THE VALUE OF LOCATION FOR AIRBNB APARTMENTS:
A HEDONIC ANALYSIS OF AIRBNB LISTING PRICE IN BEIJING

A Thesis

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ABSTRACT

This research examines the impacts of locational variables on the price of Airbnb listings. With a web-scraped sample of more than 10000 Airbnb units in Beijing, this research adopts the hedonic pricing theory as the theoretical approach and presents spatial econometric models of Airbnb apartments to test the effects. The results show that proximity to city center and airport have significant positive impacts on price whereas proximity to high-speed railway stations has significant negative impact on price. Though OLS model shows that the effects of proximity to subway stations and tourist spots are positive, these effects are not significant when spatial autocorrelation are considered in the regression models. These findings are useful for Airbnb hosts to form reasonable pricing strategies for their listings and also for P2P lodging platforms to conduct more in-depth analysis.

BIOGRAPHICAL SKETCH

Xinyi Guo is currently in her 2nd year of study in the Regional Science Program at Cornell University. In August 2020, she will graduate with a Master of Science degree, with a concentration in Urban and Regional Economics. She received a bachelor’s degree in Geography and Resource Management and graduated with first-class honors from the Chinese University of Hong Kong. Her research interests are urban housing markets and applied econometrics.

To my parents

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
LM	Lagrange Multiplier
OLS	Ordinary Least Square
P2P	Peer to Peer
POI	Point of Interest
SEM	Spatial Error Model
SLM	Spatial Lag Model

CHAPTER 1

INTRODUCTION

Background

The lodging industry is considerably affected by the development of sharing economy which has emerged since the global economic recession in 2008. The peer-to-peer (P2P) accommodation platform is the intermediary that links hosts who offer residential properties and guests who rent space temporarily (Brochado, Troilo, & Shah, 2017). Airbnb, one of the most important platforms in the field of short-term rental services, enables individuals to offer their own space to accommodate potential guests for a fee. Since its launching in 2008, Airbnb has expanded to 7 million listings worldwide, serving more than 100,000 cities, and accumulating over 500 million guest arrivals in roughly a decade (Airbnb, 2020).

The P2P accommodations has drawn much attention recently and studies on this industry has occurred since 2014 and escalated after 2016 (Liang, Choi, & Joppe, 2018). Some researchers have studied the links and differences between hotels and P2P accommodations in terms of spatial patterns and price dependencies (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017; Önder, Weismayer, & Gunter, 2019); others have investigated the price-setting behaviors in this tourism sharing economy and examined specific attributes in determining prices of Airbnb units such as site, amenities, convenience, reputation and race (Ert, Fleischer, & Magen, 2016; Kakar, Voelz, Wu, & Franco, 2018; Lorde, Jacob, & Weekes, 2019). Although a number of academic studies have focused on the relationship between Airbnb location and market price, especially the distance to city center, subway stations, coastline, sightseeing and shopping area (Perez-Sanchez, Serrano-Estrada, Marti, & Mora-Garcia, 2018; Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Chica-Olmo, González-Morales, & Zafra-Gómez, 2020), none of them have evaluated the effects of the distance to railway stations and airports.

Goals and Objectives

The goal of this research is to identify the locational determinants of the price of Airbnb listings. Specifically, the objectives of this research are 1) to examine whether the price of an Airbnb listing is dependent on its location; 2) to quantify the effects of proximity to city center, subway stations, railway stations, airports and tourist attractions on Airbnb apartment prices. Although locational attributes have been studied in previous studies, the main contribution of this study is the inclusion of locational variables such as the distance to railway stations and airports which have been scarcely examined before. This study employs the spatial hedonic pricing model for analyzing the data set of Airbnb apartments in Beijing, which incorporates the locational attributes as explanatory variables.

Significance of the Research

The boom in the peer-to-peer accommodation industry has led to the necessity of modeling the price determinants which explain the sharing economy pricing strategies applicable to these apartments. Airbnb hosts need to realize the relevance of apartment location on market value as they make decisions. P2P accommodation platforms and third party pricing organizations also need to understand the effects of location on price as they conduct analysis and offer suggestions. This research provides the tools for estimating Airbnb listing price and comparing units which differ in locations, and contributes to the literature in the field of P2P lodging. The findings are expected to be useful for Airbnb hosts, P2P lodging platforms, and professional pricing organizations.

Theoretical Approach

This research adopts a hedonic price approach which surmises that goods and services can be considered as bundles of objectively measurable, utility-affecting attributes valued by consumers (Lorde, Jacob, & Weekes, 2019). Hedonic models are widely applied in the analysis of real estate and tourism, since both of tourism products and housings are heterogeneous which incorporate a range of characteristics that consumers value (Chen & Xie, 2017). Previous studies have undertaken hedonic analysis to examine the price determinants of Airbnb apartments, and several critical groups of factors have been identified: site attributes of the properties (Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018; Wang, & Nicolau, 2017), characteristics of the hosts (Chen & Xie, 2017), consumer reviews of the listings (Chica-Olmo, González-Morales, & Zafra-Gómez, 2020), and neighborhood conditions (Kakar, Voelz, Wu, & Franco, 2018). This approach is expected to provide a thorough scrutinization of the effects of locational characteristics on Airbnb pricing.

Overview of the Thesis

The subsequent sections are structured as follows. Section 2 “Literature Review” presents a review on the relevant literature on Airbnb and hedonic models. Section 3 “Methodology” describes data and methodology adopted in this study. Section 4 “Results” shows the empirical results. Section 5 “Discussion” provides a discussion on the effects of locational attributes on Airbnb price. Section 6 “Implications” summarizes the implications, and section 7 “Conclusion” highlights the significance of the results as well as suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

Scope of the Chapter

This chapter aims to offer a review of relevant literature according to different themes. It first presents an overview of locational characteristics of Airbnb listings. It then explains the theory of hedonic price and, with a review of the applications of hedonic price in the domain of Airbnb listings, followed by a description of the price determinants of Airbnb considered in the previous hedonic models. This chapter ends with the identification of research gap and the clarification of research questions and hypotheses that guide this study.

Locational characteristics of Airbnb listings and Their Impacts

Location is one of the most important factors for success in the lodging industry (Valentin & O'Neill, 2019). Scholars have revealed that location can significantly affect the performance of Airbnb apartments (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Chica-Olmo, González-Morales, & Zafra-Gómez, 2020; Yang & Mao, 2020). Previous academic articles have explored the location of Airbnb units, particularly the spatial patterns and locational determinants of Airbnb apartments and the impacts of location on Airbnb pricing.

Previous studies have examined the locational characteristics of Airbnb in the United States, Spain, and South Korea. Scholars discovered a center-peripheral patterns of the distribution of Airbnb units in cities and identified the supply of housing units, tourist spots, points of interest, and subway stations as factors that influence the location of Airbnb apartments (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017; Eugenio-Martin, Cazorla-Artiles, & González-Martel, 2019; Adamiak, Szyda, Dubownik, & García-Álvarez, 2019; Zhang & Chen, 2019; Ki & Lee, 2019). Zhang and Chen (2019) focused on the Airbnb units in three major cities in the United States, namely New York City, Los Angeles, and Chicago, and confirmed the center-peripheral pattern of the distribution of Airbnb listings in all three cities; in addition, they found that the spatial distribution of Airbnb is significantly influenced by the supply of housing units and points of interest. Similarly, in a study of the spatial distribution of Airbnb listings in Barcelona, researchers documented that Airbnb apartments tend to concentrate in the city center; they also suggested that the supply of Airbnb decreases with distance from the center, the beach and the presence of industrial activities, but increases with the proximity of tourist spots and land uses related to the leisure, hospitality and entertainment industries (Gutiérrez, García-Palomares, Romanillos, & Salas-Olmedo, 2017). In the case of the Canary Islands of Spain, Airbnb are located near the tourism attractions and established hotels in the city, but listings are mainly located in the outskirts of the main tourist areas in the sun and beach destinations (Eugenio-Martin, Cazorla-Artiles, & González-Martel, 2019). Based on the spatial analysis of the whole territory of Spain, Adamiak, Szyda, Dubownik, and García-Álvarez (2019) found that the location of Airbnb apartments is mainly determined by the supply of vacant or secondary housings, distribution of traditional tourism lodgings, costal destinations, and the demand level of international tourists. Ki and Lee (2019) explored the spatial distribution of Airbnb in Seoul, and revealed that Airbnb apartments are mainly located in residential areas; another finding of Ki and Lee was that Airbnb units are preferentially located near universities or subway stations and also in areas with high proportions of single-person houses.

