Standing out from the crowd – an exploration of signal attributes of Airbnb listings

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Abstract

Purpose – Due to product diversity, traditional quality signals in the hotel industry such as star ratings and brand affiliation do not work well in the accommodation booking process on the sharing economy platform. From a suppliers' perspective, this study aims to apply the signaling theory to the booking of Airbnb listings and explore the influence of quality signals on the odds of an Airbnb listing being booked.

Design/methodology/approach – A binomial logistic model is used to describe the influences of different attributes on the market demand. Because of the large sample size, sequential Bayesian updating method is utilized in hospitality and tourism field for the first attempt.

Findings – Results show that, in addition to host-specific information such as "Superhost" and identity verification, attributes including price, extra charges, region competitiveness and house rules are all effective signals in Airbnb. The signaling impact is more effective for the listings without any review comments.

Originality/value – This study contributes to the literature by incorporating the signaling theory in the analysis of booking probability of Airbnb accommodation. The research findings are valuable to hosts in

improving their booking rates and revenue. In addition, government and industrial management organizations can have more efficient strategy and policy planning.

1. Introduction
Hotels, as the most common type of accommodation that tourists use, have been extensively investigated in an effort to develop the selection criteria of hotels at both the individual level through the consumer behavior perspective (Dolnicar and Otter, 2003) and the aggregate supply-demand perspective (Song *et al.*, 2011). It has been long acknowledged that room and service quality are key determinants to accommodation selection (Chu and Choi, 2000). However, thus quality cannot be experienced before the purchase. Hotels have to release observable and creditable signals to convince the customers regarding the room and service quality (Abrate *et al.*, 2011). Quality of hotels can be indicated by either star rating and brand affiliation which are standardized and reputable (Oskam and Boswijk, 2016), or online review comments on recognized platforms such as TripAdvisor and Booking.com (Möhlmann, 2016). Such signals could significantly reduce the information asymmetry between consumers and suppliers and facilitate the booking of hotels (Abrate *et al.*, 2011; Ponte *et al.*, 2015).

Airbnb provides different experiences compared with traditional hotels to accommodate visitors who seek interactions, home feelings and local authenticity (Guizzardi *et al.*, 2017). Motivated by such needs, Airbnb listings are set to offer heterogeneous experience, which are different from the standardized services provided by traditional hotels. The heterogeneity nature of Airbnb listings calls the effectiveness of the traditional signals of service quality into question. The information asymmetry between guests and hosts in Airbnb is more severe than traditional hotels. Guests have to go through a complicated process to sort out trustable signals from the information uploaded by the hosts on Airbnb platform. From the hosts' perspective, on the other hand, it is also challenging for them to figure out the listing attributes that could be more effective in signaling the service quality, improving the booking probability, and providing a prominent market position among numerous competitors on the same platform.

While there are in-depth insights in terms of quality signals of traditional hotels, no comprehensive picture is provided regarding the impact of quality signals on the listing performance in Airbnb market. This study contributes to the literature by incorporating the signaling theory in the analysis of booking probability of Airbnb accommodation. It provides insights of quality signaling mechanism in the Airbnb market by estimating and examining the influence of various attributes of Airbnb listings on its market demand. The research findings not only enrich the literature of signaling theory in the Airbnb context, but also provide valuable practical implications to current and potential hosts in understanding the demand of their listings and improving their booking rates and revenue. In addition, government and industrial management organizations can have more efficient strategy and policy planning.

2. Literature review
2.1 Asymmetric information and signaling theory
Deviating from the perfect information assumption in economic theories, asymmetric information describes a scenario in economic transactions which one party possesses more

or better information than the other. Asymmetric information leads to imbalance of power in the economic transactions and usually results in market failure (Akerlof, 1970). In the accommodation booking context, if the guests could not obtain quality information of each room, they will offer a price according to the average room quality in the market. Assuming positive correlation between room quality and cost, the offered price is not likely to cover the cost of high-quality rooms. Therefore, high quality rooms will quit the market due to unprofitability and the average room quality in the market will decrease along time. This "bad drives out good" type of problem harms both the guests and the room suppliers due to less and worse options and lower profitability, respectively.

In the above context, where the service and room quality can hardly be revealed before the purchase, guests are usually the ignorant party. They are, therefore, highly motivated to conduct information search to reduce the disadvantage brought about by information asymmetry. While guests aim to reduce information asymmetry through multiple channels, suppliers have also the incentive to signal the quality of their goods and services. According to the signaling theory in economics (Spence, 1973), it is vital for suppliers to convince consumer about the quality of their products. Among others, quality certifications are popular strategies for suppliers to reduce information asymmetry (Chen and Xie, 2017; Nicolau and Sellers, 2010).

2.2 Quality signals in hotel industry

Prior to the emergence of sharing economy, research in the field of tourism accommodation primarily concentrated on revealing the effects and relative importance of various hotel attributes on guests' selection. (Dolnicar and Otter, 2003; Chow et al., 1995; Callan, 1995, 1998). Some of the attributes are observable such as location, access, and facilities including "rooms" in Dolnicar and Otter (2003), "physical appearance" in Chow et al. (1995) and "tangible attributes" in Callan (1995, 1998), whereas some of the attributes are unobservable, such as "image", "services" and "reputation" (Callan, 1995, 1998; Chow et al., 1995; Dolnicar and Otter, 2003). Abrate et al. (2011) argued that the unobserved service quality is usually indicated by quality signals such as star rating and brand affiliation in hotels.

With the widespread usage and the emerging popularity of the internet, customers have more information sources than before, especially through diverse online platforms (Buhalis and O'Connor, 2005). Hotel features that are provided through the internet, such as "terms and conditions" are found to have a significant influence on the online booking intention of customers (Chen et al., 2011; Law and Wong, 2010). Li et al. (2016) and Wang et al. (2015) argue that hotel website quality, including usability, functionality, security and privacy of the website, can predict booking intention.

Online ratings generated by former guests and provided on third party websites are found to be essential to the marketing of hotels. In a study on the hotel sales in Paris and London, Öğüt and Onur Taş (2012) reveal a positive link between hotel sales and the online customer ratings. They also find that managers in higher star hotels can utilize the positive customer ratings and generate more revenue in comparing with the scenario of lower star hotels. Online ratings and comments from previous guests are also found to reflect the reputation of the hotel and mitigate the negative impact of low accessibility in the island tourism context (Yang et al., 2016). As argued by Yang et al. (2016), social media is a quality signal factor and plays a moderating role on the relationship between market accessibility and hotel price. The platform on which the online ratings and comments are published is also important. Ratings are perceived to be more reliable if they are published by well-recognized social media, such as TripAdvisor, or they are linked to actual reservations such as those on Booking.com (Möhlmann, 2016). Casaló et al. (2015) further assert that hotels

generate more favorable attitude if they appear in the best hotels lists in social media. Kim and Park (2017) suggest that social media review ratings have stronger power than traditional attributes to predict hotel performance.

