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Be a "Superhost": The importance of badge systems for peer-to-peer rental accommodations



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HIGHLIGHTS

- This study mainly focuses on the gamification design developed by Airbnb, which awards a "Superhost" badge to hosts.
- "Superhost" becomes who receive good reviews, which impacts accommodation's review volume and ratings.
- A negative binomial model and a Tobit model with different independent and controlled set of variables was employed.
- · Accommodations rewarded with the "Superhost" badge are more likely to receive reviews and higher ratings.
- Guests are willing to pay more for "Superhost" accommodations.

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ABSTRACT

Many sharing-economy websites like Airbnb that offer vacation-rental options for travelers are very popular. However, few studies targeting the vacation-rental industry have investigated online reviews. To narrow this gap, this study focuses mainly on the gamification design developed by Airbnb that awards a "Superhost" badge to hosts who receive good reviews and observes how this can impact an accommodation's review volume and ratings. All available information regarding Airbnb accommodation offered in Hong Kong was retrieved from Airbnb's website. We then constructed a negative binomial model and a Tobit model with different independent variables and controlled a set of variables relating to accommodation characteristics. The results show that an accommodation with the "Superhost" badge is more likely to receive reviews and higher ratings. In addition, guests are willing to spend more on "Superhost" accommodations. Based on our findings, we present implications for research and host practice.

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1. Introduction

In the e-commerce era, online reviews are increasingly important for consumers as well as various kinds of corporations. For consumers, peer evaluations are useful sources of information about products that reduce uncertainty when making purchase decisions (Zhu & Zhang, 2010). The valence of online reviews, always shown as a digitized rating, provides consumers with a direct means to filter target products. Of course, most consumers tend to

pay more attention to products with more positive ratings since their quality is affirmed and praised by fellow consumers (Hudson, Roth, Madden, & Hudson, 2015; Yeoh, Othman, & Ahmad, 2013; Yoo, Kim, & Sanders, 2015). Thus, both the volume and the valence of online reviews are critical for product and service suppliers and can boost their online sales (Chevalier & Mayzlin, 2006; Ye, Law, & Gu, 2009). The volume of online reviews is associated with the popularity of a product, and a product with more reviews will attract the attention of more potential customers (Zhang, Zhang, Wang, Law, & Li, 2013). By contrast, review valence decides potential customers' impressions or evaluations of the product after they start to look into it. In other words, consumers tend to pay more attention to "popular" products that are shown with more reviews, while they make their final purchase decisions based on

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the rating distribution of those target products (Litvin, Goldsmith, & Pan, 2008; Sparks & Browning, 2011).

Hotels are the traditional accommodation choice for travelers. However, the emergence of the concept called the "sharing economy" has provided another option: peer-to-peer vacation-rental accommodation, a trend that has become increasingly popular in recent years (Wang & Hung, 2015). Such accommodation has many advantages over traditional hotels. One is price (here and in the following used synonymously for room rate). The average price of accommodation provided by peer-to-peer websites such as Airbnb is lower than that of hotels in most cities (Permalink, 2013). Moreover, unlike standard hotels, this new kind of accommodation can offer travelers different experiences since different houses have their own distinct facilities and styles. The company's official website describes Airbnb as a community facilitating the rental of unique places to stay offered by local hosts in 190 + countries.

Peer-to-peer rental websites such as HomeAway, HouseTrip, FlipKey, and Airbnb provide platforms for both travelers and owners to share resources and information. They allow owners to post information about their available rooms, apartments, and houses, and thus earn extra income, while they offer travelers a means to select satisfactory accommodation for trips (Fang. Ye. & Law, 2016). Travelers can obtain information about accommodations from two main sources. One is the basic information on the website posted by owners and comprising details such as facilities, prices, and photos to help them picture the accommodation; the other source is reviews posted by previous users. The latter seems to be more important since it reflects real experiences and is thus perceived to be more credible (Aveh. Au. & Law. 2013; Zhu & Zhang. 2010). However, the number of online reviews of peer-to-peer accommodation rental websites is not huge, as these websites have been up and running for a short time and, in addition, the tourist capacities for each accommodation are limited. Another important aspect of reviews posted on such websites is their uneven distribution. We retrieved all available data on Hong Kong accommodations and reviews from the Airbnb website in August 2015. At that time, 3820 listings for accommodations in Hong Kong were posted on Airbnb. The most popular had attracted 154 reviews, while 2039 offers had not received any reviews. How to attract more reviews and reduce uneven distribution are critical questions for owners, especially those whose accommodations have received few or no reviews.

A common practice used by online review websites such as TripAdvisor to motivate user engagement and encourage reviews is to gamify their design (Li, Huang, & Cavusoglu, 2012). In such a model, users are rewarded with badges or higher status in the online community in return for voluntary contributions such as posting reviews. This design provides multiple intrinsic motivations for users to share their knowledge (Cavusoglu, Li, & Huang, 2015). Airbnb uses another kind of badge system, the "Superhost" badge, designed not for users or travelers but for accommodation owners (see Fig. 1). Owners must make continual contributions to the community, such as to inquiry from potential guests quickly, in order to obtain and keep this badge, which gives them higher status within the Airbnb community of owners. This system is intended to motivate the engagement of product or service providers and thus differs from the gamification design considered by previous studies.

The "Superhost" qualification is automatically evaluated every three months, and owners must satisfy the following conditions to obtain and keep the badge: (a) they should receive at least ten bookings in a year; (b) they must respond to their guests quickly and maintain at least a 90% response rate; (c) they should satisfy most of their guests and obtain more than 80% five-star ratings; (d) they rarely conceal confirmed reservations (Airbnb, 2016a). Therefore, to

obtain and keep this badge, owners must devote more energy to their listings. For example, they must cautiously screen their guests to avoid concealing reservations and unnecessary negative feedback. They must also improve facilities and service quality continually in order to satisfy guests and respond to their reviews quickly. But what are the direct benefits of this badge, and is it worth it for owners to make the efforts described above to earn and keep it? What effects can this badge system have on promoting their online performance? As noted above, two characteristics of online reviews, review volume and valence, are always linked with online sales. Accordingly, this study considered how Airbnb's "Superhost" badge system could influence guests' review posting and rating behavior.

