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PRICE DETERMINANTS OF AIRBNB LISTINGS: EVIDENCE FROM HONG KONG

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Price determinants of Airbnb listings is still in its infancy and Asian markets are underexplored. Based on existing literature, this article examines the impacts of five groups of explanatory variables on Airbnb price in Hong Kong: listing attributes, host attributes, rental policies, listing reputation, and listing location. Hedonic price regression highlights that: (a) compared with previous studies, the effect of room type on Airbnb price is exceptionally high in Hong Kong, due to the "the luxury of spaciousness" in this overpopulated city; (b) contradictory to previous findings, hosts' listings count have a negative effect on Airbnb listing price in Hong Kong, which can be explained by external (Hong Kong's fiercely competitive environment for multilisting Airbnb hosts) and internal (multilisting hosts' trade-off between booking opportunity and listing price) factors; (c) in Hong Kong, only low-end Airbnb rentals benefit from locational factors, indicating the heterogeneous effects of location on Airbnb pricing. These findings shed new light from previous studies and the authors provide possible explanations from theoretical and practical perspectives.

Key words: Airbnb; Sharing economy; Hospitality industry; Hedonic price model; Hong Kong

Introduction

In the era of sharing economy, Airbnb acts as a novel and alternative business model in the hospitality industry (Guttentag, 2015). Founded in 2008, Airbnb has grown into a leading peer-to-peer accommodation platform, with more than 5 million listings located in 81,000 cities worldwide (Airbnb Press Room, 2018). Such a sharp increase means hosts are encountering greater competition than ever. Therefore, pricing strategy is among the key business practices for Airbnb hosts to learn (Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018).

Whereas there have been numerous business models pricing traditional hotel functions and services, these models are not necessarily suitable for Airbnb. First, as personal properties, accommodation products on Airbnb show far more complexity

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than hotels in terms of listing and host attributes. Products on Airbnb vary substantially from “a cushion to an island” (Guttentag, 2015). Second, driven by the notions of sharing economy, both Airbnb hosts and guests seek more than economic values (Paulauskaite, Powell, Coca-Stefaniak, & Morrison, 2017) and the pricing strategy of hosts may seem “irrational” compared with hotels (J. Li, Moreno, & Zhang, 2015). Therefore, special academic attention is needed for the pricing of Airbnb listings.

Research into Airbnb pricing is still in its infancy and up to now there have been only a handful of studies. These studies have identified some explanatory variables unique to Airbnb, such as the attributes of the host (superhost, host verification, host race, etc.) (Chen & Xie, 2017; Kakar, Franco, Voelz, & Wu, 2016; Wang & Nicolau, 2017). Some inconsistencies are found between hotel and Airbnb pricing. For instance, flexible booking policies are related with lower Airbnb rental price, which draws a contradictory conclusion to hotels (Benítez-Aurioles, 2018; Wang & Nicolau, 2017). Many Airbnb hosts offer a fixed room rate across different dates, regardless of weekends (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018) or even Christmas (J. Li et al., 2015).

While previous studies have offered insights into the pricing of peer-to-peer accommodation products, they are mainly based on Western cities and there is a research gap for the Asian market. In this study, Hong Kong was selected for the study area because it is a world-famous urban tourism destination in Asia (United Nations World Tourism Organization [UNWTO], 2012). Moreover, the huge demand for accommodation products (Hong Kong Tourism Board, 2017) and the scarcity in urban land resources (M. Li, Fang, Huang, & Goh, 2015) makes the notion of “sharing” a high priority in this heavily populated tourism destination.

Driven from existing literature, this article first provides a comprehensive review of price determinants of Airbnb listings. Then based on a sample of 3,351 listings in Hong Kong, hedonic price regression was adopted to develop models that take into account five categories of explanatory variables: listing attributes, host attributes, listing reputation, rental policies, and listing location. This article contributes to current literature by identifying and explaining the uniqueness of the Hong Kong market. First, compared with previous studies, the effect of room type on Airbnb price is exceptionally high in Hong Kong, due to “the luxury of spaciousness” in this overpopulated city. Second, contradictory to previous findings, hosts’ listings count have a negative effect on Airbnb listing price in Hong Kong, which can be explained by external (Hong Kong’s fiercely competitive environment for multilisting Airbnb hosts) and internal (multilisting hosts’ trade-off between booking opportunity and listing price) factors. Third, in Hong Kong, only low-end Airbnb rentals benefit from locational factors, indicating the heterogeneous effects of location on Airbnb pricing, as well as the interaction between accommodation quality and accessibility.

Literature Review

Airbnb and Sharing Economy

Sharing, as a human activity, is as old as time itself (Heo, 2016). However, it was not until the booming of Internet technology that “collaborative consumption” and “sharing economy” have become a social phenomenon (Belk, 2014). In the era of sharing economy or peer economy, individuals rent, lend, or trade goods, services, transportation, or space in a peer-to-peer way (Mareike, 2015). Tourism, which involves all the above-mentioned activities, is one of the areas most affected by the sharing economy (Heo, 2016). In recent years, sharing economy-based business models have been developed in transportation (such as Uber.com) and accommodation (such as Airbnb.com and Homeaway.com) sectors due to high tourist demand (Wang & Nicolau, 2017).

Airbnb, a leading platform in peer-to-peer accommodation products, is a “creative destruction” to the traditional hospitality industry (Guttentag, 2015). Different from hotels, the host–guest relationship in Airbnb is beyond staff–customer relations. Both Airbnb hosts and guests seek more than functional values. Experiential value (Lyu, Li, & Law, 2019), authenticity (Birinci, Berezina, & Cobanoglu, 2018), sociability, and trust (Young, 2017) are high on the agenda for Airbnb users. Furthermore, Airbnb affects hotels’ performance. Airbnb is found to have a substitution effect on hotels, because Airbnb supply negatively influences hotels' financial performance (Xie & Kwok, 2017), and higher Airbnb rating score is related with a decrease in hotel RevPAR (Blal, Singal, & Templin, 2018).

