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Spatial Analysis of Airbnb Market in Prague

Master's Thesis

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Declaration of Authorship

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Abstract

This paper investigates the pricing dynamics of Airbnb in Prague, a short-term rental platform that is one of the most successful examples of the sharing economy. The pricing dynamics were investigated using a combination of hedonic and spatial regression. We estimated different spatial models and explained the importance of including spatial terms in a regression. Finally, the paper confirmed that the prices of Airbnb listings in Prague exhibit spatial autocorrelation. Furthermore, we have shown that there is a negative and significant relationship between the price of the listing and the distance to the city centre, and that the relationship between the price of a listing and the attractiveness of its location is significant and positive. Finally, we also demonstrate that the spatial distribution of Prague Airbnb listings changed in response to the COVID-19 pandemic.

Keywords

Airbnb, spatial econometrics, COVID-19, sharing economy

Abstrakt

Tato práce zkoumá cenovou dynamiku Airbnb v Praze. Airbnb, platforma pro krátkodobé pronájmy, je jednou z nejúspěšnějších společností sdílené ekonomiky. Cenová dynamika byla zkoumána pomocí kombinace hedonické a prostorové regrese. Vyhodnocovali jsme prostorové modely a vysvětlili jsme význam zahrnutí prostorových komponent do regrese. V závěru práce bylo potvrzeno, že ceny nabídek Airbnb v Praze vykazují prostorovou autokorelaci. Dále jsme ukázali, že existuje negativní a významný vztah mezi cenou nabídky a vzdáleností od centra města a že vztah mezi cenou nabídky a atraktivitou jejího umístění je významný a pozitivní. Nakonec jsme také prokázali, že prostorové rozložení pražských nabídek Airbnb se změnilo v reakci na pandemii COVID-19.

Klíčová slova

Airbnb, COVID-19, sdílená ekonomika, prostorová ekonometrie

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Acronyms

COVID-19 Coronavirus disease 2019

P2P peer-to-peer

OLS Ordinary Least Squares

SAR Spatial Autoregressive Model

SEM Spatial Error Model

SLX Spatially Lagged X Model

SDM Spatial Durbin Model

SDEM Spatial Durbin Error Model

SARAR Kelejian-Prucha Model

GNS General Nesting Model

Chapter 1

Introduction

The rise of the sharing economy has created a new era of collaborative consumption, where individuals use digital platforms to access, share and monetise under-utilised assets. At the forefront of this transformative movement stands Airbnb. Airbnb is a pioneering online accommodation platform that has redefined the way people travel, experience destinations and meet new friends. Founded in 2008, Airbnb has disrupted the traditional boundaries of the hospitality industry by providing a decentralised marketplace where individuals can rent out their homes, apartments or even spare rooms to travellers seeking unique and authentic accommodation experiences. By removing the boundaries between tourists and locals, guests and hosts, Airbnb is said to have made travelling more affordable while allowing individuals to become part of local communities and explore the destination from a local perspective. With its innovative business model, emphasis on community and commitment to provide diverse, affordable and often unique accommodation options, Airbnb has become a global phenomenon, disrupting conventional notions of hospitality and reshaping the tourism landscape one booking at a time.

Spatial analysis itself is not a new field, having its roots in geography, statistics and various other disciplines. However, advances in technology, particularly Geographic Information Systems (GIS) and computational tools, have greatly expanded the capabilities and scope of spatial analysis in recent decades. Spatial analysis involves the examination of spatial data to identify patterns, trends, and relationships within geographical areas. It encompasses a range of techniques and methods for studying spatial phenomena, including spatial statistics, spatial regression, and spatial autocorrelation. The integration of spatial data with powerful analytical techniques has led to rapid developments in the understanding of spatial relationships, patterns and processes in various domains. While it has been used for decades, its prominence and applicability have expanded with technological advances, making it an increasingly important and evolving field in research and decision making.

There are several ways to conduct a spatial analysis. We decided to focus mainly on the spatial autocorrelation between listings and its impact on the pricing dynamics of different Airbnb listings. Although there are studies examining the pricing dynamics of Airbnb listings in the Czech Republic, they do not address possible spatial autocorrelation, which, as the research suggests, may play an important role. Although there are studies using spatial lags in different countries, the results may not be transferable across regions. In addition, existing studies consider data obtained prior to COVID-19. However, the COVID-19 pandemic has reshaped tourism patterns, caused by a significant decline in short-term rental demand. Therefore, we believe that this study can fill an existing gap in the local literature and provide additional insight into the complicated issue of short-term rental price dynamics. This paper also aims to briefly investigate whether and how the pandemic affected the spatial characteristics of Airbnb listings in Prague. By comparing pre- and post-pandemic data.

The following hypotheses are tested:

1. Hypothesis: Airbnb prices are spatially dependent.
2. Hypothesis: There is significant and negative relationship between the distance to the city centre and the price of Airbnb listing.
3. Hypothesis: The relationship between the price of Airbnb listing and the attractiveness of its location is significant and positive.
4. The spatial distribution of Airbnb listings in Prague changed in response to COVID-19 pandmeic.

The thesis is structured as follows: Chapter 2 generally introduces the topic by providing a contextual overview of the sharing economy and Airbnb's transformative role within it. We examine the fundamental principles of collaborative consumption, whose rapid growth has been driven largely by significant advances in technology. With a robust theoretical framework in place, Chapter 3 provides a comprehensive literature review to explore Airbnb's evolution from a humble startup to a global hospitality giant. We provide an overview of the main topics that have been studied in relation to Airbnb. By examining the potential benefits and drawbacks of the sharing economy model, we also lay the groundwork for understanding Airbnb's impact on traditional hospitality models, market dynamics and the regulatory landscape. We synthesise existing research on Airbnb's impact on the global hospitality industry, and its implications for urban development and housing markets. We also provide valuable insights into the transformative power of Airbnb, its influence on tourist behaviour, and the challenges it poses to traditional hoteliers and local communities. We summarise the existing literature on pricing dynamics and the role of spatial methodology within it. In addition, the literature review includes a section that focuses exclusively on the local literature produced on the topic of Airbnb in Prague.

Chapter 4 describes the data collection process and the important distinction between active and inactive listings on the platform. We examine the spatial distribution of Airbnb listings in Prague and how it changed over the course of COVID-19. This chapter also includes a description of the variables under consideration and their summary statistics. Furthermore, Chapter 5 serves as the methodological foundation of our study, explaining the application of spatial econometrics and hedonic regression models to analyse Airbnb data in Prague. We introduce the field of spatial econometrics and the main models offered by this field. Moreover, the chapter also introduces and explains the baseline model that will be further estimated.

Finally, with a solid methodological framework in place, Chapter 6 presents the empirical results of our study. We demonstrate the existence of spatial autocorrelation among Airbnb listings and estimate different spatial models. We compare the performance of the different models and identify the key factors that shape Airbnb prices, including property attributes, host characteristics, marketing dynamics, and spatial attributes. We highlight the importance of spatial dependencies in explaining Airbnb price dynamics, and emphasise its importance in modelling approaches to capture the complex interplay of factors influencing Airbnb prices in Prague.

Chapter 2

Peer-to-peer Economy

The emergence of the peer-to-peer economy, also referred to as the sharing or collaborative economy, is challenging established notions of ownership and consumption. It seems to be bringing about a profound change in the way individuals can access goods, services, and even experiences. Compared to the traditional market model, which is based on ownership, the sharing economy is fundamentally based on sharing. While sharing itself is not a new phenomenon, recent technological advances have moved it from the private sphere to interactions between strangers. The sharing economy is often associated with collaborative consumption, encompassing organized systems or networks where participants engage in shared activities such as renting, lending, trading, and swapping goods, services, transport solutions, space, or money (Mohlmann 2015).

There is no single definitive definition of the peer-to-peer economy. For example, Botsman & Rogers (2010) characterise it as an economic system based on the sharing of goods and services, either for free or for a fee. Daglis (2022) adds to this definition by emphasising access-based consumption, where consumers have temporary access to goods rather than ownership, thereby prioritising the experience of using goods over ownership. Kim & Lee (2019) add to this understanding by defining the sharing economy as an activity where economic agents share economic objects to create value. enerally, this concept also seems to signify a transition from an asset-heavy ownership era to an asset-light sharing era, with transactions primarily taking place as peer-to-peer (P2P) or business-to-consumer (B2C) exchanges.

Furthermore, Eckhardt *et al.* (2019) describe the sharing economy in terms of several key characteristics: the emphasised temporary nature of access to goods and services, the transfer of economic value through sharing, the crucial role of digital platforms in facilitating transactions, the active involvement of consumers in shaping the market, and the sourcing of supply from a crowd of participants. Taken together, these definitions create a comprehensive picture of the sharing economy, capturing its diverse forms and essential characteristics.

The appeal of the sharing economy lies primarily in its promise of efficiency, cost-effectiveness and a sense of community. Both users offering and seeking services can benefit from the ability to optimise the use of resources, which are often less expensive than traditional alternatives. In addition, the peer-to-peer nature of the model fosters a sense of trust and community as participants engage in direct exchange, bypassing traditional intermediaries.

The peer-to-peer economy is certainly having a significant impact on various sectors. Examples of the phenomenon can be found for example in transportation sector (Uber), retail and consumer goods (eBay) but also in sectors such as finance (peer-to-peer lending), services (TaskRabbit), workspace (coworking spaces) or even education (Udemy, Coursera). The sectors impacted the most include also tourism and hospitality sector, where the sharing economy blurs the boundaries between consumers and service providers, as well as between local residents and businesses in destinations (Hodak & Krajinovič 2020). Examples of sharing economy in tourism sector also transform working business models and provide new economic activities and development opportunities for businesses in the tourism sector (Navickas *et al.* 2021). Moreover, the sharing economy has been found to have a positive impact on consumer satisfaction and willingness to participate, especially regarding cost savings in terms of tourism and hospitality (Ye *et al.* 2022). Some of the most successful examples of the peer-to-peer economy in the tourism sector present Airbnb and Couchsurfing.

However, the rise of the sharing economy is not without controversy and challenges. Concerns about the sharing economy are multifaceted and cover different dimensions, including privacy and security risks, trust issues, sustainability challenges, economic implications and social impacts. Privacy and security risks have been identified as predominant concerns, particularly in the context of participation in sharing economy platforms such as Uber and

Airbnb (Lee *et al.* 2018; Wang *et al.* 2019). These risks are associated with the sharing of personal data and the potential vulnerabilities in the digital infrastructure that supports sharing economy transactions.

Although it is a relatively new economy, the rise of the sharing economy has certainly been accelerated by advances in technology. Today, individuals can effortlessly connect to exchange, rent or share various assets, facilitated by digital platforms. However, this rapid expansion has led to a transformation within the sharing economy, shifting its focus from genuine sharing to a more commercialised model. We are witnessing a trend where sharing platforms are evolving into full-time businesses, moving away from their original purpose of utilising underutilised assets. This is often illustrated on the example of Airbnb, which was originally designed for hosts to rent out spare rooms in their homes. However, as the platform has gained traction, we are witnessing instances where properties are dedicated exclusively to Airbnb rentals, deviating from the ethos of sharing unused spaces.