Below, we first summarize two streams of research in the literature, including online reviews and gamification designs. Then we present several hypotheses relating to the research questions. Next, we present the data collection method, the variables, and the empirical models used, followed by the results and implications. Finally, the limitations are discussed at the end of the paper.

2. Literature review

This study intends to integrate two focuses of the literature: online reviews and gamification design. The ever-growing numbers of users and reviews in online travel communities attract a great deal of attention from scholars in the tourism industry. The mainstream of these studies can be classified as comprising two directions: Some focus on the quantitative characteristics of online reviews, such as their volume and valence, while others focus on textual or qualitative characteristics of review content based on text-mining technology. Since the purpose of this study is to observe how Airbnb's badge system influences the review volume and valence of accommodation, we summarize only tourism literature focusing on the volume and valence of online reviews.

2.1. Tourism literature on review volume and valence

The number of reviews is a highly significant factor and has been proven to be closely associated with hotel or tourism attraction performance (Xie, Chen, & Wu, 2016; Xie, Zhang, & Zhang, 2014; Yacouel & Fleischer, 2012). Some researchers, such as Ye et al. (2009), have even treated this factor as a proxy for hotel online sales and investigated its determinants. We summarize the influence of review volume on consumers' purchase decisions from two aspects. First, as an information source, one of the basic functions of online reviews is to provide information to consumers who have little prior knowledge about the products or services (Vermeulen & Seegers, 2009). Thus, the number of reviews determines how much information consumers can obtain. Consumers are unlikely to choose a hotel or tourism attraction with insufficient reviews since they have no way to reduce uncertainty from peer evaluations; therefore, a lack of reviews negatively influences online sales (Sotiriadis & van Zyl, 2013). Second, the volume of reviews also represents the popularity of a product (Zhang et al., 2013). More consumers will be aware of popular products (Godes & Mayzlin, 2004), and they tend to be more interested in products with more reviews since the quality of such products has been experienced and evaluated by a large number of their peers. This is an example of multitude-following mentality (Zhang, Ye, Law, & Li, 2010).

Review valence is another critical factor and represents mainly the sentiment of consumer evaluations (Schuckert, Liu, & Law, 2015). This factor is always measured by consumers' online ratings and is linked closely to other concepts, such as consumer satisfaction or the valence of electronic word of mouth (Xie et al., 2014; Liang, Schuckert, & Law, 2016). Review valence influences consumers' subsequent purchase decisions and online sales by sharing and

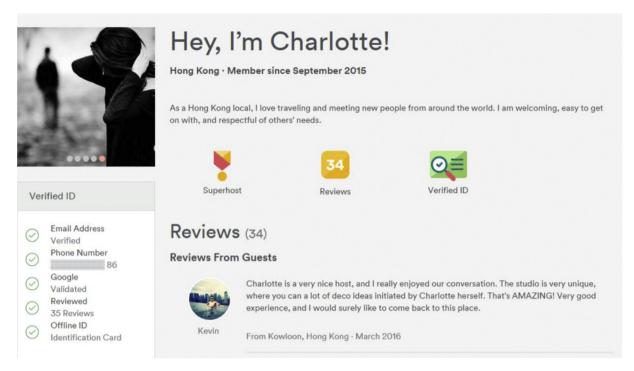


Fig. 1. Example of the "Superhost" badge in Airbnb (Source: www.airbnb.com).

spreading satisfied or unsatisfied sentiments through these digitized ratings (Litvin et al., 2008). The ratings allow consumers to make a direct comparison and judgment of product or service quality, which helps them to make a final decision (Zhang, Ye, & Law, 2011). Much empirical research based on both primary and secondary data has suggested that review valence is positively associated with consumers' booking intentions and online sales in the tourism industry (Chaves, Gomes, & Pedron, 2012; Lu, Ba, Huang, & Feng, 2013; Phillips, Zigan, Silva, & Schegg, 2015; Sparks & Browning, 2011). The importance of review valence and online ratings has also attracted significant academic interest in its determinants. A number of individual characteristics, such as consumers' online review experiences and features of hotels or tourism attractions including price and star rating, are identified as factors that can influence review valence (Liang et al., 2016; Ye, Li, Wang, & Law, 2014; Zhou, Ye, Pearce, & Wu, 2014).

2.2. Gamification design and online engagement

Following its introduction by Bunchball in 2005, "gamification" gradually became a popular trend and has been applied in many different industries (Google, 2016; Schlagenhaufer & Amberg, 2015). Gamification was initially designed for market purposes but has expanded to many other applications, such as motivating users' knowledge sharing (Li et al., 2012). Deterding, Dixon, Khaled, and Nacke (2011) provided a popular definition: "gamification" is the application of game design elements to non-game contexts. Several literature-review papers have focused on the classification of papers on gamification and obtained similar results (Hamari, Koivisto, & Sarsa, 2014; Seaborn & Fels, 2015; Schlagenhaufer & Amberg, 2015). For example, the most common gamification designs involve badges, points, and leaderboards. The application of gamification in the education industry is the domain attracting the most research attention.

The most important topic for this research direction is the verification of whether or not gamification is effective. Users' online

engagement is an important factor for estimating their activity, participation, and contribution in online communities. Gamification designs enhance online engagement by providing intrinsic motivations to support continued engagement. Cavusoglu et al. (2015) and Li et al., 2012 investigated the impacts of various types of badge systems on user engagement in a Q&A website and obtained positive results that proved the effectiveness of badge systems. Based on the case study of an innovation community, Hofferbert, Cahalane, and Finnegan (2015) identified gamification as an architecture of participation that helps users to engage. Many other studies focusing on different kinds of online communities have also obtained positive results for the effect of gamification design on users' online engagement (Grant & Betts, 2013; Hamari, 2013; Kwon, Halavais, & Havener, 2015).