As a peer-to-peer accommodation business model, pricing plays a vital role in Airbnb. First, pricing is a decisive factor of long-term success in the accommodation industry (Hung, Shang, & Wang, 2010), and in the era of sharing economy Airbnb is an important proportion of the accommodation product. Second, Airbnb is different from hotels and shows complexity in property attributes and host attributes (Guttentag, 2015), which needs special academic attention to pricing. Third, many Airbnb hosts are nonprofessional in terms of business operation (Gibbs, Guttentag, Gretzel, Yao et al. 2018; J. Li et al., 2015), thus having difficulty optimizing prices (Gibbs, Guttentag, Gretzel, Morton et al., 2018).

Price Determinants of Airbnb Listings

Academic inquiries into the pricing of sharing economy business is still in its infancy. Generally speaking, there are two pricing models in sharing economy platforms. The first model is completely based on algorithm, which means the firm has the full control over the prices of each service request (Kwok & Xie, 2018; Ye et al., 2018). Uber is a typical example of such model. The second pricing model uses algorithm tools only for reference, leaving the pricing decision open to service providers (Kwok & Xie, 2018; Ye et al., 2018). Peer-to-peer accommodation products such as Airbnb fall into the second category.

While Airbnb has developed algorithm-based dynamic pricing tools such as "Price Tips" and "Smart Pricing," it is Airbnb hosts who have the final decision on listing price. According to a research from Airbnb Pricing Modelling Team, hosts only "partially" adopt the prices generated by algorithm tools. Many hosts set their listing prices higher than suggested (Ye et al., 2018). Kwok and Xie (2018) further compared the pricing strategies between single-listing and multilisting hosts. Other factors being equal, multilisting hosts tend to position their listing prices higher and adopt a less dynamic pricing strategy. The human factors add more complexity to the pricing of Airbnb listings. Nevertheless, existing literature has very little discussion about hosts' decision-making behavior or guests' willingness to pay on Airbnb rental price. Among the few discussions is a choice experiment, which reports that the positive facial expression on the personal profile image of Airbnb hosts has a positive influence on guests' willingness to rent, whereas the absence of a profile photo cannot be compensated for a lower price (Fagerstrom, Pawar, Sigurdsson, Foxall, & Yani-de-Soriano, 2017).

Up to now, there are only a handful of journal publications on price determinants of Airbnb. Based upon hedonic regression models, these studies focus on the algorithm perspective of pricing (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Gibbs, Guttentag, Gretzel, Yao et al., 2018; Wang & Nicolau, 2017). Driven from previous research on Airbnb pricing, the authors identify five groups of explanatory variables, which are presented in Table 1: (1) listing attributes; (2) host attributes; (3) listing reputation; (4) rental policies; (5) listing location.

Listing Attributes. The first category of Airbnb price determinants is listing attributes. Accommodation type and room type determine Airbnb room rates (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017). Number of bedrooms, number of bathrooms, and number of accommodations also have a positive impact on Airbnb rental price (Chen & Xie, 2017; Ert, Fleischer, & Magen, 2016; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017).

Facilities such as car parking, swimming pool, and wireless Internet positively affect Airbnb listing price (Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017). However, it has been found in several recent studies on hotels that free car parking does not have a significant influence on hotel room rate (Latinopoulos, 2018; Rigall-I-Torrent et al., 2011; Saló, Garriga, Rigall-I-Torrent, Vila, & Fluvià, 2014; Woo Gon, Jun, Jin Soo, & Yunkyong, 2015). This may be because free car parking has already become a standard service in hotels in recent years, whereas in the peer-to-peer

Table 1
Price Determinants of Airbnb Listings

Category	Determinants	Effects	References
Listing attributes	• Room type[a] (reference group: shared room), number of bedrooms[a], number of bathrooms[a], number of accommodations[a], free parking[b], pool, gym, real bed, wireless Internet, number of accommodation photos	positive	Chen and Xie (2017), Ert et al. (2016), Gibbs, Guttentag, Gretzel, Morton et al. (2018), Kakar et al. (2016), Wang and Nicolau (2017)
	• Accommodation type (reference group: independent properties), free breakfast[b]	negative	(Gibbs, Guttentag, Gretzel, Morton et al. (2018); Wang and Nicolau (2017)
	• Months since the listing was established	insignificant	Zhang et al. (2017)
Host attributes	• Hosts' listing count, host verification, host profile picture, response time	positive	Chen and Xie (2017), Ert et al. (2016), Wang and Nicolau (2017)
	• Race (reference group: white)	negative	Kakar et al. (2016)
	• Gender, marital status, sexual orientation, acceptance rate	insignificant	Chen and Xie (2017), Ert et al. (2016), Kakar et al. (2016)
	• Superhost or not[a], professional (multilisting) or not	mixed	Chen and Xie (2017), Gibbs, Guttentag, Gretzel, Morton et al. (2018), Kakar et al. (2016), Kwok and Xi (2018), J. Li et al. (2015), Wang and Nicolau (2017)
Listing reputation	• Rating on cleanliness, rating on location	positive	Chen and Xie (2017), Kakar et al. (2016)
	• Number of reviews[a], rating on value	negative	Gibbs, Guttentag, Gretzel, Morton et al. (2018), Kakar et al. (2016), J. Li et al. (2015), Wang and Nicolau (2017), Z. H. Zhang et al. (2017)
	• Rating on accuracy, rating on check in	insignificant	Chen and Xie (2017)
	• Overall rating score[a], rating on communication	mixed	Chen and Xie (2017), Ert et al. (2016), Gibbs, Guttentag, Gretzel, Morton et al. (2018), Kakar et al. (2016), J. Li et al. (2015), Wang and Nicolau (2017), Z. H. Zhang et al. (2017)
Rental policies	• Strict cancellation policy[b], guests' phone verification required	positive	Chen and Xie (2017), Wang and Nicolau (2017)
	• Instant bookable[b], smoking allowed	negative	Gibbs, Guttentag, Gretzel, Morton et al. (2018), Kennedy et al. (2018), Wang and Nicolau (2017)
	• Guests' profile photo required	insignificant	Wang and Nicolau (2017)
Listing location	• Neighborhood value, average rental price in the district, number of Airbnb listings in the same district, price of surrounding Airbnb listings and hotels, number of points of interest (POIs) in surrounding area, located within sightseeing, eating or shopping areas, located near a continuous coastal fringe	positive	Chen and Xie (2017), Kakar et al. (2016), Önder et al. (2018), Perez-Sanchez et al. (2018)
	• Distance to city center, number of hotels in the same district	negative	Chen and Xie (2017), Gibb,s Guttentag, Gretzel, Morton et al. (2018), Perez-Sanchez et al. (2018), Wang and Nicolau (2017), Z. H. Zhang et al. (2017)
	• Distance to the nearest highway	insignificant	Z. H. Zhang et al. (2017)

