-0.3740	0.1226	-3.049	0.004
The Hague – Amsterdam	-0.6522	0.0955	-6.828	<.001
Valencia – Amsterdam	-0.0525	0.2094	-0.250	0.803
Vienna – Amsterdam	0.0316	0.1633	0.193	0.847
Quarter:				
2 – 1	0.7873	0.1542	5.105	<.001
3 – 1	0.9171	0.1539	5.959	<.001
4 – 1	0.7547	0.1544	4.887	<.001
Year:				
2022 – 2021	0.7549	0.0681	11.085	<.001
2023 – 2021	1.1865	0.1690	7.021	<.001

[a] Represents reference level

Appendix 4: Neighborhood density variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	-1.95088	0.4333	-4.5024	<.001
Neighborhoods	1.51100	1.0512	1.4374	0.157
City:				
Antwerp – Amsterdam	-0.30321	0.1198	-2.5311	0.015
Barcelona – Amsterdam	0.43567	0.1578	2.7607	0.008
Berlin – Amsterdam	0.13007	0.2584	0.5034	0.617
Brussels – Amsterdam	-0.58690	0.1960	-2.9947	0.004
Ghent – Amsterdam	-0.20509	0.0951	-2.1573	0.036
Lisbon – Amsterdam	1.10629	0.0944	11.7164	<.001
Madrid – Amsterdam	-0.24824	0.1355	-1.8319	0.073
Munich – Amsterdam	0.46821	0.1520	3.0797	0.003
Oslo – Amsterdam	-0.12262	0.1659	-0.7391	0.463
Paris – Amsterdam	-0.47964	0.1627	-2.9484	0.005
Porto – Amsterdam	0.64508	0.2878	2.2410	0.029
Prague – Amsterdam	-0.09078	0.2950	-0.3077	0.760
Rotterdam – Amsterdam	-0.92670	0.2065	-4.4866	<.001
Seville – Amsterdam	0.30437	0.1527	1.9934	0.052
The Hague – Amsterdam	-0.48120	0.0883	-5.4504	<.001
Valencia – Amsterdam	-0.00886	0.1982	-0.0447	0.965
Vienna – Amsterdam	0.12401	0.1541	0.8049	0.425
Quarter:				
2 – 1	0.68760	0.1024	6.7156	<.001
3 – 1	0.79747	0.1015	7.8557	<.001
4 – 1	0.68287	0.1020	6.6971	<.001
Year:				
2022 – 2021	0.61532	0.0551	11.1630	<.001
2023 – 2021	1.01782	0.1240	8.2084	<.001

[a] Represents reference level

Appendix 5: Listings variable on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	1.49916	0.7101	2.1112	0.038
log listings	-0.14467	0.0842	-1.7176	0.089
City:				
Antwerp – Amsterdam	-0.75780	0.1562	-4.8509	<.001
Barcelona – Amsterdam	0.52051	0.0777	6.6981	<.001
Berlin – Amsterdam	0.07511	0.0910	0.8250	0.412
Bologna – Amsterdam	-0.83411	0.1291	-6.4604	<.001
Bordeaux – Amsterdam	-0.65066	0.1255	-5.1839	<.001
Brussels – Amsterdam	-0.42476	0.0992	-4.2836	<.001
Copenhagen – Amsterdam	0.70744	0.0857	8.2525	<.001
Ghent – Amsterdam	-0.61299	0.2115	-2.8978	0.005
Lisbon – Amsterdam	1.29001	0.1031	12.5170	<.001
Madrid – Amsterdam	-0.19063	0.0897	-2.1240	0.037
Malaga – Amsterdam	-0.68774	0.1666	-4.1290	<.001
Munich – Amsterdam	0.34374	0.0951	3.6157	<.001
Oslo – Amsterdam	-0.09756	0.1035	-0.9427	0.348
Paris – Amsterdam	-0.33995	0.1618	-2.1015	0.039
Prague – Amsterdam	0.27428	0.0960	2.8566	0.005
Rotterdam – Amsterdam	-1.08044	0.2166	-4.9891	<.001
Seville – Amsterdam	0.17828	0.0922	1.9344	0.056
Stockholm – Amsterdam	-0.37186	0.1185	-3.1388	0.002
The Hague – Amsterdam	-0.89878	0.2124	-4.2322	<.001
Valencia – Amsterdam	-0.10952	0.0962	-1.1382	0.258
Vienna – Amsterdam	0.12021	0.0863	1.3923	0.167
Quarter:				
2 – 1	0.40985	0.0580	7.0713	<.001
3 – 1	0.53747	0.0627	8.5703	<.001
4 – 1	0.38618	0.0584	6.6110	<.001
Year:				
2016 – 2015	-0.00508	0.1153	-0.0440	0.965
2017 – 2015	0.27022	0.1363	1.9821	0.051
2018 – 2015	0.18496	0.1046	1.7688	0.080
2019 – 2015	0.29484	0.1574	1.8728	0.064
2021 – 2015	-0.63197	0.1092	-5.7850	<.001
2022 – 2015	0.07793	0.0889	0.8769	0.383
2023 – 2015	0.15530	0.1188	1.3072	0.195