This paper differs from the studies noted above in that the badge system we consider is designed for accommodation owners rather than users, and its purpose is to enhance user engagement, such as knowledge sharing, getting more bookings, and posting more reviews. But the question is, since the effectiveness of gamification designs in user engagement has been proven, why does Airbnb use a badge system for owners rather than users? To answer this question, we must demonstrate two factors: why a badge system for users is not effective and why one for owners is effective.

First, rational action theory provides a possible reason for the effectiveness of a users' badge system in this context; users' knowledge-sharing decisions are determined by considering the benefits and costs resulting from this behavior (Breen & Goldthorpe, 1997). Unlike the Q&A websites and other kinds of online communities investigated by the above-mentioned studies, Airbnb stipulates that users can post their reviews only after completing a booking. This creates additional costs for some of them to share their knowledge, i.e., the monetary cost of booking the accommodation. Therefore, a badge for users would be less effective since a large proportion of users are likely to hesitate, unsure that it is a rational choice to exchange money for an abstract honor (e.g., badges, points, higher rank in leaderboards). Just as

Hamari (2013) and Jung, Schneider, and Valacich (2010) have suggested, gamification may be not effective in a utilitarian service setting.

Second, the greatest motivation for Airbnb users to make a booking and then publish a review should be the quality of the accommodation. Only when they consider it worth consuming are they willing to book and, later, to publish reviews. Thus, the badge for owners provides owners with intrinsic motivation to improve their accommodations and service quality continuously in order to attract more bookings and more positive reviews from users. However, although the above expectations seem to be reasonable, there is no empirical evidence to verify these arguments. To fill this gap, this study empirically investigates the effectiveness of the "Superhost" badge on Airbnb users' engagement (posting reviews) and their evaluation (ratings) of accommodations.

3. Hypotheses

3.1. Badge system and review characteristics

As noted above, guests can post a review only after completing a booking, and one of the largest costs for guests to post reviews and share knowledge is the monetary cost of making bookings. Therefore, we present an assumption linking bookings and review volume: accommodations with more prior bookings always have more reviews. Based on this assumption, we expect, first, that "Superhosts" (owners with the "Superhost" badge) will be likely to receive more bookings and reviews from guests. One of the reasons is that accommodations owned by "Superhosts" are identified by a thirdparty website (i.e. Airbnb) as being of high value. As described on Airbnb's site, "Superhosts" are experienced hosts who are passionate about making guests' trips memorable (Airbnb, 2016a). Such hosts and their accommodations draw the attention of potential guests, who can even conduct a direct search of all "Superhost" accommodations in a designated area. The badge system is a kind of advertisement, and the effectiveness of advertising on online sales has been proven by many previous marketing and management studies (Ghose & Yang, 2009; Stephen & Galak, 2012). Thus, the advertising effect for "Superhosts" is that it pushes guests to pay more attention to their accommodations, thereby improving their chances of receiving a booking. Another benefit is "Superhost" accommodations' accumulated positive ratings (more than 80% five-star ratings). Online rating reflects guests' evaluations of the consumption experience and can be positively associated with repurchase intentions (He & Song, 2009; Posselt & Gerstner, 2005). Online ratings also significantly influence potential guests' purchase or booking decisions (Tanford, Raab, & Kim, 2012; Vermeulen & Seegers, 2009). Receiving more positive ratings always represents higher evaluations from peers; therefore, accommodations that receive many positive ratings are more attractive to potential guests. In summary, we consider that both the advertising effect and the accumulated positive ratings mean that accommodations offered by "Superhosts" attract more attention, more bookings, and more reviews. We propose:

H1a. Accommodations with the "Superhost" badge tend to receive more reviews.

Furthermore, we expect the "Superhost" badge to not only influence guests' booking behavior before consumption but also their satisfaction and/or evaluation after consumption, which is reflected by online ratings. First, we expect "Superhosts" to be motivated to keep their badge, and then tend to devote their time and energy to improving the actual quality of their accommodations in order to obtain more positive ratings. Thus, guests' satisfaction with accommodations owned by "Superhosts' should be higher than for

other accommodations. Second, as noted in the introduction, "Superhosts" are more willing to select the method to avoid unnecessary negative feedback, namely, filtering their guests carefully. By looking closely at guests' registration information, previous reviews they have posted and those they have received from other hosts, as well as talking to them directly, "Superhosts" can choose appropriate guests and avoid receiving spiteful evaluations. Finally, the higher response rate by "Superhosts" is likely to be another reason that guests post higher ratings for their accommodations following consumption (Gu & Ye, 2014; Liang et al., 2016). Based on the above, we can propose:

H1b. Accommodations with the "Superhost" badge tend to receive higher ratings.

3.2. Price and review characteristics

Another major factor influencing guests' booking behavior before consumption and rating behavior after consumption is the price of the accommodation. As noted in the literature review, rational action theory states that, before consumption, guests will consider the likely benefits and costs resulting from their booking and review-posting behavior (Breen & Goldthorpe, 1997). One of the largest costs is the monetary cost of booking the accommodation. An increase in the price of an accommodation offer will create more costs for guests to book it or post reviews of it. Thus, if the benefits are not enhanced correspondingly, guests will be less likely to book this property in order to make their choices rational. Especially for those guests with little prior knowledge of an accommodation offer, a higher price represents a greater risk. In addition, price is perceived as an extrinsic cue that can significantly reduce consumer purchase decisions (Dodds, Monroe, & Grewal, 1991). Several studies have reported the negative role of price on consumers' purchasing and booking intentions (Han & Hyun, 2015; Jiang & Rosenbloom, 2005; Wang, Lu, Chi, & Shi, 2015). Based on the above, we present a hypothesis exploring the relationship between price and review volume:

H2a. Accommodations with a higher price tend to receive fewer reviews.