Note: [a]Showing greater explanatory power according to Benítez-Aurioles's (2018) specification; [b]showing inconsistent results with hotel in previous studies.

rental accommodation sector car parking is part of the hosts' personal property. Including breakfast has a negative effect on Airbnb room rate (Wang & Nicolau, 2017), which is also inconsistent with findings in hotel research (Latinopoulos, 2018; Yang, Mueller, & Croes, 2016). The number of accommodation photos positively impacts Airbnb price (Gibbs, Guttentag, Gretzel, Morton et al., 2018) and the number of reviews (Liang, Schuckert, Law, & Chen, 2017).

Host Attributes. As a member of peer-to-peer accommodation, another notable price determinant of Airbnb is host attributes. When it comes to hosts' race, Kakar et al. (2016) discovered that, compared with white counterparts, Asian and Hispanic hosts charge a lower price on Airbnb in San Francisco. Existing research has not found a significant effect of the host's gender (Ert et al., 2016; Kakar et al., 2016), marital status (Kakar et al., 2016), or sexual orientation (Kakar et al., 2016) on Airbnb room rate.

Verifying hosts' profile (Chen & Xie, 2017; Wang & Nicolau, 2017) or providing hosts' photo on Airbnb (Ert et al., 2016; Wang & Nicolau, 2017) can lead to a price premium, as such action increases the trustworthiness of the host (Ert et al., 2016). A "superhost" badge on Airbnb also helps earning additional room rate (Gibbs, Guttentag, Gretzel, Morton et al., 2018; Kakar et al., 2016; Wang & Nicolau, 2017), with the exception of Chen and Xie's (2017) insignificant finding.

Hosts' operation capability also brings more economic income. According to several studies, "Professional hosts" ("professional" means the host has two or more listings on Airbnb) win a higher room rate (Gibbs, Guttentag, Gretzel, Morton et al., 2018) of each property than their nonprofessional counterparts. However, J. Li et al. (2015) found that while professional hosts do not offer a significant higher price than nonprofessionals, they do have a higher daily revenue of each property, as the occupancy rate is higher (J. Li et al., 2015). Wang and Nicolau (2017) reported a similar finding that the more Airbnb listings a host owns, a higher room rate is charged. Although hosts' acceptance rate does not have a significant impact on price (Chen & Xie, 2017), longer response time is related with a higher room rate (Chen & Xie, 2017).

Listing Reputation. The third category is listing reputation. The number of reviews negatively influences listing price (Gibbs, Guttentag, Gretzel, Morton et al., 2018; J. Li et al., 2015; Wang & Nicolau, 2017) but positively affects daily revenue and occupancy rate of each property (J. Li et al., 2015). A possible explanation is that the quantity of reviews stands for the size of demand and there is more demand for less expensive listings (Gibbs, Guttentag, Gretzel, Morton et al., 2018).

Customer rating shows a mixed effect on room rate. There is empirical evidence supporting both positive (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017) and negative (J. Li et al., 2015; Z. H. Zhang, Chen, Han, & Yang, 2017) impact of overall rating score. Rating score on accuracy and check-in does not affect price (Chen & Xie, 2017). Higher score on cleanliness, communication effectiveness and location wins a price premium (Chen & Xie, 2017; Kakar et al., 2016). Rating score on value, however, has a negative impact on Airbnb listing price, according to Chen and Xie (2017) and Kakar et al. (2016).

Rental Policies. The fourth category is associated with rental policies. Instant bookable listings are less expensive (Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017). Refundable cancellation policy is linked with lower rental price (Chen & Xie, 2017; Wang & Nicolau, 2017), which is contradictory to the findings in hotel research (Latinopoulos, 2018; Masiero, Yoonjoung Heo, & Pan, 2015). Permitting smoking also negatively influences Airbnb room rate (Kennedy, Douglas, Stehouwer, & Dawson, 2018; Wang & Nicolau, 2017). Furthermore, requiring guests' phone verification is related with higher room rate (Wang & Nicolau, 2017), whereas requirement on guests' profile photo does not impact Airbnb listing price (Wang & Nicolau, 2017).

Listing Location. The last category is listing location. Similar to hotels (Latinopoulos, 2018; H. Zhang, Zhang, Lu, Cheng, & Zhang, 2011), locational factors are considered in the pricing strategy of Airbnb. Closeness to the city center (Gibbs, Guttentag, Gretzel, Morton et al., 2018; J. Li et al., 2015; Wang

& Nicolau, 2017; Z. H. Zhang et al., 2017) and coastline (Perez-Sanchez, Serrano-Estrada, Marti, & Mora-Garcia, 2018) contribute to higher room rate. If a listing is located within sightseeing, eating, or shopping area, it also wins a price premium (Perez-Sanchez et al., 2018). Önder, Weismayer, and Gunter (2018) also found that the number of points of interest (POIs) in the surrounding area is positively related with Airbnb listing price in Tallinn, Estonian. Neighborhood value shows a positive but diminishing return rate on Airbnb listing price (Kakar et al., 2016). However, a shorter distance to the highway does not exert a significant impact on Airbnb rental price, according to Z. H. Zhang et al.'s (2017) research in Tennessee.

Market competition is also important, since the number of Airbnb listings in the same district gives rise to rental price whereas the density of hotels negatively affects Airbnb listing price. Higher median gross rent in the district (Chen & Xie, 2017) as well as the room rate of surrounding Airbnb listings (Önder et al., 2018) also raises Airbnb price.