In terms of the impacts of location, the distance to city center has been identified as a determinant of the price of Airbnb listings. Jiao and Bai (2020) analyzed 79,198 Airbnb listings across 40 major cities in the United States, and identified that the distance from city center is negatively associated with listing price. Chica-Olmo, González-Morales, and Zafra-Gómez (2020) employed a spatial econometric hedonic model to study the Airbnb apartments in Málaga, Spain, and confirmed the positive impact of accessibility to city center on price. However, Cai, Zhou, Ma, and Scott (2019) argued that the distance to city center only affects low-end Airbnb units but not medium- or high-end units, based on their research of Airbnb apartments in Hong Kong, indicating a heterogenous effect of the proximity to city center on Airbnb pricing.

Proximity to place of interest (POI), especially tourist spots, has been recognized as an important factor influencing Airbnb pricing. For instance, both of distance to the beach and distance to the nearest place of interest show significantly negative relationships with the price of Airbnb units in Málaga (Chica-Olmo, González-Morales, & Zafra-Gómez, 2020). Likewise, distance to shopping centers and distance to tourism attractions demonstrate significantly negative effects on both low- and medium-end Airbnb listings in Hong Kong (Cai, Zhou, Ma, & Scott, 2019). In a study of the Estonian capital city of Tallinn, the effect of the number of POIs within a radius of 650m on Airbnb pricing was found positive (Önder, Weismayer, & Gunter, 2018). The significantly negative impact of the distance to the convention center on Airbnb listing price in the central area of Metro Nashville was reported in the analysis of the business units in that area (Zhang, Chen, Han, & Yang, 2017). An exception to the aforementioned literature on this topic is that distance from the tourist spots positively affects Airbnb apartment prices in four Spanish Mediterranean Arc cities (Valencia, Alicante, Castellón de la Plana, & Elche, 2019), although Airbnb prices decrease as distance from the coastline increases, according to the research conducted by Perez-Sanchez, Serrano-Estrada, Marti, and Mora-Garcia (2018).

Transit service is another major determinant of Airbnb price. Deboosere, Kerrigan, Wachsmuth, and El-Geneidy (2019) analyzed the Airbnb transactions in New York City between August 2014 and September 2016 with a hedonic regression model. They claimed that controlling for accessibility, the price and revenue of Airbnb listings in proximity to subway stations, that is within 800 m of a subway stop, are actually less; however, Airbnb units with access to Midtown Manhattan via subway have a higher price and earn a higher revenue, which implies that it is the destinations that transits can take the guests to matters instead of the distance to transit itself. The study of Jiao and Bai (2020) indicated that Airbnb price is higher when the transit service frequency is high in the neighborhood, but it is lower if the distance between the listing and its nearest transit stop is less than three-quarters of a mile. Though they also noticed that the average listing price is likely to remain stable even if location and transit status change, since the coefficients of transit accessibility and frequency in their model is small.

All of these previous studies show that Airbnb listings are not located randomly. However, there is still a debate on the effects of different locational attributes on Airbnb pricing. Besides, previous research on the locations of Airbnb have analyzed the impacts of transits roughly, and no studies have explored the impacts of the proximity to airports or railway stations.

Hedonic Price Theory and Its Applications in Airbnb Listings

In the context of economics, the term "hedonics" refers to the utility derived from consuming goods and services. There are various statements on the first application of hedonic price theory. Bartik (1987) argued that Court made the formal contributions to this theory first in 1941, whereas others, for example, Colwell and Dilmore (1999), stated that Haas preceded Court and accomplished the first hedonic study.

Despite these contrasting arguments, it is widely acknowledged that Lancaster's (1966a, 1966b) theory of consumer behavior and Rosen's (1974) equilibrium model forms the theoretical foundation of the hedonic pricing approach. Lancaster's and Rosen's theories differ in some fundamental aspects. Lancastrian theory assumes that the relationship between the price of goods and their intrinsic attributes is linear, implicit prices are constant, and individuals consume some or all of the goods that belong to a group in combinations (Chin & Chau, 2003). Opposingly, Rosen's model presumes that the relationship is non-linear, implicit prices are not constant, and consumers choose and consume each good from a range of goods discretely to acquire preferred characteristics (Chin & Chau, 2003). Nonetheless, both approaches surmise that goods and services can be considered as bundles of objectively measurable, utility-affecting attributes valued by consumers, and an implicit market exists where each attribute can be priced to demonstrate the consumers' willingness to pay for that attribute (Lorde, Jacob, & Weekes, 2019; Chen & Xie, (2017).

Hedonic pricing models are widely applied in the analysis of real estate and tourism, as tourism products and housing are heterogeneous which incorporate a bundle of characteristics that provide consumers with value and satisfaction (Sinclair, Clewer, & Pack, 1990). Scholars have employed hedonic pricing methods to the examine the impacts of locational characteristics on real estate prices (Glaesener & Caruso, 2015). Specially, these techniques enable scholars to determine the impacts of various types of public transportation on housing prices (Armstrong & Rodríguez, 2006; Dubé, Thériault, & Rosiers, 2013; Wen, Gui, Tian, Xiao, & Fang, 2018).

With the rapid development of sharing economies in the past few years, scholars have begun to employ hedonic price model to analyze the determinants of Airbnb pricing (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018; Lorde, Jacob, & Weekes, 2019; Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Tang, Kim, & Wang, 2019; Chica-Olmo, González-Morales, & Zafra-Gómez, 2020). Research shows that the pricing model of Airbnb is not completely based on algorithm; instead it is the service providers who make the pricing decision, with algorithm tools only as references (Kwok & Xie, 2019).

Chen and Xie (2017) measured the effects of a wide array of utility-based attributes on consumers' valuation of Airbnb listings with a hedonic pricing model based on a dataset of 5,779 Airbnb listings in Austin, Texas in the United States. They found that functional characteristics of Airbnb units and behavioral attributes of hosts are significantly associated to the listing prices, whereas the influence of reputation of the listings on price is weak. Gibbs et al. (2018) applied a hedonic pricing model to 15,716 Airbnb listings in five large metropolitan areas in Canada. The results of this research are similar to the study of Chen and Xie (2017): the authors found that physical attributes, locational attributes, and host attributes are critical factors influencing the price of Airbnb apartments. An interesting finding of this research is the negative relationship between the number of reviews and the Airbnb price. The hedonic analysis conducted by Lord et al. (2019) is based on a dataset of 3026 Airbnb listings from 12 Caribbean countries, and the results of this analysis are in agreement with other studies that most of site, reputation, convenience, amenities attributes and country-level indicators positively affect prices of Airbnb listings in the Caribbean; however, a large number of ratings have negative effects on pricing, which is in accordance with the finding of Gibbs et al. (2018).

Deboosere et al. (2019) claimed that their study is the pioneer in including the neighborhood effects in the hedonic regression model to predict the average price per night and monthly revenue of Airbnb units. Their results demonstrated that both locational factors and neighborhood variation have great influence on the price and revenue of Airbnb listings, and more importantly, transit accessibility to jobs shows the largest impacts among the studied factors. Tang et al. (2019) adopted hedonic pricing model to analyze 51,125 Airbnb units in the top 10 tourism cities in the United States, and confirmed that three site factors (number of bedrooms, accommodation capacity, and overall review score) and four situational indicators (number of peer-to-peer lodging listings, population density, number of unemployed individuals, and median income in the same zip code area) have significant effects on Airbnb price, which are in accordance with Chen and Xie (2017), Wang and Nicolau (2017), and Gibbs et al. (2018). Chica-Olmo et al. (2020) employed a dataset of 2,967 Airbnb apartments in Málaga, Spain which corresponds to November 2017 with a spatial hedonic model, and revealed the significant impacts of several locational factors on Airbnb price. They found a significantly positive influence of distance to the city center, the beach, places of interest, and the walkability of the neighborhood on the prices. On the other hand, noise and certain ethnic groups in the neighborhood have negative impacts on the price, which has been verified in analysis on real estate before, but not in previous research on Airbnb listings. Their findings also demonstrate the spatial spillover effects from one listing to neighboring listings.

Generally, these studies have considered mainly five categories of explanatory variables in the hedonic models, namely listing characteristics, host attributes, listing reputation, rental policies, and listing location (Cai, Zhou, Ma, & Scott, 2019). The first category of Airbnb price determinants is site characteristics. The types of accommodation and room are critical determinants of Airbnb price, and the counts of bedrooms, bathrooms, real beds, and accommodated person capacity also have positive impacts on Airbnb price (Chen & Xie, 2017; Wang & Nicolau, 2017; Gibbs et al., 2018; Cai et al., 2019; Tang et al., 2019). Additionally, Airbnb amenities and services such as WiFi, gym, car parking and swimming pool have positive impacts on the price (Wang & Nicolau, 2017; Gibbs et al., 2018).

