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Estimating spatial effects on peer-to-peer accommodation prices: Towards an innovative hedonic model approach

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ABSTRACT

Peer-to-peer (P2P) accommodations have scaled up in the wave of enthusiasm for innovative internet technologies, which challenge the conventional hotel industry. Pricing is a significant lever a P2P lodging host needs to improve profitability. The purpose of the present study was to examine pricing determinants of P2P accommodations considering their spatial dependency. Two spatial hedonic pricing models (HPM) were examined for site attributes and situation attributes, respectively. Three site indicators (count of bedrooms, accommodated person capacity, and overall review score) and four situation indicators (counts of P2P lodging listings, population density, unemployment counts, median income) contributed to the price of a P2P lodging list. The application of spatial HPM provides marketers and hosts on P2P lodging platforms more in-depth analysis and effective strategies for pricing.

1. Introduction

Sharing economy as a shift from ownership of goods to temporary rental of them has emerged since 2009 due to the global economic recession, cumulative trust of world wide web, and development of online payment system (Dillahunt and Malone, 2015). The lodging industry is probably one of the sectors most impacted by the meteoric development of sharing economy (Johnson and Neuhofer, 2017). A peer-to-peer (P2P) accommodation platform serves as an intermediary that connects hosts who rent residential properties and guests who need temporary spaces (Brochado et al., 2017). The P2P lodging contributes to the revitalization of homestays, bed & breakfasts (B&B), and multicultural hospitality networks (e.g., https://usservas.org/) (Lampinen and Cheshire, 2016). Airbnb has risen as a dominant player of P2P accommodation platforms (Zervas et al., 2015). Although still at its nascent stage, Airbnb was valued up to $31 billion in 2017, which was worth more than that of any top international chain hotel companies (e.g., Hilton and Hyatt) except Marriott (valuation of $39 billion) (Tharakan and Reuters, 2017). Therefore, many hospitality scholars have agreed that Airbnb is a gateway for them to embark on the research of P2P accommodations (e.g., Chen and Xie, 2017; Guttentag and Smith, 2017).

Research on P2P accommodations has emerged since 2014 and soared after 2016 (Liang et al., 2018). The studies on this topic published on the leading hospitality and tourism journals are summarized in Table 1. These studies are classified into four themes, including marketing, competition/comparison with hotels, strategic management, and pricing/valuation. The marketing theme is composed of customer behavior, advertising effect, customer segmentation, and publicity (e.g., Johnson and Neuhofer, 2017; Liang et al., 2018). The second theme is to examine the difference between hotels and P2P accommodations on performance indicators, grading schemes, and spatial patterns (e.g., Gibbs et al., 2018a, b; Guttentag and Smith, 2017). The theme of strategic management focuses on business models and tactics for hosts (e.g., Chung, 2017; Fang et al., 2016). Compared with the aforementioned three themes, the studies relevant to the category of pricing/valuation are sporadic (i.e., only four out of 39 papers collected in Table 1).

Pricing has been well recognized to be a chief step toward revenue maximization in the lodging industry (Hung et al., 2010). Although many studies have investigated pricing strategies in conventional hotels (e.g., Becerra et al., 2013; Chen and Rothschild, 2010), those findings are ungeneralizable to the P2P lodging setting from two perspectives; site (internal factors) and situation (external factors) (Wang and Nicolau, 2017). First, many site/internal indicators of pricing (e.g., star ratings/review scores, chain company) in hotels are unfit to P2P

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Table 1
Summary of P2P Lodging Studies (2014–2018)*.

Research Themes	Sample Studies	Data Collection	Methodology	Summary of topics
Marketing – customer behavior	Brochado et al. (2017); Camilleri and Neuhofer (2017); Ert et al. (2016); Johnson and Neuhofer (2017); Liang et al. (2018); Mao and Lyu (2017); Mody et al., 2017; Pappas (2017); Poon and Huang (2017); Priporas et al., 2017; Tussyadiah, 2016; Tussyadiah and Pesonen (2016); Wiles and Crawford (2017); Wu et al., 2017a; Wu et al., 2017b	Range of 24 – 2461 P2P lodging listings; Range of 248-800 consumers for surveys	content analysis; conceptual study; descriptive analysis; fsQCA; regression analysis; Structural Equation Modeling; t-test and ANOVA	To establish theoretical frameworks relevant to value co-creation, repurchase intention, benefits, appeal, trustworthiness, service quality, experience economy in Airbnb; to create a conceptual map of post-Airbnb experience reflected in reviews; to test whether the presence of photos impacts guests' decision making on Airbnb
Marketing – advertising effect	Liu and Mattila (2017)	139 consumers	Experimental design	To examine advertising effect of Airbnb
Marketing – customer segmentation	Boxall et al., 2018; Guttentag et al., 2018 Olya et al., 2018	Range of 21 to 923 consumers for surveys	fsQCA; Levitas's (2013) Utopia Method; mixed method	To conduct motivation-based segmentation for Airbnb; to test the segment of disabled tourists
Marketing – publicity	Chen (2016); Hajibaba et al., 2017	995 residents; 302 news articles	CFA; descriptive analysis	To examine attributes of hosts on P2P lodging platforms during disaster strikes; to create a conceptual map of sharing economy media discourse
Competition/ comparison with hotels	Birinci et al., 2018; Gibbs et al., 2018a,b; Guttentag and Smith (2017); Gutierrez et al., 2017; Hajibaba and Dolnicar (2017); Martin-Fuentes et al., 2018; Williams and Horodnic (2017)	Range of 14,500 -39,837 Airbnb listings; range of 670 -33,000 hotels; range of 391 -15,883 consumers for surveys	ANOVA; chi-square tests; regression analysis; spatial analysis; Support Vector Machine classification technique	To examine the differences of key performance indicators, grading scheme, spatial patterns between hotels and Airbnb listings
Strategic management	Chung (2017); Fang et al. (2016); Gunter (2018); Kannisto (2017); Karlsson and Dolnicar (2016); Karlsson et al. (2017)	Range of 657 – 40,060 Airbnb listings; range of 192 – 244 Airbnb hosts for surveys	Descriptive analysis; fixed-effect linear model; regression analysis; social network analysis; spatial analysis; thematic analysis	To test the influential factors of employment on Airbnb; to examine attributes of a booking request which influences hosts' inclination to grant/refuse permission; to test the online friendship between local residents and tourists; to explore business models for sharing economy; to examine criteria of obtaining Airbnb superhost status.
Pricing/valuation	Chen and Xie (2017); Wang and Nicolau (2017); Xie and Kwok (2017); Xie and Mao (2017)	Range of 197-180,533 Airbnb listings	Regression analysis	To investigate the determinants of listing performance
Summative	Heo (2016)	N/A	Descriptive analysis	To discuss the current trends, its impacts on tourism industry and research prospects of sharing economy