Research Aim

Given the difference between Airbnb and hotels, further studies are needed to reexamine the factors influencing Airbnb pricing. Furthermore, previous studies have been mainly based on Western cities and the Asian market is underexplored. Driven from these gaps, this study aims to examine the price determinants of Airbnb listings in Hong Kong, as well as estimating the effect of some potential new variables. Explanatory variables are chosen based on the following criteria:

1. Variables showing high explanatory power: room type, bedrooms, bathrooms, accommodations, superhost, number of reviews, and review score. These variables are selected based on Benítez-Aurioles's (2018) specification.
2. Variables showing inconsistent results with hotels: breakfast, parking, instant bookable, and cancellation policy.
3. Other variables important to Airbnb pricing derived from previous studies: host listings count, listing density, and distance to city center.
4. Potential variables important to Airbnb pricing but have not been examined: kid and family friendly, doorman, host membership month, distance to shopping center, and distance to tourism attraction.

Methodology

Study Area

This article chooses Hong Kong as the study area for the following reasons. First, Hong Kong is a world-famous urban tourism destination. It was ranked among the 21 most-visited cities according to UNWTO's Global Report on City Tourism (UNWTO, 2012). In 2016, Hong Kong attracted 26,552,681 overnight visitors, with an average stay of 3.3 nights (Hong Kong Tourism Board, 2017). This means a huge demand for accommodation products. Second, Hong Kong is a highly populated megacity but its urban land resource is very limited (M. Li et al., 2015), which makes the notion of "sharing" a high priority.

Data and Variables

Sample listings for this study were obtained from insideairbnb.com, a noncommercial third-party website compiling data that are publicly available on Airbnb.com. This site was also chosen as the source of data in other previous research (Benítez-Aurioles, 2018; Wang & Nicolau, 2017). The Airbnb data were obtained on August 7, 2016. In total, 6,474 listings were web-scrapped. However, this study filtered the listings with at least one customer review, guaranteeing that our sample listings were "active" (Wang & Nicolau, 2017). In doing so, the sample size of this study was reduced to 3,351 listings. The spatial distribution of sample listings is presented in Figure 1 and Table 2.

Table 3 presents and defines the variables relevant to this study. The dependent variable of this study was the logarithm of listing price. Log form of price was used to estimate the semielasticity of price with respect to the explanatory variables (Wooldridge, 2014). Independent variables of this study were chosen based on the criteria in shown above in "Research Aim."

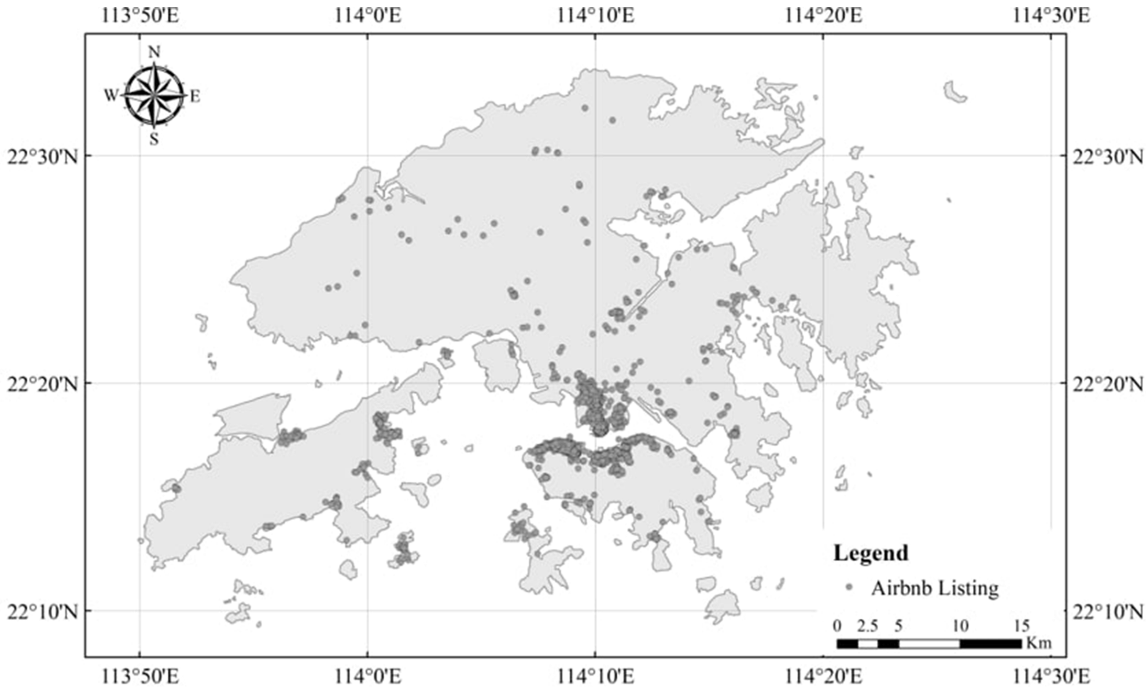

Figure 1. Airbnb listings in Hong Kong.

Table 2
Airbnb Listings by District

Region	District	No. of Airbnb Listings	Proportion	High Density
Hong Kong Island	Central & Western	888	26.50%	Yes
	Eastern	53	1.58%	No
	Southern	46	1.37%	No
	Wan Chai	571	17.04%	Yes
Kowloon	Sham Shui Po	69	2.06%	No
	Kowloon City	53	1.58%	No
	Kwun Tong	12	0.36%	No
	Wong Tai Sin	5	0.15%	No
	Yau Tsim Mong	1319	39.36%	Yes
New Territories	Islands	179	5.34%	No
	Kwai Tsing	6	0.18%	No
	North	7	0.21%	No
	Sai Kung	47	1.40%	No
	Sha Tin	36	1.07%	No
	Tai Po	20	0.60%	No
	Tsuen Wan	20	0.60%	No
	Tuen Mun	6	0.18%	No
	Yuen Long	14	0.42%	No