The second category of Airbnb price determinants comprises host attributes. Kakar, Voelz, Wu, and Franco (2018) examined the influence of online host attributes on the price of Airbnb units in San Francisco and revealed that Asian and Hispanic hosts charge 8%-10% lower prices on Airbnb listings compared with white counterparts. The impacts of host's gender, marital status, or sexual orientation are shown to be insignificant on Airbnb prices (Kakar et al.,2018). A price premium exists if the host's identity is verified, host's photos are provided, or host is qualified as "superhost" on Airbnb website (Ert, Fleischer, & Magen, 2016; Chen & Xie, 2017; Wang & Nicolau, 2017; Cai et al., 2019). According to Cai et al. (2019), if an Airbnb host owns more listings, he/she charges a lower room price, which contradicts the findings of Wang and Nicolau (2017).

The third category is associated with listing reputation. Previous research has identified that the number of reviews has a negative effect on listing price, and the possible explanation is that the number of reviews indicate the size of demand and the demand for inexpensive listings are greater (Chen & Xie, 2017; Wang & Nicolau, 2017; Gibbs et al., 2018; Cai et al., 2019). Empirical evidence also shows that the impact of the overall rating score on listing price is positive (Chen & Xie, 2017; Wang & Nicolau, 2017; Gibbs et al., 2018; Cai et al., 2019).

The fourth category is related to rental policies. Scholars found that instantly bookable policy, refundable cancellation policy, and smoking permission are associated with lower apartment rate positive (Chen & Xie, 2017; Wang & Nicolau, 2017; Gibbs et al., 2018; Cai et al., 2019). On the other hand, a rental policy which requires the verification of guests' identity is linked with a higher rental price (Wang & Nicolau, 2017).

The last category of Airbnb price determinants comprises listing location. As discussed above, locational factors, including distance to the city center, coastline, sightseeing and shopping area, have a positive impact on Airbnb pricing (Perez-Sanchez et al., 2018; Chica-Olmo, et al., 2020). Furthermore, the number of points of interest (POIs) in the neighborhood is also positively linked with the price of Airbnb unit (Önder et al., 2018). Proximity to subway stations, that is within 800 m of a subway stop, on the contrary, has a negative effect on the price of Airbnb listings, controlling for accessibility (Deboosere et al., 2019).

As manifested in previous research, the hedonic pricing model is an ideal model to analyze heterogenous commodities and services, like Airbnb, as it helps to decompose the total value into values of various intrinsic attributes. This model is able to identify a set of factors affecting prices and listing performance. These attributes are assumed to be implicitly priced in the model. Thus, it is appropriate to adopt the hedonic pricing approach in this research.

Research Gaps

The hedonic price model has been applied in multiple studies focused on Airbnb pricing. The role of several locational factors, including distance to the city center, coastline, sightseeing and shopping area, highway, subway station and number of points of interest in the neighborhood, have been examined in past research. Other control variables, including site characteristics, host attributes, listing reputation, and rental policies, have also been identified in the previous literature. However, a comprehensive analysis of the value of location on Airbnb price has not been conducted, and little attention has been paid to the effects of certain locational characteristics such as the proximity to airports and railway stations. Besides, previous studies mainly used the dataset of Airbnb listings in Western countries like Spain and the United States; their findings might not be applicable in other countries with different culture backgrounds. Thus, further research is needed to employ the hedonic pricing approach, evaluate the effects of location on the price of Airbnb listing, and produce a clear and comprehensive insight of these effects in the context of China. This study aims at filling these gaps.

Research Questions and Hypotheses

As shown above, it is important to investigate the relationships between locational characteristics and the value of Airbnb listings. Thus, the main research question of this study is "What are the effects of locational attributes on the price of Airbnb listings?". Based on the literature review, a few sub-questions and corresponding hypotheses are raised for analysis.

According to the central place theory developed by Alonso (1974) and Muth (1969), real estate rent is determined through the bid-rent gradient function as a function of location which decreases as distance from the city center increases. Scholars have adopted this theory to examine the value of centrality for lodging industry and confirmed that the effect of distance to the city center on hotel room rates is negative (Valentin & O'Neill, 2019). Therefore, it is anticipated that an Airbnb unit closer to city center would have a higher price compared with an Airbnb unit located further from the city center.

Hypothesis 1: The impact of distance to city center on Airbnb listing price is negative.

Although contradictory findings have been documented regarding the effects of proximity to tourism points of interest on Airbnb pricing (Valencia et al., 2019), plenty of evidence shows that Airbnb guests value proximity to tourist attractions (Cai et al., 2019; Chica-Olmo et al., 2020). Thus, it is anticipated that proximity to tourist spots might affect the price of Airbnb listings positively.

Hypothesis 2: The impact of proximity to tourist spots on Airbnb listing price is positive.

Airports and high-speed railway stations are the principal points of entry in Chinese cities. Permanent residents may perceive proximity to airports and railway stations negatively, however, Airbnb guests may regard this proximity as a benefit. Though few studies have analyzed the impacts of proximity to airports and high-speed railway stations on Airbnb units, research has been conducted in the lodging industry which revealed the positive relationship between proximity to airports and hotel room rates (Lee & Jang, 2011). Therefore, a positive relationship is expected to exist between proximity to airports and high-speed railway stations and the price of Airbnb listings.

Hypothesis 3: The impacts of proximity to airports and to high-speed railway stations on Airbnb listing price are positive.

Proximity to subway stations is considered as another important factor for guests in an urban context, however, its effects are controversial. Deboosere et al. (2019) claimed that Airbnb units located within 800 m of a subway station have lower prices compared with units located further away from the subway station in New York. On the contrary, Valentin and O'Neill (2019) suggested that the price premium for hotels located within 0.5 mile from a Chicago Transit Authority or Metro station is roughly 17% in Chicago. This study would hypothesize a negative relationship between distance to a subway station and Airbnb listing price in Beijing.

Hypothesis 4: The impact of distance to the nearest subway station on Airbnb listing price is negative.

CHAPTER 3

METHODOLOGY

Scope of the Chapter

This chapter aims to explain the methods that will be applied in this research in detail. It first describes the study area, and then introduces the methods of data collection and analysis, followed by the clarification of the list of variables included in the model at the end of the chapter.

Study Area

This study focused on the Airbnb market in Beijing. Beijing, the capital of the People's Republic of China, is the political headquarter and the cultural center of the country. It is the second largest city in China after Shanghai, with more than 21 million inhabitants in an area of 16410.54 km^2. Beijing is also a world-famous tourism destination. In 2019, Beijing attracted 320 million tourists (2019 Beijing Tourism Market, 2020, February 9), which indicates a huge demand for accommodation products.

Enclosed by ring roads, Beijing can be regarded as a monocentric city. The clear dominant center of Beijing is the Tiananmen Square with the surrounding traditional hub of cultural, administrative, and commercial activities (Zhang, Zhang, Lu, Cheng, & Zhang, 2011). Beijing is an important transportation center in China, with dozens of railway lines passing through the city. Beijing West railway station and Beijing South railway station are the major high-speed railway stations in the city. Beijing is also a major entry point of many international flights arriving in China. Beijing Capital International Airport has been the world's second busiest airport in terms of passenger traffic since 2010, and its annual passengers reached more than 100 million in 2018. In addition, Beijing has the longest subway system in terms of route length in operation in the world, which is also the world busiest subway system. At the end of 2019, Beijing had 23 subway lines (including 19 rapid transit lines, 2 airport rail links, one maglev line and one light rail line with 405 subway stations. The total length of subway lines in Beijing was 699 km. According to the 2019 Beijing Transport Annual Report, Beijing subways served 3.85 billion trips in 2018, and subway has become the most important public travel mode for inhabitants' daily needs (Beijing Transport Institute, 2019).