[a] Represents reference level

Appendix 6: Listings variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	0.59044	0.6728	0.8776	0.383
log listings	-0.11306	0.0794	-1.4240	0.158
City:				
Antwerp – Amsterdam	-0.59897	0.1470	-4.0733	<.001
Barcelona – Amsterdam	0.40268	0.0731	5.5116	<.001
Berlin – Amsterdam	-0.12941	0.0851	-1.5210	0.132
Bordeaux – Amsterdam	-0.41569	0.1177	-3.5317	<.001
Brussels – Amsterdam	-0.33485	0.0935	-3.5820	<.001
Ghent – Amsterdam	-0.39300	0.1999	-1.9657	0.053
Lisbon – Amsterdam	1.14144	0.0964	11.8425	<.001
Madrid – Amsterdam	-0.21921	0.0841	-2.6056	0.011
Munich – Amsterdam	0.28866	0.0899	3.2098	0.002
Oslo – Amsterdam	0.09739	0.0975	0.9994	0.321
Paris – Amsterdam	-0.45355	0.1519	-2.9858	0.004
Porto – Amsterdam	1.04439	0.0776	13.4620	<.001
Prague – Amsterdam	0.33468	0.0985	3.3992	0.001
Rotterdam – Amsterdam	-0.82314	0.2046	-4.0228	<.001
Seville – Amsterdam	0.14095	0.0919	1.5343	0.129
The Hague – Amsterdam	-0.71428	0.2007	-3.5597	<.001
Valencia – Amsterdam	-0.21995	0.0904	-2.4322	0.017
Vienna – Amsterdam	0.04891	0.0809	0.6049	0.547
Quarter:				
2 – 1	0.32866	0.0643	5.1128	<.001
3 – 1	0.43768	0.0669	6.5453	<.001
4 – 1	0.34708	0.0628	5.5262	<.001
Year:				
2016 – 2015	-0.01249	0.1121	-0.1114	0.912
2017 – 2015	0.27402	0.1282	2.1381	0.036
2018 – 2015	0.16530	0.0981	1.6848	0.096
2019 – 2015	0.31958	0.1480	2.1593	0.034
2021 – 2015	-0.57093	0.0973	-5.8676	<.001
2022 – 2015	-0.00487	0.0838	-0.0581	0.954
2023 – 2015	0.08945	0.1182	0.7570	0.451