After consumption, guest satisfaction and evaluation are also significantly associated with price. In this study, we expect accommodations with higher prices to receive higher ratings based on two considerations. First, more expensive accommodations always have higher initial costs (such as more rooms and luxury facilities, more personal service) and are therefore more likely to obtain positive feedback. In addition, the revenue resulting from a higher price allows the host to continually improve the quality of his or her accommodation. Second, the dominant role of perceived product or service performance in influencing consumer satisfaction has been proven by numerous marketing and tourism studies (e.g. Churchill & Surprenant, 1982, Severt, Wang, Chen, & Breiter, 2007; Tse & Wilton, 1988). In this study, since users search and select accommodations within a certain location and price range, according to their needs, the accommodation's perceived performance mainly indicates its perceived quality, including facilities and service quality. Early studies such as that of Zeithaml (1988) presented a definition for perceived quality as "the consumers' judgement about a product's overall excellence or superiority" and reported a positive relationship between perceived quality and price based on theoretical frameworks. As suggested by studies such as those of Erickson and Johansson (1985) and Völckner and Sattler (2005), prospective guests tend to use price as a cue for the quality of products or services. Many subsequent studies further verified and recognized the price-perceived quality relationship and began to observe the effects of introducing other cues on this relationship (Erdem, Keane, & Sun, 2008; Miyazaki, Grewal, & Goodstein, 2005). Several tourism scholars have also investigated this relationship empirically. For example, through consulting online review data from TripAdvisor, Ye et al. (2014) found that the price of a hotel accommodation is positively associated with consumers' ratings of perceived quality. Gallarza and Saura (2006) obtained similar results with an experiment. Based on the above, we expect price to be positively associated with guest satisfaction and ratings after consumption, mainly through influencing perceived quality. Thereby, we propose:

H2b. Accommodations with a higher price tend to receive higher ratings.

3.3. Badge system and price

The price of an accommodation is negatively associated with guests' booking and review-posting decisions due to the increased cost and risk created by higher prices. An accommodation with the "Superhost" badge is perceived as being of high quality by prospective guests; therefore, this badge provides added value to the host and his or her accommodation. After noting the "Superhost" badge in addition to the characteristics of an accommodation, such as facilities, space, location, or price, higher peer evaluations and good after-sales service are also singled out as adding value. Much of the marketing literature suggests that perceived quality. perceived value, and brand uniqueness should be the direct factors driving consumers to pay a premium price for a brand (Li, Li, & Kambele, 2012 and; Netemeyer et al., 2004). Applying this finding to this context, if there are two offers with near-identical external conditions, but one has the "Superhost" badge, we expect prospective guests to be more likely to pay a premium price for the offer with the "Superhost" badge due to its higher added value. Additionally, an accommodation with the "Superhost" badge is considered more credible, and this can affect potential guests' perceived risk. Perceived risk has been identified as one of the main factors reducing guests' intentions to book, and a common method for reducing this in the online environment is to use site recommendations (Stone & Grønhaug, 1993 and; Garbarino & Strahilevitz, 2004). The "Superhost" badge represents a recommendation by Airbnb and can effectively reduce perceived risk, especially among potential users with little prior knowledge. We thus propose a hypothesis exploring the moderating effect of the "Superhost" badge:

H3a. The negative association of price and review volume can be positively moderated by the "Superhost" badge.

Another question is whether or not the "Superhost" badge also moderates the association between price and guests' ratings. Since we have reported that price influences ratings, mainly via the price-perceived quality relationship, we can ask the following question: Does this relationship change with the introduction of a cue relating to the accommodation or the host badge? Brand-related external cues, including brand name and country of origin, are identified as major factors affecting the price-perceived quality relationship. Dodds et al. (1991) verified the impact of three extrinsic cues on this relationship and found that brand name played a dominant role in positively inflecting this relationship. Another important aspect of cues identified by previous studies involves price cues including price manipulation and price level (Chao, 1989; Völckner & Hofmann, 2007). However, several studies have found that the impact of extrinsic cues on the price—quality

relationship is based on the assumption that information presented by two cues must be consistent. Brucks, Zeithaml, and Naylor (2000) reported that the interaction effect between brand cues and price on perceived quality is most prominent when the price of a product is aligned with a consistent brand cue. Summarizing previous studies, Miyazaki et al. (2005) performed a series of experiments and found that two consistent extrinsic cues can be significantly predictive of perceived quality; however, this interaction effect disappears when the information provided by these two cues is inconsistent. In this study, although the cues relating to the "Superhost" badge can be linked to brand cues (it presents some added brand value), the information presented by price and this badge is obviously inconsistent. The "Superhost" badge, in part, represents the efforts of the host/owner; it is not correlated with the price of the accommodation. Accommodations at any price can obtain and keep this badge if the owner is willing to make efforts to improve the facilities and service quality. Thus, we do not expect the cues provided by the "Superhost" badge to influence the priceperceived quality relationship. We present the following hypothesis:

H3b. The association of price and ratings is not significantly moderated by external cues provided by the "Superhost" badge.

The conceptual framework of this study is shown in Fig. 2.

4. Methodology

4.1. Data collection

The intention of Airbnb, one of the largest sharing-economy websites, is to establish "a trusted community marketplace for people to list, discover, and book unique accommodations around the world." More than 60 million registered guests can enjoy unique homestay experiences in more than 34,000 cities across 190 countries. In addition, Airbnb represents the easiest way for owners to profit from an online community with an ever-growing number of users (Airbnb, 2016b). In this study, we selected Hong Kong as the target destination for two reasons. First, as a very famous tourist destination, Hong Kong attracts millions of visitors who travel, shop, and book accommodations each year. In 2015, a total of 59,308 million tourists traveled to Hong Kong, and this number grew in 2014 to 60,839 million (Census and Statistics Department, 2016). Therefore, demand for accommodations is very large, and

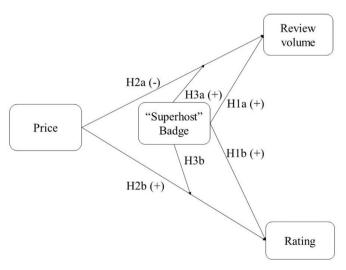


Fig. 2. Conceptual framework.

the numbers of owners willing to rent unoccupied houses, apartments, and rooms and guests wanting to book rental accommodations should be larger than those for many other cities. Second, Hong Kong is an international city with tourists coming from all over the world (Liu, Schuckert, & Law, 2015). Selecting Hong Kong as the target destination thus ensures a diverse sample of guests, diluting the effect of cultural background on accommodation selection.