* The articles were collected from seven leading journals in hospitality and tourism management, including International Journal of Hospitality Management, Journal of Hospitality and Tourism Research, International Journal of Contemporary Hospitality Management, Tourism Management, Journal of Travel Research, Cornel Hospitality Quarterly, Annals of Tourism.

accommodations, of which quality ranking systems are deficient and hosts are mini-entrepreneurs (Guttentag, 2015). Therefore, unique site indicators of P2P lodging spaces (e.g., accommodation types) for pricing need to detected (Li et al., 2015). Second, compared with hotels, the P2P lodging guests are more conscious about demographic/socio-economic characteristics of the neighborhood where the rental property is located (i.e. a situation/external perspective). One reason is that guests are inclined to know more about the community since the hosts cannot guarantee the same protection of guests' physical security like conventional hotels do (Lehr, 2015). The other reason is that meeting residents as a component of tasting local culture is highly relevant to population features of the neighborhood (Reisinger, 1994).

Considering that the P2P lodging market is dynamic, multi-dimensional, and interrelated, hedonic pricing model (HPM) was fit to the purpose of the present study. Especially, the premise of HPM is that price is determined both by site and situation attributes, which could detect the aforementioned unique features of P2P lodging. However, the typical HPM based on Ordinary Least Squares (OLS) estimation cannot identify the variation in geographic distributions across the P2P accommodations. P2P lodging properties in proximity to one another in a neighborhood demonstrate similar invisible attributes (e.g., ambiances, amenities) where not all such attributes are included in typical HPM. It results in a bias in the OLS estimates of the price equation for P2P accommodations. Therefore, adding the spatial autocorrelation is expected to improve the precision of the estimated model.

The purpose of this research was to comprehensively identify the price determinants of P2P accommodations. Airbnb is a dominant player in P2P lodging platforms, which was used as the setting of this study. Specifically, the present research analyzed spatial dependency and heterogeneity among the Airbnb listings in the specification and estimation of HPM. Spatial regression analysis was conducted to identify site and situation determinants with two pricing models, respectively. This research contributes to the pricing literature in an emerging context (i.e. P2P lodging) and examples the innovative application of spatial hedonic pricing analysis with a large-scale dataset. The results are expected to provide effective strategies for pricing mechanism used by hosts, P2P lodging platforms, and professional pricing organizations.

2. Literature review

2.1. Hedonic pricing model and P2P accommodation platforms

The characteristics theory (Lancaster, 1966) is one of the theoretical foundations for the valuation of heterogeneous products or services (e.g., Chen and Xie, 2017; Feenstra, 1995). Lancaster (1966) assumed an implicit value is present for any characteristic of a product or service, and each characteristic could be valuated which demonstrates consumers' intention to pay for it. Similarly, hedonic demand theory suggested that the valuation of a product or service is viewed as a summation of its features. Consumers' demand for the features is the essential object of the demand theory, rather than the product or service itself (Woods, 1960). The characteristics theory and hedonic demand theory provide scholars and industry practitioners a direction to assess the valuation of products and services in the hospitality and tourism industry, since the features of the offering are heterogeneous and the final price of the offering entails a precise valuation of the feature package (Espinet et al., 2003; Falk, 2008; Thrane, 2005).

To take the idea further, Rosen (1974) created the hedonic pricing model (HPM). And many subsequent researchers have further contributed to both theoretical and practical development of the HPM (e.g., Bonnieux and Desaigues, 1998; Dube and Legros, 2014). The price a customer affords is actually for the features and benefits provided by the product/service, which is termed as "hedonic pricing". Considering the heterogeneity of lodging products/services, the HPM has widely been utilized in the setting of hotels (e.g., Roubi and Litteljohn, 2004; Schamel, 2012). However, sporadic studies with the adoption of this technique have been found in the research of P2P accommodations (e.g., Chen and Xie, 2017; Gibbs et al., 2018a,b).

Previous studies which tested either hotels or P2P accommodations with HPM primarily investigated the features of lodging businesses from two perspectives; site and situation. The site factors describe a lodging business's physical attributes (e.g., number of rooms, amenities, parking, pool) (e.g., Thrane, 2007; White and Mulligan, 2002) and reputation (e.g., customer review, brand, hotel chain) (e.g., Israeli, 2002; Yim et al., 2014). The situation factors are composed of any external features that impact the price of a lodging business. Previous studies have primarily examined location-specific attributes (e.g., distance from the attractions, transport hubs, shopping centers) (e.g., Becerra et al., 2013; Roubi and Litteljohn, 2004) and marketing conditions (e.g., marketing competitions) (e.g., Becerra et al., 2013; Hung et al., 2010). However, to the knowledge of the present authors, very sporadic studies have investigated demographic/socio-economic factors. The only two studies (Roubi and Litteljohn, 2004; White and Mulligan, 2002) we identified focused on the traditional hotel industry. Specifically, White and Mulligan (2002) confirmed the importance of geographic location when investigating the situational factors on hotel pricing.

The spaces for the P2P accommodations are mostly located in residential areas (Kaplan and Nadler, 2015). The guests choose P2P lodging options instead of conventional hotels, with the purpose of experiencing the residents' life, learning culture, and immersing themselves into local communities (Forgacs and Dimanche, 2016). In other words, guests pursue a home feeling during their stays at the dwelling places provided by hosts (Guttentag, 2015). Therefore, the present authors argued that the influential factors for the rental rates of P2P accommodations have some similarities with the attributes explaining the prices of residential properties. HPM has been used in real estate assessment (e.g., Osland, 2010). When a customer purchases a residential unit, s/he not only considers the internal characteristics of a real estate property (e.g., age, lot) and neighborhood characteristics (e.g., public facilities, shopping malls), but also demographic/socio-economic attributes in the area (e.g., crime, population) (Song and Knaap, 2004). Based on the discussions above, we proposed to test both site and situation attributes of P2P accommodations for pricing. The specific site and situation attributes are explained in detail below.

2.2. Site determinants of P2P lodging listing price

2.2.1. Counts of bedrooms and bathrooms, and accommodate person capability

Bedrooms and bathrooms as a benchmark of physical facilities predict how much customers would like to pay for hotels (e.g., Thrane, 2005; White and Mulligan, 2002). The size of the living space which is measured with the counts of bedrooms and bathrooms determines the maximum number of people accommodated. Therefore, all the three aforementioned measures, including counts of bedrooms and bathrooms as well as allowed guest number, were expected to impact the price of P2P accommodations (Chen and Xie, 2017). Similarly, Wang and Nicolau (2017) confirmed that Airbnb listing pricing is determined by these three indicators.