[a] Represents reference level

Appendix 7: Entire acc. variable on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	0.21563	0.10779	2.0004	0.049
Entire acc.	0.00454	0.00203	2.2392	0.028
City:				
Antwerp – Amsterdam	-0.52985	0.07616	-6.9570	<.001
Barcelona – Amsterdam	0.45092	0.06653	6.7776	<.001
Berlin – Amsterdam	-0.00420	0.07393	-0.0568	0.955
Bologna – Amsterdam	-0.70939	0.10141	-6.9954	<.001
Bordeaux – Amsterdam	-0.63277	0.12384	-5.1098	<.001
Brussels – Amsterdam	-0.33935	0.08549	-3.9697	<.001
Copenhagen – Amsterdam	0.65101	0.07960	8.1787	<.001
Ghent – Amsterdam	-0.30509	0.10140	-3.0087	0.003
Lisbon – Amsterdam	1.18779	0.08503	13.9688	<.001
Madrid – Amsterdam	-0.36192	0.08418	-4.2997	<.001
Malaga – Amsterdam	-0.66852	0.16377	-4.0820	<.001
Munich – Amsterdam	0.41072	0.08477	4.8454	<.001
Oslo – Amsterdam	-0.02880	0.09156	-0.3145	0.754
Paris – Amsterdam	-0.57973	0.07069	-8.2005	<.001
Prague – Amsterdam	0.30655	0.09292	3.2991	0.001
Rotterdam – Amsterdam	-0.75443	0.09155	-8.2408	<.001
Seville – Amsterdam	0.22684	0.08604	2.6365	0.010
Stockholm – Amsterdam	-0.23711	0.08604	-2.7559	0.007
The Hague – Amsterdam	-0.58091	0.09155	-6.3452	<.001
Valencia – Amsterdam	-0.07427	0.09155	-0.8112	0.419
Vienna – Amsterdam	0.11048	0.08509	1.2984	0.198
Quarter:				
2 – 1	0.42490	0.05828	7.2909	<.001
3 – 1	0.53371	0.05986	8.9162	<.001
4 – 1	0.39998	0.05856	6.8300	<.001
Year:				
2016 – 2015	-0.06776	0.09589	-0.7066	0.482
2017 – 2015	0.12571	0.11250	1.1174	0.267
2018 – 2015	0.09647	0.07771	1.2413	0.218
2019 – 2015	0.17300	0.12151	1.4237	0.158
2021 – 2015	-0.67827	0.09746	-6.9597	<.001
2022 – 2015	0.03284	0.07306	0.4495	0.654
2023 – 2015	0.12420	0.10381	1.1965	0.235

[a] Represents reference level

Appendix 8: Entire acc. variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	-0.18737	0.08766	-2.137	0.036
Entire acc.	0.00129	0.00143	0.901	0.370
City:				
Antwerp – Amsterdam	-0.34474	0.05303	-6.501	<.001
Barcelona – Amsterdam	0.34177	0.04482	7.625	<.001
Berlin – Amsterdam	-0.13292	0.05138	-2.587	0.012
Bordeaux – Amsterdam	-0.38741	0.08333	-4.649	<.001
Brussels – Amsterdam	-0.27073	0.05767	-4.694	<.001
Ghent – Amsterdam	-0.16131	0.06833	-2.361	0.021
Lisbon – Amsterdam	1.06203	0.05718	18.573	<.001
Madrid – Amsterdam	-0.34441	0.05671	-6.073	<.001
Munich – Amsterdam	0.30879	0.05781	5.341	<.001
Oslo – Amsterdam	0.14369	0.06170	2.329	0.023
Paris – Amsterdam	-0.66694	0.04789	-13.926	<.001
Porto – Amsterdam	1.06281	0.05664	18.765	<.001
Prague – Amsterdam	0.34428	0.06848	5.028	<.001
Rotterdam – Amsterdam	-0.57613	0.06170	-9.338	<.001
Seville – Amsterdam	0.16721	0.06170	2.710	0.008
The Hague – Amsterdam	-0.47356	0.06170	-7.676	<.001
Valencia – Amsterdam	-0.20016	0.06170	-3.244	0.002
Vienna – Amsterdam	0.03931	0.05739	0.685	0.495
Quarter:				
2 – 1	0.16565	0.05806	2.853	0.006
3 – 1	0.22526	0.05792	3.889	<.001
4 – 1	0.15094	0.05661	2.667	0.009
Year:				
2016 – 2015	-0.16753	0.07251	-2.310	0.024
2017 – 2015	0.08708	0.07683	1.133	0.261
2018 – 2015	0.04920	0.05312	0.926	0.357
2019 – 2015	0.12996	0.08378	1.551	0.125
2021 – 2015	-0.58239	0.06388	-9.116	<.001
2022 – 2015	-0.05781	0.04949	-1.168	0.246
2023 – 2015	-0.15409	0.08591	-1.794	0.077