Being one of the largest city in the country and also in the world, Beijing has been the subject of many hedonic analysis focused on residential property prices (Geng, Bao, & Liang, 2015; Zhang, Cromley, & Hanink, 2016; Zhang, Zhang, Lu, Cheng, & Zhang, 2011; Li, Chen, & Zhao, 2019; Zhang, Zheng, Sun, & Dai, 2019). The distance to Tiananmen Square has been identified as an important predictor of housing price in Beijing (Zhang, Cromley, & Hanink, 2016; Dai, Bai, & Xu, 2016; Zhang, Meng, Wang, & Xu, 2014). The impacts of mass transit on housing price have also been widely examined. Geng, Bao, and Liang (2015) revealed that Beijing high-speed railway station affects property values within 11.74 km radius from the station. They found that property value and distance to the high-speed railway station is positively correlated within distance range of 0.475 km and 0.891 km but negatively correlated within distance range of 0.891 km to 11.704 km. Several studies have assessed the impacts of subway service on housing prices. Zhang, Meng, Wang and Xu (2014) argued that the range of impact of a metro rail transit extends to 1 mile, and on average, houses near the metro station enjoy a proximity premium of 248.31 yuan/m^2 for every 100 m closer to the station. Li, Yang, Qin and Chonabayashi (2016) identified a significantly positive impact of subway proximity on housing prices that a reduction in the distance to a subway station by 1 km increases the prices of properties within 3 km of the station by 15 percent, and by 3.4 percent for properties within 3-5 km. Dai, Bai and Xu (2016) focused on the subway transfer stations and suggested that the range of impact of a transfer station is greater, reaching 1200-1400 m, whereas that of a non-transfer station is up to 1000 m, and a reduction in the distance to a transfer station by 100 m increases the residential unit price by 96.5 yuan/m^2, which is much higher than that around a non-transfer station 23 yuan/m^2. Li, Chen and Zhao (2019) confirmed that properties with access to more than one metro line within 800 m buffer area have higher prices than those without access. Previous research also shows that distance to the nearest tourist destination has a negative relationship with the housing values (Geng, Bao, & Liang, 2015).

Methods of Data Collection

The data set of Airbnb listings in Beijing was collected from Inside Airbnb, an independent, non-commercial tool that complies information of listings on the Airbnb website. This site has been used as the source of data in many previous studies on Airbnb listings (Wang & Nicolau, 2017; Cai et al., 2019). This data set provides information about each Airbnb unit, including the latitude-longitude coordinates, the number of bedrooms, bathrooms, and beds, the maximum number of accommodates, if the host is a superhost, the review scores of the listing, etc. The raw dataset of Airbnb apartments in Beijing consists of 38,814 listings as of 24 November, 2019. Although each Airbnb unit has its geographical coordinates, not all of these coordinates are the actual location of the unit: due to the spatial obfuscation methods Airbnb applied to its apartments, the coordinates could be a random point within a 200 m radius of the exact location of the listing (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019). Thus, this study filtered the listings that don't have exact locations. In addition, to ensure that the analysis only contains active Airbnb units, the model excluded apartments that required minimum stay nights longer than 5 days or has a price higher than 3,000 RMB per night, and also removed listings that contain missing values in their attributes. Furthermore, this research focused on the Airbnb listings in the urban area, so listings located outside of the sixth ring road of Beijing were omitted. The resulting population for this model is 10,904. The spatial distribution of sample listings is presented in Figure 1.

The 5A scenic areas which represents world class touristic attractiveness in Beijing are adopted as tourism POIs in this research, namely Place Museum, Temple of Heaven, Summer Palace, Badaling-Mutianyu Great Wall, Ming Tombs, Prince Kung's Mansion, and Beijing Olympic Park. Using the web-crawling Python program, geographical locations of Beijing tourism POIs, airports, rail stations, and subway stations were obtained from Baidu coordinates collection system. The direct distance between an Airbnb listing and the aforementioned sites was calculated with Python program based on their geographical coordinates.

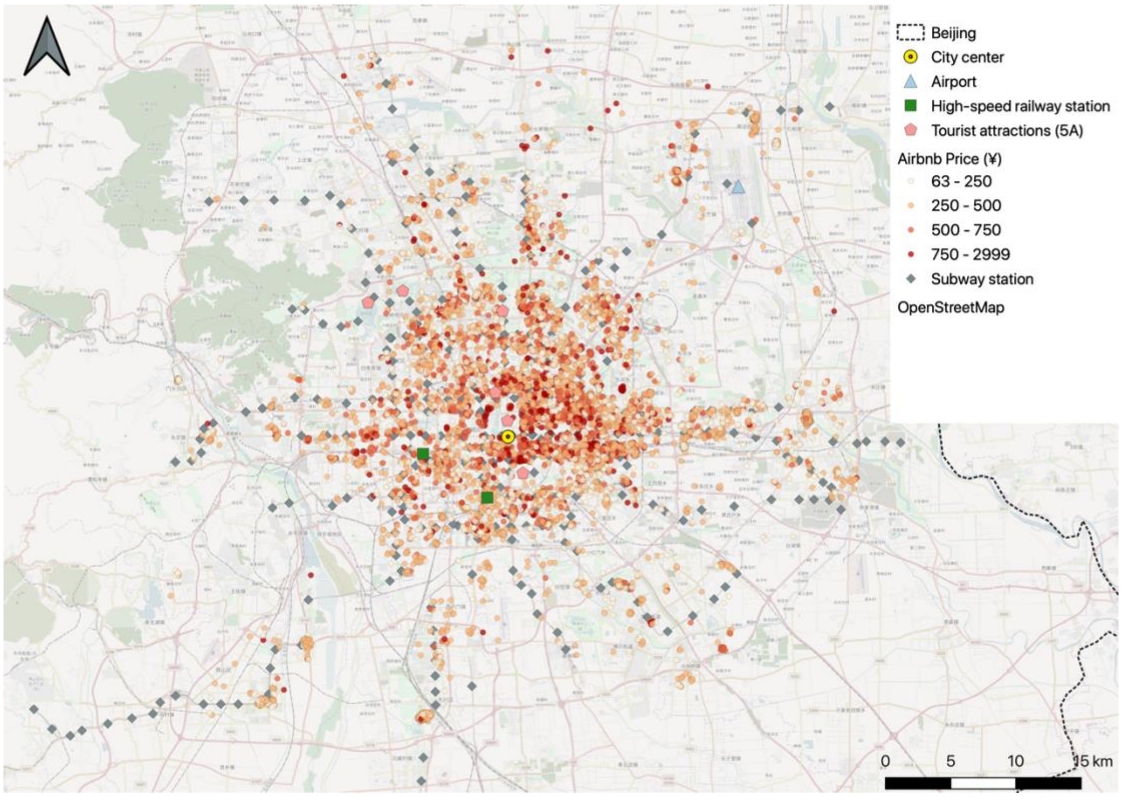

Figure 1 Spatial distribution of Airbnb units in Beijing

Methods of Analysis

This study employed the hedonic price approach to examine the influence of locational factors on individual Airbnb listing's price. The assumptions of this approach is that a bundle of attributes can represent the good and service under consideration. In terms of Airbnb, a renter pays the price to purchase both the access to the space and the attributes of that space. The hedonic model of Airbnb listing price used in this research can be specified as a function with semi-logarithmic form of a bundles of characteristics, which is recommended by Rosen (1974) and widely applied in research (Andersson, Shyr, & Fu, 2010).

This research incorporated spatial autocorrelation into regression analysis. The conventional OLS method assumes uncorrelated error terms and independent observations (LeSage & Pace, 2009), however, geographical data like Airbnb listing price are inclined to be spatially dependent, which means that the price of a unit observed in one location depends on the prices observed at the neighboring locations. Adjacent listings share almost the same physical and socio-economic environment, and such adjacent effects should be capitalized into their prices (Tang, Kim, & Wang, 2019). This leads to the presence of spatial autocorrelation in the model, which makes the OLS estimation less efficient (LeSage & Pace, 2009; Anselin, 2010). Thus, spatial hedonic pricing models were adopted to examine Airbnb listing price in this research.

In the first step, OLS model was used to estimate the coefficient of each independent variable.

$$y = X\beta + \varepsilon$$

Where y is the natural logarithm of the price of Airbnb unit; X is a vector of explanatory variables; β is the associated parameter; ε is a vector of error items. The OLS estimates β by minimizing the sum of squared prediction errors. Step two was to examine Moran's I statistic which is commonly used for testing spatial autocorrelation. The third step was to check the statistical significance (*p*-value) of simple Lagrange Multiplier (LM) for a missing spatially lagged dependent variable

(LM-Lag) and the simple LM for error dependence (LM-Error). Robust LM diagnostics should be performed to find the better spatial regression model if both of LM-Lag and LM-Error are statistically significant. Step four was to run the spatial error model or the spatial lag model based on the p-values in the previous step.

Spatial lag model assumes spatial autocorrelation in the dependent variable that the price of Airbnb unit in place i is influenced by the explanatory variables in both place i and j in this study.