Yang *et al.* (2016) reveal that, benefited from the development of information and communication technology, online review comments have been widely used by guests as quality signals in booking behaviors. Kim and Park (2017) further argue that nowadays, e-word of mouth (e.g. online reviews and review ratings) plays a more important role than traditional customer satisfaction in influencing consumer purchase behavior. Peer to peer review comments are perceived as an important signal in the decision-making process of customers, when they book hotels online (Au *et al.*, 2014; Ladhari and Michaud, 2015; Yu *et al.*, 2016; Zhao *et al.*, 2015). Positive and negative comments have different effects on the decision-making process of customers (Tsao *et al.*, 2015).

2.3 Quality signals in Airbnb

Although quality signals in Airbnb market are investigated by researchers (Chen and Xie, 2017; Dogru and Pekin, 2017; Gibbs *et al.*, 2018; Li *et al.*, 2016; Wang and Nicolau, 2017), it is noticed that most of their studies focus on the impact of quality signals on pricing. Factors including host attributes, property attributes, house rules, review ratings and services and amenities are effective signals used by guests and have significant correlation with price (Li *et al.*, 2016; Wang and Nicolau, 2017). Images of the listing are found to be important signals in determining the booking behaviors of consumers on Airbnb (Dogru and Pekin, 2017). In particular, room pictures (Rahimi *et al.*, 2016) and host photos (Ert *et al.*, 2016) exhibit significant influence on the market demand of the Airbnb listings. In addition to photos, Teubner *et al.* (2017) and Xie and Mao (2017) suggest that a long duration of membership of the host can enhance the trust of guest and play as a signal in pricing. Interestingly, while review rating is generally considered to be a signal that is positively correlated with quality, Gibbs *et al.* (2018) find a negative but marginal association between number of reviews and room price.

It is undeniable that the abovementioned studies contribute to the understanding of Airbnb phenomenon. However, the results should be considered with cautions. According to signaling theory, price itself is also an effective signal influencing the behavior of the consumer (Wolinsky, 1983, p.647). The impact of price as a signal and the relationship between quality signals and listing behaviors in Airbnb sector have been overlooked. Therefore, it is important to retailor the signaling theory and explore the effective quality signals in the Airbnb context.

2.4 Research gaps

As a market pioneer in peer-to-peer accommodation service, the Airbnb hosts are encouraged to make guests feel at home and bond with the local environment. Compared with the standard service provided by hotels, room settings and services of Airbnb are different from listing to listing. This feature leads to significant heterogeneity in terms of the quality of the listings. The quality signals used by guests in hotel sector may be neither appropriate nor efficient, because in Airbnb market, the options for guests are much more than those provided in the hotel market (Chen and Xie, 2017; Gutt and Herrmann, 2015). Thus, the potential guests are utilizing different quality signals to identify the good listings.

Throughout the literature of online booking of both hotels and Airbnb, the existence of information asymmetry is well recognized. Online reviews and ratings from peer-guests are popular signals through which guests predict products or services quality in both hotel and Airbnb markets (Senecal and Nantel, 2004; Yang *et al.*, 2016). Abrate *et al.* (2011), and Henley

et al. (2004) show that star ratings and brand affiliations are frequently used by guests as quality signals for hotel room booking. However, such signals do not exist on the Airbnb platform. As noticed by Gutt and Herrmann (2015), with the peer-to-peer nature of the Airbnb platform and the heterogeneous guest groups, the determinants of Airbnb booking probabilities differ from those of traditional hotels.

To bridge the gaps, a comprehensive list of Airbnb listing attributes is examined to explore their influence on the booking probability of Airbnb listings. In particular, the attributes are analyzed on their ability of indicating room and service quality of Airbnb listings. According to different level of information asymmetry, the sampled listings are differentiated into two subgroups, namely "with review" group and "no review" group. The impacts of listing attributes are discussed and compared accordingly within and between two subgroups. Methodologically, to handle the big volume of data, the current study represents the first attempt of using sequential Bayesian updating approach in hospitality and tourism field.

3. Methodology
3.1 Data
The data of Airbnb listings in London are retrieved from Insideairbnb.com. After removing redundant and irrelevant variables, the pairwise correlations among all variable-pairs were checked. Variable-pairs were either combined or have one variable omitted if they have similar meaning and exhibit high correlation. The latitude and longitude coordinates of listings are used to calculate the distance from the listing to the city center and to the nearest tube station. The two calculated variables capture the location of the listings and the convenience of the listings, respectively. In order to capture the spatial spillover effect, the total number of neighboring listings and the number of available neighboring listings are calculated, for each listing, every calendar day. A distance of 5 km is adopted as the criteria for two listings to be identified as neighbors (Yang *et al.*, 2012). The neighboring variables not only capture the popularity of the region but also the potential competition within in the region. Thirty-four variables are eventually considered as the attributes that influence the booking probabilities of Airbnb listings. Differentiated by their ability on signaling the quality, the 34 attributes were labeled as functional attributes, signal attributes, or dual attributes. The categorization is inspired by the classifications used in marketing literature (Jacoby *et al.*, 1971; Kostyra *et al.*, 2016). Functional attributes include the features of Airbnb listings that are directly consumed by the guests or directly related to the consumption process. Signal attributes are provided by the hosts or the platform as quality or value indicators. Dual attributes are listing attributes that exhibit features of both functional attributes and signal attributes. The labeling of the listing attributes is further validated by a Delphi survey with five academic professionals and three current Airbnb hosts. After three rounds of anonymous surveys, eight experts achieved agreement regarding the categorization of the attributes. The final categorization is presented in Figure 1.

In the retrieved dataset, listings with unreasonable length of availability (e.g. fully booked for the next 365 days) and with incomplete information were omitted. Although the booking information of 365 days in advance could be accessed, the data pointed further from the current time (i.e. the time of data retrieval) contained limited information on the market demand. Since most people are concerned about room reservation around 30 days prior to the stays (Chen and Schwartz, 2008), the current research used up to 31-day-ahead booking information as the sample period. The final dataset contains booking information of 41,124 listings from 5 March 2017 to 4 April 2017 (31 days), resulting in a panel dataset with 1,274,844 observations (41,124 listings × 31 days).