In addition, the sharing economy has raised governance concerns, including regulatory, legal, tax and labour issues, as well as political and societal impacts, with implications for social inequality and economic growth (Huurne *et al.* 2018; Hwang 2019). In addition, the sharing economy has been linked to concerns about sustainability, social capital and community building, with debates about its impact on economic development and the environment (Penz *et al.* 2018). The sharing economy has also been criticised for its potential negative externalities, such as the commodification of time and space, which can lead to a sense of alienation rather than community (Huurne *et al.* 2018). The transition from solid to liquid consumption within the sharing economy has also been scrutinised, with discussions about the failure to generate substantive, higher-level consumption alternatives (Saravade *et al.* 2020).

The regulatory challenges surrounding the sharing economy stem from its hybrid nature, combining elements of traditional markets and the sharing of personal assets. Governments are grappling with how to regulate these platforms without stifling innovation or infringing on individual rights. However, issues such as insurance, liability, taxation and consumer protection need to be addressed to ensure a fair and level playing field for all participants.

Chapter 3

Literature Review

The emergence of the sharing economy has transformed the tourism and hospitality industry. Platforms such as Airbnb have become major disruptors in the hospitality sector. The popularity of short-term rental platforms has skyrocketed as travellers seek unique, affordable and local experiences. This has reshaped urban spaces and challenged traditional hospitality models. Among the many cities around the world affected by this phenomenon, Prague stands out as a compelling case study due to its rich historical heritage, vibrant culture and thriving tourism industry. This literature review provides an insight into different areas of research related to Airbnb, highlighting the existing literature on the pricing dynamics and the context of spatial analysis, while also summarising the literature published on the topic of Airbnb in the Czech Republic.

3.1 Airbnb

Airbnb is a San Francisco-based company founded in 2008 by Brian Chesky, Joe Gebbia and Nathan Biecharczyk. As a pioneer of the sharing economy, Airbnb has disrupted the traditional hospitality industry. The idea for Airbnb was born in 2007 when the founders rented out beds in their home to three conference attendees who could not find suitable hotel rooms. As their idea resulted to be successful and both parties of the experiment were satisified, the company officially entered the market in 2008 as a short-term rental service in major cities, but has since expanded to remote and regional areas, reaching a global audience (Mahmuda *et al.* 2021).

Airbnb can be defined as a two-sided market platform that has redefined the relationships between market, state and civil society actors, positioning itself as a new urban institution (Doorn 2019; Chiappini 2020). The fact that anyone can offer their home on the platform to potential guests for a fee has made the platform very attractive, as tourists can stay with locals, which allows them to explore the destination from a different perspective. Bresciani *et al.* (2021) and Kim *et al.* (2021) also characterise the nature of Airbnb through an innovative business model that prioritises community, unique experiences, social interaction and competitive pricing. The growth of the platform has been significant, changing the way people access accommodation and hotel services and challenging traditional hospitality models (Oskam & Boswijk 2016). Airbnb has had a significant impact on the hotel market, as it has been one of the largest marketplaces for vacation rentals since 2012. Not only provides the platform a convenient way for property owners to share their spaces with visitors for a fee (Krajčík 2019; Koh *et al.* 2019) but Dann *et al.* (2019) and Kim *et al.* (2021) also suggest that the success of the platform is based on its creative and original use of technology providing a smooth experience for both hosts and guests. This has been boosted by the rise of smartphone technology, which has made it even easier for people to find and book listings. Airbnb's transformation from a startup to a global hospitality giant is therefore said to demonstrate the impact of innovation, technology and community-driven experiences in shaping the modern travel industry. The current state of the platform reflects a dynamic and ever-evolving service that is permanently redefining the way people access and experience accommodation around the world. It is not surprising that the company has a presence in over 34,000 cities in 191 countries (Malazizi *et al.* 2018), which highlights its significant impact not only on the peer-to-peer accommodation market (Ghosh *et al.* 2023).

Airbnb has shown adaptability and resilience in responding to external shocks, such as the COVID-19 pandemic. However, the COVID-19 pandemic did indeed have an initial significant impact on Airbnb, leading to changes in its operations and market dynamics. The pandemic at its early stages led to a drastic collapse in tourism and demand for short-term rentals, resulting in a decrease in Airbnb supply and a reallocation of apartments to the long-term rental market (Hu & Lee 2020; Boros *et al.* 2020). This shift in market dynamics also affected rental prices and overall activity on the Airbnb platform. In response to the challenges posed by the pandemic, Airbnb has certainly undergone business model innovation and organizational restructuring to adapt to the changing landscape. The impact of COVID-19 has necessitated a deeper understanding of the evolving dynamics of the pandemic and its influence on Airbnb's market behavior and consumer preferences (Sthapit *et al.* 2022). The spatial distribution of Airbnb providers has also been affected, with a decline in supply and a shift towards the long-term rental market (Endrich *et al.* 2022). These changes reflect the significant impact of the COVID-19 pandemic on Airbnb and the broader sharing economy. Overall, the peer-to-peer system that underlies Airbnb's business model has demonstrated agility in navigating such challenges. This suggests profound implications for the future of the hospitality market, as noted by Kourtit *et al.* (2022).

Consumers are drawn to Airbnb due to the enjoyment derived from the unique experiences offered at Airbnb accommodations, emphasizing the role of enjoyment in their evaluation of the platform (So *et al.* 2020). Consumer loyalty towards Airbnb is shaped by factors such as satisfaction, trust, entertainment, and recognition, all of which influence consumer behavior (Kim 2019). Research also emphasizes that consumer satisfaction and trust in Airbnb are the most important factors for consumers returning to the platform (Kim 2019). The COVID-19 pandemic has further altered consumer behavior in the context of Airbnb by modifying the role of perceived risk in determining trust and repurchase intention (Qi & Chen 2022). Moreover, Airbnb's introduction of standardized sub-branded offerings, such as Airbnb Plus and Airbnb Luxe, has made the platform more similar to hotels. Consumers now seem to value Airbnb listings differently, with internal reference prices from hotels affecting their room rate expectations and subsequent booking behavior (Yong & Xie 2017). This has influenced customers to view Airbnb as a viable alternative to traditional hotels (Dogru *et al.* 2021). The platform has not only challenged the traditional hotel industry but has also induced changes in travel behavior (Mao & Lyu 2017). The rise of Airbnb increased economic activity in several local communities. As Airbnb listings are scattered all over the city and Airbnb travelers often intentionally seek local restaurants and shops for the most genuine travel experience. The rise of the sharing economy, exemplified by Airbnb, has transformed the traditional way of providing services to consumers, leading to shifts in consumer preferences and choices (Chen *et al.* 2020).

Moreover, consumer behavior research indicates that perceived risks can impact repurchase intention, highlighting the importance of addressing concerns related to safety and trust on platforms like Airbnb (Braje *et al.* 2021). While consumers benefit from Airbnb through increased choices and potentially lower prices, the platform's growth has raised issues related to affordability, competition, and community dynamics in certain areas (Schafer & Tran 2020). Factors such as trust, likability, brand loyalty, and brand personality play crucial roles in shaping consumer behavior and intentions towards using Airbnb (Chua *et al.* 2020; Tran *et al.* 2023; Cardoso *et al.* 2022). While Airbnb has revolutionized the accommodation industry, offering unique experiences and opportunities for both hosts and guests, it also presents challenges and negative consequences that need to be addressed to ensure sustainable and equitable growth in the hospitality sector.

The Airbnb platform has been criticized for the way it has affected the traditional hotel industry. Reshaping the already competitive sector, Airbnb has had a significant impact on the hotel industry taking market share away from the hotels and putting pressure on the hotel industry prices. Research indicates that the entry of Airbnb into the accommodation market has led to a substitution effect, affecting hotel revenues and performance (Mhlanga 2019). Studies have also shown that the increased supply of Airbnb listings can also negatively impact hotel metrics such as room rates, occupancy rates, and revenue per available room (RevPAR) (Mhlanga 2019). Moreover, Airbnb's presence has influenced consumer behavior, attracting budget leisure travelers seeking competitive prices, local atmospheres, and convenient locations (Lu & Tabari 2019). The platform's unique appeal as a trusted community for discovering local accommodations has drawn customers away from traditional hotels (Zhang 2019). Therefore, the growth of Airbnb has been associated with a decrease in hotel room prices and occupancy rates, particularly affecting 4-star hotels and hotels with fewer services and lower categories (Mate Sanchez Val 2020; Gómez *et al.* 2021). While Airbnb has led to challenges for the hotel industry, it has also prompted hotels to respond with strategies to compete and adapt to changing market dynamics (Gyódi 2021). Overall, Airbnb's disruptive presence has forced the hotel industry to reconsider pricing strategies, service offerings, and customer experiences to remain competitive in the evolving accommodation market.

The mixed effect of Airbnb on the tourism industry stems also from possible overtourism. More personalized and often also more affordable alternatives to traditional accommodation led to more people visiting popular destinations. The exponential growth of Airbnb was also associated with tourism pressure over residential areas in city centres (Heo *et al.* 2019).

The impact of Airbnb on the rental and real-estate market has been a subject of much debate with studies indicating both positive and negative effects. On one hand, the platform certainly provided a new source of income for homeowners and landlords, who can rent their properties to travelers. On the other hand, the platform's presence has been associated with the creation of rent gaps in cities globally, potentially affecting housing markets by introducing a new revenue stream (Wachsmuth & Weisler 2018). Concerns have been raised regarding the negative effects of home-sharing platforms like Airbnb on traditional housing markets, leading to reactions from community groups and housing advocates (Franco & Santos 2021). Airbnb's influence on the rental market has been observed in various locations, such as Berlin, where the platform's supply negatively correlates with the number of owner and rental households (Duso *et al.* 2021). Studies have shown that the introduction of limitations on the misuse of regular rental apartments as short-term accommodations can reduce the availability of Airbnb listings for booking, impacting rental dynamics (Duso *et al.* 2021). Additionally, the rapid growth of Airbnb has been associated with an increase in housing prices and rents, particularly in European and American markets (Zhu 2022). Converting apartments into short-term rentals, can drive up proprerty values and rents, which makes them unaffordable for long-term residents. In conclusion, Airbnb's presence in the rental market has brought about significant changes, including rent gaps, increased rental costs, and regulatory challenges. Understanding the complex interactions between Airbnb and traditional rental markets is crucial for policymakers, housing advocates, and communities to address the implications of short-term rental platforms on housing affordability and market dynamics. The emergence of Airbnb has also been linked to social conflicts, security issues, and noise problems in communities (Sun *et al.* 2021).