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

Where W is the spatial weight matrix representing the neighborhood's spatial structure between unit i and j; Wy is the spatially lagged dependent variable, which is incorporated in this model as an additional predictor of spatial effects; ρ represents the spatial coefficient, which equals 0 if there is no spatial dependence.

Spatial error model assumes spatial autocorrelation in the residuals that the error terms across different spatial units are correlated.

$$y = X\beta + u$$

$$u = \lambda W u + \varepsilon$$

Where u is a spatially weighted vector of error terms using the weight matrix W; Wu represents the spatial disturbances; λ is the spatial error coefficient, which equals 0 if there is no spatial dependence; ε is the normal vector of independent and identically distributed error terms. To properly explain the spatial simultaneity, the maximum likelihood was applied in the spatial regression model to estimate the coefficients.

This research adopted semi-log form with the natural log of the dependent variable, namely the price of Airbnb listings, in the regression models, which reduces heteroscedastic and narrows the range of the dependent variable. In the case of OLS and SEM, the coefficients β represent the semi-elasticities that are the percentage influence of the explanatory variables on the dependent variable. For continuous variables, the expression is 100*β; for dummy variables, the expression is 100*[exp(β)-1]. Since the equations are in the semi-log form, the marginal implicit value of any explanatory variable *m* for each listing *i*, is calculated as the product of the estimated coefficient and the price of the listing: $\pi_{im} = \beta_m \times p_i$.

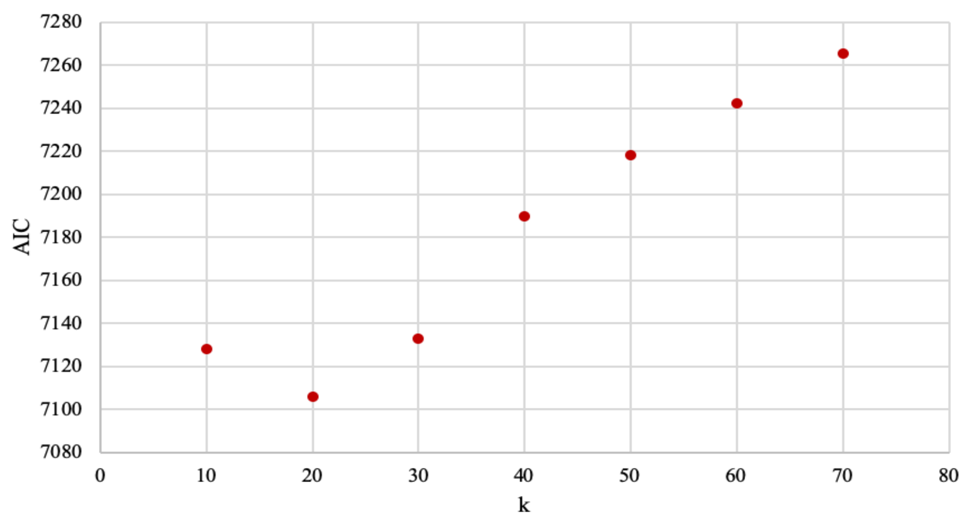

Figure 2 AIC of spatial error models with different numbers of neighboring units

K-nearest spatial weight matrix was employed in this study, and k is number of apartments closest to apartment i. Specially $w_{ij} = 1$ if apartment j is located within the k-nearest neighbors of apartment i and $w_{ij} = 0$ otherwise. To determine the appropriate number of neighboring units to listing i, different numbers were used to estimate the performance of the spatial error model with the explanatory variables, from 10 to 70. The Akaike information criterion (AIC) results are shown in Figure 2, which implies that 20 neighbors has the lowest AIC value. Thus, 20 is chosen as the number of neighboring units for the spatial autocorrelation models in this research.

Model Variables

Regression models included one dependent variable and 26 independent variables, and the description of these variables are presented in Table 1. The dependent variable is the average price per night, which is the same variable used in other studies (Deboosere, et al., 2019; Chica-Olmo, et al., 2020). The independent variables can be divided into several categories: structural characteristics, amenities, rules, host/guest, and location. Variables in terms of structural characteristics, amenities, rules and host/guest were chosen based on previous literature (Chen & Xie, 2017; Gibbs et al., 2018; Lorde et al., 2019; Deboosere et al., 2019; Tang, et al., 2019; Chica-Olmo, et al., 2020), however, less commonly studied variables related to listing location were added in this research which helps to examine the research hypotheses.

Structural variables included are the number of bathroom, the number of bedrooms, and the maximum number of people that can be accommodated, a dummy variable that equals 1 if the type listing is villa, a dummy variable that equals 1 if the type listing is townhouse, a dummy variable that equals 1 if the type listing is bungalow, a dummy variable that equals 1 if the listing is an entire home, and a dummy variable that equals 1 if the listing is a private room.

Amenities variables included are a dummy variable equal to 1 if air conditioning is available, a dummy variable equal to 1 if an elevator is available to enter the listing, a dummy variable equal to 1 if a television is available, a dummy variable equal to 1 if a pool is available, and a dummy variable equal to 1 if a garden or backyard is available.

Host/guest variables included are the number of comments left by the guests, the review score rating of the listing that scales 0-100 where 100 is the maximum rating, the number of listings that the host has, and a dummy variable equal to 1 if the host has superhost status.

Rules variables included are a dummy variable equal to 1 if the listing is smoking allowed, a dummy variable equal to 1 if the listing is friendly/kid friendly, a dummy variable equal to 1 if the cancellation policy is flexible, and a dummy variable equal to 1 if the cancellation policy is moderate.

Locational variables included are the distance to Beijing city center in km, the distance to the nearest subway station in km, a dummy variable equal to 1 if a listing is located within 1.5 km of a high-speed railway station, a dummy variable equal to 1 if a listing is located within 5 km of an airport, and a dummy variable equal to 1 if a listing is located within 0.8 km of 5A tourist attraction. The studied scope of the impacts of high-speed railway transit and airport are specified as 1.5 km and 5 km respectively, since Airbnb units located within these buffer areas tend to be described as "close to high-speed railway station/airport" in Beijing. The studied scope of the impacts of tourist attractions are specified as 800 m since 800 m is a walkable distance (approximately 10-min walk).

Table 1 Variable names, definitions and expected effects

Variable Name	Definition	Expected Effects
Structural variables		
bathrooms	Number of bathrooms	Positive (+)
bedrooms	Number of bedrooms	Positive (+)
accommodates	Maximum numbers of people to be accommodated	Positive (+)
villa	Value of 1 if the type of listing is villa, 0 otherwise	Positive (+)
townhouse	Value of 1 if the type of listing is townhouse, 0 otherwise	Positive (+)
bungalow	Value of 1 if the type of listing is bungalow, 0 otherwise	Positive (+)
entire_home	Value of 1 if the type of listing is 'entire home', 0 otherwise	Positive (+)
private_room	Value of 1 if the type of listing is 'private room', 0 otherwise	Positive (+)
Amenities variables		
ac	Value of 1 if air conditioning is available, 0 otherwise	Positive (+)
elevator	Value of 1 if an elevator is available, 0 otherwise	Positive (+)
tv	Value of 1 if a TV is available, 0 otherwise	Positive (+)
pool	Value of 1 if a pool is available, 0 otherwise	Positive (+)
garden	Value of 1 if a garden or backyard is available, 0 otherwise	Positive (+)
Host/guest variables		
number_of_reviews	Number of comments left by guests	Negative (-)
review_scores_rating	Guest ratings. Scale 0-100, where 100 is the maximum rating	Positive (+)
host_listings_count	Number of units that the host has	Positive (+)
host_is_superhost	Value of 1 if host is a superhost, 0 otherwise	Positive (+)

Table 1 (continued)

Variable Name	Definition	Expected Effects
Rules variables		
smoking_allowed	Value of 1 if the listing is smoking allowed, 0 otherwise	Negative (-)
family_friendly	Value of 1 if the listing is family/kid friendly, 0 otherwise	Positive (+)
flexible	Value of 1 if the cancellation policy is flexible, 0 otherwise	Positive (+)
moderate	Value of 1 if the cancellation policy is moderate, 0 otherwise	Positive (+)
Locational variables		
center_distance	Distance to the city center (km)	Negative (-)
min_subway_distance	Distance to the nearest subway station (km)	Negative (-)
railway	Value of 1 if the listing is located within 1.5 km of a high-speed railway station	Positive (+)
airport	Value of 1 if the listing is located within 5 km of an airport, 0 otherwise	Positive (+)
poi	Value of 1 if the listing is located within 0.8 km of a 5A tourist attraction, 0 otherwise	Positive (+)

CHAPTER 4

RESULTS

Scope of the Chapter

This chapter aims at offering a presentation of the hedonic model results. It first summarizes the descriptive statistics of the dependent and independent variables in the models. Then, it shows and compares the results of four regression models. At the end of this chapter, marginal implicit expenditures are calculated to provide a qualitative look at the estimation results.