2.2.2. Overall review score

Reputation of a lodging business has been used as a quality-signaling factor (Grossman, 1981). Customers are willing to accept a higher price for a brand or venture with positive quality signals, because its reliable quality reduces search cost and lowers purchase risk (Lynch and Ariely, 2000). Different from conventional hotels, online customer evaluations on the P2P lodging platforms are the dominant quality signal available which assists customers' decision-making process (Wang and Nicolau, 2017). Online customer evaluations include both numerical score/rating and textual assessment. Due to the challenges of including textual assessment into the pricing model, previous lodging studies on the topic of pricing have mostly used numerical score/rating provided by customers (e.g., Ogut and Tas, 2012; Schamel, 2012).

2.3. Situation determinants of P2P lodging listing price

2.3.1. Population density

Population density is a signal for the comfortableness of dwellings in an identified region (Green et al., 2005). Crowding has been identified as a determinant for pricing on the real estate market. Different from most other studies investigated in urban areas (e.g., Anderson and West, 2006; Palmquist et al., 1997), Santana-Jimenez et al. (2011) indicated that crowding in a local community negatively influences the price of a rural house since tourists visit countryside to get rid of whirl and cram. Since the present study investigated the lodging market of the top tourism cities in the U.S., population density was expected to influence the price of P2P lodging offerings.

2.3.2. Crime counts

Safety is one of Maslow's hierarchy of needs which describes humans' desire for security and protection (Maslow, 1971). Marshall (1993) suggested that safety is one of the criteria for tourists to select a hotel. Since security could increase tourists' confidence and trust, they are willing to pay more for it (Clow et al., 1994). In the same vein, security in the neighborhood where a P2P lodging space is located is expected to influence its price. In the present study, security was measured by crime counts in a zip code area, since "crime serves as an important catalyst for change in the socio-economic composition of communities" (Tita et al., 2006, p299).

2.3.3. Unemployment counts, median income, and median house value

Unemployment and median income are the barometers of economic situations in a community (Cutter et al., 2003). To the knowledge of the present authors, very limited studies investigated how local economic conditions influence hotel valuations. Specifically, Roubi and Litteljohn (2004) proved the significant impact of GDP per capita and employment on hotel value. White and Mulligan (2002) confirmed median income and employment as the antecedents of hotel room rates. Furthermore, unemployment and median income in an area are both determinants of valuation for residential properties (e.g., Clapp and Giaccotto, 1994; Mankiw and Weil, 1989). Therefore, the three factors were expected to be the determinants of P2P lodging prices.

2.3.4. Median age

Median age is another demographic measure in a zip code area where a P2P lodging listing is located. The lower the median age of residents, the higher the population density in younger age groups (Troy and Grove, 2008). Burnell (1988) suggested that the median age of population in a community is negatively related to the valuation of a residential property, since the concentration of young and energetic people may be linked to a high crime rate. However, Kiel and Zabel (1996) supported that median age of individuals in the area where a rental property is located positively influences its price. Furthermore, considering the demographic features (e.g., age, gender) and travel purposes (e.g., family travelers, senior travelers) of guests, they may show different interests in meeting local people at distinct age groups (Harrison, 2003). Therefore, the relationship between median age of population in a zip code area and P2P lodging price was examined in the present study.

2.3.5. The competitions with lodging options in the same area

Considering that sharing economy changed the lodging industry, the competitions among P2P accommodations and between P2P accommodations and hotels in the same community cannot be ignored for the pricing strategies. For example, Zervas et al. (2015) suggested that Airbnb listings and hotels are both priced based on similar attributes (e.g., facilities, neighborhood), thus Airbnb listings weaken the power of hotels' pricing and decrease their revenues. Xie and Kwok (2017) investigated the determinants of revenue per available room of a hotel. The number of Airbnb listings and number of hotels in the same census tract both positively influence hotel performance. Therefore, counts of P2P accommodations and hotels in a zip code area were used as the indicators of the price for a given P2P accommodation listing.

2.4. Spatial autocorrelation of P2P accommodations

The typical HPM is based on OLS estimation, which cannot detect the disparity in spatial distributions across the P2P accommodations (Bell and Bockstael, 2000). Therefore, the present study applied spatial autocorrelation into regression analysis. Spatial autocorrelation measures the degree to which near and distant things are related (Anselin and Bera, 1998). It is the correlation of a variable with itself across space, which indicates dependency influenced by neighboring observations (Yang and Wong, 2013). Spatial autocorrelation offers both theoretical and practical advantages over other conventional OLS due to the presence of spatial correlation (Sunak and Madlener, 2012). If without adopting spatial autocorrelation, to correct geographic distribution bias scholars have to test a sample of observations (i.e. P2P accommodations in this study) with similar spatial characteristics, so that the net effects of the internal attributes of the rental property and the external attributes of the neighborhood are locationally insensitive (Tse, 2002). Accordingly, the pricing models generated are ungeneralizable.

Furthermore, even if P2P accommodations with similar spatial characteristics are used as the study sample, prices of these rental spaces are inclined to be spatially autocorrelated since they share public infrastructure, amenities, and local residents with the same demographic/socio-economic features (Geoghegan et al., 1997). And a set of spatial spill-over effects are observed on both physical quality of residential spaces and social environment in the surroundings (Goodman and Thibodeau, 1998). These adjacent effects are capitalized into the nearby short-term rental prices and thus result in spatial dependence which plays an important role in the determination process of P2P rental rates (Tse, 2002). Therefore, the technique of incorporating spatial effects into the hedonic pricing structure provides an innovative approach for hospitality research.

3. Methodology

3.1. Variables and data

The data of site attributes were primarily gained from www.airbnb.com with the web scraping technique during the time period of Nov 1–28, 2017. The lodging information for the 51,125 Airbnb listings among the top 10 tourism cities in the U.S. was collected, including Seattle, New York City, Austin, Chicago, San Francisco, San Diego, Los Angeles, Washington D.C., Miami, and New Orleans (Tripadvisor, 2016). 14 variables gathered are shown in Table 2.