[a] Represents reference level

Appendix 9: Correlation of listings and entire acc. variables on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	1.08354	0.73537	1.4735	0.144
log listings	-0.10272	0.08610	-1.1931	0.236
Entire acc.	0.00388	0.00210	1.8516	0.068
City:				
Antwerp – Amsterdam	-0.69482	0.15777	-4.4040	<.001
Barcelona – Amsterdam	0.49874	0.07753	6.4327	<.001
Berlin – Amsterdam	0.05790	0.09027	0.6415	0.523
Bologna – Amsterdam	-0.80370	0.12838	-6.2602	<.001
Bordeaux – Amsterdam	-0.64327	0.12385	-5.1942	<.001
Brussels – Amsterdam	-0.39884	0.09879	-4.0375	<.001
Copenhagen – Amsterdam	0.68786	0.08520	8.0736	<.001
Ghent – Amsterdam	-0.52934	0.21345	-2.4799	0.015
Lisbon – Amsterdam	1.25775	0.10312	12.1971	<.001
Madrid – Amsterdam	-0.28982	0.10346	-2.8014	0.006
Malaga – Amsterdam	-0.68892	0.16426	-4.1940	<.001
Munich – Amsterdam	0.36112	0.09422	3.8327	<.001
Oslo – Amsterdam	-0.08384	0.10233	-0.8193	0.415
Paris – Amsterdam	-0.40407	0.16325	-2.4752	0.015
Prague – Amsterdam	0.28282	0.09480	2.9833	0.004
Rotterdam – Amsterdam	-0.99174	0.21887	-4.5311	<.001
Seville – Amsterdam	0.19034	0.09112	2.0890	0.040
Stockholm – Amsterdam	-0.33467	0.11855	-2.8231	0.006
The Hague – Amsterdam	-0.81253	0.21455	-3.7872	<.001
Valencia – Amsterdam	-0.10515	0.09492	-1.1078	0.271
Vienna – Amsterdam	0.11859	0.08515	1.3927	0.167
Quarter:				
2 – 1	0.43483	0.05873	7.4041	<.001
3 – 1	0.55651	0.06270	8.8764	<.001
4 – 1	0.41120	0.05917	6.9494	<.001
Year:				
2016 – 2015	0.00594	0.11387	0.0521	0.959
2017 – 2015	0.21982	0.13717	1.6025	0.113
2018 – 2015	0.17774	0.10320	1.7223	0.089
2019 – 2015	0.28881	0.15529	1.8598	0.066
2021 – 2015	-0.62255	0.10785	-5.7723	<.001
2022 – 2015	0.09157	0.08794	1.0412	0.301
2023 – 2015	0.19424	0.11904	1.6318	0.106

[a] Represents reference level

Appendix 10: Correlation of listings and entire acc. variables on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	0.28288	0.71044	0.3982	0.692
log listings	-0.08297	0.08237	-1.0073	0.317
Entire acc.	0.00265	0.00204	1.2989	0.198
City:				
Antwerp – Amsterdam	-0.55269	0.15068	-3.6680	<.001
Barcelona – Amsterdam	0.38736	0.07369	5.2567	<.001
Berlin – Amsterdam	-0.14009	0.08511	-1.6460	0.104
Bordeaux – Amsterdam	-0.41082	0.11725	-3.5038	<.001
Brussels – Amsterdam	-0.31495	0.09432	-3.3390	0.001
Ghent – Amsterdam	-0.33120	0.20466	-1.6182	0.110
Lisbon – Amsterdam	1.11923	0.09747	11.4822	<.001
Madrid – Amsterdam	-0.28475	0.09779	-2.9119	0.005
Munich – Amsterdam	0.30359	0.09027	3.3631	0.001
Oslo – Amsterdam	0.10852	0.09740	1.1142	0.269
Paris – Amsterdam	-0.49830	0.15511	-3.2125	0.002
Porto – Amsterdam	1.04039	0.07730	13.4587	<.001
Prague – Amsterdam	0.33666	0.09804	3.4339	<.001
Rotterdam – Amsterdam	-0.75825	0.20976	-3.6149	<.001
Seville – Amsterdam	0.14679	0.09158	1.6029	0.113
The Hague – Amsterdam	-0.65115	0.20561	-3.1670	0.002
Valencia – Amsterdam	-0.21554	0.09010	-2.3922	0.019
Vienna – Amsterdam	0.04895	0.08051	0.6081	0.545
Quarter:				
2 – 1	0.35612	0.06740	5.2835	<.001
3 – 1	0.46046	0.06885	6.6881	<.001
4 – 1	0.37359	0.06578	5.6796	<.001
Year:				
2016 – 2015	0.00129	0.11214	0.0115	0.991
2017 – 2015	0.24165	0.13001	1.8587	0.067
2018 – 2015	0.16112	0.09774	1.6485	0.103
2019 – 2015	0.31758	0.14736	2.1551	0.034
2021 – 2015	-0.56440	0.09701	-5.8181	<.001
2022 – 2015	0.00363	0.08367	0.0434	0.966
2023 – 2015	0.12733	0.12121	1.0505	0.297