Descriptive Statistics

Table 2 and Table 3 provide summaries of both continuous and discrete independent variables in this research. The mean of the average price per night was 430.1 RMB in this study. However, statistics shows that the distribution of listing price is significantly left skewed. With the logarithm transformation, the distribution of natural log of listing price is more symmetric, as shown in the figure below.

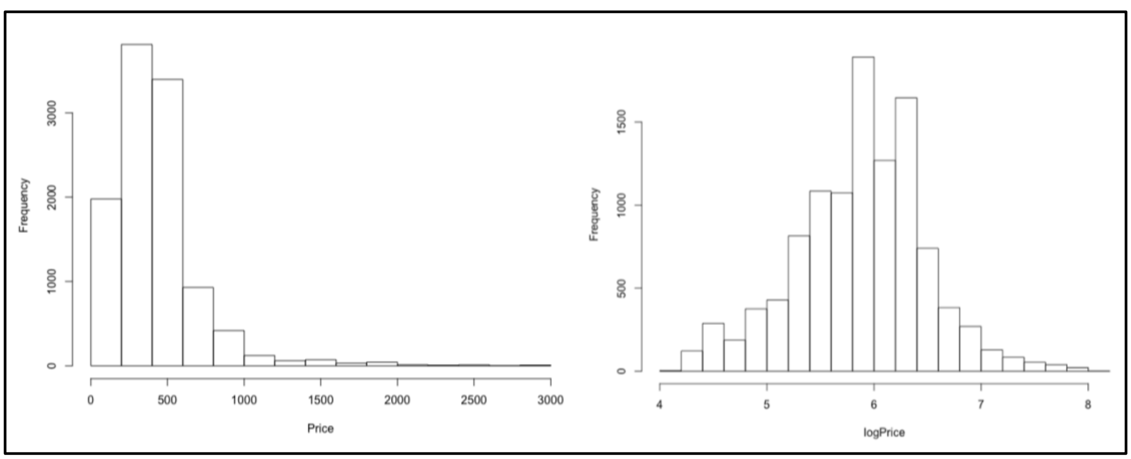

Figure 3 Histograms of Airbnb listing price in original and logarithm forms

Table 2 Summary statistics of continuous variables

Variable	*Mean*	*SD*	*Min*	*Max*
price	430.10	293.22	63	2999
bathrooms	1.17	0.40	0	9
bedrooms	1.37	0.71	0	10
accommodates	3.19	1.93	1	16
number_of_reviews	12.03	19.54	1	266
review_scores_rating	94.64	10.68	20	100
host_listings_count	12.06	24.19	0	258
center_distance	10.69	6.95	0.55	36.43
min_subway_distance	0.75	0.69	0.00	9.89

Table 3 Summary statistics of discrete variables

Variable	*Percentage %*	*Type*
host_is_superhost	42.98	Dummy
villa	0.48	Dummy
townhouse	0.39	Dummy
bungalow	1.27	Dummy
ac	97.66	Dummy
elevator	73.54	Dummy
tv	77.71	Dummy
pool	3.41	Dummy
garden	5.27	Dummy
smoking_allowed	32.99	Dummy
family_friendly	8.18	Dummy
entire_home	66.54	Categorical
private_room	28.53	Categorical
flexible	41.87	Categorical
moderate	37.70	Categorical
railway	1.83	Dummy
airport	2.27	Dummy
poi	0.38	Dummy

The mean of the distance to city center was 10.69 km with a standard deviation of 6.95 km, and the mean of the distance to the nearest subway stations was 0.75 km with a standard deviation of 0.69 km. 1.83% of the listings were located within 1.5 km of a high-speed railway station; 2.27% of the listings were located within 5 km of the airport; 0.38% of the listings were located within 0.8 km of a 5A tourist attraction.

Model Results

As described in the previous chapter, hedonic price models are constructed for Airbnb listings in Beijing to evaluate the value of location on listing price. Table 4 displays the results of the OLS, SAR, and SEM models. Model 1 is the OLS estimation of the hedonic model excluding the locational variables, and model 2 the OLS estimation of the hedonic model including the locational variables. The likelihood ratio test (chisq = 1617.3, p = 0.000) rejected the null hypothesis that model 1 is the better model and suggests that including locational variables enhances the goodness-of-fit of OLS model significantly. The score of Moran's I for model 2 was 75.897 which is significant, rejecting the null hypothesis of no spatial autocorrelation of the residuals. Since both LM-error and LM-lag tests were statistically significant, the presence of spatial autocorrelation is confirmed in the disturbances. Thus, robust LM-error and robust LM-lag were further tested. Given that the RLM-lag statistic was insignificant and RLM-error statistic was significant, the spatial error model should be retained for spatial regression analysis.

As shown in the table, all the dependent variables were significant at 99%, except for Pool which was significant at 95% in the model 2. The adjusted R-squared of the model 2 was 0.654, indicating that approximately 35% of the variation in the Airbnb market price is not explained by the model specifications. The inclusion of locational variables increased the adjusted R-squared by approximately 5% (from 0.599 to 0.654), showing that including locational variables enhance the explanatory capacity of the hedonic model.

Among the structural indicators, an extra bathroom is associated with a rise of 8.28% in price, an extra bedroom is associated with a rise of 15.97% in price, and an additional number of people that can be accommodated is associated with 4.9% increase in price. Entire-home listings charge a 237.1% higher price than shared-room listings, and private-room listings charge a 104.48% higher price than shared-room listings. Villa listings are priced 17.46% higher than normal listings, townhouse listings are priced 30.67% higher than normal listings, and bungalow listings are priced 34.23% higher than normal listings.

Among the amenity indicators, having air conditioning is associated with a rise of 11.44% in price, having an elevator to the unit is associated with a rise of 5.16% in price, having a television is associated with a rise of 15.81% in price, having a pool is associated with a rise of 4.82% in price, and having a garden or backyard is associated with a rise of 9.3% in price.

Among the host/guest indicators, the superhost status enables hosts to charge a premium about 3.7%, and an extra listing owned by the host is associated with 0.13% increase in price. One additional review is associated with a 0.2% decrease in price, but one additional point in review scores rating is associated with a price increase of 0.13%.

Among the rules indicators, being smoking allowed is associated with a price decrease of 2.8%, being family/kid friendly is associated with a price increase of 5.22%. Listings with a flexible cancellation policy have a 2.7% lower price and listings with a moderate cancellation policy have a 3.1% lower price than those with a strict cancellation policy.

Distance to city center and the nearest subway stations, proximity to the high-speed railway station, airport and 5A tourist attractions are strong predictors of the listing price. Listings charge a higher price per night (2.25%) for each 1 km closer to the city center (Tiananmen Square), and they also charge a higher price (2.23%) for each 1 km closer to the nearest subway station. Listings in proximity to the high-speed railway stations charge less per night (21.9%), however listings in proximity to the airport and 5A tourist attractions charge more per night (25.16% and 21.73% respectively).

The results of both the SAR and SEM spatial regression models are also shown in Table 4. The coefficient on the spatially correlated errors shown in this table suggested a strongly significant effect ($\lambda = 0.6575$, $p < 0.001$). Comparing the performance indicators of four regression models, the Log likelihood of SEM was the greatest, the Sigma-square and AIC of SEM were the smallest, which implies that SEM improved the model fit and performance the most.

The spatial error model suggests that listings charge a higher price per night (2.35%) for each 1 km closer to the city center, listings in proximity to the high-speed railway stations charge less per night (13.6%), and listings in proximity to the airport charge more per night (15.4%). It also shows that the relationship between the distance to the nearest subway station and listing price is negative, and the relationship between proximity to tourist attraction and listing price is positive. However, unlike the OLS model, the spatial error model indicates that the relationships between neither of these two relationships are significant.

The magnitude of the effects of variables Accommodates, Townhouse, Elevator, number_of_reviews, host_is_superhost, center_distance becomes stronger in the SEM model. On the contrary, the magnitude of the effects of other variables become weaker. All the variables in the SEM model have the same sign as those in the OLS model, except for Smoking_allowed which has a coefficient of 0. The results of SEM also show that the coefficient of Smoking_allowed is not significant, the coefficients of Pool and Flexible are significant at 90% confidence level, and the coefficients of Villa, Family_friendly, and Railway are significant at 95% confidence level. The coefficients of other variables are significant at 99% confidence level.