The success of Airbnb as the largest vacation rental marketplace is evident in its global reach and the vast amount of accommodation available on its platform. This success is also recognised in the start-up business sector, where online travel, including vacation rentals, has been identified as one of the five sectors with the largest market coverage. Furthermore, the significant transaction value of online paid peer-to-peer accommodation platforms, including vacation rental platforms, further highlights Airbnb's dominance in the sharing economy (Farmaki & Miguel 2022). However, while the platform has provided new opportunities for homeowners and travellers, it has also raised concerns about possible gentrification, effect on local business and its impact on the rental and real estate markets. Governments around the world try to find ways of Airbnb regulation that would ensure reasonable operations and would not harm the Airbnb communities. Ongoing research and debate focus on the platform's sustainability and impact on cities, including issues such as gentrification and sustainability. Álvarez-Herránz & Macedo-Ruíz (2021) discuss these subjects as the platform continues to evolve.

3.2 Airbnb Pricing Dynamics

Numerous studies have been conducted to understand the determinants of Airbnb prices. In this part of the literature review, we summarise findings from a number of academic articles to provide insights into Airbnb price dynamics.

Studies use different methodological approaches to analyse Airbnb price dynamics, including hedonic price modelling, ordinary least squares (OLS) regression, quantile regression and geographically weighted regression (GWR) (Zhang *et al.* 2017). These techniques allow researchers to identify and quantify the impact of different variables on Airbnb prices.

The existing research consistently highlights several key factors that influence Airbnb prices. Property-related attributes such as size, quality, amenities (e.g. air conditioning, free internet) and services (e.g. breakfast) have been identified as important determinants of pricing (Gyódi & Nawaro 2021; Voltes-Dorta & Sánchez-Medina 2020; Perez-Sanchez *et al.* 2018; Wang & Nicolau 2017a). The results of the existing literature confirm that listings from the entire apartment category tend to be more expensive compared to the private and shared rooms. Furthermore, listings with more space generally command higher prices Perez-Sanchez *et al.* (2018). In addition, host characteristics such as reputation, number of ratings, review score and length of membership on the platform play a crucial role in determining prices. Hosts with higher ratings and longer membership often charge higher prices (Teubner *et al.* 2017). Gyódi & Nawaro (2021) also highlight the ambigous effect of number of reviews in the existing literature suggesting a problem of reverse causality. Furthermore, factors such as the number of photos posted by hosts and the responsiveness of hosts to enquiries also seem to influence pricing decisions (Voltes-Dorta & Sánchez-Medina 2020).

Despite this, the literature focusing on the spatial characteristics of Airbnb listings and their potential spatial effects is relatively scarce. However, spatial econometrics remains a valuable methodological approach, also for analysing the spatial distribution and dynamics of the Airbnb market. Taking a broader perspective and considering research on housing and rental markets, it becomes apparent that spatial analysis is essential for understanding this topic and can provide valuable insights across different research areas.

The study by Tang *et al.* (2019) investigates the pricing determinants of peer-to-peer (P2P) accommodation, taking into account their spatial dependence. Using spatial hedonic pricing models, the study examines the influence of both location and situational attributes on pricing. Key findings show that the number of peer-to-peer listings in an area, population density, unemployment rates and median income significantly contribute to the pricing of peer-to-peer accommodation listings.

Furthermore, Gyódi & Nawaro (2021) employed a spatial econometric approach to investigate the determinants of Airbnb prices in European cities. They applied a wide range of spatial econometric techniques to analyse the spatial patterns of Airbnb prices and identified the factors influencing price variation across locations. They also highlight the significant presence of spatial autocorrelation in European cities and demonstrate the importance of implementing spatial models, rather than simple ordinary least squares, when assessing the pricing dynamics of Airbnb listings.

Studies also highlight the importance of location in determining Airbnb prices, with results suggesting that location-related variables have a significant impact on pricing decisions (Gyódi & Nawaro 2021; Onder *et al.* 2018). Lawani *et al.* (2019) estimated the determinants of Airbnb pricing considering spatial factors, and showed that not only distance to the city centre but also distance to other popular areas may significantly influence the price of listings.

Traditional measures of location, such as distance to tourist attractions, city centre or coastline, have been frequently used to assess the spatial distribution of Airbnb listings and their pricing dynamics (Wang & Nicolau

2017b). However, recent research suggests that new kinds of indexes based on neighbourhood attractiveness, derived from sources such as TripAdvisor data, provide more robust insights into the impact of location on pricing. In addition, spatial regression models have been used to account for spatial dependencies and heterogenity in pricing across areas (Gyódi & Nawaro 2021). Spatial econometric techniques have proved valuable in analysing the spatial relationship between the price of Airbnb listings and established hotels, particularly in distinguishing between different types of tourist destinations (Onder *et al.* 2018).

In conclusion, the integration of spatial analysis techniques in the study of the Airbnb market provides valuable insights into spatial variations. In addition, the existing literature highlights that location-related attributes such as proximity to tourist attractions, city centres or coastlines, as well as neighbourhood characteristics, have been found to have a significant impact on Airbnb prices (Gyódi & Nawaro 2021).By considering spatial aspects, researchers and policymakers can make more informed decisions regarding Airbnb market dynamics, plan for future housing needs, and implement effective policy interventions. Unfortunately, according to our knowledge there is currently no study that would have taken Prague into account. Studying the determinants of Airbnb prices and the role of location at the local level is important for several reasons. First, conducting research at the local level allows for a more nuanced understanding of how contextual factors, such as city characteristics, tourism demand, regulatory environment and cultural norms, shape pricing decisions (Zhang 2019). This contextual understanding is crucial for policymakers and regulators who need empirical evidence specific to their region in order to develop effective policies that balance the interests of different stakeholders, including residents, hosts, tourists and the wider community. In addition, local markets have unique supply and demand dynamics, competitive landscapes and consumer preferences. Therefore, insights from local studies enable stakeholders, including hosts and platform operators, to make informed decisions on pricing strategies, real estate investments and market positioning (Thackway *et al.* 2022).

3.3 Airbnb in the Czech Republic

The Czech Republic was presumably among the first countries with an Airbnb accommodation. Even though the origin of the platform is dated to 2007, Kostková (2020) states the first Czech Airbnb accommodation appeared in 2009. The overall popularity of Airbnb worldwide reflects also on the Czech market especially on the capital - Prague. Compared to other European cities, Prague appears to have the highest occupancy rate among the 14 biggest cities in Europe, indicating the significant success of Airbnb in Prague (Ključnikov *et al.* 2018).This data suggests that the Czech Republic, particularly in the capital, has a well-established and booming Airbnb sector. Even though majority of the Airbnb listings is located in Prague, the listings are also sccattered all over the country (Kostková 2020).

Perhaps one of the most important factors influencing Airbnb's success is the price difference. According to Deloitte (2019), there is an average 2% price difference in Prague between staying in an Airbnb and a hotel. In addition to reduced rates, Airbnb also offers a wider selection of prices. Furthermore, Štollová (2020) examined the daily rate of Airbnb listings of Prague using 2017 data with ordinary least squares and showing the importance of listings location.

The largest increase in Airbnb listings was noticed in 2018, when the increase in the number of toursits accommodated via Airbnb dynamically grew by 52% ČTK (2018). However, COVID-19 seems to have imposed huge shock on the Czech Airbnb market (Fialová & Vasenská 2020). Both Hromada (2021) and Ondruška (2021) suggest significant temporary migration of listings to both long-term rental and real-estate markets. Šáchová (2022) also suggests that the number of listings after COVID-19 decreased by 52% comparing June 2019 and June 2022.

As the Airbnb market in the Czech Republic is considered to be well established and thriving, it goes hand in hand with possible negative aspects of Airbnb. Both Schwarzová (2019) and Ondruška (2021) suggest that the increasing number of Airbnb listings is associated with an increase of the residential prices in Prague.

Chapter 4

Data

This chapter of the thesis presents the dataset used for the analysis, outlines the data cleaning process, and addresses the challenges associated with active and inactive listings on the platform. It also provides an overview of the variables used for estimation and their summary statistics, evaluates the Airbnb market in Prague, and illustrates the spatial distribution of Airbnb listings, including changes observed during the COVID-19 pandemic.

4.1 Data

For the purposes of this thesis, we have chosen to analyse data from Prague specifically, as Prague is undoubtedly considered to be the epicentre of tourism in the Czech Republic. The city of Prague is located in the centre of Europe, in the Czech Republic. The area of the city is 496 km2 and the city has approximately 1,357,326 inhabitants distributed in 10 districts (Prague 1 - Prague 10). Prague has a rich history and offers a variety of architectural styles. The historic centre of Prague has even been declared a UNESCO World Heritage Site. In recent years, however, the city has been recovering from the COVID-19 pandemics. In 2022, Prague was visited by almost 6 million tourists, which is approximately 75% of the total number of visitors before COVID-19.

The data used in this study was downloaded from the Inside Airbnb platform, an independent, non-commercial online platform that provides granular Airbnb data for various cities around the world. The data presented on the website represents a snapshot of Airbnb listings at a given point in time.

The dataset includes 54 available variables that provide complex information about individual listings: ID of both the listing and the host, respective URL address, name and description of the property, name of the host, concrete location given by coordinates, property type, number of bedrooms, number of bathrooms, description of the neighbourhood, various price and availability indices, both overall and specific review scores (cleanliness, communication, ...), policies implemented by the host (cancellation, maximum and minimum number of guests) and other characteristics of the hosts (superhost identification, host location, total number of listings). The dataset includes the coordinates of the Airbnb listings, but it is important to highlight that the specific location information is anonymised by Airbnb, which means that the real location of the Airbnb listing on the map is 150 metres away from the actual address. In addition, as listings are randomised individually, listings in the same building may appear scattered on the map.

4.2 Data Cleaning

In order to avoid duplicate observations and to ensure that there were no missing values for the variables we would use in the future, we carried out a thorough examination of the data. We found some missing values in our data. We decided to omit the variables that were missing the price of the listing or the specific ID, as this made the observation unreliable. There were also variables with missing data indicating the number of reviews, review score and superhost status. [1] Missing values for reviews and review scores were replaced with zeros. In addition, the host may not have been considered a superhost due to the age of the listing. All listings with missing values were relatively new and unlikely to have received any reviews or review scores, making it impossible for them to be a superhost. Finally, some of the observations were missing the neighbourhood value, which we added based on their coordinates.

4.2.1 Activity of a Listing

Quantifying supply and demand in the Airbnb market is difficult, as this information cannot be determined directly from Airbnb data. Differentiating between active and inactive listings on the supply side is a challenge. The simplest way to identify supply is to assume that every scraped listing that appears

[1] Superhosts are designated by Airbnb as exceptionally hospitable and giving hosts.

on the Airbnb website is active. However, hosts often keep their listings on the platform and present them as available even if they are no longer active. This can lead to an overestimation of supply. It is therefore important to be cautious in our assumptions. This is usually caused either by hosts forgetting or neglecting to remove their inactive listings. Findings from Fradkin (2015) suggest that between 20% and 30% of booking requests are automatically rejected due to the inactivity of a listing.