[a] Represents reference level

Appendix 11: Reviews variable on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	2.04679	1.1485	1.7821	0.078
log reviews	-0.14671	0.1032	-1.4221	0.159
City:				
Antwerp – Amsterdam	-0.77381	0.1860	-4.1604	<.001
Barcelona – Amsterdam	0.52694	0.0832	6.3310	<.001
Berlin – Amsterdam	0.00321	0.0757	0.0424	0.966
Bologna – Amsterdam	-0.83381	0.1301	-6.4092	<.001
Bordeaux – Amsterdam	-0.71935	0.1335	-5.3895	<.001
Brussels – Amsterdam	-0.42810	0.0978	-4.3758	<.001
Copenhagen – Amsterdam	0.63721	0.0919	6.9367	<.001
Ghent – Amsterdam	-0.57936	0.2148	-2.6966	0.008
Lisbon – Amsterdam	1.31965	0.1241	10.6357	<.001
Madrid – Amsterdam	-0.22291	0.0928	-2.4023	0.019
Malaga – Amsterdam	-0.70722	0.1615	-4.3785	<.001
Munich – Amsterdam	0.23558	0.1365	1.7264	0.088
Oslo – Amsterdam	-0.21389	0.1586	-1.3486	0.181
Paris – Amsterdam	-0.41611	0.1505	-2.7647	0.007
Prague – Amsterdam	0.42482	0.0984	4.3177	<.001
Rotterdam – Amsterdam	-1.09492	0.2564	-4.2708	<.001
Seville – Amsterdam	0.19333	0.0879	2.2006	0.031
Stockholm – Amsterdam	-0.41177	0.1733	-2.3767	0.020
The Hague – Amsterdam	-0.91267	0.2507	-3.6402	<.001
Valencia – Amsterdam	-0.11613	0.0931	-1.2474	0.216
Vienna – Amsterdam	0.08530	0.0823	1.0368	0.303
Quarter:				
2 – 1	0.30961	0.0708	4.3754	<.001
3 – 1	0.43241	0.0764	5.6624	<.001
4 – 1	0.30439	0.0745	4.0845	<.001
Year:				
2016 – 2015	-0.05880	0.1275	-0.4612	0.646
2017 – 2015	0.23698	0.1440	1.6459	0.104
2018 – 2015	0.23051	0.1517	1.5196	0.132
2019 – 2015	0.32339	0.2084	1.5514	0.125
2021 – 2015	-0.54310	0.1619	-3.3542	0.001
2022 – 2015	0.20003	0.1683	1.1883	0.238
2023 – 2015	0.17575	0.2144	0.8196	0.415