Table 4 Model results

	Model 1 - OLS	*Model 2 - OLS*	*Model 3 - SLM*	*Model 4 - SEM*
Constant	4.1016***	4.2797***	2.3374***	4.3083***
Structure				
Bathrooms	0.0175*	0.0828***	0.0798***	0.0660***
Bedrooms	0.1371***	0.1597***	0.1656***	0.1593***
Accommodates	0.0704***	0.0490***	0.0433***	0.0500***
Entire_home	1.1675***	1.2152***	1.1910***	1.1957***
Private_room	0.6886***	0.7153***	0.7021***	0.6904***
Villa	0.0802	0.1609***	0.1516***	0.1538**
Townhouse	0.1361**	0.2675***	0.2807***	0.2695***
Bungalow	0.3749***	0.2944***	0.2421***	0.1397***
Amenities				
AC	0.1730***	0.1083***	0.1262***	0.0990***
Elevator	0.0054	0.0503***	0.0390***	0.0785***
TV	0.1476***	0.1486***	0.1237***	0.1317***
Pool	0.0481**	0.0471**	0.0453**	0.0322*
Garden	0.0974***	0.0889***	0.0794***	0.0659***
Host/guest				
number_of_reviews	-0.0013***	-0.0020***	-0.0021***	-0.0023***
review_scores_rating	0.0009***	0.0013***	0.0013***	0.0013***
host_listings_count	0.0014***	0.0013***	0.0011***	0.0012***
host_is_superhost	0.0440***	0.0363***	0.0380***	0.0481***
Rules				
Smoking_allowed	-0.0491***	-0.0277***	-0.0257***	0.0000
Family_friendly	0.0735***	0.0509***	0.0486***	0.0251**
Flexible	-0.0497***	-0.0266***	-0.0250***	-0.0177*
Moderate	-0.0130	-0.0306***	-0.0245***	-0.0237***
Location				
Center_distance		-0.0225***	-0.0153***	-0.0235***
Min_subway_distance		-0.0223***	-0.0174***	-0.0058
Railway		-0.1981***	-0.1378***	-0.1273**
Airport		0.2244***	0.0873***	0.1433***
Poi		0.1966***	0.1836***	0.0993
W_log(price)			0.3322***	
λ				0.6575***

Table 4 (Continued)

	Model 1 - OLS	*Model 2 - OLS*	*Model 3 - SLM*	*Model 4 - SEM*
Spatial autocorrelation tests				
Moran's I	126.8***	75.897***		
LM-error	15714***	5500.9***		
LM-lag	2954.4***	833.07***		
RLM-error	12778***	4668.3***		
RLM-lag	18.4***	0.5133		
Fit model				
Adjusted R-squared	0.599	0.654		
AIC	10162.2	8554.9	7870.2	7105.7
Log likelihood	-5058.1	-4249.5	-3906.1	-3523.9
Sigma Squared	0.1484	0.1280	0.1193	0.1089

Notes: *90% significance level, **95% significance level, ***99% significance level.

Marginal Implicit Prices

Table 5 presents the estimated marginal implicit prices of each housing attribute in concrete monetized terms in terms of Chinese Yuan (RMB). The OLS results shows that on average marginal implicit prices of about: – ¥9.68 per kilometer further away from the city center; – ¥9.59 per kilometer further away from the city center; – ¥85.2 if the listing is located with 1.5 km of a high-speed railway station; ¥96.51 if the the listing is located with 5 km of a high-speed railway station; and ¥84.56 if the the listing is located with 0.8 km of a 5A level tourist attractions. The SEM results shows that on average marginal implicit prices of about: – ¥10.11 per kilometer further away from the city center; – ¥2.49 per kilometer further away from the city center; – ¥54.75 if the listing is located with 1.5 km of a high-speed railway station; ¥61.63 if the the listing is located with 5 km of a high-speed railway station; and ¥42.71 if the the listing is located with 0.8 km of a 5A level tourist attractions.

Table 5 Monetary value of estimated marginal implicit prices (RMB)

	OLS (Model 2)		*SEM (Model 4)*	
	Mean	Standard Deviation	Mean	Standard Deviation
Structure				
Bathrooms	35.61	24.28	28.39	19.35
Bedrooms	68.69	46.83	68.51	46.71
Accommodates	21.07	14.37	21.50	14.66
Entire_home	522.66	356.32	514.27	350.60
Private_room	307.65	209.74	296.94	202.44
Villa	69.20	47.18	66.15	45.10
Townhouse	115.05	78.44	115.05	78.44
Bungalow	126.62	86.32	60.08	40.96
Amenities				
AC	46.58	31.76	42.58	29.03
Elevator	21.63	14.75	33.76	23.02
TV	63.91	43.57	56.64	38.62
Pool	20.26	13.81	13.85	9.44
Garden	38.24	26.07	28.34	19.32
Host/guest				
number_of_reviews	-0.86	0.59	-0.99	0.67
review_scores_rating	0.56	0.38	0.56	0.38
host_listings_count	0.56	0.38	0.52	0.35
host_is_superhost	15.61	10.64	20.69	14.10
Rules				
Smoking_allowed	-11.91	8.12	0	0
Family_friendly	21.89	14.92	10.80	7.36
Flexible	-11.44	7.80	-7.61	5.19
Moderate	-13.16	8.97	-10.19	6.95
Location				
Center_distance	-9.68	6.60	-10.11	6.89
Min_subway_distance	-9.59	6.54	-2.49	1.70
Railway	-85.20	58.09	-54.75	37.33
Airport	96.51	65.80	61.63	42.02
Poi	84.56	57.65	42.71	29.12

Table 6 summarizes the statistics of monetized values of each attribute broken out by quintile of distance from the Beijing city center, namely Tiananmen Square. The statistics shows that except for variable Smoking_allowed, the absolute values of the estimated marginal implicit prices of all variables drop sharply from the first quintile to the second quintile, remain relatively stable from the second quintile to the third quintile, and gradually decrease from the third quintile to the fifth quintile. These results reveal that almost all housing attributes have higher prices (in terms of absolute value) close to the city center and have lower prices away from the city center.

Table 6 Monetary value of estimated marginal implicit prices of the spatial error model by distance to city center in quintile (RMB)

	Quintile = 1	**Quintile = 2**	**Quintile = 3**	**Quintile = 4**	**Quintile = 5**
Structure					
Bathrooms	37.21	28.39	27.65	25.92	22.75
Bedrooms	89.82	68.53	66.74	62.57	54.91
Accommodates	28.19	21.51	20.95	19.64	17.24
Entire_home	674.20	514.35	500.94	469.62	412.18
Private_room	389.29	296.99	289.25	271.16	238.00
Villa	86.72	66.16	64.44	60.41	53.02
Townhouse	150.83	115.07	112.07	105.06	92.21
Bungalow	78.77	60.09	58.53	54.87	48.16
Amenities					
AC	55.82	42.59	41.48	38.88	34.13
Elevator	44.26	33.77	32.89	30.83	27.06
TV	74.26	56.65	55.18	51.73	45.40
Pool	18.16	13.85	13.49	12.65	11.10
Garden	37.16	28.35	27.61	25.88	22.72

Table 6 (Continued)

	Quintile = 1	**Quintile = 2**	**Quintile = 3**	**Quintile = 4**	**Quintile = 5**
Host/guest					
number_of_reviews	-1.30	-0.99	-0.96	-0.90	-0.79
review_scores_rating	0.73	0.56	0.54	0.51	0.45
host_listings_count	0.68	0.52	0.50	0.47	0.41
host_is_superhost	27.12	20.69	20.15	18.89	16.58
Rules					
Smoking_allowed	0	0	0	0	0
Family_friendly	14.15	10.80	10.52	9.86	8.65
Flexible	-9.98	-7.61	-7.42	-6.95	-6.10
Moderate	-13.36	-10.19	-9.93	-9.31	-8.17
Location					
Center_distance	-13.25	-10.11	-9.85	-9.23	-8.10
Min_subway_distance	-3.27	-2.49	-2.43	-2.28	-2.00
Railway	-71.78	-54.76	-53.33	-50.00	-43.88
Airport	80.80	61.64	60.04	56.28	49.40
Poi	55.99	42.72	41.60	39.00	34.23

CHAPTER 5

DISCUSSION

The main goal of this study is to estimate the value of location on Airbnb pricing, and regression models demonstrate that locational attributes have considerable effects on the price of Airbnb listings. To test the impact of centrality within an urban context, the distance to city center (namely Tiananmen Square) is included in model 2 to 4, and the coefficients of this variable are significantly negative at the 99% confidence level in all three models, which support Hypothesis 1. OLS model indicates that Airbnb price decreases from the city center at an average rate of 2.25% per kilometer, and SEM model indicates that Airbnb price decreases at an average rate of 2.35% per kilometer. This finding matched with Chica-Olmo, Gonzalez-Morales, and Zafra-Gomez (2020).