For our purposes, however, we need to work specifically with active listings only in order to get the most accurate description of price dynamics. There are different approaches to this problem among scholars. For example, Kourtit *et al.* (2022) consider a listing to be active if it has received at least one review in the last three months. However, we consider this methodology to be rather strict, especially for the period over the COVID-19 pandemic, and we believe it may lead to an underestimation of the supply, as ReviewTrackers (2022) states that only 40% of satisfied customers and 48% of unsatisfied customers leave a review. As in Šáchová (2022), we compared the following methods for identifying activity: the first method considers any visible listing on the site to be active, while the second method considers a listing to be active if its availability is between 0 and 90 days, excluding 0 and 90 days. This restriction is based on the assumption that 0 means no vacancy and 90 means full availability, which is rather unlikely. Finally, the third approach is based on what Kourtit *et al.* (2022) suggested. However, we have decided to relax the requirements and assume that listings that have been checked within the last six months can be marked as active. The following figure provides comparison of the methods over time:

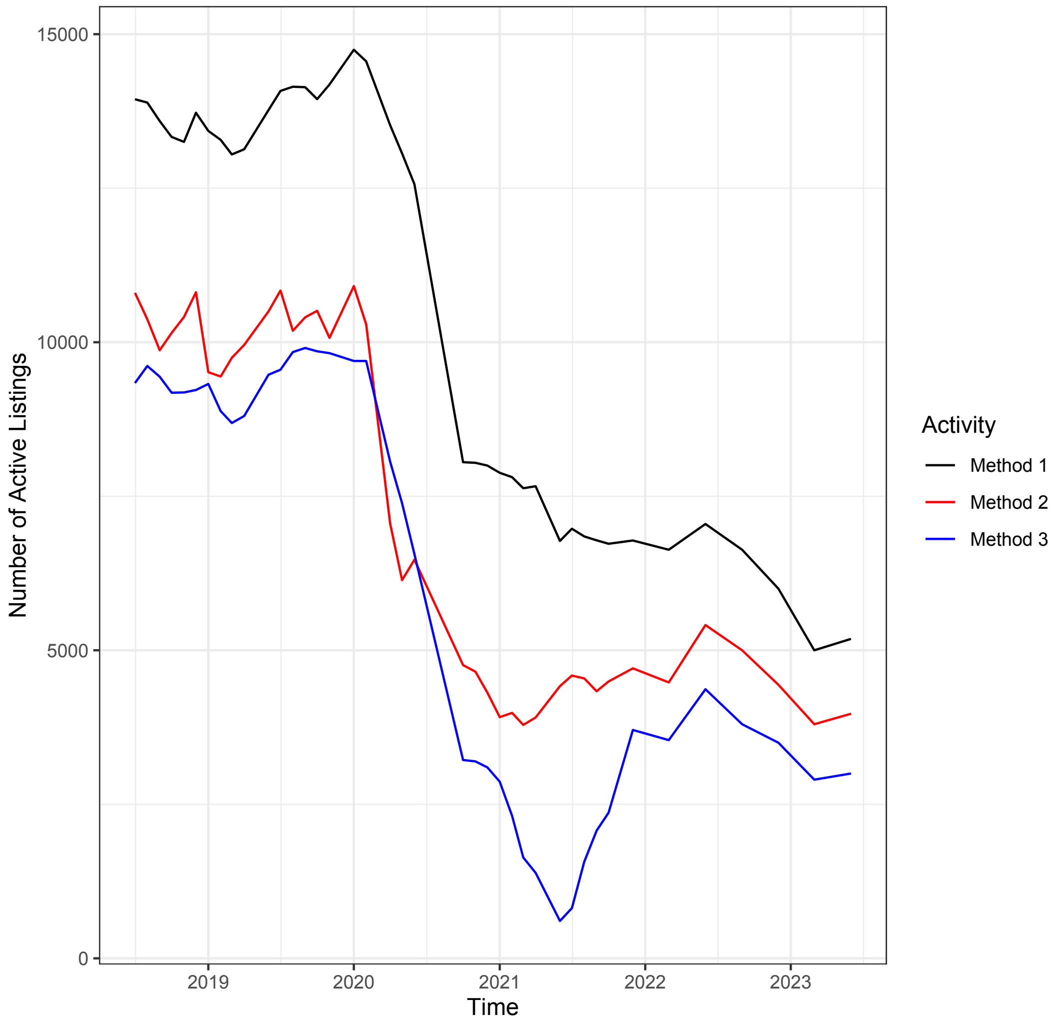

Figure 4.1: Comparison of Methods of Determining Listing Activity

Method 1 suggests that all listings displayed on the platform are active, method 2 considers only the listings whose availability in the next 90 days is between 0 and 90, and method 3 considers a listing active if it has received at least one review in the last 3 months. Looking at the figure, we can see that the trend over time is very similar for all three methods. However, the first method suggests significantly higher numbers compared to methods 2 and 3. Methods 2 and 3 give very similar results, except for the COVID period, where method 3 suggests a significantly lower number of active listings. We believe that method 3 may be too strict, therefore, we have decided to proceed with method 2. This resulted in having 3970 active listings for the June 2023 period, which we used for the estimation.

4.3 Variables

The following table provides list of variables that were chosen from the dataset and considered for the baseline model.

Table 4.1: List of Variables

Price	Average price per night in CZK.
Accommodates	Number of guests that can be accommodated.
Bedrooms	Number of bedrooms available in a listings.
Entire Apartment	Dummy variable indicating entire apartment.
Private Room	Dummy variable indicating private room.
Shared Room	Dummy variable indicating shared room.
Hotel room	Dummy variable indicating hotel room.
Acceptance Rate	Accepted : not accepted guests scaled to 100
Responsiveness	Responded : not responded messages scaled to 100
Superhost	Dummy variable indicating a superhost.
Multi	Dummy variable - 2-5 listings owned by the host.
Business	Dummy variable - 6-10 listings owned by the host.
Multibusiness	Dummy variable - host owning more than 11 listings.
Reviews LTM	Number of reviews obtained in the lat 12 months
Review Score	Total review score received scaled to 500
DistCentre	Distance from the listing to the centre in meters.
Min. Metro	Minimum distance between listing and the nearest metro.
Attractive Neigh.	Dummy variable - location in attractive neighbourhood.

Looking at the table providing the list of variables that were chosen from the dataset for further consideration, we can see that the variables may be divided to following groups: listing attributes, host attributes, marketing/reputation attributes, spatial attributes and the dependent variable to be - price. We have opted for these variables based on the literature review and the provided dataset. Looking at the table, we can see a mix of numerical variables and dummy variables. However, not all dummy variables were used in the model in order to avoid dummy variable trap see Chapter 5 for more details.

The following summary statistic provides a comprehensive snapshot of the Airbnb landscape in Prague:

Table 4.2: Summary Statistics

Variable	Min	Median	Max	Mean	SD
Price	450	2300	54406	2893.24	2717.07
Accommodates	1	4	16	4.2	2.4
Bedrooms	1	1	18	1.52	0.96
Acceptance Rate	0	100	100	94.70	14.28
Responsiveness	0	100	100	96.41	11.35
Reviews LTM	0	13	439	21.98	24.82
Review Score	0	483	500	473.21	39.31
DistCentre	56.76	1573.87	18558.53	2118.23	2080.48
Min. Metro	15.52	371.76	11516.78	577.85	774.19

The following table provides summary of dummy variables:

Table 4.3: Summary of Dummy Variables

Variable	Proportion
Entire Apartment	93.57%
Private Room	6.43%
Shared Room	0.00%
Hotel Room	1.00%
Superhost	44.82%
Multi	30.82%
Business	17.87%
Multibusiness	27.94%
Attractive Neigh.	46.24%

A brief examination reveals a remarkably professionalised environment, underlined by the high Acceptance Rate and Responsiveness metrics among hosts. Specifically, the median values for Acceptance Rate and Responsiveness are 100 and 96.41 respectively, with corresponding mean values of 94.70 and 96.41. In addition, a significant proportion, approximately 44.82%, of listings are managed by superhosts, indicating a prevalence of experienced and highly trusted hosts within the platform.

Looking more closely at the ownership distribution of listings, it is clear that a significant proportion of hosts have a high level of commitment to the platform. In particular, 30.82% of listings are associated with hosts managing 2-5 properties, while 17.87% are associated with hosts managing 6-10 listings. Furthermore, a considerable 27.94% of listings are associated with hosts who have more than 11 properties under their management. Conversely, only a modest 23.37% of listings are attributed to hosts managing a single property, indicating a significant deviation from Airbnb's original philosophy as a means for individuals to earn extra income. This pattern suggests a notable shift towards an increased level of professionalism within the platform, reflecting the evolving landscape of the sharing economy. High level of professionalism is also reflected in the review score variable. We can see that the average review score is 473.21 out of 500 and that a listing has received an average of 22 reviews in the last twelve months.

Furthermore, Airbnb has traditionally focused on three primary accommodation types: entire apartments, private rooms and shared rooms. However, an examination of the distribution of these accommodation types reveals a notable trend. Specifically, the data shows that nearly 94% of listings are entire apartments, while the shared room category has virtually disappeared from the platform. There has also been a notable increase in the number of hotel rooms offered on the platform, accounting for around 1% of active listings.

In terms of spatial characteristics, the typical distance to the city centre is 2.2 kilometres and the average distance to the nearest metro station is 0.6 kilometres. In addition, 46.24% of offers are located in attractive neighbourhoods.

4.4 Spatial Distribution of Airbnb Listings in Prague

The spatial distribution of Airbnb listings in Prague is highly concentrated in the city centre. Beyond the central area, however, Airbnb listings are scattered throughout the different neighbourhoods of the city. In general, the spatial distribution of Airbnb listings seems to have changed after the COVID-19 pandemic. Comparing the spatial distribution figures for 2019 and 2023, we can see that the central area was significantly more occupied in 2019. There was also a significant decrease in the number of listings in the southern and eastern suburbs of Prague.