Table 3
Variables and Descriptive Statistics

Variable	Definition	Mean	*SD*	Min.	Max.
Price	Price of a given listing.	700.66	653.98	93	24,818
Ln(price)	Logarithm of listing price.	6.34	0.64	4.53	10.12
Room type[a]	Room type of a listing (reference group: shared room).				
Entire home (dummy)	Whether a listing is entire home (1 = yes, 0 = no).	0.55	0.50	0	1
Private room (dummy)	Whether a listing is private room (1 = yes, 0 = no).	0.40	0.49	0	1
Shared room (reference group)					
Bedrooms[a]	Number of bedrooms in a listing.	1.25	0.79	0	7
Bathrooms[a]	Number of bathrooms in a listing.	1.18	0.61	0	8
Accommodations[a]	Number of accommodates in a listing.	3.58	2.71	1	16
Breakfast (binary)[b]	Whether a listing offers free breakfast (1 = yes, 0 = no).	0.05	0.21	0	1
Parking (binary)[b]	Whether a listing provides free parking (1 = yes, 0 = no).	0.02	0.15	0	1
Kid and family friendly (binary)[d]	Whether a listing is "kid and family friendly" (1 = yes, 0 = no).	0.59	0.49	0	1
Doorman (binary)[d]	Whether a listing has doormen (1 = yes, 0 = no)	0.42	0.49	0	1
Superhost (binary)[a]	Whether a host has a "superhost" badge on Airbnb (1 = yes, 0 = no).	0.06	0.24	0	1
Host listings count[c]	Number of listings a host has on Airbnb.	9.25	13.15	1	103
Multilisting or not (binary)	Whether a property is owned by a multi-listing host (1 = yes, 0 = no).	0.68	0.47	0	1
Host membership month[d]	Months since a host's registration in Airbnb.	28.33	16.69	0	82
Review score[a]	Average review score of a listing.	89.18	10.36	20	100
Number of reviews[a]	Number of reviews of a listing.	20.11	28.40	1	242
Instant bookable (binary)[b]	Whether a listing can be booked instantly (1 = yes, 0 = no).	0.24	0.43	0	1
Cancellation strict (binary)[b]	Strictness of cancellation policy (1 = strict, 0 = flexible or moderate).	0.64	0.48	0	1
High listing density (binary)[c]	Whether the listing is located in a high-density district (1 = yes, 0 = no).	0.83	0.38	0	1
Distance to city center[c]	Distance from a listing to Tsim Sha Tsui East MTR Station (km).	2.99	4.55	0.009	30.70
Distance to shopping center[d]	Distance from a listing to the nearest shopping center (km).	1.18	2.41	0.007	19.40
Distance to tourism attraction[d]	Distance from a listing to the nearest tourism attraction (km).	0.44	0.86	0.002	8.12

Note. [a]Showing greater explanatory power according to Benítez-Aurioles's (2018) specification; [b]showing inconsistent results with hotel in previous studies; [c]other important variables in Airbnb pricing; [d]first examined in this article (under the context of Airbnb pricing).

Analytical Models

To estimate the effects of five groups of explanatory variables on price, the authors employed eight semilogarithm hedonic price models (see Table 5). Hedonic price model was developed by Rosen (1974) to quantify the marginal effects of a product's attributes on price. The original function was written as:

$$P = F(Z, \varepsilon) \tag{1}$$

where P is the observed price of a product, Z is a vector of the product's attributes or utilities, and ε is the standard error.

This study used the semilog form of hedonic price function, which is specified as:

$$\ln P = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{2}$$

where ln$P$ is log form of the observed price of a sample listing, β_0 is the constant term, X_i is the ith explanatory variable, β_t is the semielasticity of P with respect to X_i, and ε is the error term.

According to Wooldridge (2014), in semilogarithm functions, the exact percentage change in y caused by a change in x_i (controlling all other factors) is predicted as:

$$\Delta\hat{y} = \left(e^{\hat{\beta}_i \Delta x_i} - 1\right) \times 100\% \quad (3)$$

Specifically, if $\Delta x_i = 1$, which means x_i changes by one unit, the marginal effect of x_i on y is estimated as:

$$\Delta\hat{y} = \left(e^{\hat{\beta}_i} - 1\right) \times 100\% \quad (4)$$

In Table 4, Model 1 estimates the effect of listing attributes on price using OLS estimation. Model 2 adds variables concerning host attributes. Model 3 adds variables about listing reputation. Model 4 estimates the effect of listing attributes, host attributes, listing reputation, and rental policies in one function. Based on Model 4, Model 5 to Model 8 examine the effect of high listing density, distance to city center, distance to shopping center, and distance to

Table 4
Model Estimation

Category	Price Determinant	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Listing attributes	Entire home	1.561*	1.502*	1.515*	1.502*	1.495*	1.501*	1.503*	1.505*
	Private room	1.010*	1.006*	1.039*	1.024*	1.021*	1.026*	1.026*	1.030*
	Bedrooms	0.164*	0.163*	0.154*	0.155*	0.159*	0.157*	0.156*	0.158*
	Bathrooms	0.073*	0.070*	0.059*	0.063*	0.061*	0.062*	0.062*	0.062*
	Accommodations	0.031*	0.034*	0.043*	0.041*	0.040*	0.041*	0.041*	0.040*
	Breakfast	0.127*	0.100**	0.088**	0.097**	0.109*	0.103**	0.102**	0.105**
	Parking	0.230*	0.184**	0.154**	0.148***	0.171**	0.165***	0.163**	0.193**
	Kid and family friendly	0.030**	0.040*	0.043*	0.043*	0.043*	0.044*	0.043*	0.041*
	Doorman	0.089*	0.087*	0.088*	0.087*	0.082*	0.084*	0.084*	0.084*
Host attributes	Superhost		0.194*	0.197*	0.193*	0.198*	0.197*	0.196*	0.198*
	Host listings		−0.005*	−0.003*	−0.004*	−0.004*	−0.004*	−0.004*	−0.004*
	Host membership months		0.003*	0.004*	0.004*	0.004*	0.004*	0.004*	0.004*
Listing reputation	Number of reviews			−0.002*	−0.002*	−0.002*	−0.002*	−0.002*	−0.002*
	Review score			0.006[a]	0.006*	0.006*	0.006*	0.006*	0.006*
Rental policies	Instant bookable				−0.035**	−0.037**	−0.035**	−0.037**	−0.037**
	Strict cancellation policy				0.046*	0.043*	0.044*	0.044[a]	0.043*
Listing location	High listing density					0.067*			
	Distance to city cenetr						−0.003		
	Distance to shopping center							−0.005	
	Distance to tourism attraction								−0.031*
Constant		4.615*	4.571*	4.057*	4. 043*	3.990*	4.049*	4.045*	4.045*
F		572.36*	495.24*	443.39*	392.55*	369.48*	369.37*	370.37*	371.10*
R^2		0.6116	0.6330	0.6467	0.6482	0.6496	0.6486	0.6485	0.6497
Mean VIR		2.48	2.15	2.04	1.97	1.93	1.93	1.93	1.93
Maximum VIF		6.42	6.44	6.55	6.67	6.67	6.67	6.68	6.68