[a] Represents reference level

Appendix 12: Reviews variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	1.1260	1.1405	0.9872	0.327
log reviews	-0.1333	0.1021	-1.3049	0.196
City:				
Antwerp – Amsterdam	-0.6377	0.1843	-3.4604	<.001
Barcelona – Amsterdam	0.4194	0.0825	5.0850	<.001
Berlin – Amsterdam	-0.1663	0.0743	-2.2370	0.028
Bordeaux – Amsterdam	-0.4832	0.1322	-3.6553	<.001
Brussels – Amsterdam	-0.3386	0.0974	-3.4778	<.001
Ghent – Amsterdam	-0.3922	0.2137	-1.8357	0.070
Lisbon – Amsterdam	1.1857	0.1222	9.7042	<.001
Madrid – Amsterdam	-0.2101	0.0907	-2.3169	0.023
Munich – Amsterdam	0.2022	0.1362	1.4853	0.141
Oslo – Amsterdam	-0.0112	0.1579	-0.0711	0.944
Paris – Amsterdam	-0.4750	0.1484	-3.2019	0.002
Porto – Amsterdam	1.0736	0.0854	12.5738	<.001
Prague – Amsterdam	0.3797	0.0972	3.9043	<.001
Rotterdam – Amsterdam	-0.8718	0.2548	-3.4213	<.001
Seville – Amsterdam	0.1858	0.0869	2.1396	0.036
The Hague – Amsterdam	-0.7614	0.2492	-3.0552	0.003
Valencia – Amsterdam	-0.2246	0.0925	-2.4289	0.017
Vienna – Amsterdam	0.0274	0.0815	0.3368	0.737
Quarter:				
2 – 1	0.3416	0.0668	5.1103	<.001
3 – 1	0.4494	0.0709	6.3353	<.001
4 – 1	0.3721	0.0694	5.3585	<.001
Year:				
2016 – 2015	0.0105	0.1263	0.0835	0.934
2017 – 2015	0.2945	0.1417	2.0783	0.041
2018 – 2015	0.2416	0.1494	1.6173	0.110
2019 – 2015	0.4074	0.2052	1.9856	0.051
2021 – 2015	-0.4665	0.1560	-2.9910	0.004
2022 – 2015	0.1223	0.1670	0.7326	0.466
2023 – 2015	0.2407	0.2091	1.1513	0.253

[a] Represents reference level

Appendix 13: Multi-listings variable on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	0.41633	0.1451	2.8690	0.005
Multi-listings	-0.78851	0.6428	-1.2268	0.223
City:				
Antwerp – Amsterdam	-0.33594	0.1721	-1.9524	0.054
Barcelona – Amsterdam	0.77814	0.2730	2.8503	0.005
Berlin – Amsterdam	0.02350	0.0814	0.2889	0.773
Bologna – Amsterdam	-0.45751	0.2225	-2.0566	0.043
Bordeaux – Amsterdam	-0.59592	0.1306	-4.5638	<.001
Brussels – Amsterdam	-0.18370	0.1553	-1.1827	0.240
Copenhagen – Amsterdam	0.57392	0.1055	5.4383	<.001
Ghent – Amsterdam	-0.18538	0.1367	-1.3565	0.179
Lisbon – Amsterdam	1.56032	0.3122	4.9983	<.001
Madrid – Amsterdam	-0.00833	0.2297	-0.0363	0.971
Malaga – Amsterdam	-0.28425	0.3464	-0.8206	0.414
Munich – Amsterdam	0.43421	0.0879	4.9377	<.001
Oslo – Amsterdam	-0.07738	0.1051	-0.7360	0.464
Paris – Amsterdam	-0.57268	0.0732	-7.8203	<.001
Prague – Amsterdam	0.68942	0.3250	2.1210	0.037
Rotterdam – Amsterdam	-0.61602	0.1400	-4.4008	<.001
Seville – Amsterdam	0.58832	0.3047	1.9311	0.057
Stockholm – Amsterdam	-0.22359	0.0881	-2.5372	0.013
The Hague – Amsterdam	-0.43110	0.1469	-2.9339	0.004
Valencia – Amsterdam	0.20925	0.2414	0.8668	0.388
Vienna – Amsterdam	0.32356	0.1957	1.6533	0.102
Quarter:				
2 – 1	0.40280	0.0583	6.9141	<.001
3 – 1	0.50560	0.0592	8.5451	<.001
4 – 1	0.37635	0.0583	6.4521	<.001
Year:				
2016 – 2015	-0.09646	0.0967	-0.9970	0.322
2017 – 2015	0.15620	0.1152	1.3557	0.179
2018 – 2015	0.07724	0.0786	0.9825	0.329
2019 – 2015	0.15467	0.1247	1.2405	0.218
2021 – 2015	-0.64995	0.1126	-5.7719	<.001
2022 – 2015	0.06052	0.0939	0.6444	0.521
2023 – 2015	0.12663	0.1216	1.0417	0.300