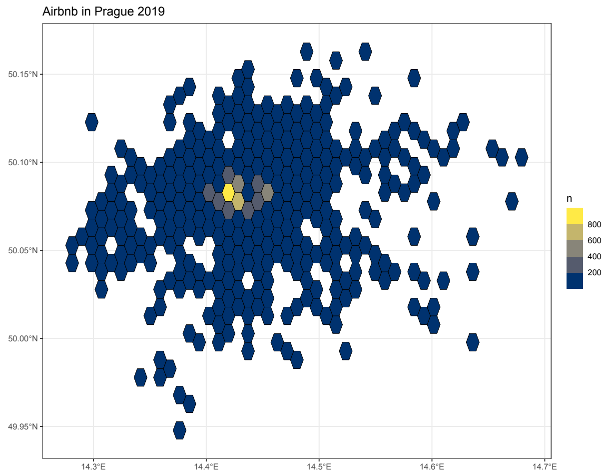

Figure 4.2: Spatial Distribution 2019

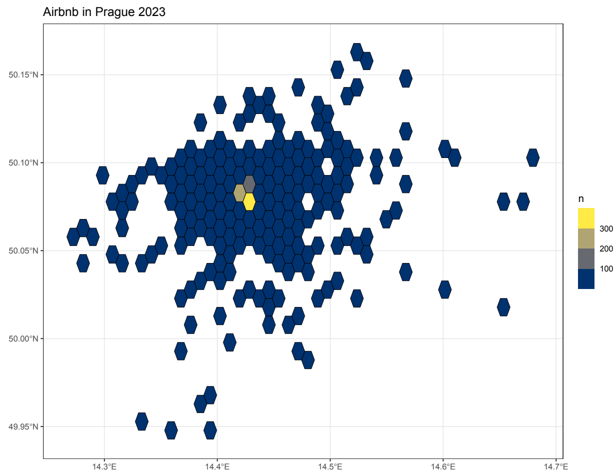

Figure 4.3: Spatial Distribution 2023

This finding is supported by the following table, which shows the proportional difference in the number of listings in different Prague municipalities. We can see a proportional decrease in all Prague districts, except for Prague 1, Prague 2, Prague 4 and Prague 9, where the proportion increased. This suggests not only that there are fewer listings in Prague's suburbs, but also that the number of listings has increased proportionally in the city centre and in popular districts such as Prague 2 - Vinohrady.

Table 4.4: Proportional Change in Spatial Distribution

	June 2019	June 2023
Total Number of Listings	13769	5185
Active Listings	10502	3970
Prague 1	32.44%	34.87%
Prague 2	16.64%	20.05%
Prague 3	13.64%	9.02%
Prague 4	4.25%	5.21%
Prague 5	9.68%	9.32%
Prague 6	4.59%	3.60%
Prague 7	5.31%	5.25%
Prague 8	6.27%	4.99%
Prague 9	2.30%	2.89%
Prague 10	4.89%	4.80%

Furthermore, when examining the table, a significant decrease in the number of listings is evident. Before COVID-19, there were almost 14,000 listings available on the Airbnb platform in Prague, while by June 2023 this number had dropped to only 4,000. There are several possible explanations for this phenomenon. It is likely that a significant number of listings were removed from the platform or discontinued (Šáchová 2022). However, as shown in the table below, the character of Airbnb in Prague also appears to have changed compared to the pre-COVID-19 period. Prior to the pandemic, there were more listings of private and shared rooms on the platform. However, by 2023, the proportion of private rooms had halved compared to 2019, and shared rooms appear to have disappeared altogether. It is possible that listings previously offered as private or shared rooms are now presented on the platform as a single listing in the entire housing category. In addition, there is a higher proportion of listings with superhost status, which typically indicates a higher level of professionalism. Therefore, the decline in private and shared rooms on the platform may also be due to changes in host behaviour, suggesting that locals who previously offered spare rooms in their homes may have left the platform.

Table 4.5: Proportional Change in Airbnb Categories

	June 2019	June 2023
Entire Apartment	81.66%	93.75%
Private Room	14.10%	6.43%
Shared Room	1.09%	0.00%
Hotel Room	3.15%	1.00%
Superhost	33.54%	44.82%

Chapter 5

Methodology

The spatial analysis of Airbnb in Prague was conducted using the spatial econometric methodology described in this chapter. The choice of spatial econometrics was based on its ability to identify and simulate the spatial dependencies present in the data, allowing for a more comprehensive understanding of the spatial patterns of Airbnb listings and their impact on neighbouring areas.

The introductory section of this chapter begins with an overview of spatial econometrics, presenting its basic concepts and relevance within the broader field of econometric analysis. Following this introduction, the following sections provide an overview of the various models and estimation techniques relevant to the discipline of spatial econometrics. Emphasis is placed on explaining the differences between these models and methods, while highlighting their applicability in dealing with spatially dependent data. Attention is also given to the description of the weight matrix, a central component of spatial econometric analysis. In addition, the chapter provides a careful presentation of the hypotheses under investigation, examining their theoretical foundations and empirical implications. Finally, the chapter concludes with a brief presentation of the baseline model that is estimated in the following chapter.

5.1 Spatial Econometrics

Spatial econometrics is a branch of econometrics that deals with the complex relationships between economic phenomena and spatial attributes. Traditional econometric models often tend to assume independence between observations, neglecting the spatial interdependencies that may exist in many real-world economic scenarios. Spatial econometrics aims to overcome this limitation by incorporating spatial relationships into models, thus providing a more accurate representation of economic processes influenced by geographical attributes. The recognition of the role of space and spatial connections in economic theory, together with the availability of datasets that allow for geo-referenced observations, has led to the increasing popularity of spatial econometrics in the social sciences.

A key concept of spatial econometric models is to involve so called spatial effects which can be further categorised to spatial autocorrelation and spatial heterogeneity (Fischer & Nijkamp 2014). At its core, spatial econometrics is based on acknowledging that economic units and observations nearby are likely to exhibit spatial autocorrelation, a phenomenon in which the values of neighbouring locations are systematically related. This spatial dependence poses the main challenge to the assumptions of classical econometric models and has led to the development of specialised techniques to capture and provide adequate analysis of these spatial patterns. Spatial autocorrelation is often characterised as two dimensional and multidirectional. On the other hand, spatial heterogenity acknowledges that the effects of economic variables may differ across locations. This spatial non-stationarity raises the question of how local characteristics might influence economic relationships, and highlights the significance of geographical context in understanding various economic phenomena. This may result either in heteroscedasticity (nonconstant error variances in a regression model) or spatially varying regression coefficients (Fischer & Nijkamp 2014).

Spatial econometric models extend traditional econometric frameworks to account for spatial interdependencies. For instance, the spatial lag model introduces a spatially lagged dependent variable to account for the effect of neighbouring observations on the current one. Similarly, the spatial error model introduces a spatially correlated error term, allowing for the presence of unobserved factors that may be spatially correlated. Spatial econometric techniques involve the use of spatial weight matrices to quantify the strength of connections between spatial units. These matrices are crucial in defining the spatial relationships within a dataset and facilitate the inclusion of spatial effects in econometric models.

Despite being relatively new, spatial econometrics finds applications in various fields such as regional economics, urban studies, environmental economics, and public finance. Its techniques analyse spatial spillovers, identify clusters of economic activity, and account for spatial heterogeneity in policy evaluations. However, the use of spatial econometrics also presents challenges. Some challenges in spatial econometrics include selecting the appropriate spatial weight matrix, identifying spatial outliers, and addressing potential endogeneity issues. Additionally, interpreting spatial econometric results requires careful consideration of the underlying spatial processes and their implications for economic relationships.

5.1.1 Spatial Econometric Models

For a thorough understanding of spatial econometric models, it is essential to clarify the sources of spatial interactions. In general, three main sources of spatial spillovers can be identified. First, the value of the dependent variable may be influenced by its counterpart in neighbouring areas. In our context, this means that the price of a particular Airbnb listing may be influenced by the prices of neighbouring Airbnb listings. Second, the values of the independent variables may affect or have a relationship with the dependent variable in neighbouring areas. For example, the rating of an Airbnb listing in a neighbouring area may affect the price of other Airbnb listings. Finally, residuals (ϵ) may be associated with or influence residuals in the neighbouring areas. Let us define the traditional OLS model in the following way:

$$y = X\beta + \epsilon$$

We may then present the Manski model in the following manner:

$$y = \rho W y + X\beta + W X\theta + u$$

$$\text{u} = \lambda W u + \epsilon$$

Where W denotes the spatial weights matrix.

The Manski model also referred to as GNS (General Nesting Spatial Model) is a powerful framework for capturing the complex dynamics of spatial spillovers. It combines all three primary sources of such phenomena. Its equation clearly expresses these spatial interactions. The term $\rho W y$ represents the spillover effect in the dependent variable, commonly known as the lag of y. Similarly, $W X\theta$ represents the second spillover effect, also known as the lag of X. The equation also includes the residual spatial effect, often referred to as spatial autocorrelation, which is denoted as: $u = \lambda W u + \epsilon$. Although the Manski model provides a comprehensive treatment of spatial spillovers, its practical utility is limited due to certain drawbacks. The model tends to become overspecified, leading to problems such as inefficient estimation and biased inference. Additionally, the computational complexity involved in estimating such a model further reduces its practical usefulness (Elhorst 2014). The Manski model is thus more theoretical than practical for empirical research. However, the model can be simplified and become more suitable for empirical research. These simplified models retain the theoretical underpinnings of the Manski framework but are more convenient and applicable in empirical research settings.

If W denotes the spatial matric, we may simplify the model in following ways:

If we set $\theta = 0$ we obtain so called Kelejian-Prucha model. As we can see below the Kelejian-Prucha model does not incorporate the spatial correlation among independent variables.

$$y = \rho Wy + X\beta + u$$

$$\text{u} = \lambda Wu + \epsilon$$
$$\epsilon \sim i.i.d.$$

We may also set $\lambda = 0$ and obtain Spatial Durbin Model (SDM). This model ommits the spatial autocorrelation term.

$$y = \rho Wy + X\beta + WX\theta + \epsilon$$
$$\epsilon \sim i.i.d.$$

Setting $\rho = 0$ we obtain Spatial Durbin Error Model (SDEM). This model ommits the spatial autocorrelation term.

$$y = X\beta + WX\theta + \epsilon$$

$$\text{u} = \lambda Wu + \epsilon$$
$$\epsilon \sim i.i.d.$$

If we set both $\rho = 0$ and $\lambda = 0$ we get Spatially Lagged X Model also known as SLX model. This model keeps the spatial correlation only in the independent variables.

$$y = X\beta + WX\theta + \epsilon$$
$$\epsilon \sim i.i.d.$$

Furthermore, if we set both $\theta = 0$ and $= 0$ we get Spatial Lag Model also known as Spatial Autoregressive Model (SAR). This model keeps the spatial correlation only in the dependent variable.

$$y = \rho W y + X\beta + \epsilon$$

$$\epsilon \sim i.i.d.$$

Finally, the last frequently used spatial model obtained by simplification of the Manski model is the Spatial Error Model denoted as SEM. This model can by obtained from the Manski model by setting both $\rho = 0$ and $\theta = 0$.

$$y = X\beta + u$$

$$\text{u} = \lambda W u + \epsilon$$
$$\epsilon \sim i.i.d.$$

In the field of spatial econometrics, estimating models can be challenging due to spatial interdependencies and heterogeneity. To address this challenge, advanced statistical techniques are required. Maximum likelihood estimation is a conventional method for estimating spatial econometric models, providing a robust approach to model parameters (Elhorst 2014). Bayesian methods have become also increasingly popular in spatial econometrics due to their efficient estimation approaches, despite computational challenges. These methods have been applied to spatial autoregressive models and limited dependent variable spatial autoregressive models, improving the estimation process. Geostatistics are also commonly used to estimate missing data and incorporate spatial effects in the estimation of spatial econometric models (Turizo *et al.* 2022). Ordinary Least Squares (OLS) is a frequently used technique for estimating econometric models. However, it may not fully account for spatial effects, which emphasises the importance of using specialised spatial estimation methods (Fischer & Nijkamp 2014).