To reflect geographical relevancy and dependency at a cluster level, zoning regression analysis based on zip code was conducted for the situation attributes. Seven situation variables aforementioned were converted to zonal data at a zip code level. A total of 654 sampling units based on zip code were identified for the Airbnb listings collected. The hotel data in the same 10 cities was gathered from www.hotels.com during the time period of Oct 2 – Oct 14, 2017. A total of 3009 hotels in 561 zip code areas were used for spatial regression analysis. The five socio-economic variables (population density, crime counts, unemployment counts, median income, median house value, and median age) were collected at a zip code level in the same 10 cities from the secondary data bank of ArcGIS website. These variables are also demonstrated in Table 2.

Table 2
The Variable List.

Data Category	Note	Source	Abbreviation
Site Attributes			
Room ID	Each accommodation has a unique ID value assigned by Airbnb	www.airbnb.com	N/A
Host ID	Each host has a unique ID value assigned by Airbnb	www.airbnb.com	N/A
Price ($)	Price per night input by the host. Natural log of price per night instead of price per night was used in data analysis	www.airbnb.com	PRICE. The natural log of price per night used in data analysis is abbreviated as lnPRICE
Overall review score	Overall assessment for the listings that have at least three reviews (on a 1-100 grading system)	www.airbnb.com	REV
Accommodated person capacity	Maximum guests allowed input by the host	www.airbnb.com	APC
Number of bedrooms	Input by the host	www.airbnb.com	BED
Number of bathrooms	Input by the host	www.airbnb.com	BATH
latitude and longitude of the address	As listed in the webpage source based on the address provided by the host	www.airbnb.com	N/A
Situation Attributes			
Number of Airbnb listings	The total number of Airbnb properties in a designated zip code area	www.airbnb.com	AIRBNB
Number of hotel properties	The total number of hotels in a designated zip code area	www.hotels.com	HOTEL
Median age	Median age of population in a designated zip code area	www.arcgis.com	AGE
Population density	The total number of population per square mile in a designated zip code area. Natural log of population density instead of population density was used in data analysis	www.arcgis.com	POP. The natural log of population density used in data analysis is abbreviated as lnPOP
Crime counts	The total number of crimes in a designated zip code area. Natural log of crime counts instead of crime counts was used in data analysis	www.arcgis.com	CRM. The natural log of crime counts used in data analysis is abbreviated as lnCRM
Unemployment counts	The total number of unemployed individuals in a designated zip code area. Natural log of unemployment counts instead of unemployment counts was used in data analysis	www.arcgis.com	UEP. The natural log of unemployment counts used in data analysis is abbreviated as lnUEP
Median income	Median income of population in a designated zip code area. Natural log of median income instead of median income was used in data analysis	www.arcgis.com	INC. The natural log of median income used in data analysis is abbreviated as lnINC
Median house value	Median house value in a designated zip code area. Natural log of median house value instead of median house value was used in data analysis	www.arcgis.com	HOUSE. The natural log of median house value used in data analysis is abbreviated as lnHOUSE

3.2. Data analysis

3.2.1. Spatial hedonic pricing models

Two spatial hedonic pricing models (HPM) were examined for site and situation attributes, respectively. Specifically, the present study adopted the OLS regression with spatial autocorrelation. GeoDa software program was employed to precisely perform the geographically weighted spatial regression analysis. The flow chart of spatial regression analysis is illustrated in Fig. 1.

In the first step, OLS model was adopted to analyze spatial autocorrelation and coefficient of each independent variable. The second step was to check Moran's I statistic. Moran's *I* (Moran, 1950) has been probably the most widely used technique of testing spatial autocorrelation or spatial dependencies. Generally, the ranges of Moran's I are from -1 to 1. A Moran's *I* of 1 means a perfectly positive spatial correlation while a value of -1 means negative spatial autocorrelation. If Moran's *I* statistic is highly significant ($p < 0.001$), it indicates strong spatial autocorrelation in the residuals. If the presence of spatial dependence is identified, step three is used to check 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). Based on the p-value of LM-Lag (spatial lag model if significant) and LM-Error (spatial error model if significant), one of the options, including spatial error model, spatial lag model, or robust LM diagnostics, for step four is used.

Spatial error model is used when spatial autocorrelation is in residuals. This model incorporates spatial effects through error term. Besides the information that appeared in OLS regression output, this study designed a spatial weight file to reflect the spatial dependence inherent in the data measuring the average influence on observations by their neighboring observations. A coefficient on the spatially correlated errors (Lambda) was added as an additional indicator in the spatial error model (Anselin et al., 2006).

$$y = x\beta + \varepsilon$$

$$\varepsilon = \lambda W \varepsilon + \xi$$

Where ε is the vector of error terms, spatially weighted using the weights matrix; λ is the spatial error coefficient; ξ is a vector of uncorrelated error terms. If there is no spatial correlation between the errors, $\lambda = 0$.

On the other hand, spatial lag model is used when spatial autocorrelation is in dependent variables (i.e., price in the present study). This model incorporates spatial effects by incorporating a spatially lagged dependent variable as an additional predictor.

$$y = \rho Wy + x\beta + \varepsilon$$

Where Wy is the spatially lagged dependent variable for weight matrix W; x is a matrix of observation on the explanatory variables; ε is a vector of error terms; ρ is the spatial coefficient. If there is no spatial dependence, and y does not depend on neighboring y values, $\rho = 0$.

If both of LM-Lag and LM-Error are statistically significant, robust LM diagnostics should be conducted (step four) to figure out a proper spatial regression model. In this step, *p*-values of statistic of robust measure for error (robust LM-Error) and the robust measure of lag (robust LM-Lag) indicate whether spatial error model or spatial lag model is ultimately chosen for spatial analysis.

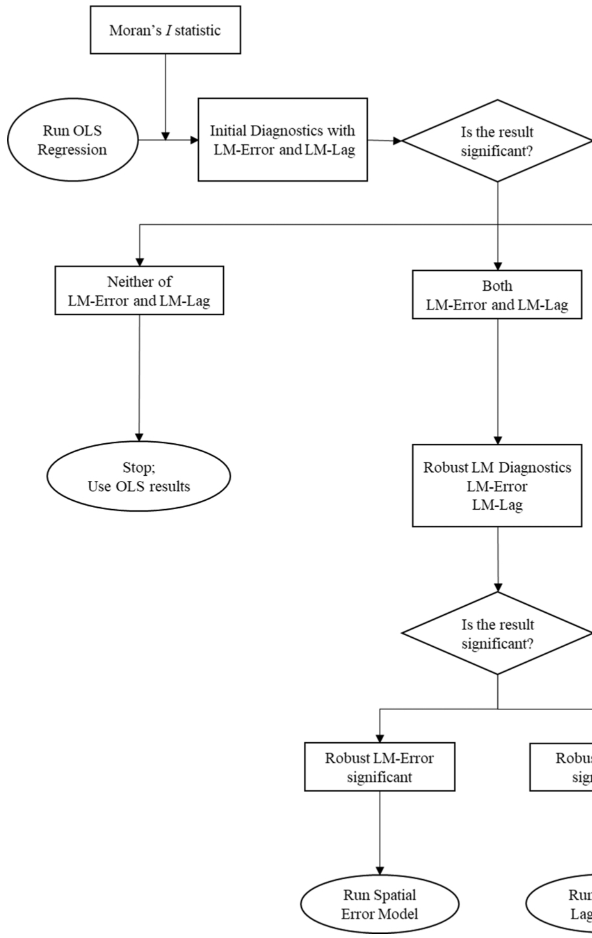

Fig. 1. Procedure of Spatial Regression Analysis.