The overall aim of this study is to examine how Airbnb's badge system influences guests' booking, review-posting, and ratingposting decisions. Therefore, a web crawler based on Ruby was developed in August 2015 to retrieve information relating to all accommodation offers in Hong Kong. During the retrieval process, we found that Airbnb shows only the first 56 pages (nearly 1000 results) when we search using the keyword Hong Kong. Therefore, to ensure that our dataset included all accommodations in Hong Kong, we looped through all the districts of Hong Kong, such as Tsim Sha Tsui, and retrieved data for 7906 offers of accommodation. After removing duplicates, 3830 offers of accommodation were included in our dataset. We also used accommodation IDs to retrieve all the available information regarding hosts, including when they joined Airbnb, personal information, and previous reviews. Finally, 3830 accommodations belonging to 1872 hosts were included in our further analysis.

4.2. Variables

The dependent variables for this study are the review volume and valence of each accommodation. The variable *Review* represents the review volume of each accommodation; *Rating* displays the overall rating of each accommodation. Following our hypothesis, our independent variables include two variables, *Badge* and *Price*. *Badge* refers to whether or not a host has the "Superhost" badge; *Badge* is coded as 1 when a host is identified as a "Superhost" and 0 otherwise. *Price* is the total price for each accommodation and is measured as the total rent plus the cleaning fee.

We also considered several control variables relating to the accommodation's characteristics in order to control more factors in our empirical models comprehensively. Three variables were retrieved to represent space, including Capacity (the number of guests an accommodation can serve), Room (the number of bedrooms a house or apartment can provide), and Bed (the number of beds provided in each house/apartment). Regarding other factors relating to price, in addition to the total price of each accommodation, we also control the following variables. Extra represents whether the host charges additional fees for extra guests. Two variables, Week and Month, are used to estimate whether an accommodation offers a competitive price for weekly or monthly bookings. Available is a variable measuring the minimum required stay. Cancel, which is coded as 1, 2, or 3, represents Airbnb's different cancellation policies. The higher the value of this variable, the more a guest will need to spend to cancel a booking on Airbnb. The last variables concerning accommodation characteristics relate to the detailed introduction in Airbnb listings. Photo is the number of photos shown. Describe and Rule indicate whether a detailed introduction and listing of rules for guests are posted by hosts. We also denote a variable named Time, a measure of how long each host had been registered with Airbnb at the time of the study in August 2015 (measured in months). A detailed description of the above variables is given in Table 1.

4.3. Empirical model

In this study, we must construct two empirical models focusing on review volume and valence of accommodation respectively. To test the hypotheses, multivariate econometric models are needed to investigate the effect of the independent variables by controlling other variables. However, due to the different types of dependent variables involved, using a single type of empirical model for further analysis may produce biased results. Accordingly, we present two models appropriate for the data format of review volume and valence (rating) to test our hypotheses contrapuntally.

4.3.1. Review volume model

For our model targeting review volume, the dependent variable is the number of reviews received by each accommodation. As noted in the introduction, a problem with reviews on Airbnb is their uneven distribution, meaning that a considerable proportion of accommodations have received no reviews or only a few. Fig. 3 shows the distribution of this variable, and it is clearly not normal. Therefore, we constructed a count model since a dependent variable with many zero and small values and a discrete nature possesses the characteristics of a count variable (Winkelmann, 2013). The Poisson Regression Model is the fundamental model for the analysis of count data. However, a major disadvantage of this model is its assumption of the equality of conditional mean and variance functions (Greene, 2011). To avoid this assumption, we applied the negative binomial model of Cameron and Trivedi (1986). The equations for this model are as follows:

$$\operatorname{Prob}(Y = y_i | x_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(y_i + 1)\Gamma(\theta)} r_i^{y_i} (1 - r_i)^{\theta}$$
(1)

This distribution has the conditional mean $\lambda_i = \exp(x_i'\beta)$ and conditional variance $r_i = \lambda_i(\theta + \lambda_i)$; x_i and β are the vectors representing the explanatory variables (including independent and control variables) and the parameters, respectively.

4.3.2. Rating model

After removing accommodations with no reviews or ratings, we constructed a model to estimate the effect of various factors on online ratings. Unlike the number of reviews, the ratings for each accommodation represent a continuous variable with no negative values. The variable Rating is bounded in its range (from 1 to 5). Thus, in this situation, we applied the censored regression model or Tobit model (Tobin, 1958) due to the censored nature of the sample. A second reason for selecting this model is the potential selection problem (Mudambi & Schuff, 2010). As we have previously described, the costs for users to post a review on Airbnb are higher than in other online communities since they must first make a booking. The majority of guests will choose accommodations cautiously, based on their own prior knowledge or after consulting online reviews, in order to secure a better experience. Thus, we expect a potential selection problem since the number of guests who have posted higher ratings should be larger than predicted.

The results of this model are obtained by setting the mean in the preceding of a classical regression model; the specific model formulation is always given by the following equation:

$$y_{i}^{*} = x_{i}^{'}\beta + \varepsilon_{i} \tag{2}$$

where y_i is measured as 0 if $y_i^* \le 0$, and $y_i = y_i^*$ if $y_i^* > 0$. The vector of x_i includes all explanatory variables, while β is a vector of parameters in our analysis.