Listing Attributes

Functional attributes

- Instant reservation
- Refund policy
- Guest verification required

Ease of booking

- Distance to the nearest Tube station
- Distance to city center

Location

- Number of bedrooms
- Number of bed per bedroom
- Bathroom per guest
- Number of amenties
- With internet
- With kitchen
- Atmosphere setting
- Property type
- Room type
- Bed type

Property/room function

Dual attributes

- Price per night per guest
- Security deposit
- Cleaning fee
- Fee for extra person
- Weekly discount
- Monthly discount

Price

Signal attributes

- Superhost
- Host with verified ID

Platform signal

- House rules
- Property description
- Description about space
- Number of listing pictures
- Host profile

Host signal

- Number of neighboring listings
- Available neighboring listings

Market signal

- Number of reviews
- Total rating score
- Reviews per month
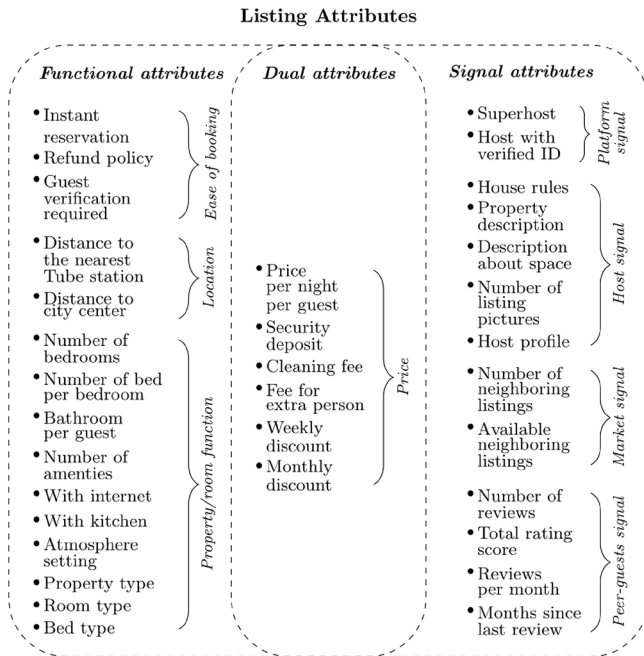- Months since last review

Peer-guests signal

Figure 1.
Labels of listing
attributes

Online reviews play as a key signal in the booking process of guests (Yu *et al.*, 2016; Zhao *et al.*, 2015). Attributes other than online reviews may influence the market demand differently with or without the presence of review information. The sample was divided further into two subsamples, while estimating the influence of various attributes on the market demand. The first subsample, namely the "with review" group, contained 30,112 listings that had at least one review in the past. The second subsample, namely the "no review" group, contained 11,012 listings that had no review in the online system. The estimation of the two subsamples was conducted separately, as the model of "with review" group had four extra review-related variables (i.e. total number of the reviews, total score of the reviews, number of reviews per month, and months since previous review). The descriptive statistics of the two subsamples are provided in the Appendices.

3.2 Binomial logistic model
A binomial logistic model is specified to characterize the influence of listing attributes on the market demand. The market demand of an Airbnb listing is measured by the probability of the listing being booked. The equation (1) describes the probability of observed data given a parameter vector:

$$p(y_{i,t} = 1, \boldsymbol{x_{i,t}}|c_t, \boldsymbol{\beta}) = \frac{\exp\left\{c_t + \boldsymbol{x'_{i,t}}\boldsymbol{\beta}\right\}}{1 + \exp\left\{c_t + \boldsymbol{x'_{i,t}}\boldsymbol{\beta}\right\}}, \tag{1}$$

where $y_{i,t}$ indicates the booking status of listing i on date t, which is equal to one if listing i is booked on date t and zero otherwise; $\boldsymbol{x_{i,t}}$ is a vector of attributes of listing i observed on date t; c_t is a time-varying constant that captures the time effect on booking probability of Airbnb

listings; and $\boldsymbol{\beta}$ is a vector of coefficients evaluating the relative importance of various attributes of the listings on booking probability.

A likelihood function can, therefore, be written as:

$$\ell\big(c_t, \boldsymbol{\beta}|y_{i,t}, \boldsymbol{x_{i,t}}\big) = \prod_t \prod_i p\big(y_{i,t} = 1, \boldsymbol{x_{i,t}}|c_t, \boldsymbol{\beta}\big)^{y_{i,t}} \ \big[1 - p\big(y_{i,t} = 1, \boldsymbol{x_{i,t}}|c_t, \boldsymbol{\beta}\big)\big]^{1-y_{i,t}}.$$

(2)

With observed data $(y_{i,t}, \boldsymbol{x_{i,t}})$, the likelihood function can be maximized relative to the unknown parameter vector c_t and $\boldsymbol{\beta}$.

3.3 Sequential Bayesian updating

In the current study, Bayesian approach is utilized to handle the large volume of data. One of the challenges in managing large volume of data is the difficulty in data storage and computation. In frequentist statistics, model estimation is statistical inference process from the sample (data) to the population (reality), and the data are commonly examined all together at once. The storage and computational burdens on computers increase exponentially as the volume of the data increases. In contrast, Bayesian statistics consider model estimation as an updating process of prior beliefs based on observed data. The "updating" concept makes Bayesian statistics very handy in handling large dataset. The data can be partitioned into manageable subsets and the updating process can be conducted sequentially.

In Bayesian statistics, prior distribution is described as the current state of knowledge regarding parameters and posterior distribution is the updated belief on parameter values after observing some data. Therefore, after estimation and when new data become available, the estimated posterior distribution can be regarded as a new prior distribution. A new posterior distribution can be generated with the new data. Crucially, while estimating the new posterior distribution, the calculation of likelihood using old data would not be necessary because information regarding the old data is contained sufficiently in the previous posterior distribution. Through sequential Bayesian updating, the large dataset can be partitioned into several smaller and manageable subsets. The model fitting can be performed sequentially, using the posterior distribution of each subset as the prior distribution for the next subset. Some theoretical discussions and examples on sequential Bayesian updating can be found in Oravecz *et al.* (2016).

In the current study, the entire dataset is partitioned according to time, with each subset consists of the booking information of one calendar day. For each subset, following the classical Bayesian presentation, the posterior distribution of parameter is proportional to the product of the likelihood function, $\ell(c_t, \boldsymbol{\beta} | y_{i,t}, \boldsymbol{x_{i,t}})$ and the prior distribution, $p(c_t, \boldsymbol{\beta})$:

$$p\big(c_t, \boldsymbol{\beta}|y_{i,t}, \boldsymbol{x_{i,t}}\big) \propto \ell\big(c_t, \boldsymbol{\beta}|y_{i,t}, \boldsymbol{x_{i,t}}\big) p(c_t, \boldsymbol{\beta}).$$

(3)

The prior distribution in equation (3) is sampled using Markov chain Monte Carlo (MCMC) methods, in particular the *Metropolis-Hastings* algorithm. Uninformative prior (mean = 0, standard deviation = 100) is used in the estimation of the first subset and informative prior equal to the previous posterior is adopted subsequently. Updating of the posterior distributions of the parameters does not involve c_t. The series representing the time-specific constant, $\{c_t, c_{t+1}, \ldots\}$, is estimated successively using data from each subset with uninformative prior.