3.2.2. The application of natural logs of dependent variable and independent variables

This study used semi-log form with natural log of the dependent variable (i.e., price) for both two spatial HPMs. The semi-log form mitigates heteroscedastic or skewed distribution and narrows the range of a variable, so that the explanative power of the model can be enhanced (Wooldridge, 2015). This study also used the natural log of population density, crime counts, unemployment counts, median income, and median house value because of high levels of kurtosis and skewness. These logarithmically transformed independent variables can represent full price elasticity (%ΔPrice = β_1%Δχ).

4. Results

4.1. Spatial hedonic pricing model for site attributes

Following the flow chart of spatial HPM discussed above, OLS regression for site attributes was conducted with the following equation. The abbreviation of each variable is explained in Table 2.

$$\ln PRICE = CONST + \alpha_1 BED + \alpha_2 BATH + \alpha_3 APC + \alpha_4 REV + \varepsilon$$

As shown in Table 3, OLS model indicates three explanatory independent variables showed statistically significant positive effects on price per night; including BED, APC, and REV.

The results of step 1–4 discussed in Section 3.2.1 are shown in Table 4. In step 2, Moran's *I* score of 46.6328 was highly significant, indicating strong spatial autocorrelation of the residuals. The step 3 showed the statistical significance of both simple LM error and LM lag models. Thus, robust models were further tested in step 4. Robust LM lag model was proved to be insignificant and robust LM error model remained statistically significant. Therefore, spatial error model was adopted for spatial regression analysis, which is explained below.

Table 3
OLS Result of Spatial HPMs for site attributes and situation attributes.

Variable	Coefficient	Std.Error	t-Statistic	Probability
OLS result of spatial HPM for site attributes				
CONSTANT	0.7578	0.0266	28.3855	0.0000***
BED	0.0385	0.0035	10.8449	0.0000***
BATH	−0.0062	0.0043	−1.4369	0.1506
APC	0.0837	0.0013	63.7148	0.0000***
REV	0.0051	0.0002	18.4923	0.0000***
OLS result of spatial HPM for site attributes				
CONSTANT	1.0487	0.3628	2.8906	0.0039*
lnCRM	−0.0622	0.0389	−1.5985	0.1104
lnPOP	−0.0622	0.0304	−2.0401	0.0417*
lnUEP	−0.1927	0.0473	−4.0748	0.0001***
lnINC	0.2335	0.0543	4.299	0.0000***
lnHOUSE	0.0908	0.0521	1.7411	0.0822
AGE	0.0012	0.0035	0.3557	0.7222
AIRBNB	0.0017	0.0001	9.4093	0.0000***
HOTEL	0.0034	0.0019	1.7485	0.0809

Note: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*.

Considering the endogeneity of explanatory variables in the spatial regression model, coefficient estimates would be biased (inconsistent) or invalid (flawed) if OLS is used to estimate the coefficient in Spatial Lag Model and Spatial Error Model. Due to simultaneity which results in non-zero correlation between the spatial lag and the error term, specialized estimation methods must be employed that properly account for the spatial simultaneity in the model. Instead of OLS,

Table 4
Moran's *I* statistics and LM Diagnostics.

Test	DF	Value	Prob.
Spatial HPM for site attributes			
Moran's I (error)	0.2778	107.3742	0.00000
Lagrange Multiplier (lag)	1	9968.0152	0.00000
Robust LM (lag)	1	14.2273	0.06020
Lagrange Multiplier (error)	1	11524.6414	0.00000
Robust LM (error)	1	1570.8535	0.00000
Spatial HPM for situation attributes			
Moran's I (error)	0.1697	7.4603	0.00000
Lagrange Multiplier (lag)	1	87.2220	0.00000
Robust LM (lag)	1	50.3428	0.00009
Lagrange Multiplier (error)	1	50.7072	0.00000
Robust LM (error)	1	5. 8279	0.08165

Table 5
Comparison between OLS Model and Spatial Error Model for Site Attributes and Situation Attributes.

	Site Attributes		Situation Attributes	
	OLS model	Spatial error model	OLS model	Spatial lag model
R-squared	0.2035	0.345565	0.2138	0.3246
Sigma-square	0.2042	0.1677	0.1919	0.1625
Akaike Info Criterion	63865.30	56194.20	756.91	686.98
Log likelihood	−31927.70	−28092.08	−369.45	−333.49
Coef. BED	0.03858**	0.0576**		
Coef. BATH	−0.0063	−0.0035		
Coef. APC	0.0838**	0.0760**		
Coef. REV	0.0052**	0.0042**		
Lambda	N/A	0.4875**		
W_lnPRICE				0.4349**
Coef. lnCRM			−0.0623	−0.0528
Coef. lnPOP			−0.0622*	−0.0728**
Coef. lnUEP			−0.1928**	−0.1058*
Coef. lnINC			0.2335**	0.1631**
Coef. AIRBNB			0.0017*	0.0012**
Coef. HOTEL			0.0034	0.0020

Note: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*.

Maximum Likelihood (ML) Method was used to estimate the coefficient by considering potential endogeneity and simultaneity (Anselin, 1998).

First, a coefficient on the spatially correlated errors (Lambda) shown in Table 5 indicated a highly significant positive effect (0.48749, $p < 0.001$). Consistent with OLS regression results, spatial error model indicated that BED, APC, and REV had a significant impact on InPRICE. Second, improvement of general model fit was identified by checking model performance. The comparison of four model performance indicators (R-squared, Sigma-square, Akaike Info Criterion (AIC), and Log likelihood) was used. When R-squared and Log likelihood are greater, Sigma-square is lower, and AIC is smaller, general model fit improvement can be defined. Table 4 also describes the results of the general model fit and comparison between OLS model and spatial error model. The spatial model had greater R-squared and log likelihood and lower sigma square and AIC compared to the OLS model. Therefore, it was concluded that controlling spatial dependence would improve the model performance.