Note: Heteroskedasticity-robust standard error was used in Model 1 to Model 8.
$*p < 0.01$, $**p < 0.05$, $***p < 0.1$.

tourism attraction, respectively. As these four variables are highly correlated, the authors put them into four different regression functions to avoid biased estimation. Such action can also be found in Rigall-I-Torrent et al. (2011), which examines the effect of various beach characteristics on hotel room rate.

All models in our study performed well. First, they passed the *F* test ($p < 0.001$), which means they are 'linear in parameter' (Wooldridge, 2014) and can be estimated through OLS. Second, the R^2 of the models ranged from 0.6116 to 0.6496, which means more than 60% of variances in ln*P* can be explained by our models. Third, heteroskedasticity robust standard error was used in all models to avoid the concern of heteroskedasticity. Last, there is no multicollinearity, because the maximum VIF of the models are below 10. Data were analyzed in STATA 15.0.

Result

Descriptive Statistics

Table 3 presents the descriptive statistics of variables. The average rental price of Airbnb listings in Hong Kong is 700.66 HKD (*SD* = 653.98). Of all the room types, an entire home accounts for the largest proportion (55%), followed by private room (40%), which means only 5% of our sample listings are shared rooms. An average listing has 1.25 bedrooms (*SD* = 0.79), 1.18 bathrooms (*SD* = 0.61), and accommodates 3.58 people (*SD* = 2.71); 59% listings are suitable for family markets and 42% listings have a doorman. Only 5% of listings offer free breakfast and only 2% offer free parking. "Superhost" badge is owned by 6% of the listings, a minor share of the market. In Hong Kong, a host has 9.25 Airbnb listings on average (*SD* = 13.15) and 68% of hosts own more than one listings. The average month of host membership is 28.33 (*SD* = 16.69); 64% of the listings have a strict cancellation policy and 24% of the listings are instant bookable. The average number of reviews is 20.11 (*SD* = 28.40), and the average rating score is 89.18 (*SD* = 10.36). Most (83%) listings are located in three districts: Yau Tsim Mong (39.36%), Central & Western (26.5%), and Wan Chai (17.04%). The other 15 districts accommodate only 17% of the listings. On average, a listing is 2.99 km from the city center (*SD* = 4.55), 1.18 km from the nearest shopping center (*SD* = 2.41), and 0.44 km from the nearest tourism attraction (*SD* = 0.86).

Model Estimation

Impacts of Listing Attributes. Model 1 illustrates the effect of listing attributes on Airbnb rental price. The rental price of an entire home and a private room is respectively 376.36% ($e^{1.561} - 1$) and 174.56% ($e^{1.010} - 1$), higher than a shared room. An additional bedroom can give rise to Airbnb price by 17.82% ($e^{0.164} - 1$). Providing free car parking accounts for a remarkable contribution of 25.86% ($e^{0.230} - 1$) price increase. Moreover, listings friendly to family market are 3.05% ($e^{0.030} - 1$) more expensive. Listings with a doorman may charge a price premium of 9.31% ($e^{0.091} - 1$). When it comes to breakfast, this study estimates that listings offering free breakfast are 13.54% ($e^{0.127} - 1$) more expensive.

Impacts of Host Attributes. Model 2 presents the effect of host attributes on Airbnb listing price. The most important explanatory variable among host attributes is the badge of "superhost," whose marginal effect on price is 21.41% ($e^{0.194} - 1$). The number of a host's listings has a negative effect on Airbnb listing price. One more host listing cuts down the price by 0.50% ($e^{-0.005} - 1$). This study also examines the effect of host months on Airbnb listing price. Other factors being similar, if a host registered on Airbnb 1 year earlier than his counterparts, the price of his listing is likely to increase by 3.67% ($e^{0.003*12} - 1$).

Impacts of Listing Reputation. Model 3 discusses the impact of listing reputation. The semi-elasticity of review quantity is −0.002, indicating that 10 more customer reviews is associated with a 1.98% ($e^{-0.002*10} - 1$) drop in price. Review score, as expected, has a positive effect on Airbnb listing price. An additional point in rating score is associated with 0.6% ($e^{0.006} - 1$) increase in price.

Impacts of Rental Policies. Model 4 adds another two variables associated with rental policies to the regression function: instant bookable and cancellation policy and requiring guest profile picture. Instant bookable listings are 3.44% ($e^{-0.035} - 1$) cheaper, while strict cancellation policy is associated with a price increase of 4.71% ($e^{0.046} - 1$).

Impacts of Listing Location. According to the OLS estimation in Model 5 to Model 8, distance to city center and shopping center does not significantly affect Airbnb listing price. Being located in high-density districts increases listing price by 6.93% ($e^{0.067} - 1$). Distance to tourism attraction, as expected, is negatively related to Airbnb listing price. It is estimated that 1 km closer to the nearest tourism attraction leads to 3.05% ($e^{-0.031*(-1)} - 1$) increase in Airbnb listing price.