5. Results

5.1. Data description and analysis preparation

Table 2 shows the description statistics for all variables in our analysis. The accommodations in our dataset have received an

Table 1Description of the variables

Variable	Description		
Dependent variables			
Review	The number of reviews of each accommodation		
Rating	The overall rating of each accommodation		
Independent variables			
Super	Whether a host has obtained and kept the "Superhost" badge		
Price	The total price (room rate) of each accommodation (including cleaning fee)		
Control variables			
Capacity	The maximum number of guests each accommodation can house		
Room	The number of bedrooms in each accommodation		
Bed	The number of beds in each accommodation		
Extra	Whether guests need to pay an additional fee for extra persons		
Week	Whether a listing displays information about weekly price (rate)		
Month	Whether a listing displays information about monthly price (rate)		
Available	The minimum stay for each accommodation		
Cancel	The cancellation policies of each accommodation		
Photo	The number of photos displayed in the listing of each accommodation		
Describe	Whether a listing contains a detailed description		
Rule	Whether a listing contains a detailed accommodation rule		
Time	The length of time the host has offered accommodation on Airbnb		

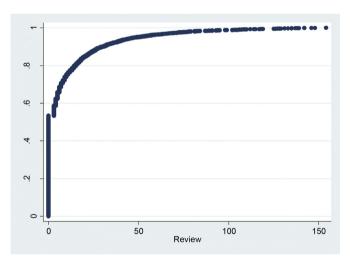


Fig. 3. The distribution of review volume.

average of 9.811 reviews (SD = 19.835) and an average rating of 4.429 (SD = 0.432). Only 2.9% of hosts have earned the "Superhost" badge,

Table 2Descriptive statistics and the collinearity diagnostics test of the variables.

			-				
Variables	Mean	Std. Dev.	Min	Max	VIF	SQRT VIF	Tolerance
Review	9.811	19.835	0	154			
Rating	4.429	0.432	2.5	5			
Super	0.029	0.168	0	1	1.02	1.01	0.9841
Price (rate)	881.834	1295.170	78	58,000	1.12	1.06	0.8906
Capacity	3.440	1346.085	1	16	4	2	0.2498
Room	0.781	1.065	0	10	1.77	1.33	0.566
Bed	1.996	1.606	1	16	2.62	1.62	0.381
Extra	0.159	0.366	0	1	1.57	1.25	0.6355
Week	0.474	0.499	0	1	1.58	1.26	0.6339
Month	0.438	0.496	0	1	1.52	1.23	0.6598
Available	1.860	2.043	1	27	1.08	1.04	0.9301
Cancel	2.274	0.858	1	3	1.2	1.1	0.8308
Photo	18.047	14.866	2	100	1.37	1.17	0.729
Describe	0.904	0.294	0	1	1.18	1.09	0.8478
Rule	0.535	0.499	0	1	1.31	1.14	0.763
Time	20.241	14.738	0	80	1.21	1.1	0.829

Note. Conditional index places between 1 and 16.5440.

which indicates that only a very small proportion of hosts qualify for this honor. In addition, the average daily rate (ADR) for accommodations is HKD 881.834 (SD = 1346.085). Focusing on the description statistics of the control variables, accommodations can house an average number of 3.44 guests (SD = 2.574) in 0.781 bedrooms (SD = 1.065) and 1.996 beds (SD = 1.606). Additional fees for extra guests were required by 15.9% of owners, and 47.4% and 43.8% provided preferential weekly and monthly prices, respectively. In order to avoid cancellations, hosts stipulated that guests stay at least 1.86 nights (SD = 2.043) on average. In addition, 54.3% of owners employed a strict booking policy, with 26.9% and 18.8% using flexible and moderate policies, respectively. Most owners in our dataset were willing to add detailed descriptions of their accommodation in order to attract guests. They posted 18.047 photos on their Airbnb listing on average, and 90.4% and 53.5% posted a detailed description and a house rule. Finally, the average duration of owners' Airbnb membership was 20.241 months (SD = 14.738).

Before the empirical analysis, we undertook some preparations in order to better show the results and to ensure the accuracy of estimations, including unit transformation and collinearity check. Table 2 shows that the values of some variables, *Price*, *Photo*, and *Time*, are obviously higher than others. Thus we divided *Price* by 1000 and *Photo* and *Time* by 10 to avoid displaying excessively low coefficients in the results, which cannot influence the explanation of results

We next checked the collinearity among all explanatory variables to avoid its influence on the significance of our results. Variance inflation factors (VIF), tolerance, and conditional index, used by many previous studies, such as Liu and Park (2015), were applied for the above purposes. The results are also presented in Table 2. It can be seen that all VIF values are less than 10, thus the values of tolerance measured as the reciprocal of VIF are over 0.1. The conditional indexes are also all below 30. All the above results indicate that collinearity cannot influence the accuracy of the results in this study.

5.2. Estimation results

We first ran the negative binomial model to analyze the results of equation (1). These are presented in column 1 of Table 4. Hypothesis 1a is supported since the coefficient of *Super* is positive and significant (coeff. = 0.778, p < 0.001). The coefficient and significance level of *Price* (coeff. = -0.544, p < 0.001) further support

Hypothesis 2a. Finally, we are also interested in the moderating effect of *Super* and thus presented Hypothesis 3a, adding a variable representing the interaction effect between *Super* and *Price*. The coefficient of this variable is positive and significant (coeff. = 0.447, p < 0.001), thus supporting Hypothesis 3a.

We then removed the accommodation that had no reviews or ratings and ran the Tobit model to focus on the determinants of ratings (see equation (2)). The results are shown in column 2 of Table 3; they support Hypothesis 1b, which aimed to determine the association between badge and ratings. This is mainly because the variable relating to the accommodation's "Superhost" badge is positive and significant (coeff. = 0.468, p < 0.001). The positive coefficient of *Price* indicates that the total price of an accommodation is positively associated with rating (coeff. = 0.109, p < 0.001), thus supporting Hypothesis 2b. We also verified the final hypothesis, 3b, by introducing the interaction effect into the rating model. However, the coefficient of the interaction effect is very small and not significant, indicating that the "Superhost" badge has no moderating effect on the relationship between price and rating, thus supporting Hypothesis 3b.

5.3. Robustness check

We also conducted a set of comparison analyses in order to check the rationality and robustness of our models (see Table 4). First, to check the robustness of equation (1) (negative binomial model), a

Table 3 Model results.