The Moran's I test statistic of residual (Fig. 2) was changed from 0.27782 in OLS to -0.00348 in spatial error model, which was negligible. Thus, incorporating the spatially autoregressive error term into the model eliminated almost all spatial autocorrelation.

4.2. Spatial hedonic pricing model for situation attributes

OLS regression for situation attributes was conducted with the following equation. The abbreviation of each variable is explained in Table 2.

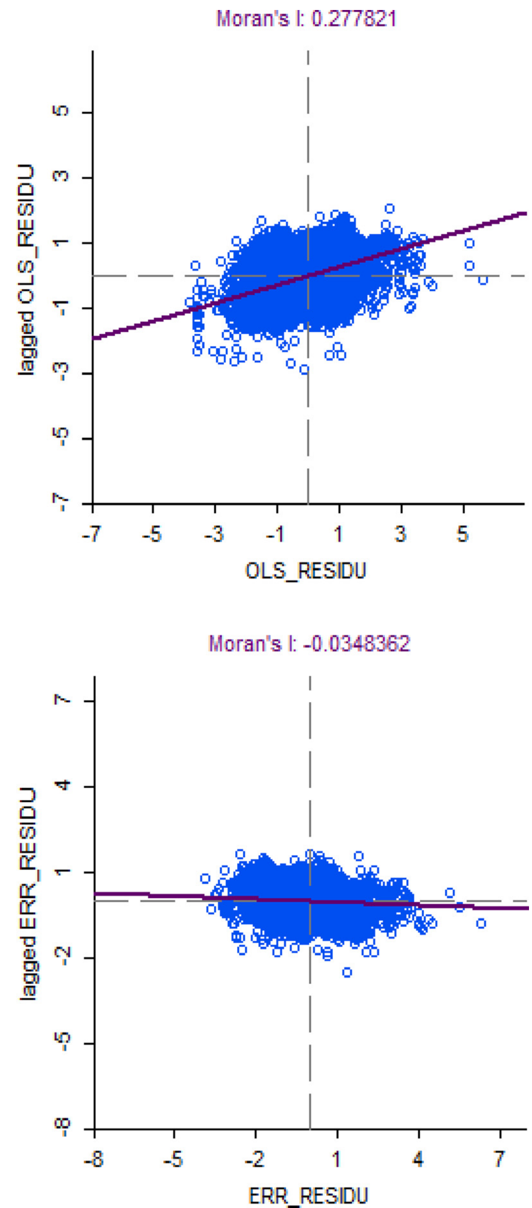

Fig. 2. Moran Scatter Plot for Residuals of OLS and Spatial Error Model for Site Attributes.

$$\ln PRICE = CONST + \alpha_1 \ln CRM + \alpha_2 \ln POP + \alpha_3 \ln UEP + \alpha_4 \ln INC + \alpha_5 \ln HOUSE + \alpha_6 AGE + \alpha_6 AIRBNB + \alpha_6 HOTEL + \varepsilon$$

As shown in Table 4, Moran's *I* score of 7.4603 was statistically significant, noting that strong spatial autocorrelation of the residuals existed in the OLS model. Since both simple LM error and lag models indicated statistical significance, robust models were further tested. Robust LM error model was proved to be insignificant and robust LM lag model remained statistically significant. Thus, the spatial lag model was employed to control the spatial dependence.

As in the site attribute hedonic model, ML estimation method was employed to take endogeneity of spatially lagged dependent variables into spatial lag model. The simultaneous spatial autoregressive model found out that POP, UEP, INC, and AIRBNB are significant pricing determinants after controlling spatial dependence in the spatial lag model, which is consistent with OLS model. Comparing the spatial lag model with ML estimation and OLS model (Table 5), the general model fit of spatial lag model was improved by controlling spatial dependence, as

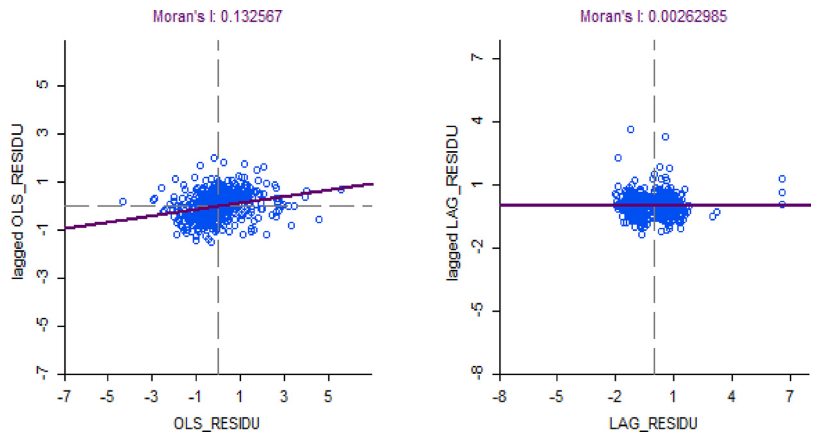

Fig. 3. Moran Scatter Plot for Residuals of OLS and Spatial Lag Model for Situation Attributes.

indicated in higher values of R-squared and Log likelihood and lower values of Sigma-square and AIC. Positively significant coefficient parameter (Rho) of the spatial lag term of average price per night of Airbnb properties within a designated zip code area (which is abbreviated as W_lnPRICE in Table 5) indicates the spatial dependence and endogeneity of spatially lagged dependent variable in the spatial lag model, which means average influence on properties by their neighboring properties are statistically significant in the data.

Moran scatter plots presented that Moran's I test statistic was changed from 0.13257 in OLS model to -0.00263 in spatial lag model (Fig. 3), which confirmed the significant contribution of the spatially autoregressive error term on eliminating spatial autocorrelation.

5. Discussion and conclusion

Compared to traditional regression analysis, spatial autocorrelation improves the preciseness of hedonic pricing models by considering the geographic features of site factors. Such an innovative application of the updated pricing model explains the unique aspects of every Airbnb listing based on its spatial characteristics. The present study confirmed that three site indicators (counts of bedrooms, accommodated person capacity, and overall review score) determine the price of a P2P lodging listing, which are consistent with Xie and Mao (2017) and Gibbs et al. (2018a,b). Among the situational indicators, counts of P2P lodging listings, population density, unemployment counts, median income in the same zip code area are significant contributors to the price of a specific listing. These findings matched with Anderson and West (2006); Wang and Nicolau (2017); White and Mulligan (2002), and Xie and Mao (2017).