[a] Represents reference level

Appendix 14: Multi-listings variable on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	-0.1797	0.1392	-1.291	0.201
Multi-listings	-1.1400	0.6075	-1.876	0.064
City:				
Antwerp – Amsterdam	-0.1443	0.1618	-0.892	0.375
Barcelona – Amsterdam	0.8202	0.2580	3.178	0.002
Berlin – Amsterdam	-0.1443	0.0751	-1.921	0.058
Bordeaux – Amsterdam	-0.3453	0.1206	-2.864	0.005
Brussels – Amsterdam	-0.0414	0.1452	-0.285	0.776
Ghent – Amsterdam	0.0147	0.1271	0.116	0.908
Lisbon – Amsterdam	1.5976	0.2943	5.428	< .001
Madrid – Amsterdam	0.1006	0.2163	0.465	0.643
Munich – Amsterdam	0.3725	0.0812	4.585	< .001
Oslo – Amsterdam	0.0728	0.0979	0.744	0.459
Paris – Amsterdam	-0.6223	0.0676	-9.203	< .001
Porto – Amsterdam	1.5648	0.2981	5.250	< .001
Prague – Amsterdam	0.9155	0.3090	2.962	0.004
Rotterdam – Amsterdam	-0.3759	0.1301	-2.890	0.005
Seville – Amsterdam	0.6959	0.2858	2.435	0.017
The Hague – Amsterdam	-0.2570	0.1367	-1.881	0.064
Valencia – Amsterdam	0.2098	0.2264	0.927	0.357
Vienna – Amsterdam	0.3513	0.1838	1.911	0.060
Quarter:				
2 – 1	0.3364	0.0640	5.256	< .001
3 – 1	0.4226	0.0637	6.637	< .001
4 – 1	0.3544	0.0625	5.673	< .001
Year:				
2016 – 2015	-0.0691	0.0949	-0.728	0.469
2017 – 2015	0.1979	0.1068	1.852	0.068
2018 – 2015	0.0909	0.0727	1.250	0.215
2019 – 2015	0.2359	0.1160	2.034	0.045
2021 – 2015	-0.5374	0.1000	-5.372	< .001
2022 – 2015	0.0320	0.0880	0.364	0.717
2023 – 2015	0.1362	0.1230	1.108	0.271

[a] Represents reference level

Appendix 15: Correlation of reviews and multi-listing variables on tourist density of bednights