5.1.2 Spatial Weight Matrix

Spatial weight matrices are a fundamental part of spatial econometrics. They capture the spatial relationships between observations in geographical space and a large number of spatial econometric methods are based on them. They are essential for understanding spatial autocorrelation, spatial heterogeneity and spatial spillovers. Tradiotanlly, the matrix is refrred to as W_{ij}. If the matrix is of size nxn, n is the number of observations, i the observation and j the neighbour of that observation.

$$W_{ij} = \begin{cases} 1, & \text{i is neighbour of j} \\ 0, & \text{otherwise} \end{cases}$$

One of the key properties of spatial weight matrices is symmetry, meaning that the relationship between two locations is the same in both directions (if i is a neighbour of j, j is a neighbour of i). Additionally, row standardization process is applied to ensure that each row of the matrix sums to one. This also means that each observation must have at least one neighbour. This process generally enables easier interpretation. Despite often being sparse, spatial weight matrices provide valuable insights into the spatial structure of data.

There are various types of spatial weight matrices. Among the most common types of spatial weight matrices are Queen's contiguity and Rook's contiguity. These matrices define neighbors based on their shared boundaries or vertices. However, Rook's contiguity is stricter in its criteria, considering only shared boundaries as indicators of neighbourhood. Another common type present inverse distance matrices, which assign weights inversely proportional to the distance between features, reflecting spatial relationships regardless of administrative boundaries. However, when investigating spatial patterns where proximity matters, K-nearest neighbors (KNN) matrices are often used. As they offer a flexible and adaptive approach. KNN matrices connect each feature to its nearest neighbors based on a specified threshold, capturing localized spatial relationships and accommodating spatial variations in the data.

5.2 Hedonic Regression

In economics, hedonic regression, also known as hedonic demand theory, is a revealed preference method for estimating the demand or value of a product or service. It involves breaking down the item under consideration into its individual characteristics and determining the contributing value of each. This approach is based on the premise that the composite product (the item being studied and valued) can be broken down into its constituent elements, each of which has value in the marketplace.

Each characteristic or group of characteristics is assigned an attribute vector, which may also take the form of a dummy or panel variable. Hedonic models are flexible enough to accommodate non-linear relationships, variable interactions, and other intricate valuation scenarios.These models are widely used in various fields, including property valuation or real estate economics.

Hedonic price regression uses statistical methods such as ordinary least squares or more advanced regression techniques such as quantile regression or spatial methods to measure the impact of various factors on the price of a product or property, such as a house. In this analytical framework, price serves as the dependent variable and is regressed against a set of independent variables that are thought to influence price dynamics. These variables are typically selected on the basis of economic principles, the expertise of the researcher or insights from consumer research.

5.3 Baseline Model

As we suggested in chapter 2 Literature Review, the factors that affect the price of an Airbnb listing can be divided into the following groups: listing attributes, host attributes, marketing attributes, and spatial attributes. The following section will introduce and highlight the variables used in the selected regression model, in order to enhance the understanding of their role and importance in the analysis of Airbnb pricing dynamics. This section will introduce the Ordinary Least Square (OLS) model, which will be further modified to fit different spatial models. However, for the purpose of this chapter, we will continue with OLS only. In this context, the dependent variable price per night serves as a key indicator of the monetary value associated with renting an Airbnb accommodation. Looking at the distribution of the price per night variable, we noticed that it was heavily skewed to the left (see Appendix 1). For this reason, we decided to implement a logarithmic interpretation of the price variable. This conclusion is also in line with the existing literature.

Among the independent variables, accommodation attributes play a crucial role. Variables such as entire apartment, private room, shared room and hotel room, represented as dummy variables, describe the type of accommodation available and provide insights into the preferences and choices of potential guests. These variables are implemented in the form of dummy variables. We omitted the variable entire apartment from the model in order to avoid dummy variable trap and thus the attribute of entire apartment is denoted by setting all dummy variables - private room, shared room and hotel room to zero. Capacity variable indicates the number of people that can be accommodated, and bedrooms, represents the availability of sleeping places. These attributes reflect the physical characteristics of the property and shape its perceived value and attractiveness to potential guests.

Host attributes such as acceptance rate, superhost status, responsiveness, and number of listings owned have a significant impact on Airbnb's pricing dynamics. A host's acceptance rate, which reflects their willingness to accommodate guests, is essential for establishing trust and reliability. A high acceptance rate implies quick approval of reservations, which positively influences guests' willingness to book and it may also potentially justify higher prices for the perceived reliability of the host. Similarly, the prestigious superhost status signifies exceptional hospitality and guest satisfaction. This leads to superhost managed listings having premium prices due to the assurance of superior service and quality provided. In addition, a host's responsiveness plays a critical role in facilitating smooth interactions between guest and host. This enhances the overall guest experience and potentially justifies higher prices. Furthermore, the number of listings owned by a host indicates the scale of their business and may significantly influence pricing dynamics. Hosts with multiple listings may benefit from economies of scale and operational efficiencies. This allows them to offer competitive prices while staying profitable. On the other hand, a larger portfolio of listings may also signal experience and expertise, which may result in higher prices. Generally, the approach to managing the number of host's listing differs accross literature. Authors often treat the variable as numerical, distinguish between having one and multiple listings or dividing the variable into multiple categories. We have decided to apply the last approach and distinguish between having 1 listing, 2-5 listing, 6-10 listings and more than 10 listings. We conducted this categorization using set of dummy variables.

In addition to listing and host attributes, marketing attributes also contribute to understanding price variation. Availability rate provides insight into the availability of the property over the next 30 days, reflecting supply dynamics and potential demand fluctuations. Number of reviews in the last twelve months provides a measure of the listing's popularity and guest satisfaction over the past twelve months, influencing guests' perceptions of value and desirability. Finally, review rate provides a standardised measure of guest feedback and satisfaction.

Several spatial attributes that were considered significant were not included in the dataset under consideration. The most important of these variables is the distance to the city centre. The choice of the old town square as the central reference point was made on the basis of its perceived attractiveness to tourists. Another spatial measure used is the distance to the nearest metro station. The coordinates of the metro stations were taken from the Prague metro Wikipedia page. All calculations of these variables were performed using the Haversine distance formula, which measures the angular distance between two points on a sphere. It should be noted that this method provides an approximation rather than an exact measure of distance. Finally, the last spatial attribute we decided to implement relates to the attractiveness of the location of the listing. We decided to use data from the Tripadvisor website, which publishes the list of popular neighbourhoods in Prague. Based on that was created a dummy variable indicating whether the listing is located in such an area or not.

The top 5 attractive neighbourhoods of Prague are: Malá Strana, Hradčany, Staré Město, Josefov and Krymská.

Finally applying the above, we obtained the following baseline model:

$$log(price_i) = \beta_0 + \beta_1 privateroom + \beta_2 sharedroom + \beta_3 hotelroom +$$

$$+\beta_4 accomodates + \beta_5 bedrooms + \beta_6 superhost + \beta_7 responsiveness +$$
$$+\beta_8 acceptance + \beta_9 multilistings + \beta_1 businesslistings +$$
$$+\beta_1 1 multibusinesslistings + \beta 12 availability 30 + \beta 13 reviewsLTM +$$
$$+\beta 14 reviewscore + \beta 15 centre + \beta 16 metro + \beta 17 neigbourhood + \epsilon$$

Chapter 6

Empirical Results

The main objective of this study is to explore the price determinants of Airbnb listings using spatial econometric techniques. The first step of our analysis is to confirm the presence of spatial autocorrelation. Subsequently, the proposed baseline model is first estimated without incorporating any spatial methodology. After the baseline estimation, different spatial econometric approaches are applied to treat the observed spatial autocorrelation, the presence of which was confirmed in the previous section. The results of the estimated models are compared and commented. Finally, we present a robustness check to confirm the validity of our results.

6.1 Spatial Correlation

The analysis starts with the initial stage of examining the dataset for the possible presence of spatial correlation.

In the area of spatial autocorrelation evaluation, researchers have developed a variety of methods and tests for this purpose. One of the most commonly used techniques is Moran's I statistic. This method is widely used because of its effectiveness in identifying overlapping patterns within spatial datasets (Liang and Wilhelmsson, 2011). The Moran's I statistic produces a numerical output ranging from -1 to 1. Higher positive values indicate a stronger positive correlation among neighboring locations, while values closer to zero suggest a weaker degree of interdependence between spatial units.

Moran's I statistic has several advantageous features. Moran's I statistic is known for its simplicity in computation and its ability to provide a clear and easily interpretable indication of spatial autocorrelation. This makes it particularly valuable for researchers investigating the interconnections between different geographic areas (Lieske et al., 2012). However, it is important to note that Moran's I statistic only detects spatial autocorrelation and does not provide guidance on how to address any observed correlations. However, its usefulness as a diagnostic tool for identifying spatial correlation remains valuable in the field of spatial analysis (Dube and Legros, 2013). Running the Moran test on our data, we have obtained the following results.