Different from Chen and Xie (2017) and Wang and Nicolau (2017), the present study found that the number of bathrooms cannot effectively predict the price of a P2P lodging listing. We argued that the P2P platforms encourage sharing space and utilities (e.g., share an apartment) which is different from conventional hotels, thus the impact of bathroom number needs to be further examined in different space sharing options. Similarly, most of previous studies only investigated and confirmed the influence of bedroom or bed counts instead of bathrooms on hotel rate (e.g., Coenders et al., 2003; Hung et al., 2010). Therefore, the present authors argued that it is controversy whether the bathrooms play a significant role in a short-term rental, which needs further investigation in future studies.

Different from Marshall (1993) and Clow et al. (1994), the present study did not report any impact of crime counts on the P2P lodging listing price. Hotel room rate is usually decided by a professional marketing team which establishes a foundation of pricing structure and shows sensitivity to market change. Security negatively influences traveler demand. The impact of crimes in the marketplace could be quickly reflected in the hotel rate. However, except those requesting the pricing service of third-party organizations, most individual hosts, especially those non-superhosts, cannot detect timely the relationship between the crimes in a destination and guest demand due to the lack of professional techniques.

The present study failed to identify the impact of median age in a zip code area on the P2P lodging listing price. Guests in different segments based on their demographic features or travel purposes may show distinct interests in contacting with local people at diverse age groups (Harrison, 2003), which thus influences their choices of lodging places. For example, family travelers prefer living in a neighborhood with the middle-aged residents dominant since the children could meet new friends during the trips. Young travelers opt to live in an energetic neighborhood with more young adults, who are close to nightclubs, shows, and other entertainment venues. Therefore, considering the diverse preferences of travelers in different segments, median age in a neighborhood cannot predict the price that guests would like to pay.

Median house value in a zip code area is not a determinant of the P2P lodging listing rate. It indicates that hosts do not link the price of a P2P lodging listing and the value of real estate properties in a neighborhood. It is quite similar to the real estate rental market (e.g., monthly or yearly rental lease). The price-to-rent ratio (i.e., the ratio of home price to annual rental rate) vary significantly by city. For example, Price-to-rent ratio during the year of 2017 in San Francisco was 45.9, while the ratio in Detroit was 6.3 (Daibes, 2017). Furthermore, considering the discount factor of rents, the relationship between median residential house value and the rent would be even more complicated (Richard and Nancy, 1994). P2P lodging could be viewed as a type of short-term rental. Thus, the median house value cannot predict P2P lodging listing rate in a zip code area.

The number of hotels does not predict the P2P lodging rate in the same zip code area. It may be caused by the adoption of natural log of PRICE in the present research. When the authors used Airbnb average price per night as a dependent variable, hotel counts was found to be a significant determinant. These results indicate that one unit increase of hotel counts (one property) contributes to one unit increase of PRICE ($1 of average Airbnb listing price per night), but not significantly contributes to the percentage increase of Airbnb price (1% increase of Airbnb price), which is termed as price semi-elasticity. It means that hosts take hotel counts into P2P lodging pricing. However, hosts do not make much price fluctuation based only on a total number of hotels in the same zip code area. The reason is that Airbnb hosts price their properties collectively based on the areal characteristics as a general that are shared with other Airbnb listings. Therefore, the hotel counts are not considered separately, which accordingly does not generate the percentage increase of pricing.

6. Implications

6.1. Theoretical implications

The present study has significant theoretical implications. First, the current research enriched the knowledge body of the characteristics theory, hedonic demand theory, and hedonic pricing model in a new context – Airbnb listings. It further proves the applicability of these three theoretical foundations in pricing systems of the hospitality and tourism industry. Moreover, previous limited studies which investigated hedonic pricing of Airbnb listings dominantly focused on the site factors or intrinsic features of the offerings. The present study is a pioneer of incorporating the demographic and socio-economic features as situation factors into the hedonic pricing model. It is expected to expand and deepen the understanding of Airbnb listings' pricing from a theoretical perspective.

Second, the present study is a pioneer in applying spatial regression analysis in the context of P2P accommodations. It innovatively evaluates the role of the predictive variable (i.e. price) by incorporating spatial autocorrelation in parameter estimation and hypothesis testing. Spatial regression analysis has been widely used in the literature of housing pricing (e.g., Cellmer, 2013). The transaction price of a real estate property is shaped by a combination of factors, among which location shows significantly importance. Since P2P lodging provides guests with temporary living spaces in residential properties, its pricing system shows some similarities with the mechanism for valuing real estate properties. Thus, this research offers a new approach to incorporating the spatial correlation into pricing strategies in hospitality and tourism studies.

Third, demographic and socio-economic factors of a neighborhood have rarely been investigated in the pricing models for either P2P accommodations or hotels. These factors are principal societal forces that affect the macro marketing environment, which cannot be ignored in the pricing mechanism (Morrison, 2010). The present study added knowledge relevant to pricing in the lodging industry by encompassing these commonly overlooked indicators into the HPM. Furthermore, these demographic and socio-economic factors are geographically sensitive. Thus, spatial regression analysis could improve the accuracy of prediction for the impacts of situational factors on pricing.

Fourth, most of hospitality scholars replied on surveys of individual respondents to investigate P2P accommodations (e.g., Karlsson et al., 2017; Mao and Lyu, 2017). However, the affluent information warehouses via the collaborative consumption websites and census statistics available on governmental websites offer numerous research opportunities. Very sporadic studies have applied big data analytics to assess P2P accommodations. The present research was one of the pioneers which utilized the large-scale dataset relevant to both site and situation factors of sharing lodging pricing in top 10 tourism cities of the U.S.

6.2. Practical implications

The present study also provides unique contributions to industry practitioners. First, the listing price on P2P accommodation platforms is closely tied to the site attributes of the rental spaces, particularly count of bedrooms and accommodated person capacity. The hosts should use these utility-bearing attributes as the foundation of their pricing strategies. Customer review score is an effective indicator of the P2P lodging price. The forms of reputation identification for conventional hotels include stars grading/classification (Israeli, 2002), chain-association (Becerra et al., 2013), and online customer evaluation (Schamel, 2012). Because P2P lodging listings are operated by mini-entrepreneurs, online peer reviews are mostly used by customers during the decision-making process. Therefore, it is advised that hosts spend time and efforts on improving and maintaining a fantastic customer review profile. It is not only one of the most valuable marketing assets, but also a conversion optimization technique for the micro-entrepreneurs on P2P lodging platforms. Furthermore, hosts should consider the fluctuation of customer reviews in designing pricing strategies. When the customer review score is lower than the average among the P2P lodging listings in the same area, the host should consider decreasing the price or providing more benefits to allure potential guests. When the customer review score rebounds above the average level of P2P lodging lists in the neighborhood due to effective service failure recovery and quality improvement on the perspectives of facilities and services, the host could gradually raise the listing price.