4. Findings and discussions

4.1 The general estimation results

Model predictions are generated for both the "with review" and the "no review" groups and presented in Figure 2. The proportion of the listings being booked is adopted as the actual booking rate for each group. Predictions are generated by logit function using the means of posterior distribution of the parameters. The mean absolute percentage error (MAPE), which is the most widely used measurement of forecasting error in the tourism and hospitality field (Wu *et al.*, 2017), is employed to evaluate the predictability of the models. The predictions for the "with review" group are very accurate with a MAPE of 2.84 per cent. The predictions for the "no review" group are slightly worse than its counterpart with a MAPE of 9.60 per cent. Both models show accurate predictability (with MAPE below 10 per cent), indicating the good explanatory power of the models employed. Without the information from the review comments, the "no review" group exhibit higher degree of information asymmetry. Increased randomness is therefore revealed in the booking process in thus group, and further leads to the lower prediction accuracy in the "no review" group. The longer the distance between the intended check-in data and the data observation date, the more uncertain it would appear. Consequently, predictions for both groups are slightly worse in the last two weeks than in the first two weeks.

As also revealed by Figure 2, the online reviews exhibit significant influence on the market demand of Airbnb listings. In general, an average listing with online reviews has a 15 per cent to 20 per cent higher probability of being booked than the listings with similar attributes but without online review. Since online review is frequently used by guests in evaluating the quality of the listings, the degree of information asymmetry is lower in the "with review" market segment than the "no review" counterpart. As a result, the guests would be more confident on the listing quality while booking a listing with online reviews.

Time constant, c_t, captures the pattern of listings' booking probability along time. Figure 3 shows the trend of the mean value of the series $\{c_t, c_{t+1}, \ldots\}$ for two subsamples with the shaded area representing the 99.5 per cent high density interval (HDI). For both subsamples, the series $\{c_t, c_{t+1}, \ldots\}$ decreases along time with significant spikes during weekends. This trend reveals the likelihood of a listing being booked decreases as the intended check-in date moves away from the data observation date. This phenomenon is most obvious within the first week away from the date of observation. The likelihood of a listing being booked is significantly higher during weekends in contrast to those during weekdays, which reveals a significant weekly seasonality in Airbnb booking.
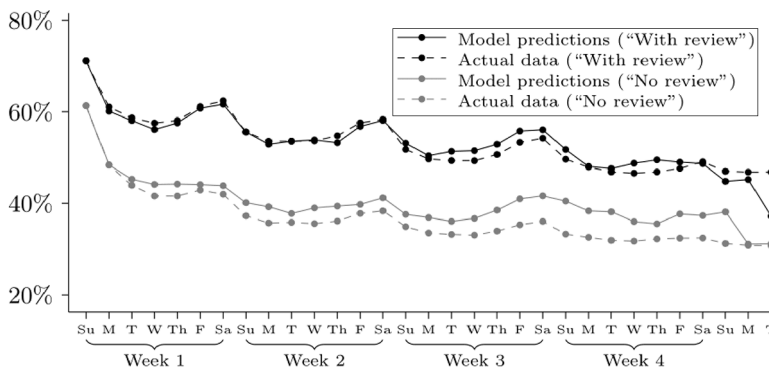

Figure 2.
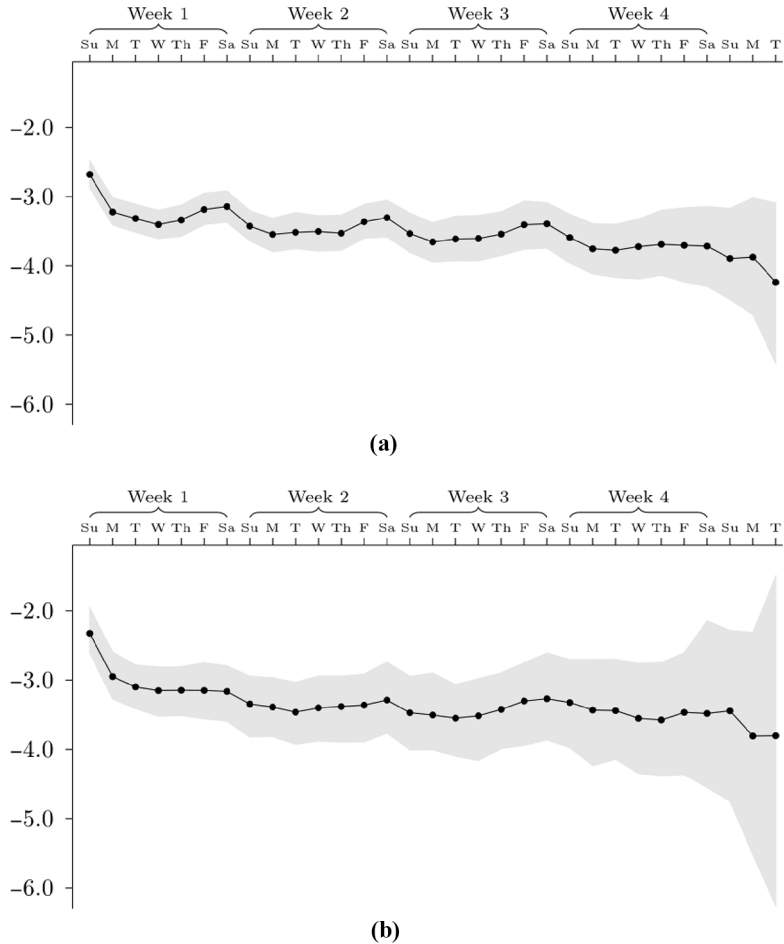Model predictions of booking probability

Figure 3.
The mean estimation
of time effect

Notes: (a) Time effect of "With review" group; (b) time effect of "No review"
group

4.2 The influencing attributes of booking probability

Tables I summarizes the posterior distribution of the parameters of functional attributes and
Table II presents the same information for signal and dual attributes. The first column
describes the attributes and the second to fifth columns present the estimation results of the
"with review" group, where the mean and 99.5 per cent HDI of posterior distributions are
provided in columns 2 to 4. The fifth column shows the change in odds, assuming other
attributes remain fixed. An attribute is considered to have significant influence on booking
probability if the associated 99.5 per cent HDI excludes zero. Columns 6 to 9 present these
results of the "no review" group. The tenth column ($p \neq$) provides the credibility of the two
posterior distributions of the "with review" group and the "no review" group being different.
The calculation of this credibility largely follows Kruschke (2013) and the results are