Variables	Review volume model	Rating mode
Constant	-0.599***	4.330***
	(-3.325)	(73.588)
Independent variables		
Super	0.778***	0.468***
	(3.376)	(6.093)
Price	-0.544***	0.109***
	(-7.074)	(4.557)
Super × Price	0.447***	-0.004
_	(3.124)	(-0.047)
Control variables		
Capacity	-0.031	-0.009
	(-0.965)	(-1.194)
Room	-0.104**	-0.030**
	(-2.059)	(-2.129)
Bed	1.600***	0.003
	(3.948)	(0.034)
Extra	0.448***	-0.035
	(3.885)	(-1.228)
Month	0.232***	-0.121***
	(2.847)	(-5.254)
Week	-0.228***	0.095***
	(-2.850)	(4.143)
Available	-0.127***	0.035***
	(-6.245)	(4.934)
Cancel	0.366***	-0.041***
	(7.645)	(-2.812)
Photo	0.280***	-0.001
	(8.402)	(-0.088)
Describe	0.239*	0.009
	(1.827)	(0.186)
Rule	0.685***	0.174***
	(8.766)	(7.388)
Time	0.400***	-0.005
	(13.557)	(-0.660)
Log likelihood	-9394.1269	-879.03233
LR χ^2	9100.88***	276.22***
Observations	3731	1744

Note. Coefficients are shown in the table; z and t (column 2) values are shown in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Poisson regression model with the same variables was constructed. The results are presented in column 2 of Table 4. Comparing these results with the original model shown in column 1, with the exception of one control variable, there is almost no change in the meanings of all variables, indicating relatively good sensitivity. We then used the likelihood-ratio test to compare these two models. The result of the χ^2 test is 43942.82, which indicates that independent variables are more likely to present a negative binomial distribution than a Poisson distribution. Furthermore, to consider the possibility of whether the dependent variable is a continuous variable, we also reran the model using the ordinary least squares method. The results are shown in column 3 of this table. It can clearly be seen that, although the meaning and significance level of a few control variables are different, most control variables and all the independent variables show almost no change. The likelihood-ratio test was then conducted on these two models, and the reported result also favors the negative binomial model ($\chi^2 = 12990.82$, p = 0.000). The above comparisons all support our model selection for review volume.

Second, for the Tobit model focusing on ratings, we reran the model using an ordinary linear regression model as a robustness check. The results are reported in column 5 of Table 4. It is clear that the ordinary linear regression model cannot meaningful change the coefficient or significance level of all estimates. The results also indicate the good sensitivity and robustness of the selected model.

6. Discussion and implications

6.1. Main findings

This study essentially has two sets of findings. The first relates to review volume. According to our empirical results, an accommodation with the "Superhost" badge is more likely to receive reviews, while price is negatively associated with review volume. In addition, due to the significant interaction effect between the "Superhost" badge and price shown in our results, we can safely predict that guests are happy to spend more for accommodations with the "Superhost" badge.

The results of the tests of the control variables also present many findings that can help hosts understand how to raise their review volume by improving the characteristics of their accommodations. In terms of variables relating to the space of an accommodation, the number of bedrooms and beds show different effects on review volume. Accommodations with fewer bedrooms but more beds are more likely to attract reviews. The results also indicate that guests are more willing to make a booking and subsequently post a review of an accommodation whose owners require an additional fee for extra guests, quote a monthly price, and/or have a stricter cancellation policy. Finally, more detailed information, including a description, house rules, and photos, can make an accommodation more attractive and increase its review volume.

Another set of findings focuses on ratings. Guests tend to post higher ratings for accommodations with a "Superhost" badge and/or higher prices after consumption. However, the "Superhost" badge cannot influence the positive relationship between price and ratings. Similarly, we also controlled several factors relating to accommodation characteristics, and the results of these tests offer valuable information to hosts about how to improve ratings by changing accommodation characteristics. The results also show that the number of bedrooms can be negatively associated with guests' evaluations. Guests are more likely to give a higher rating to accommodations with a weekly price, a flexible cancellation policy, and/or a longer cancellation period. In addition, although detailed information presented in listings, including a description and photos, cannot influence ratings, guests favor accommodations with a detailed description of house rules.