Table 6.1: Moran's I Statistics Test Results

Moran's I Statistics	**p-value**
0.298	0.000

We further demonstrate the results on a Moran's Plot:

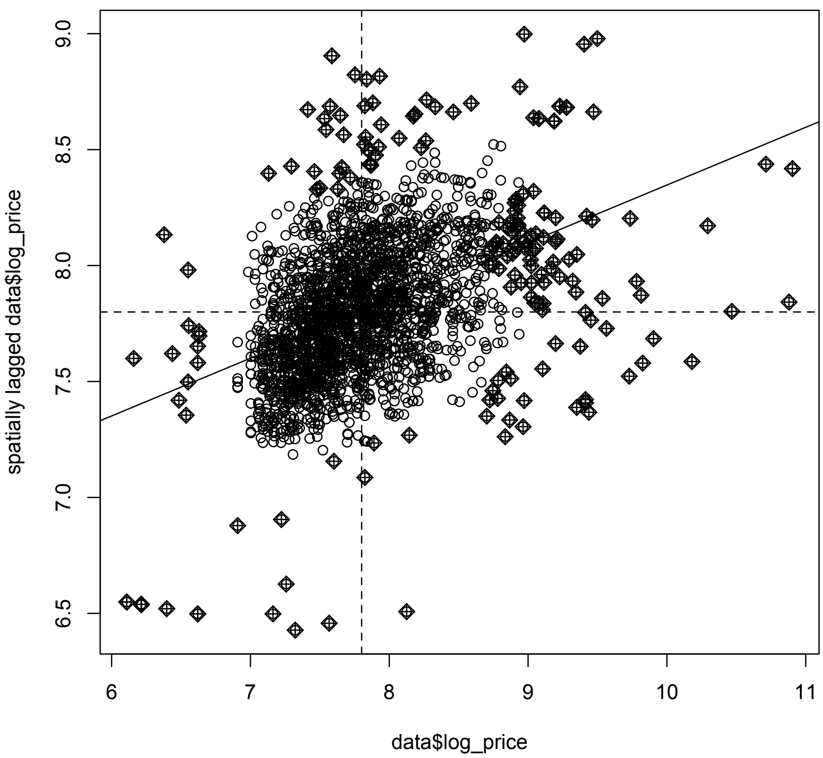

Figure 6.1: Moran's Plot

The results of the Moran's I statistic for Airbnb prices show significant spatial autocorrelation in the price distribution. The moderate Moran's I value of 0.298 indicates that areas with similar Airbnb prices tend to cluster together spatially. Moreover, the extremely low p-value (0.000) highlights the statistical significance of this spatial autocorrelation. This provides strong evidence against the null hypothesis of no spatial dependence. In summary, the spatial pattern of Airbnb prices shows strong clustering tendencies, where regions with similar price levels are spatially grouped together, indicating a spatially correlated distribution of Airbnb prices across the study area. Therefore, we may conclude that Airbnb prices are spatially dependent, which confirms our initial hypotheses.

6.2 Model Estimation

Given the evident presence of spatial autocorrelation in our observations, it's essential to use spatial models to ensure the efficiency of our estimates. There are several ways to incorporate spatial lags into our models, and we will explore different versions of spatial models to identify the most accurate one.

There are various methods for estimating spatial models, but two common approaches stand out. The first is to start with the most complicated model and then simplify it, while the second is to start with a basic OLS model and then gradually incorporate spatial terms. We have chosen the latter approach. Our decision stems from the recognition that the Manski model, also known as the General Nesting Model (GNS), which includes all variations of spatial lags, tends to be over-specified, potentially leading to problems of model interpretation and efficiency. We therefore intentionally choose not to estimate the Manski model in our analysis. We proceeded as follows: first we estimated the OLS model, then the Spatial Lag Model (SAR), followed by the SLX model, then the Spatial Error Model, and finally the Spatial Durbin Model (SDM), which is a combination of the SLX and SAR models.

In order to control for correlation between the explanatory variables, we decided to include only one of the bedrooms and accommodation variables. As these two variables presented a rather high correlation of 0.74. We tested them separately in a model and finally decided to proceed with bedrooms only, as it turned out to have a greater impact on the price. Furthermore, after dropping observations with missing values, we did not use the shared room variable as there were no observations with this attribute. Furthermore, after estimating the OLS model, we tested the model for multicolinearity and we can conclude that multicolinearity is not present in the model. Finally, we also tested the OLS model for the presence of heteroscedastic errors using the Breusch-Pagan test. The result of the test indicated the presence of heteroskedasticity. Therefore, we re-estimated the model using the robust standard errors.

Spatial weight matrix plays a crucial role in estimating the spatial models. There are different ways in which the matrix can be obtained. Since we are working with data based on longitude and latitude, we considered two matrix types - k nearest neighbours (knn) matrix and distance matrix. Since all listings need to have at least one neigbour appropriate treshold needs to be set for the distance matrix. However, when we applied the largest nearest treshold neighbour distance, we obtained treshold of 3km, which resulted in majority of listings having more than 2000 neighbours, which was not ideal scenario as we are working with 4000 active listings. Therefore, we decided to apply the knn approach only. We tested different number of neighbours and finally decided to continue with 10 nearest neighbours, as it yielded the best performance results. The performance of models based on 5 and 15 nearest neighbours can be found in appendix Table 2 and Table 3.

Applying the above, we have estimated the modified baseline model using the following model specifications: OLS, SLX, SAR, SEM, SDM, SDEM and SARAR. After estimating the models, we have decided to compare the models using the AIC Score and the LogLikelihood.

Table 6.2: Model AIC Score and LogLikelihood for KNN n=10

	Model	AIC Score	LogLikelihood
1	OLS	2325.401	−1145.700
2	SLX	2305.563	−1120.780
3	SAR	2139.610	−1051.805
4	SEM	2135.146	−1049.573
5	SDM	2140.457	−1037.229
6	SDEM	2141.045	−1037.522
6	SARAR	2134.205	−1048.100

Analysing the AIC scores and LogLikelihood values, it's clear that the OLS model has the lowest AIC score of 2325.401 and the highest LogLikelihood of -1145.7. These results indicate the poor performance of the OLS model, which is in line with our expectations. Conversely, the SARAR model emerges as the top performer, with the lowest AIC of 2141.918 and a higher LogLikelihood. Notably, the SEM model also stands out for its low AIC score among models with only one spatial term. We believe that the SARAR model shows the best perofrmance and has strong theoretical foundation - the prices of neighbouring listings are taken into account by the hosts. Therefore, we will further comment on the results of this model, which we will also briefly compare with OLS, SAR and SEM models' results. The results for these models are provided in table 6.4.

6.3 Model Estimation Results

The SARAR specification of our baseline model, commonly known as the Kelejian-Prucha model, proved to be the outstanding performer within the range of models subjected to our analysis. This model is based on the incorporation of combination of the spatial lag of the dependent variable and spatial lag of the error term.

If we define the SARAR model as:

$$y = \rho W y + X\beta + u$$

$$\text{u} = \lambda W u + \epsilon$$
$$\epsilon \sim i.i.d.$$

The estimated coefficient of the spatial lag of the dependent variable *rho* was estimated to be 0.218 with p-value of 0.00, indicating a strong statistical significance of including this term. The estimated coefficient of the spatial error term *lambda* is 0.265 and has an estimated p-value of 0.00. These estimation results suggest the importance of including these spatial terms in the equation.

While it is easy to interpret the coefficient of the OLS model, this is not the case when interpreting the coefficients of the spatial models. When interpreting the spatial models, the direct, indirect and total effects are used, where the total effects represent the sum of the direct and indirect effects. Since our interest is in estimating the determinant of Airbnb prices, we will focus on the direct effects, which are presented in the following tables. The direct effects explain the impact of the change in the independent variable on the dependent variable in the same location. Furthermore, we have used the logarithmic transformation of the price variable, so the coefficients provided indicate the expected percentage change in the logarithm of the dependent variable for each unit increase in the independent variable, holding all other variables constant.

Looking at the estimation results, we can see that the physicial attributes of a listing play a dominant role on the pricing dynamics. Both variables *bedrooms* and *privateroom* are statisticallly significant at 1% significance level. While the variable *bedrooms* affects the price positively (the more bedrooms, the higher the price) with the coefficient of 0.273 suggesting 31.3% increase in price with the addition of a single bedroom. Conversely, when the listing presents a private room, it is associated with a price decreases of 17.8% (coefficient of -0.164) according to our model compared to the case when the listing is an entire apartment. We can also see that, the variable indicating hotel room is postive and significant at 10% significance level. This indicates that the hotel rooms tend to be more expensive compared to the traditional Airbnb listings.

Furthermore, host attributes do not seem to play as significant a role as we expected. The only factor that seems to be statistically significant in terms of the price per night of the offer is if the host is a superhost. This attribute is associated with an 8.5% increase in price at the 1% level of significance. The other host attributes such as host responsiveness or acceptance rate do not seem to be significant. The same goes for the number of listings owned by the host. This figure is not statistically significant, but what is interesting is that there seems to be a turning point in the effect. According to our estimation, it seems that when the host owns 2-5 listings, the price is lower than when the host owns one or more than 5 listings.

Looking at the marketing attributes, the coefficients associated with the number of reviews in the last twelve months and the review score suggest different effects on price. However, it's worth considering that a high number of reviews could potentially stem from negative feedback, thereby influencing the direction of their effect on price. Therefore the coefficient of -0.003 of number of reviews in the last twelve months seems reasonable. One additional review thus seems to be connected with 0.3% decrease in price. On the other hand, the scaled review rate (multiplied by 100) has coefficient of 0.01. An increase of 0.01 in the number of reviews is associated with an average price increase of 1%. Furthermore, both variables are significant at the 1% level. Finally, the availability ratio also indicates higher price. As the availability ratio has reverse relationship to demand (the lower the ratio, the higher the demand), we would expect it to have negative effect on the price of a listing. However, we can see that the coefficient is positive and statistically significant at 1% level. One explanation for this phenomenon might be that properties with limited availability implement higher pricing strategies.

Finally, we comment on the coefficients of the spatial attributes. The coefficients for distance to the centre are in line with our expectations. The further away from the city centre, the lower the price. In addition, we would expect the listings located near the metro station to be associated with a higher price as it may be more comfortable to the potential guests. However, looking at the estimation results, we can see that our model suggests the opposite relationship. This may possibly stem from the fact, that the area surrounding the metro stations may be considered less safe. Finally, listings located in attractive neighbourhoods seem to be strongly associated with higher prices. All variables indicating spatial characteristics are statistically significant.

The reported coefficients of the OLS, SAR, SEM and SARAR models are very similar in both magnitude and direction. However, they differ in the coefficients of the spatial terms that differentiate them. Therefore, OLS estimation of price determinants may not lead to accurate results due to the omission of the spatial terms.

Table 6.3: Estimation Results of OLS, SAR, SEM and SARAR 1/2

	Dependent variable: log_price			
	OLS	*SAR*	*SEM*	*SARAR*
	(1)	(2)	(3)	(4)
Responsiveness	−0.0001	0.0002	−0.0004	−0.0001
	(0.001)	(0.001)	(0.001)	(0.001)
Acceptance	0.0003	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Private room	−0.183***	−0.155***	−0.165***	−0.164***
	(0.034)	(0.033)	(0.036)	(0.035)
Hotel room	0.111*	0.104*	0.113*	0.109*
	(0.059)	(0.056)	(0.060)	(0.058)
Bedrooms	0.285***	0.273***	0.277***	0.273***
	(0.008)	(0.008)	(0.008)	(0.008)
Reviews LTM	−0.003***	−0.003***	−0.003***	−0.003***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Review Score	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Min. Metro	0.0001***	0.00004**	0.0001***	0.00004**
	(0.00002)	(0.00001)	(0.00002)	(0.00001)
distCENTRE	−0.0001***	−0.00004***	−0.0001***	−0.00005***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Attractive Neigh.	0.171***	0.098***	0.123***	0.116***
	(0.019)	(0.019)	(0.023)	(0.022)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6.4: Estimation Results of OLS, SAR, SEM and SARAR 2/2

	Dependent variable: log_price			
	OLS	*SAR*	*SEM*	*SARAR*
	(1)	(2)	(3)	(4)
Availability 30	0.307***	0.287***	0.290***	0.291***
	(0.028)	(0.027)	(0.027)	(0.027)
Superhost	0.091***	0.080***	0.082***	0.082***
	(0.018)	(0.017)	(0.018)	(0.018)
Multi	−0.019	−0.019	−0.017	−0.018
	(0.023)	(0.022)	(0.022)	(0.022)
Business	0.013	0.023	0.033	0.029
	(0.027)	(0.026)	(0.026)	(0.026)
Multibusiness	0.018	0.016	0.021	0.018
	(0.024)	(0.023)	(0.025)	(0.024)
Constant	6.788***	3.743***	6.813***	3.743***
	(0.121)	(0.243)	(0.120)	(0.243)
Rho		0.387***		0.218***
Lambda			0.466***	0.265***
Note:				*p<0.1; **p<0.05; ***p<0.01

6.4 Robustness Check

To further confirm the validity of our results, we have decided to provide the following robustness checks. The model estimation was conducted using data from June 2023. However, we have decided to also inspect the period of September and December 2023 for spatial correlation and subsequently estimate the chosen SARAR model for these periods as well. Furthermore, we have compared the direction and the magnitude of the coefficients as well as the significance of the different variables across the periods. Finally, we may conclude, that spatial correlation was present in all 3 periods and that there were only small nuances in the coefficients of the variables obtained in the robustness check.