Description	"With review" group			"No review" group			
	Mean	99.5% HDI	ΔOdds (%)	Mean	99.5% HDI	ΔOdds (%)	$p(\neq)$ (%)
Property/room function							
Number of bedrooms	0.0212	(0.0120, 0.0298)	2.14	0.0297	(0.0177, 0.0401)	3.01	94.20
Number of bed per bedroom	−0.0810	(−0.0931, −0.0708)	−7.78	−0.0729	(−0.0937, −0.0555)	−7.03	83.60
Bathroom per guest	0.2527	(0.2327, 0.2729)	28.75	0.0201	(−0.0113, 0.0605)	2.03	99.90
Number of Amenities	0.0063	(0.0048, 0.0078)	0.64	0.0109	(0.0081, 0.0131)	1.10	99.90
With internet (Dummy)	0.1372	(0.1073, 0.1657)	14.71	0.3327	(0.2903, 0.3795)	39.48	99.90
With kitchen (Dummy)	0.3143	(0.2884, 0.3441)	36.93	0.3040	(0.2633, 0.3487)	35.53	72.30
Property function (Group of dummies)							
None (Benchmark)							
Family	0.1565	(0.1356, 0.1799)	16.94	0.3222	(0.2414 0.3679)	38.02	99.90
Business	−0.1120	(−0.1193, −0.1082)	−10.60	0.1000	(0.0221, 0.1638)	10.52	99.90
Romantic	−0.0351	(−0.0891, 0.0217)	−3.45	0.4388	(0.1861, 0.6717)	55.08	99.90
Social	−0.0284	(−0.0333, −0.0271)	−2.80	−1.1982	(−1.3263, −1.0642)	−69.82	99.90
Property type (Group of dummies)							
Others (Benchmark)							
Apartment	−0.0349	(−0.0731, 0.0024)	−3.43	0.0801	(0.0057, 0.1580)	8.34	99.90
House and townhouse	0.0351	(−0.0071, 0.0790)	3.57	0.2454	(0.1724, 0.3232)	27.82	99.90
Bed and Breakfast	−0.2160	(−0.2771, −0.1659)	−19.43	−0.2057	(−0.3143, −0.0942)	−18.60	59.50
Room type (Group of dummies)							
Shared room (Benchmark)							
Private room	0.4723	(0.4197, 0.5253)	60.37	0.4051	(0.3109, 0.4844)	49.94	96.30
Entire property	1.3915	(1.3407, 1.4429)	302.09	1.3387	(1.2484, 1.4157)	281.42	92.30
Bed type (Group of dummies)							
Others (Benchmark)							
Couch	−0.1699	(−0.3038, −0.0237)	−15.63	−0.8158	(−1.2296, −0.3412)	−55.77	99.90
Pull-out sofa/real bed	0.2224	(0.1440, 0.2988)	24.90	0.6125	(0.4331, 0.7991)	84.51	99.90
Location							
Distance to the nearest Tube station (1 km)	−0.0554	(−0.0681, −0.0445)	−5.39	−0.1163	(−0.1331, −0.0982)	−10.98	99.90
Distance to city center (1 km)	−0.0702	(−0.0721, −0.0685)	−6.78	−0.0641	(−0.0668, −0.0612)	−6.20	99.90

(continued)

Table I.
Summary of the estimation results (functional attributes)

| Description | "With review" group | | | "No review" group | | | |
	Mean	99.5% HDI	ΔOdds (%)	Mean	99.5% HDI	ΔOdds (%)	$p(\neq)$ (%)
Ease of booking							
Instant reservation (Dummy)	0.2173	(0.2053, 0.2318)	24.27	0.4180	(0.3970, 0.4433)	51.89	99.90
Refund policy (Dummy)	0.0457	(0.0345, 0.0595)	4.68	0.0972	(0.0803, 0.1186)	10.21	99.90
Guest verification required (Dummy)	−0.0479	(−0.0763, −0.0175)	−4.67	−0.0366	(−0.1003, 0.0197)	−3.59	68.90

Table I.

Description	"With review" group Mean	99.5% HDI	ΔOdds (%)	"No review" group Mean	99.5% HDI	ΔOdds (%)	$p(\neq)$ (%)
Price signal							
Price per person per night (£10)	−0.1499	(−0.1544, −0.1461)	−13.92	−0.0344	(−0.0385, −0.0308)	−3.38	99.90
Security deposit (£10)	−0.0026	(−0.0032, −0.0021)	−0.26	−0.0004	(−0.0012, 0.0003)	−0.04	99.90
Cleaning fee (£10)	−0.0162	(−0.0191, −0.0133)	−1.60	0.0044	(0.0012, 0.0075)	0.44	99.90
Fee for extra person (£10)	−0.0907	(−0.0956, −0.0855)	−8.67	−0.1111	(−0.1234, −0.1074)	−10.52	99.90
Weekly discount (Dummy)	0.1093	(0.0906, 0.1277)	11.55	−0.0883	(−0.1444, −0.0316)	−8.45	99.90
Monthly discount (Dummy)	0.1229	(0.1049, 0.1407)	13.08	0.4340	(−0.0132, 0.1114)	4.44	99.90
Market signal							
Number of neighboring listings (100)	0.0049	(0.0030, 0.0070)	0.49	0.0253	(0.0213, 0.0290)	2.56	99.90
Available neighboring listings (100)	−0.0088	(−0.0120, −0.0057)	−0.88	−0.0464	(−0.0526, −0.0398)	−4.54	99.90
Host provided signal							
House rules (100 words)	−0.1024	(−0.1145, −0.0907)	−9.73	0.0717	(0.0440, 0.0970)	7.43	99.90
Property description (100 words)	0.0176	(0.0133, 0.0213)	1.77	0.1232	(0.1164, 0.1319)	13.11	99.90
Description about space (Dummy)	0.0477	(0.0337, 0.0621)	4.88	0.0103	(−0.0184, 0.0377)	1.03	99.90
Number of listings pictures (Dummy)	0.1437	(0.1378, 0.1484)	15.46	0.2210	(0.2118, 0.2296)	24.73	99.90
Host profile (Dummy)	0.3157	(0.2031, 0.4342)	37.12	0.3681	(0.2451, 0.4722)	44.50	81.20
Platform provided signal							
Superhost (Dummy)	0.1073	(0.0866, 0.1255)	11.33	0.4073	(0.3473, 0.4858)	50.28	99.90
Host with verified ID (Dummy)	0.1231	(0.1132, 0.1345)	13.10	0.2109	(0.1920, 0.2282)	23.48	99.90
Peer−guests provided signal							
Number of reviews	0.0014	(0.0011, 0.0017)	0.14				
Total rating score	0.0193	(0.0187, 0.0199)	1.95				
Review per month	0.1173	(0.1117, 0.1227)	12.45				
Months since last review	−0.0120	(−0.0150, −0.0119)	−1.21				

Table II.
Summary of the estimation results (signal attributes)

discussed in terms of the change in odds. In statistics, the odds of an event reflect the likelihood that the event will take place. In the current context, the odds of a listing being booked are calculated by the ratio between the probability of the listing being booked and the probability of the listing being available. For continuous variables, the change in odds reflects the percentage change in the odds of a listing being booked when the independent variable changes by one unit. For dummy variables, it reflects the change in odds when the listing moves into a certain category (from the benchmark category in the case of group of dummy variables).