Second, the hosts of P2P accommodations should incorporate population density of the neighborhood into the pricing mechanism. The present study suggested that lower population density contributes to the higher P2P lodging rate. However, it should be aware that population density shows significant distinctions between downtowns and peripheral areas even for the top 10 tourism destinations in the U.S. investigated in the study. Although population density represents the comfortableness of a place, travelers may have different expectations of crowdedness based on their trip purposes. For example, guests are inclined to stay in densely-populated downtowns when they involve into urban tourism, since they could easily access sightseeing, shopping centers, business venues, and entertainment venues. However, to get relief from the stress of everyday life, tourists originated from urban areas prefer to stay in untraversed communities when they engage into rural tourism. Travelers choose to stay in P2P accommodations in either downtowns or peripheral areas for different travel purposes. Future studies could conduct spatial regression analysis separately for the two types of regions, which may bring more informative implications.

Unemployment and median income are two vital indexes of economic goodness in a neighborhood. Guests expect to get high-quality short-term rental experience located in such a community. Therefore, the host could set a high listing rate for the space in a community with the lower-level unemployment counts and greater-level median income. The hosts are usually unaware of information sources which provide the census statistics in a zip code area. A P2P accommodation platform is advised to offer the links to census statistics by zip code in the section of host pricing help on its website. It is helpful for the hosts who do the research and set the rate themselves without referring to third-party pricing services.

Third, spatial autocorrelation among P2P accommodations plays a significant role in pricing models. Therefore, the present authors suggest that geographic distribution correlation among the P2P lodging options be included in the pricing mechanism. This technique is over complicated for individual hosts without the knowledge background of spatial regression analysis. Therefore, we only recommend spatial autocorrelation analysis to the third-party pricing companies. Many P2P platforms recommend the third-party pricing websites to the hosts. For example, Airbnb partners Wheelhouse Corp., which charges hosts for customized pricing. These third-party pricing websites use algorithms to detect the changes in the local P2P accommodation demands and then they price the specific rental for maximum income. Although these third-party pricing websites have not published the indicators used in their pricing algorithms. From their promotional materials and the information that hosts input for the services, the indicators used by these pricing websites are relevant to marketing competitions, such as local occupancy rates, hotel prices, other competitor prices, seasonality, special events, and weekday vs. weekend (e.g., Airbnb, 2017; Manonthelam, 2015; Properly, 2015). These third-party pricing websites are advised to incorporate spatial autocorrelation into their pricing algorithm. Moreover, the present authors also suggest these websites consider population density, unemployment counts, and median income of a neighborhood as effective predictors of the P2P lodging rate. Besides these, the third-party organizations also could test the potential influences of other demographic/socio-economic indicators on P2P lodging rates before including them into the pricing algorithm.

7. Limitations and future research

Although the results provide important implications from both theoretical and practical perspectives, several limitations cannot be ignored and need further investigations. First, the present study only tested six demographic and socio-economic factors in the census tract. Future research should include a broader range of such factors, including gender, education level, occupation, and others. Second, the present study only tested four site factors. Future studies should consider more ones (e.g., number of reviews, superhost). Especially, the number of reviews is a disputed site factor of hotel or P2P lodging pricing in previous studies (e.g., Ert et al., 2016; Wang and Nicolau, 2017). Future studies are advised to further examine the influence of the number of reviews on pricing with spatial autocorrelation. Third, whether the host is professional or not (i.e., superhost) is expected to have some impact on pricing, although it is still controversy in previous studies (e.g., Chen and Xie, 2017; Gibbs et al., 2018a,b; Gunter, 2018). Including superhost as a site factor of the spatial regression model could more precisely investigate the role of superhost in pricing, which may contribute to the dispute resolution.

Fourth, the present study used the secondary data to investigate the site and situation factors for the P2P lodging listing price. However, compared with hotels, hosts of P2P accommodations are lack of resources and knowledge to accurately assess the rationality of their proposed rates. Intuition plays a significant role of deciding the P2P lodging listing price for individual hosts, especially those non-superhosts. Therefore, future research is advised to investigate potential guests' feedback or assessment of the listing prices for P2P accommodations. Travel purpose (e.g., business travel, agritourism) and guest segmentation (e.g., budget-conscious travelers, family travelers) of the guests could be used as moderators in the assessment. Fifth, the present study used counts of crimes and unemployment instead of crime rate and unemployment rate as situation indicators. Either way was acceptable in the previous studies of business administration, sociology and economy (e.g., Assaad and Krafft, 2015; Downes et al., 2016; Heilman, 2017). We chose total counts of the two indicators since they could give guests more straightforward clues of the neighborhood where a P2P lodging listing is located. Future studies could adopt the unemployment rate and economy rate, which may generate different implications.

Six, Garrod (1994) suggested that the HPM has some statistics flaws, including mission of important features, uncertainty about the mathematical specification of the model. The hospitality scholars could incorporate spatial autocorrelation into other pricing models as alternatives, such as ridge regression or principal component regression. Seventh, the average review score is 94.32 out of 100 in the present study. It is consistent with that in the Airbnb sample used by Ert et al. (2016). Such a distribution of review ratings for P2P accommodations is distinct from that in the traditional hotel industry (Nieto-García et al., 2017). Thus, the role of numerical review ratings as signals of quality is limited in the context of P2P lodging. Future studies should consider applying summary results from written reviews into the regression analysis of P2P lodging pricing, since written reviews are composed of more comprehensive or customized findings of quality and experience than numerical review scores or ratings (Ganu et al., 2009).

Eighth, there are two types of spatial dependence; spatial dependence across observations on the dependent variable, and spatial dependence across error terms. The present study adopted spatial dependence across error terms. Future research could apply the alternative, which is more powerful to separate the neighborhood effects from the random disturbance. Last but not least, due to potential endogeneity and error autocorrelation, it is recommended to conduct robust spatial two stage least squares with instrument variables (IV) to compare results of OLS and ML models. If future studies use optimal instruments after controlling endogeneity and error autocorrelation, it is expected that spatial interaction would be almost ignorable and difference between spatial two stage least squares and ML would be almost zero.

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