To further analyze the effect of location on different price segmentations, the authors performed a quantile regression on Model 5 to Model 8 and focused on the estimation results of locational factors (see Table 5). Quantile regression suggests that all location variables do not have a statistically significant impact on Airbnb listing price at high (75th and 90th) quantile, underlining that highly priced listings are not sensitive to locational factors. High listing density and closeness to tourism attraction have significant impacts on low and medium price segmentations, with a diminishing rate. Closeness to shopping center only plays significant role in low-price segmentation (10th and 25th quantile). Closeness to city center does not have a significant impact on Airbnb pricing except for the 25th quantile.

Conclusion and Discussion

This article investigates the effects of five categories of variables on Airbnb listing price in Hong Kong: listing attributes, host attributes, listing reputation, rental policies, and listing location. Among the 20 explanatory variables, five of them are firstly examined under the context of Airbnb pricing: kid and family friendly, doorman, host membership months, distance to shopping center, and distance to tourism attraction. According to OLS regression, most of the explanatory variables can significantly predict Airbnb price in Hong Kong.

Findings Consistent With Previous Studies

Several factors have a similar effect with previous findings. Property capacity and functions such as the number of bedrooms, bathrooms, accommodations, and offering free parking are associated with a higher price in various cities (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017), and Hong Kong is no exception. As expected, superhost badge also helps winning a price premium in Hong Kong. With the exception of Chen and Xie's (2017) insignificant finding, most previous studies (Benítez-Aurioles, 2018; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Kakar et al., 2016; Wang & Nicolau, 2017) have estimated a positive relation between superhost and Airbnb price. Instant bookable and flexible cancellation policy negatively influence Airbnb rental price, which is consistent with previous Airbnb studies (Benítez-Aurioles, 2018; Wang & Nicolau, 2017) while drawing a contradictory conclusion with hotels (Latinopoulos, 2018; Masiero, Nicolau, & Law, 2015). The negative link can be explained by both emotional (Wang & Nicolau, 2017) and economic (Benítez-Aurioles, 2018) considerations. In respect to listing reputation, review score, as a signal of listing quality, can positively

Table 5
The Effect of Location on Different Price Quantiles

			Quantiles				
Model	Variable	OLS	10th	25th	50th	75th	90th
5	High density	0.067*	0.144*	0.113*	0.044**	0.026	0.015
6	D-City center	−0.003	−0.003	−0.005*	−0.001	0.001	−0.002
7	D-Shopping center	−0.005	−0.014**	−0.009*	−0.000	−0.000	−0.003
8	D-Tourism attraction	−0.031*	−0.057*	−0.031*	−0.034*	−0.003	−0.022

*$p < 0.01$, **$p < 0.05$.

predict Airbnb price in Hong Kong, which draws similar findings with several other cities (Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017). Number of reviews, on the other hand, is negatively related with Airbnb price in Hong Kong as well as other cities (Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017). The negative coefficient can be explained by the following reason: "review quantity" is an indicator of market demand, and in the peer-to-peer accommodation rental sector like Airbnb there is more demand for the less expensive accommodation.

Findings Different From Previous Studies

Apart from confirming with previous studies, this research also sheds new light on the uniqueness of the Hong Kong market. Table 6 presents the comparison between findings of this research and previous studies. First, the effect of room type on Airbnb price is exceptionally high in Hong Kong. The rental price of an entire home and a private room is respectively 376.36% and 174.56% higher than a shared room. This marginal effect is much higher than Wang and Nicolau's (2017) estimation in 33 cities (144.68% for entire home and 40.76% for private room) as well as all other studies (Benítez-Aurioles, 2018; Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton et al., 2018). (Benítez-Aurioles, 2018; Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018). An additional bedroom and free parking also contribute substantially (17.82% and 25.86%) to Hong Kong Airbnb price. These interesting findings are embedded from the unique land and housing market of our study site. In Hong Kong, the government owns almost all the land in city and imposes severe restrictions on the usage of land (L. Li, Cheung, & Sun, 2015). The transference of land in Hong Kong is through public auction and land buyers only have the rights of occupation and development (Aura, Cheung, & Ni, 2016). Consequently, about 84% of land in Hong Kong is undeveloped

Table 6
Comparison With Previous Findings

Variables	Expected Sign	Result	Comparison with Previous Findings
Listing attributes			The coefficients of room types are exceptionally high compared with previous findings
Room type- entire home	+	+	
Room type- private room	+	+	
Bedrooms	+	+	
Bathrooms	+	+	
Accommodates	+	+	
Breakfast	+	+	
Parking	+	+	
Kid & family friendly	+	+	First examined in this study.
Doorman	+	+	First examined in this study.
Host attributes			
Superhost	+	+	
Host listing count	+	–	Contradictory to previous findings.
Host membership month	+	+	First examined in this study.
Listing reputation			
Review score	+	+	
Number of reviews	–	–	Number of reviews is an indicator for market demand and there is a larger demand for less expensive peer-to-peer accommodations.
Rental policies			
Instant bookable	–	–	The effects of rental policies are consistent with Airbnb studies while contradictory to hotel literature.
Strict cancellation policy	+	+	
Listing location			
High listing density	+	OLS: +	Quantile regression suggests that highly-priced Airbnb listings in Hong Kong (75th and 90th quantile) are not sensitive to locational factors.
Distance to city center	–	OLS: n/a	
Distance to shopping center	–	OLS: n/a	
Distance to tourism attraction	–	OLS: –	

(Aura et al., 2016). Even if considering the terrains hard to develop, there is still a considerable amount of developable public land.

Due to the scarcity of developed urban land resources, as well as the profit taxes and real estate transaction taxes driven from land sales, the housing price of Hong Kong is among the highest in the world. Furthermore, in this heavily populated metropolitan city, the living space per capita is only about 13 m^2, only the half of that in Beijing and Singapore (Aura et al., 2016; L. Li et al., 2015). As a result of the small and squeezing property size, the value of residential property in Hong Kong is calculated based on price per square foot. A research in Hong Kong residential housing market has shown that the unit price of large residential flats is even higher than that of small flats, making large flats substantially more expensive (L. Li et al., 2015), which offers empirical support for our findings. This may be because in Hong Kong, where most working class families can only afford small flats, larger flats are undersupplied and living in a spacious environment is an enjoyment or even "luxury" (L. Li et al., 2015).