4.2.1 Functional attributes. Since accommodation is the primary product of Airbnb listings, property/room functionality is the area that has the most attributes. In general, large properties with more bedrooms and amenities are more popular. Each additional bedroom would boost up the booking odds for the "with review" listings by 2.14 per cent and for the "no review" listings by 3.01 per cent. Internet connection and kitchen could enhance the booking odds by 14.71 per cent and 36.93 per cent, respectively for the "with review" listings, and 39.48 per cent and 35.53 per cent, respectively for the "no review" listings. The dramatic change of odds led by internet connection indicates that the internet has become a necessity in our daily life. It is also reasonable that listing with kitchen attract more bookings, as cooking activity is a distinguished feature of Airbnb, which most hotel rooms cannot accommodate. Not every item provided by the hosts exhibit "the more is better" rule, an extra bed per bedroom makes the room crowded and less desirable. While social interaction is considered as a key motivation for tourist to use peer-to-peer accommodations (Lin *et al.*, 2019; Tussyadiah and Pesonen, 2015), the current study found that privacy is still an important feature for Airbnb listings. In comparison with shared rooms, listings with a private room are preferred with additional odds of 60.37 per cent and 49.94 per cent for the two groups. Listings of entire property are preferred with additional odds of 302.09 per cent and 281.42 per cent for the two groups. That is, the host should always consider privacy while providing social interactive features in the property. A "social interaction" area should be appropriately separated from the bedrooms. Additional and private bathrooms are also favored (with additional odds of 28.75 per cent for the "with review" listings and 2.03 per cent for the "no review" listings), indicating a preference towards more private facilities. Listings with themes are more popular than the ones without themes. In particular, the theme of "family" is the most preferable. This result is not surprising as "Welcome Home" has long been a motto of Airbnb. Regarding the property type, houses and townhouses are more prominent in the market with additional odds of 3.57 per cent and 27.82 per cent for the two groups, whereas bed and breakfast accommodation are significantly disliked as they are not really in the style of Airbnb. When guests select listings, the ones with real beds are more likely to be booked than the ones with merely couches. This indicates a general desire on the basic living quality from the guests.

Geographical location of the listing is another crucial attribute. The location of accommodation can be generally related to the neighborhood environment, neighborhood convenience, and accessibility (Masiero *et al.*, 2019). The location convenience of the listing could facilitate booking of the listing. Taking London as an example, 1 km away from the tube station will lead to a decline of the booking odds by 5.39 per cent and 10.98 per cent for the two groups. Whereas, 1 km away from the city center of London will decrease the booking odds by 6.78 per cent and 6.20 per cent for the two groups. For a metropolitan such as London, the city center could be crowded and noisy. However, for Airbnb guests, living in the city center and close to tube station means excellent neighborhood convenience and accessibility. These benefits would provide the guests with a flexible schedule, which enhances the traveling experience. The ease of the booking process also affects the odds of a

listing being booked. A listing with instant booking policy could stimulate the booking odds by 24.27 per cent and 51.89 per cent for the "with review" listings and "no review" listings, respectively, in comparing with that of the listings without instant booking. Listings that need guest verification, either by ID or by phone, have the odds 4.67 per cent and 3.59 per cent lower than the listings without verification requirement. Flexible refund policy is also found to be well-received in the market for both groups.

The attributes discussed above describe one or more aspects of the Airbnb listings that are directly related to the consumption process of the guests. Judging by the credible level provided in the tenth column of Table I, it can be confidently concluded that the influence of each attribute on market demand for the "with review" listings are different from that for the "no review" listings. In terms of the direction of the influence, heterogeneity can be observed in a few attributes that are related to property function or theme. For the listings without any review, having a theme is generally considered as a benefit, whereas only the "family" type is preferred in the case of "with review" group. On average, the functional attributes for the "no review" group have 15.46 per cent larger marginal effects than those for the "with review" group. This observation can be well explained by the redistribution of attention: with the absence of online review, the guests would pay more attention to the attributes they have information on.

4.2.2 Dual attributes and signal attributes. While price is an essential attribute which is directly related to the consumption process of guests, it also exhibits strong signal effect in the information asymmetry scenario. Similar to other commodities, price is an important attribute that determines the sales of listings. A ten Pounds (£10) decrease in the price per night per capita would increase the booking odds by 13.92 per cent and 3.38 per cent for the listings with and without online reviews, respectively. Compared with the "with review" group, the price sensitivity of the "no review" group is lower. While the market demand is negatively correlated with price in the classical economic theory, the strong price signaling effects for the "no review" group weakens the correlation. With the price considered as a signal on quality, the price increases for the "no review" group may not be a bad thing after all. Without any reviews in the online system, discounts on price would be a relatively ineffective marketing tool. While the discount on price provides the guests with economic benefits, it may also "discount" the confidence of the guests. For example, the weekly discounts provided by "no review" listings decrease the booking odds by 8.45 per cent, whereas the weekly discounts of "with review" listings have a significantly different effect, increasing the odds by 11.55 per cent. Extra charges, such as cleaning fees, fees for extra person, and security deposit generally keep the listing from being booked. Interestingly, extra charges on the cleaning fees could increase the booking odds for listings without review. This "counter-intuitive" result may be attributed to the scenario in which no accurate information could be retrieved from online reviews. Hence the charges on cleaning fees are used by guests as a strong signal on the cleanliness of the listing.

Some signal can be released through the market attributes. Regarding the total number of neighboring listings, every additional 100 neighbors would bring up the odds of the listing being booked by 0.49 per cent and 2.56 per cent for the two groups. This finding reflects the positive effect of the popularity of the region on booking probability. In terms of the number of available neighboring listings, the competition brought by others weaken the odds of a listing being booked (-0.88 per cent and -4.54 per cent for the two groups). These two regional attributes have significantly stronger influence for the "no review" listings, emphasizing the signaling effects of regional popularity and market competition in that group. More precisely, a large number of listings within the region would deliver a message to the guests that the region is popular among the peer-guests due to some regional traits

(e.g. popular attractions, safe neighborhoods, or convenience transportation). Nonetheless, the available neighboring listings provide more options to the guests and also put the "no review" listings in an unfavorable position.

The Airbnb platform also allows hosts to post descriptions from different aspects to signal the quality of their listings. For listings with reviews, detailed description of the listings in terms of texts and pictures may enhance the booking odds by 1.77 per cent and 15.46 per cent, respectively, whereas the complication of house rules may decrease the booking odds by 9.73 per cent. In particular, the odds of the listing being booked for those with detailed description on the space are 4.88 per cent higher than that of the listing without such descriptions. In the case of "no review" group, any additional information guests could retrieve from the website, including house rules, would be beneficial for the booking odds (7.43 per cent, 13.11 per cent, 24.73 per cent for house rules, property description, and number of listing pictures, respectively). Without review information in the online system, guests are more likely to rely on information uploaded by hosts in the decision-making process. The detailed description provided by the host not only informs the guest regarding the functionality of the listing but also conveys the signal on how well and careful the host manages the property.