Model Coefficients - log density bednights

Predictor	Estimate	SE	t	p
Intercept [a]	1.9164	1.1599	1.652	0.102
log reviews	-0.1276	0.1056	-1.208	0.230
Multi-listings	-0.5448	0.6245	-0.872	0.386
City:				
Antwerp – Amsterdam	-0.6118	0.2630	-2.326	0.023
Barcelona – Amsterdam	0.7413	0.2594	2.857	0.005
Berlin – Amsterdam	0.0253	0.0799	0.316	0.753
Bologna – Amsterdam	-0.6505	0.2473	-2.630	0.010
Bordeaux – Amsterdam	-0.6801	0.1410	-4.822	<.001
Brussels – Amsterdam	-0.3090	0.1681	-1.838	0.070
Copenhagen – Amsterdam	0.5864	0.1089	5.387	<.001
Ghent – Amsterdam	-0.4677	0.2504	-1.868	0.065
Lisbon – Amsterdam	1.5567	0.2988	5.209	<.001
Madrid – Amsterdam	-0.0489	0.2201	-0.222	0.825
Malaga – Amsterdam	-0.4430	0.3433	-1.290	0.201
Munich – Amsterdam	0.2703	0.1423	1.899	0.061
Oslo – Amsterdam	-0.2303	0.1599	-1.440	0.154
Paris – Amsterdam	-0.4289	0.1514	-2.832	0.006
Prague – Amsterdam	0.6871	0.3164	2.172	0.033
Rotterdam – Amsterdam	-0.9616	0.2988	-3.218	0.002
Seville – Amsterdam	0.4386	0.2946	1.489	0.140
Stockholm – Amsterdam	-0.3780	0.1778	-2.126	0.037
The Hague – Amsterdam	-0.7727	0.2980	-2.593	0.011
Valencia – Amsterdam	0.0786	0.2419	0.325	0.746
Vienna – Amsterdam	0.2360	0.1914	1.233	0.221
Quarter:				
2 – 1	0.3189	0.0717	4.450	<.001
3 – 1	0.4351	0.0765	5.684	<.001
4 – 1	0.3111	0.0750	4.146	<.001
Year:				
2016 – 2015	-0.0570	0.1277	-0.446	0.657
2017 – 2015	0.2314	0.1443	1.604	0.113
2018 – 2015	0.2159	0.1528	1.413	0.162
2019 – 2015	0.3160	0.2089	1.512	0.134
2021 – 2015	-0.5198	0.1643	-3.163	0.002
2022 – 2015	0.2234	0.1707	1.309	0.194
2023 – 2015	0.2056	0.2174	0.945	0.347

[a] Represents reference level

Appendix 16: Correlation of reviews and multi-listing variables on tourist density of arrivals

Model Coefficients - log density arrivals

Predictor	Estimate	SE	t	p
Intercept [a]	0.90192	1.1365	0.7936	0.430
log reviews	-0.09893	0.1032	-0.9589	0.341
Multi-listings	-1.01934	0.6207	-1.6422	0.105
City:				
Antwerp – Amsterdam	-0.33726	0.2583	-1.3058	0.196
Barcelona – Amsterdam	0.82168	0.2582	3.1825	0.002
Berlin – Amsterdam	-0.12634	0.0775	-1.6312	0.107
Bordeaux – Amsterdam	-0.40993	0.1382	-2.9667	0.004
Brussels – Amsterdam	-0.11745	0.1655	-0.7095	0.480
Ghent – Amsterdam	-0.18683	0.2456	-0.7606	0.449
Lisbon – Amsterdam	1.63027	0.2965	5.4992	<.001
Madrid – Amsterdam	0.11419	0.2169	0.5266	0.600
Munich – Amsterdam	0.26345	0.1398	1.8849	0.063
Oslo – Amsterdam	-0.04560	0.1576	-0.2893	0.773
Paris – Amsterdam	-0.49678	0.1474	-3.3710	0.001
Porto – Amsterdam	1.54453	0.2990	5.1664	<.001
Prague – Amsterdam	0.86878	0.3130	2.7757	0.007
Rotterdam – Amsterdam	-0.62735	0.2927	-2.1430	0.035
Seville – Amsterdam	0.64291	0.2913	2.2071	0.030
The Hague – Amsterdam	-0.50443	0.2920	-1.7275	0.088
Valencia – Amsterdam	0.13755	0.2387	0.5762	0.566
Vienna – Amsterdam	0.30854	0.1892	1.6308	0.107
Quarter:				
2 – 1	0.35373	0.0665	5.3160	<.001
3 – 1	0.45087	0.0702	6.4237	<.001
4 – 1	0.38237	0.0690	5.5427	<.001
Year:				
2016 – 2015	0.00872	0.1249	0.0698	0.945
2017 – 2015	0.28497	0.1403	2.0313	0.046
2018 – 2015	0.21522	0.1487	1.4475	0.152
2019 – 2015	0.39567	0.2031	1.9483	0.055
2021 – 2015	-0.42177	0.1567	-2.6919	0.009
2022 – 2015	0.16878	0.1676	1.0070	0.317
2023 – 2015	0.29924	0.2099	1.4257	0.158

[a] Represents reference level