The second finding different from previous studies is that hosts' listing count has a negative influence on Airbnb price in Hong Kong. According to OLS estimation, one more host listing cuts down the price by 0.5% in Hong Kong Airbnb market. However, the marginal effect of host listing number to Airbnb price is positive in previous studies. Wang and Nicolau (2017) reported a significantly positive correlation between host listing counts and Airbnb listing price within a database of 33 Western cities. J. Li et al. (2015) also found that the coefficient of host listing counts is positive (though not statistically significant) in relation with listing rent per day. In a database of 10 major US cities, Kwok and Xie (2018) estimated that multilisting hosts position their listings at a higher price than their single-listing counterparts, which further drives listing revenue.

Such inconsistency with previous findings may be attributed to the unique settings in Hong Kong Airbnb market; 68% hosts in our sample have multilistings and a host owns 9.25 listings on average ($SD = 13.15$). This draws a very different picture from previous studies, as Wang and Nicolau (2017) reported an average host listing count of 5.66 ($SD = 27.48$) within a database of 33 cities. In 10 major US cities, 84.31% of hosts only have one listing, according to Kwok and Xie (2018)'s estimation. The large percentage of multilisting hosts in Hong Kong implies a higher proportion of business operation of Airbnb rentals. From an external perspective, higher percentage of multilisting hosts means fiercer competition from professional counterparts. It has been examined in the traditional hospitality industry that greater competition pressure from surrounding hotels of the same quality leads to a fall in room rates (Balaguer & Pernías, 2013). Therefore, the highly competitive market in Hong Kong partially explains the negative influence of listing counts on rental price.

From an internal perspective, hosts' trade-off between listing quantity and listing price may also explain the negative coefficient. According to the algorithm of Airbnb pricing tools such as "Price Tips" and "Smart Pricing," a listing price is correlated with a booking probability on each calendar night. Airbnb also informs hosts of booking opportunity, which will be hurt if the price increases (Ye et al., 2018). To ensure that more listings are rented on each calendar night, professional hosts may reduce the price, especially in such a competitive market as Hong Kong. In this study, the authors find that the review quantity of listings owned by multiproperty hosts ($M = 23.60$, $SD = 30.55$) is significantly larger than those owned by single-listing hosts [$M = 12.70, SD = 21.41; t(2873.65) = -11.923, p < 0.001$]. Since review quantity is an indicator of market demand as well as bookings, it can be assumed that multilisting hosts in Hong Kong lower the price in exchange for occupancy rate. While previous studies reported both higher price and booking rate of professional hosts (Kwok & Xie, 2018; J. Li et al., 2015), these markets are less competitive than Hong Kong, especially among multilisting hosts. Therefore, the interaction between market competition and hosts' trade-off behavior should be considered when setting the "optimal" price on sharing accommodation platforms.

The third finding inconsistent with previous research lies in the effect of listing location. OLS estimation in this study does not show a significant linear effect of distance to city centre or shopping centre in relation to Airbnb rental price. Quantile regression reveals that these two factors only play a role in low-price segmentation. Furthermore, listing density and distance to tourism attractions only show significant effects in low-and medium-price segmentations. In other words, highly priced Airbnb listings in Hong Kong are not sensitive to locational factors (i.e. listing density, distance from city center, shopping center, or tourism attraction). Previous Airbnb studies discovered a negative linear effect of distance from city center (Gibbs, Guttentag, Gretzel, Morton et al., 2018; Wang & Nicolau, 2017; Z. H. Zhang et al., 2017). Research on Hong Kong's residential housing market also reports a negative correlation between housing price and MTR travel minutes to central (Tang & Yiu, 2010).

Although it has been widely agreed that location, especially proximity to city center, is a critical factor determining the value of accommodation products, the heterogeneous effect of locational factors on price is also gaining attention. According to one recent research in Lisbon, Portugal, an increasing number of upper-grade hotels are located further away from city center (Cro & Martins, 2018). In other words, location strategies of upscale hotels do not prioritize accessibility. These hotels exchange the "nightlife" of city center for a safer and quieter environment. On the other hand, only lower grade hotels seek the benefits of agglomeration effects (Cro & Martins, 2018). These recent findings provide empirical support for our study, since only the lower quantiles of Hong Kong Airbnb rentals are sensitive to locational factors. Another possible explanation is the interaction effect between the quality of accommodation products and their accessibility, as suggested by Yang, Mueller, and Croes (2016). When the quality of a hotel reaches an upscale level, the effect of accessibility on its price will diminish. In other words, quality factors are stronger drivers of prices than accessibility, especially for well-established vacation accommodations (Yang et al., 2016).

This study also examines new potential variables predicting Airbnb pricing. Listings that are friendly to kids and family win a price premium. The availability of a doorman, as an indicator for both property quality and security, also positively predicts listing price. Hosts with longer membership months also charge higher prices, which may be because they have more expertise in the operation of peer-to-peer accommodation products.

Limitations and Future Research

This research has various limitations. First, the methodology of this study is nondynamic. It only uses cross-sectional data extracted on a single date. However, Airbnb forecasts the demand curve on a daily basis, taking into account dynamic factors such as listing views, number of available listings in the neighborhood and searches/contacts rates (Ye et al., 2018). Temporal factors such as seasonality (holiday, events, and days within a week) and calendar availability are also concerned (Ye et al., 2018). Due to the inherent weakness of nondynamic hedonic pricing model, this article fails to capture these price determinants. Second, this study fails to consider the human factors that influence the pricing of Airbnb listings. The price model is based on algorithm, which examines the marginal effect of objective factors. Since it is Airbnb hosts who make the final decision on listing price, future studies are encouraged to conduct choice experiments to investigate hosts' price decision-making behavior as well as guests' willingness to pay. Third, this study is still an exploratory one, which examines the impact of numerous variables without focusing on a specific theory or subtopic within the context of Airbnb pricing. Several past studies have focused on a more specific area, such as the "race discrimination" (Kakar et al., 2016) on the pricing of Airbnb, or the difference in pricing strategies between single-listing and multilisting hosts (Kwok & Xie, 2018). Future studies can follow this line of research and examine the effect of more social–psychological features of hosts on sharing economy platforms.

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