Similar to star ratings for hotels and *Michelin* stars for restaurants, the Airbnb platform honors good hosts with the "Superhost" title. Being a "Superhost", as suggested by Liang *et al.* (2017), has a very strong effect on the odds of the listings being booked. For the "with review" group, holding all other attributes fixed, the odds of being booked for a listing by a "Superhost" would be 11.33 per cent higher than that of properties listed by normal hosts. In the case of the "no review" group, the "Superhost" title would come from other properties that are listed by the host (hosts with multiple listings). The "Superhost" title would boost up the odds of the listing being booked by 50.28 per cent in such a case. In addition, detailed hosts' profile would enhance the odds by 37.12 per cent and 44.50 per cent for the "with review" group and "no review" group, respectively. If the identity of the host is verified, the odds of the listing being booked would increase by 13.10 per cent and 23.48 per cent for the two groups.

Consistent with the scenario in the hotel industry, online reviews are also valuable information that enhance the market demand of a listing. In the "with review" group, one additional review could boost up the booking odds by 0.14 per cent. The total rating of reviews, the frequency of reviews, and timeliness of the reviews further enhance this effect of word of mouth (1.95 per cent, 12.45 per cent, and 1.21 per cent, respectively). A peer-to-peer review system is applied by Airbnb which incentivizes hosts and guests to give positive reviews to each other (Zervas *et al.*, 2015). Keeping this system in mind, the quantity of the reviews is less influential than the actual contents of the reviews. This fact explains the limited effect of the number of reviews and relatively higher influence of other review-related factors on the booking odds of Airbnb listings found in the current study. The frequency of the reviews also indicates the popularity of the listing and thus has a more important position in the decision-making process of guests than other review-related factors.

Confirmed by the credible level in the tenth column of Table II, the signal attributes reveal different influences on market demand for the "with review" group and the "no review" group. Price attributes, which can be labeled with both "functional" and "signal", have dual function in influencing the market demand. On one hand, as functional attributes, according to classical economic theory, an increase in price would discourage demand and a discount would do the opposite. On the other hand, however, the price signaling effect suggests a positive correlation between price and the perceived quality. The increase in

price would lead to an increase in the perceived quality and then an increase in the market demand. In the current case of London, the information asymmetry is more severe in the case of "no review" group than that of the "with review" group. Therefore, it is more obvious in the "no review" group that the stronger price signaling effect offsets the negative correlation between price and market demand. On average, the price attributes of the "no review" group have 84.52 per cent smaller marginal effect than those of the "with review" group. Furthermore, signaling effects of the cleaning fee and weekly discount are so strong that the originally negative correlation between price and market demand is reversed.

In terms of other signal attributes, the signaling effect would enhance the marginal effect of the attributes. In particular, more text description of the property for the "no review" listings have a 639.53 per cent larger marginal effect in comparing with the case of "with review" listings. The "Superhost" title is 343.70 per cent more valuable for the listings without any online review than for the listings with online review. On average, the signal attributes for the "no review" group have 191.99 per cent larger marginal effects than those for the "with review" group. This number is far larger than the boost in the case of functional attributes (15.46 per cent). This comparison reveals the significant role of signal attributes for the "no review" listings.

5. Implications and conclusions

5.1 Conclusions

From a suppliers' perspective, the current study explores the signaling theory in the context of Airbnb booking probability by investigating the influence of listing attributes on the market demand of Airbnb listings in London. Binomial logistic model and sequential Bayesian updating approach are utilized in the analysis. For the 41,127 listed properties considered in the current study, daily booking data starting from 5 March 2017 up to 31 days ahead bookings are used to estimate the model. The findings of the current study show that, in addition to the functional attributes such as room functions and listing locations, signal attributes which are designated to indicate the quality of the listings are found to be important, especially for the listings without online review. The findings confirm previous literature (Liang *et al.*, 2017; Xie and Mao, 2017) in the sense that information on the hosts are found to be important quality signals, including the "Superhost" title, hosts' profile, and verification status. In addition, price of the listings, extra charges (such as cleaning fees), regional competitiveness and popularity, and house rules also emerge as important signals that indicate the quality of the listings and influence the booking probability. In general, comparing with other types of listings, an entire house/ townhouse with real beds, more bedrooms, bathrooms, and amenities, particularly with internet and kitchen, is more likely to be booked by guests. Geographical factors, such as regional competition, regional popularity, and geographical convenience also make the listing stand out from the crowd.

5.2 Theoretical implications

The originality of the study is the exploration of quality signals in Airbnb context which is also an expansion of the signaling theory applications. Although the signal effect has been brought up by previous literature (Chen and Xie, 2017; Li *et al.*, 2016), the current study further examines it from a more comprehensive perspective. A distinctive group of signal attributes is explicitly identified and discussed. In absence of online reviews, which is a major information source for the guests, signal attributes are found to be critical for attracting market demand for Airbnb listings. However, the importance of signal attributes depreciates when the number of reviews accumulates. A decremental margin of 191.99 per

cent is observed on average for the signal attributes, once the listings move from the "no review" group into the "with review" group. Under the circumstances, guests retrieve information from online reviews and pay less attention to the signals. In contrast, the depreciation in the marginal effect is much less for the attributes that are actually consumed by the guests. A decremental margin of 15.46 per cent is found on average for the functional attributes for the listings which move from the "no review" group into the "with review" group. The estimation of time effect also consolidates the "weekly seasonality" feature of the property booking in the Airbnb industry. Methodologically, the sequential Bayesian updating approach, which is very convenient for the rich data feature of the sharing economy literature, is introduced into the hospitality literature for the first time.

5.3 Practical implications

Managerial implications also emerge from these research findings. Strategically Airbnb entries need to provide the sense of safety and security that consumer expect from accommodation establishments. They also need to demonstrate that they have large space and provide differentiated experiences, often enabling guests to stay like a local. Therefore, hosts should upload more information regarding the property and boost the popularity of the listing. Information should be provided for both the property and the context/location of the property demonstrating the attractiveness of the proposition. This is for listings currently without review information and also for new properties or for those off the bitter track. When the listing is initiated without any online review, the host should work on signal attributes to reduce information asymmetry. Visual information in terms of photographs, links and other clues can reduce the perceived uncertainty and enhance consumer confidence. This is critical as in the hospitality alternatives consumers can trust brand name propositions and standards, such as Hilton, Marriott, or Jumeirah. Airbnb properties rely almost exclusively on near real time descriptions to support (Buhalis and Sinarta, 2019). Strategically, the information provided in both textual and visual forms need to reduce ambiguity and address areas of criticism. For example, for the listings without reviews on the cleanliness, the use of cleaning fee charges as well as photographs that demonstrate that property is spotless can be useful. Nonetheless, as the information asymmetry reduces with the increasing number of online reviews, the effect of signal attributes depreciates fast.