Chapter 7

Conclusion

Airbnb is becoming a powerful showcase in the sharing economy landscape. The peer-to-peer accommodation platform has had a significant impact as a key player of the hospitality sector. This platform has created a major paradigm shift in the travel practices as it has been offering individuals enriching opportunities to engage in localised experiences in new destinations. It has disrupted the traditional hospitality sector, affecting the hotel occupancy rates. On the other hand, Airbnb has also enabled property owners to increase their revenues through additional rental opportunities. However, the evolution of the platform appears to have moved away from its original ideals towards increased professionalisation, which has a negative impact on both the housing and rental markets. Given its significance and possible negative impact, Airbnb certainly deserves scholarly investigation to clarify operational mechanisms and inform potential regulatory frameworks, thereby facilitating a more comprehensive understanding of its diverse impacts.

This thesis has provided a comprehensive overview of the sharing economy and its key principles. Moreover, it summarized the existing literature on Airbnb. We have explained the origin and functioning of the platform, highlighting the importance of this short-term rental accommodation platform. The literature review also discussed the behaviour of both hosts and potential guests to better understand how the platform operates and where its popularity comes from. While we highlight the resilience of Airbnb during COVID-19, we also emphasise the impact it has had. We have also paid attention to the possible challenges that Airbnb poses to the traditional hotel industry. Finally, in the general part of the literature review, Airbnb has also been presented as a disruptor in the rental and housing markets and as a topic for proposing possible regulatory frameworks.

In the specific part of the literature review, we have presented the available literature on the topic of pricing dynamics of Airbnb and, in particular, the use of spatial methods in the study of this topic. Furthermore, we have also provided an overview of the local literature that has been produced on the topic of Airbnb in the Czech Republic highlighting the possible gap, that this study aims to fill.

While there are different approaches to spatial analysis, we have chosen to focus on the spatial autocorrelation between listings and its potential impact on Airbnb's pricing dynamics. We have shown that current research suggests that it is important to study the topic at the local level. Although there is existing literature on pricing dynamics in the Czech Republic, to our knowledge, this paper is the only one that considers possible spatial dependencies. Furthermore, compared to the existing literature, this paper contributes to the local literature by analysing data from the period after COVID-19.

The primary aim of this thesis was to test the following hypotheses:

1. Hypothesis: Airbnb prices are spatially dependent.
2. Hypothesis: There is a significant and negative relationship between the distance to the city centre and the price of an Airbnb listing.
3. Hypothesis: The relationship between the price of an Airbnb listing and the attractiveness of its location is significant and positive.
4. Hypothesis: The spatial distribution of Airbnb listings in Prague changed in response to COVID-19 pandmeic.

Firstly, we have provided a solid methodological overview. The thesis highlighted the importance of spatial econometrics and the role of spatial dependence and continued explaining different spatial models such as SAR, SEM or SLX but also more advanced methods including combinations of spatial components for example SDM (Spatial Durbin Model), SDEM (Spatial Durbin Error Model) or SARAR (Kelejian-Prucha model.

Secondly, we tested the data for spatial correlation. Using Moran's I statistics, we confirmed the first hypothesis that states that Airbnb prices in Prague are indeed spatially dependent. This result confirms our initial hypotheses and enables us to further continue with our analysis. Furthermore, by choosing a weight matrix based on 10 nearest neighbours and running a spatial regression, we estimated several models: SAR, SEM, SDM, SDEM, SARAR and traditional OLS. Comparing the performance of these models based on AIC and LogLikelihood, we selected the SARAR model for further investigation. The reason for choosing the SARAR model, also known as the Kelejian-Prucha model, was not only because of its performance, but also because of its solid theoretical foundation. Overall the results of our analysis are in line with the existing literature. The results of our analysis suggest that there is a negative and significant relationship between the distance to the city centre and the listing, which shows the validity of the second hypothesis. Finally, the attractiveness of the location of the listing has been shown to be associated with an increase in the price of the listing confirming the third hypothesis. Furthermore, the estimates of the model indicate the importance of review score and the total number of reviews to be significant determinants of Airbnb prices. The listing attributes regarding the size of the listing and respective category were also shown to be important price predictors.

Furthermore, by examining the data obtained, we illustrate how COVID-19 has changed the spatial distribution of Airbnb in Prague. We highlight a higher proportion of listings in the centre of Prague and fewer listings in the suburbs. This finding confirms Hypothesis 4. However, we have also shown that it was not only the spatial distribution that changed after COVID-19. We also show that the platform seems to have become more professionalized. For example, the category of shared rooms disappeared from the platform altogether. Overall, the proportion of offerings of entire apartments has increased and represents the vast majority of listings.

Finally, the results were validated estimating different periods and comaparing the obtained coefficients and their significance.

We believe that this study has contributed to existing research, especially the local one. There is certainly room for further investigation of the topic. Although we have implemented the main methods of spatial regression, there are other methods that could be used, such as the SARQR method, which combines quantile regression with the spatial autoregressive model.

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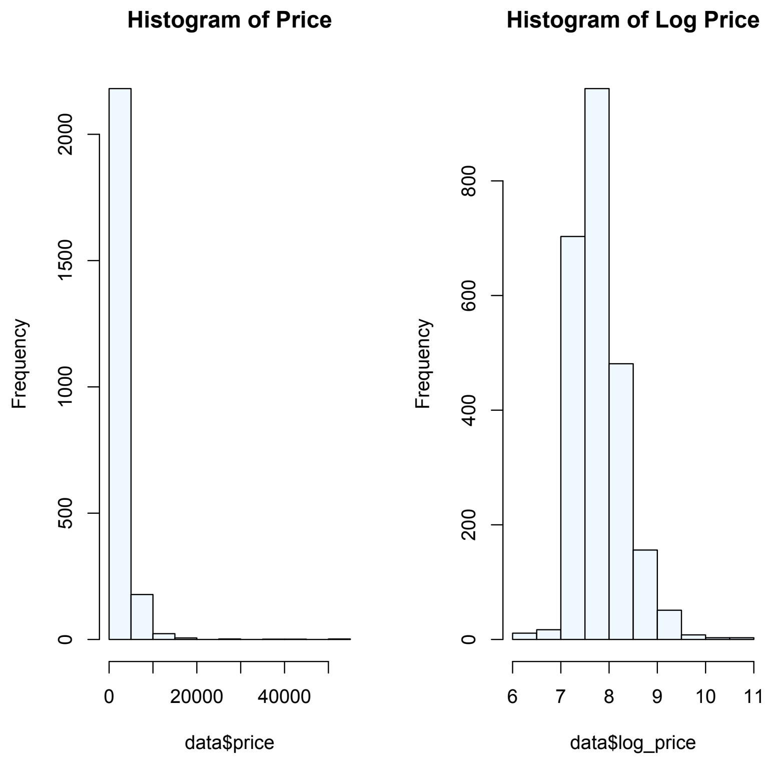

Figure 1: Histogram of Price vs Natural Log of Price

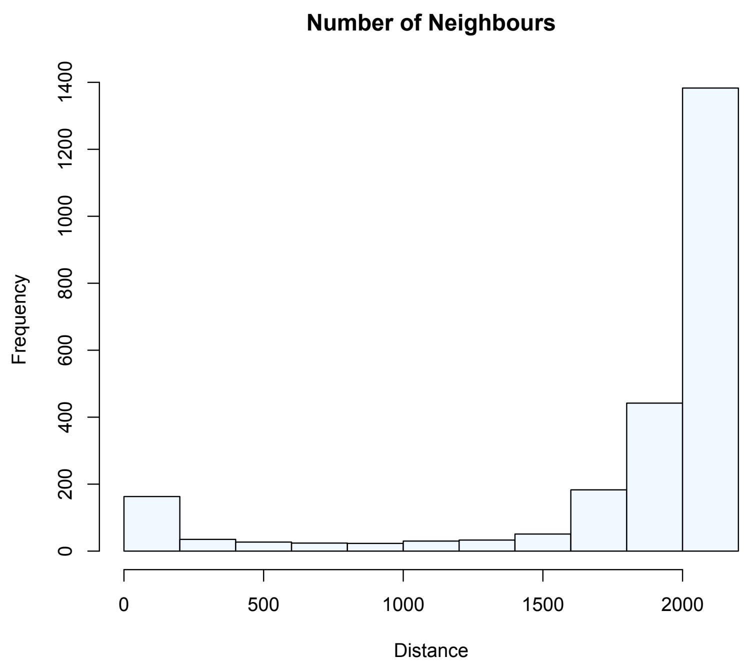

Figure 2: Distance Weight Matrix - Number of Neighbours

Table 1: Moran's I Test for Different KNN

n	Moran's Statistics	p-value
n=5	0.298	0.000
n=10	0.249	0.000
n=15	0.219	0.000

Table 2: Model AIC Score and LogLikelihood for KNN n=5

	Model	AIC Score	LogLikelihood
1	OLS	2325.401	−1145.7
2	SLX	2306.34	−1121.17
3	SAR	2144.398	−1054.199
4	SEM	2149.904	−1056.952
5	SDM	2147.333	−1040.667
6	SDEM	2146.05	−1040.025
6	SARAR	2141.918	−1051.959

Table 3: Model AIC Score and LogLikelihood for KNN n=15

	Model	AIC Score	LogLikelihood
1	OLS	2325.401	−1145.7
2	SLX	2304.725	−1120.362
3	SAR	2153.408	−1058.704
4	SEM	2148.160	−1056.08
5	SDM	2153.377	−1043.689
6	SDEM	2155.623	−1044.811
6	SARAR	2149.299	−1055.65