Table 7 Expected and empirical results of locational variables

Variable Name	Expected effect	Empirical effect, OLS	Empirical effect, SAR	Empirical effect, SEM
center_distance	Negative (-)	Negative (-)	Negative (-)	Negative (-)
min_subway_distance	Negative (-)	Negative (-)	Negative (-)	Negative (-)
railway	Positive (+)	Negative (-)	Negative (-)	Negative (-)
airport	Positive (+)	Positive (+)	Positive (+)	Positive (+)
poi	Positive (+)	Positive (+)	Positive (+)	Positive (+)

The variables Poi and Min-subway_distance are shown significant in the OLS model but insignificant in the SEM model. The impacts of proximity to tourist attractions and subway stations on Airbnb pricing might be incorporated as spatial effects through the error items in SEM, which could lead to the insignificant coefficients of Poi and Min_subway_distance. Despite being insignificant, the impact of proximity to 5A tourist attractions is positive and the impact of the distance to the nearest subway station is negative in the SEM model. Therefore, the OLS results support Hypothesis 2 and 4, but SEM results don't support these two hypotheses.

The variable Railway and Airport are shown significant in both the OLS model and the SEM model. An Airbnb unit located within five kilometers of the airport carries a premium of 25.2% and 15.4%, suggested by OLS and SEM respectively. However, the sign of the coefficient associated with proximity to high-speed railway stations is not the same as that in Hypothesis 3. Results shows that located with 1.5 km from a high-speed railway station reduces Airbnb prices by 21.9% and 13.6%, suggested by OLS and SEM respectively. Thus, Hypothesis 3 can only be supported partially, as results indicate that Airbnb price is positively influenced by proximity to an airport but negatively influenced by the high-speed railway stations.

The findings of this research generally matched with those of previous studies on housing values in Beijing. The price premium of proximity to the city center exists in both Airbnb market and housing market (Sun, Zheng, & Wang, 2015; Li, Chen, & Zhao, 2019). Similarly, proximity to subway stations is an important variable that positively affects housing price and housing rent (Cui, Gu, Shen, & Feng, 2018; Li, Chen, & Zhao, 2019). Researchers have also identified a negative relationship between distance to tourist attractions and housing price; however, this relationship is statistically insignificant (Geng, Bao, & Liang, 2015). Previous research suggested that housing price declines with a decline in distance from high-speed railway stations within 0.475 to 0.891 km, which is similar the finding of this research. The impacts of distance from airport on housing value or housing rent have not been examined before. From the comparison, it can be seen that both Airbnb users and local dwellers value the proximity to city center and subway stations; local dwellers might not value the proximity to tourist attraction as Airbnb users; both local residents and Airbnb users dislike the proximity to high-speed railway stations, probably due to the fact that high-speed railway stations can bring congestion, noise and other nuisance to the neighborhood.

CHAPTER 6

IMPLICATIONS

Results of this study provide important implications in the theoretical perspective. First, this research supplements the knowledge of the hedonic theory and hedonic pricing model in a relatively new field – Airbnb listings, and confirms the applicability of these theories in the tourism and lodging sectors. Second, this is the first study to include the proximity to railway stations and airport as locational factors in the hedonic price model, which have been scarcely evaluated in the context of P2P accommodations. This study is anticipated to advance the understanding of value of locational variables on the pricing of Airbnb units based on the theoretical foundations. Third, this research further proves the importance of incorporating spatial autocorrelation in the regression analysis in the context of Airbnb industry, as spatial regression models have not been extensively applied in the research of Airbnb units.

Moreover, this study also provides practical implications for Airbnb operators. Hedonic regression models help hosts understand the pricing of each attributes of the listings, which enables them to choose the pricing strategy that fits the market based on listing characteristics in all aspects of structure, amenities, host/guest, rules and location. These models are also useful for P2P accommodation platforms to decide their operation and marketing tactics. The models suggest that structure and amenities variables have significantly positive effects on the pricing of Airbnb units, so hosts should adopt these characteristics as the fundamental determinants of their pricing strategy. As for the factors belonged to the category host/guest, the superhost status, the review scores, and the count of listings managed by the host are positively associated with the Airbnb price, which implies that the more professionally Airbnb listings are managed, the higher price are charged. For individual hosts, it is important for them to improve and maintain a good guest review profile, and hosts can gradually raise the price as their review score rises. In terms of rules attributes, being family/kid friendly has a positive impact since placing restrictions (no kid or family) reduce demand. Other rules variables have negative impacts, which suggest that allowing smoking or adopting flexible/moderate cancellation policies will decrease the listing price.

Regarding the influence of locational variables on Airbnb pricing, a greater distance to city center (Tiananmen Square) implies a lower price. This finding implies that tourists are also concerned about accessibility to the city center as permanent dwellers, which matches the Central Place Theory. Practitioners in the P2P accommodation industry shouldn’t overlook the difference in price of listings located closer to or further from the city center. Proximity to airports implies a higher price; on the contrast, proximity to high-speed railway station implies a lower price. Hosts should be aware of the huge difference in the way tourists valuing proximity to different transportation nodes.

This research provides evidence that spatial autocorrelation has important influence in the pricing models of Airbnb listings. Thus, P2P lodging platforms and professional pricing organizations should include spatial autocorrelation analysis in their pricing mechanism to make better pricing and operating recommendations for the Airbnb hosts. These organizations should also consider the significant variables in this study as effective predictors of listing prices in their models.

CHAPTER 7

CONCLUSION

The results of this research demonstrate that locational attributes can have significant impacts on the average price per night of Airbnb listings in Beijing. All models show that proximity to airport has a significant positive impact, and distance to the city center and proximity to high-speed railway stations have significant negative impacts on price; OLS model shows that accessibility to the subway stations and proximity to tourist attractions have significant positive impacts on price. Among these attributes, the effects of proximity to airport and railway stations have not been examined in previous studies. The opposite effects of proximity to airport and railway stations are probably due to that Airbnb guests value the accessibility to airport but dislike the negative influence of being around high-speed railway stations (crowdedness, noise, safety issues, etc.).

Additionally, this research has verified the existence of spatial autocorrelation in Airbnb prices. Such effects could be the results of sharing the public infrastructure, amenities, and local residents by adjacent Airbnb units. The explanatory capacity of the hedonic pricing model has been increased by taking spatial autocorrelation into account. Understanding the influence of locational characteristics and spatial autocorrelation could enable Airbnb hosts and P2P accommodation platforms to adopt right strategies and helps pricing organizations develop better pricing models.

Although the results of this study offer both theoretical and practical implications, some limitations of this study need to be acknowledged. First, due to the limitation of the Airbnb dataset, some relevant variables that could affect the listing price have not been considered in the models, for example, the age and area of the dwelling or whether the housing has views. Second, this study doesn't test the effects of demographic, socio-economic or environmental factors since these data are not available at the neighborhood or street level in Beijing. Future research could incorporate these variables into consideration, such as income, education level, population density, and pollution. Third, instead of the direct distance between a listing and studied location calculated based on their geographical coordinates, travel time and route distance might be better indicators of accessibility to certain locations. Further studies could adopt these indicators to estimate the effects of location on listing price more accurately.

Another limitation is the possible selection bias in the dataset of Airbnb units. Owners of the housing units might have chosen deliberately to put their units in the short-term rental market like Airbnb instead of conventional long-term rental market if their units possess the attributes such as close to tourist attractions or airports, which are the very locational attributes examined in this research. Though such selection bias doesn't hamper the validity of the results of this research, future studies could explore how does location influence hosts' decision on whether put their listings on Airbnb or other rental markets. An additional weakness is that the price of Airbnb units might not reflect the true market of value since non-professional Airbnb hosts are not wellequipped with resources and knowledge to set rational prices. Instead, individual hosts' price setting decisions are probably influenced by their own intuition. Further studies on the guests' evaluation or opinions of the listing prices should be performed to complement current understanding of Airbnb price, which will be beneficial for both researchers and practitioners.

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