The host should also carefully monitor the review status of his/her listings to convey quality information and to respond to all comments both negative and positive as well as work on functional attributes. Since guests are more likely to book an entire property or private rooms, the host should enhance the privacy of the listing. Capitalizing on feedbacks and understanding customer needs and guest priorities within the context of the property can offer exceptional service to guests. Hosts can offer more convenient amenities and policies. Facilities such as internet connection and instant reservation as well as amenities such as bicycles, baby strollers, or umbrellas may be appropriate and desirable additional services that guests may appreciate. The findings of this study could be utilized to conduct revenue simulation in what-if scenarios to ensure that profitability is maximized through yield management and ancillary services. Such a simulation can be useful to the current and potential hosts in property management and strategy planning. Finally, public sector and regulators can use the findings to ensure that there is harmony between the formal hospitality sector and the Airbnb type of accommodation and to create the appropriate regulatory and investment environment to maximize the benefits for all the stakeholders at the destination.

5.4 Limitation and future direction
This study is not without limitations. Due to data limitations, the effects of local hotels on Airbnb listings are omitted from the estimation. It would be interesting to integrate the interaction effect between Airbnb listings and traditional hotels in the model. The integration could further improve the predictability of the current model. Another limitation is that the model only examined data on London, which is a mature market of Airbnb. More practical implications could be found once the model is applied to an emerging market in future studies. In future studies, it is also valuable to integrate the emerging brand in Airbnb market such as "Airbnb Plus" and other psychological and sociological factors into the model and provide a more updated and comprehensive understanding of Airbnb market.

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Appendix 1

Listing attributes (Numerical)	Mean	SD	Median	Minimum	Maximum
Number of bedrooms	1.33	0.81	1	0	10
Number of bed per bedroom	1.27	0.64	1	0	16
Bathroom per guest	0.51	0.33	0.5	0	8
Number of Amenities	14.58	4.64	15	2	35
Distance to the nearest Tube station (km)	0.79	0.53	0.68	0.01	7.47
Distance to city center (km)	6.68	4.07	5.74	0.03	28.42
Price per person per night (£)	31.74	89.65	27	0.56	14026.5
Security deposit (£)	122.98	219.48	0	0	4079
Cleaning fee (£)	24.03	29.09	17	0	500
Fee for extra person (£)	8.04	12.91	0	0	230
Number of neighboring listings	8559.17	4727.5	9435	5	15813
Available neighboring listings	4566.82	2767.73	4849	0	11416
House rules	0.36	0.48	0.19	0	2.13
Property description	2.91	1.65	2.82	0	21.53
Number of listing pictures	3.61	1.01	4	1	4
Number of reviews	20.27	31.48	9	1	396
Total rating score	91.75	9.9	94	20	100
Review per month	1.45	1.49	0.95	0.01	16.87
Months since last review	3.5	5.46	1.8	0	70.7

Listing Attributes (Categorical and Dummies)	Proportion
With internet	Yes = 97.36%; No = 2.64%
With kitchen	Yes = 92.19%; No = 7.81%
Property function	Family = 1.98%; Business = 2.70%; Romantic = 0.99%; Social = 2.03%; Standard = 92.30%
Property type	Apartment = 72.12%; House and Townhouse = 23.49%; B&B, Guesthouse, and Hostel = 2.55%; Others = 1.83%
Room type	Shared room = 1.24%; Private room = 47.03%; Entire home/apartment = 51.73%
Bed type	Real Bed = 99.18%; Couch/Futon = 0.21%; Others = 0.61%
Instant reservation	Yes = 23.22%; No = 76.78%
Refund policy	Yes = 51.39%; No = 48.61%
Guest verification required	Yes = 4.73%; No = 95.27%
Weekly discount	Yes = 17.46%; No = 82.54%
Monthly discount	Yes = 17.57%; No = 82.34%
Description about space	Yes = 77.32%; No = 22.68%
Host profile	Yes = 99.78%; No = 0.22%
Superhost	Yes = 12.56%; No = 87.44%
Host with verified ID	Yes = 67.50%; No = 32.50%
Total number of listings ("With review")	30112

Table AI.
Descriptive statistics of listing attributes ("with review" listings)

Appendix 2

Listing attributes (Numerical)	Mean	SD	Median	Min	Max
Number of bedrooms	1.36	0.91	1	0	10
Number of bed per bedroom	1.22	0.62	1	0.1	16
Bathroom per guest	0.57	0.36	0.5	0	5
Number of Amenities	12.66	4.96	13	2	29
Distance to the nearest Tube station (km)	0.83	0.59	0.7	0	6.76
Distance to city center (km)	7.62	4.39	6.59	0.06	28.6
Price per person per night (£)	38.19	94.69	30	0.75	6880
Security deposit (£)	112.03	240.99	0	0	4098
Cleaning fee (£)	20.69	36.51	0	0	517
Fee for extra person (£)	5.71	13.41	0	0	240
Number of neighboring listings	8555.14	4725	9428	5	15813
Available neighboring listings	4308.77	2616.87	4586	0	11380
House rules	0.17	0.33	0	0	2.01
Property description	1.98	1.66	1.57	0	12.73
Number of listing pictures	3.57	1.05	4	1	4

Listing Attributes (Categorical and Dummies)	*Proportion*
With internet	Yes = 91.24%; No = 8.76%
With kitchen	Yes = 88.92%; No = 11.08%
Property function	Family = 0.27%; Business = 0.42%; Romantic = 0.15%; Social = 0.36%; Standard = 98.80%
Property type	Apartment = 67.53%; House and Townhouse = 27.78%; B&B, Guesthouse, and Hostel = 2.49%; Others = 2.21%
Room type	Shared room = 2.04%; Private room = 53.32%; Entire home/apartment = 44.63%
Bed type	Real Bed = 99.46%; Couch/Futon = 0.16%; Others = 0.38%
Instant reservation	Yes = 26.53%; No = 73.47%
Refund policy	Yes = 66.37%; No = 33.63%
Guest verification required	Yes = 2.00%; No = 98.00%
Weekly discount	Yes = 6.00%; No = 94.00%
Monthly discount	Yes = 5.34%; No = 94.66%
Description about space	Yes = 50.60%; No = 49.40%
Host profile	Yes = 99.18%; No = 0.82%
Superhost	Yes = 2.20%; No = 97.80%
Host with verified ID	Yes = 48.34%; No = 51.66%
Total number of listings ("No review")	11012

Table AII.
Descriptive statistics
of listing attributes
("No review" listings)

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