Table 4
Robustness check

Constant −0.599*** 0.230*** −3.987*** 4.330*** Constant −0.599*** 0.230*** −3.987*** 4.330*** Independent variables (5.247) (−3.102) 70.5588) Super 0.778*** 0.368*** 4.949*** 0.468*** 1,376 (8.686) (2.839) (6.093) Price −0.544*** −0.525*** −1.883*** 0.109*** Super × Price (rate) (4.47** 0.424*** 1.836*** −0.004 Super × Price (rate) (4.447** 0.424*** 1.836*** −0.004 Super × Price (rate) (4.447*** 0.402*** 1.836*** −0.009 Control variables (5.69) 0.152 −0.009 −0.012*** −0.017** −0.0010*** Romanic Varia	Variables	Review volume mode	el	Rating model		
		NB	Poisson	OLS	Tobit	OLS
Independent variables Super 0.778*** 0.368*** 4.949*** 0.468*** 13.376 (8.686) (2.839) (6.093) Price -0.544*** -0.525*** -1.883*** 0.109*** Super × Price (rate) 0.447*** 0.424*** 1.836*** -0.004 Super × Price (rate) 0.447** 0.424*** 1.836*** -0.004 Control variables -0.031 -0.002 0.152 -0.009 Room -0.104** 0.095** -0.477 -0.030** Room -0.104** 0.095** -0.477 -0.030** Bed 0.160** 0.021*** -0.477 0.003 Extra 0.448*** 0.405*** 7.993*** -0.030* Extra 0.448*** 0.405*** 7.993*** -0.035* Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -6.623*** 0.095** Available -1.27*** -0.154***	nstant	-0.599***	0.230***	-3.987***	4.330***	4.330***
Super 0,778*** 0,368*** 4,949*** 0,468*** (3,376) (8,686) (2,839) (6,093) Price -0,544*** -0,525*** -1,883*** 0,109*** (-7,074) (3,7418) (-5,683) (4,557) Super × Price (rate) 0,44**** 0,424*** 1,836*** -0,004 Control variables -0.031 -0.002 0,152 -0,009 Capacity (-0,965) (-0,523) (0,689) (-1,194) Room -0,104** 0,095*** -0,477 -0,030** Room -0,160*** 0,021*** -0,077 0,003 Extra 0,468** 0,402*** -0,993** -0,103* Extra 0,448*** 0,402*** -7,993*** -0,003 Extra 0,448*** 0,402*** -7,993*** -0,121*** Month 0,232*** 0,276*** 3,473*** -0,121*** Week -0,228*** -0,357*** -4,623*** 0,095** Available		(-3.325)	(6.247)	(-3.102)	(73.588)	(73.25)
Super 0,778*** 0,368*** 4,949*** 0,468*** (3,376) (8,686) (2,839) (6,093) Price -0,544*** -0,525*** -1,883*** 0,109*** (-7,074) (3,7418) (-5,683) (4,557) Super × Price (rate) 0,44**** 0,424*** 1,836*** -0,004 Control variables -0.031 -0.002 0,152 -0,009 Capacity (-0,965) (-0,523) (0,689) (-1,194) Room -0,104** 0,095*** -0,477 -0,030** Room -0,160*** 0,021*** -0,077 0,003 Extra 0,468** 0,402*** -0,993** -0,103* Extra 0,448*** 0,402*** -7,993*** -0,003 Extra 0,448*** 0,402*** -7,993*** -0,121*** Month 0,232*** 0,276*** 3,473*** -0,121*** Week -0,228*** -0,357*** -4,623*** 0,095** Available	lependent variables	, ,	• •	•		, ,
Price -0.544*** -0.525*** -1.883*** 0.109*** Super × Price (rate) 0.447*** 0.424*** 1.836*** -0.004 Super × Price (rate) 0.447*** 1.836*** -0.004 (3.124) (11.078) (4.149) (-0.047) Control variables Capacity -0.031 -0.002 0.152 -0.009 Room -0.104** 0.095*** -0.477 -0.030** Room -0.104** 0.095*** -0.477 -0.030** Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.468*** 0.402*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -4.623*** 0.095*** Week -0.228*** -0.35*** -4.623*** 0.095*** Cancel 0.366*** 0.297*** -1.58*** <t< td=""><td>per</td><td>0.778***</td><td>0.368***</td><td>4.949***</td><td>0.468***</td><td>0.468***</td></t<>	per	0.778***	0.368***	4.949***	0.468***	0.468***
Super × Price (rate) (-7.074) (-37.418) (-5.683) (4.557) Super × Price (rate) 0.447*** 0.424*** 1.836*** −0.004 Control variables −0.031 −0.002 0.152 −0.009 Room −0.104** 0.095*** −0.477 −0.030** Room −0.104** 0.095*** −0.477 −0.030** Bed 0.160*** 0.021*** −0.077 0.003 Extra 0.48*** 0.405*** 7.993*** −0.035 Extra 0.448*** 0.405*** 7.993*** −0.035 Month 0.232*** 0.276*** 3.473*** −0.121*** Week −0.228*** −0.357*** −4623*** −0.095*** Week −0.228*** −0.357*** −4623*** 0.095*** Cancel 0.366*** −0.154*** −0.892**** 0.035*** Cancel 0.366*** 0.297*** 1.207*** −0.041*** Cancel 0.366*** 0.297*** 1.207*** −0.041*** Cancel 0.366*** 0.297** 1.207***		(3.376)	(8.686)	(2.839)	(6.093)	(6.065)
Super × Price (rate) 0.447*** 0.424*** 1.836*** -0.004 Control variables -0.031 -0.002 0.152 -0.009 Room -0.104** 0.095*** -0.477 -0.030** Room -0.104** 0.095*** -0.477 -0.030** (-2.059) (13.41) (1.345) (-2.129) Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448*** 0.405*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -4.623*** 0.095*** Week -0.228*** -0.357*** -4.623*** 0.095*** Cancel 0.366*** 0.297*** 1.207*** -0.041*** Cancel 0.366*** 0.297*** 1.207*** -0.041*** Photo 0.280*** 0.129*** 2.158*** -0.001 <t< td=""><td>ce</td><td>-0.544***</td><td>-0.525***</td><td>-1.883***</td><td>0.109***</td><td>0.109***</td></t<>	ce	-0.544***	-0.525***	-1.883***	0.109***	0.109***
Control variables (-0.047) Capacity -0.031 -0.002 0.152 -0.009 Room (-0.965) (-0.523) (0.689) (-1.194) Room (-2.059) (13.41) (-1.345) (-2.129) Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448*** 0.405*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -4.623*** 0.095*** Week -0.228*** -0.357*** -4.623*** 0.095*** Available -0.127*** -0.154*** -0.892*** 0.035*** Cancel 0.366*** 0.297*** 1.207*** -0.041*** Photo 0.280*** 0.129*** 1.207*** -0.001** Describe 0.239* 0.053* -0.766 0.009 Rule 0.685*** 0.849*** </td <td></td> <td>(-7.074)</td> <td>(-37.418)</td> <td>(-5.683)</td> <td>(4.557)</td> <td>(4.536)</td>		(-7.074)	(-37.418)	(-5.683)	(4.557)	(4.536)
Control variables (4.149) (-0.047) Capacity -0.031 -0.002 0.152 -0.009 Room (-0.965) (-0.523) (0.689) (-1.194) Room (-0.104** 0.095*** -0.477 -0.030** Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448** 0.405*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -4.623*** 0.095*** Week -0.228*** -0.357*** -4.623*** 0.095*** Available -0.127*** -0.154*** -0.892*** 0.035*** Cancel 0.366*** 0.297*** 1.207*** -0.041*** Photo 0.280*** 0.129** 2.158*** -0.001 Describe 0.239* 0.053* -0.766 0.009 1.827) (1.699)	per × Price (rate)	0.447***	0.424***	1.836***	-0.004	-0.004
Control variables Capacity -0.031 -0.002 0.152 -0.009 Room -0.104** 0.095*** -0.477 -0.30** Room -0.104** 0.095*** -0.477 -0.030** Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448*** 0.405*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** 0.276*** 3.473*** -0.121*** Veek -0.228*** -0.357*** -4.623*** 0.095*** Available -0.127*** -0.154*** -0.892*** 0.035*** Arailable -0.127*** -0.154*** -0.892*** 0.035*** Cancel 0.366*** 0.299*** 1.207*** -0.041*** Photo 0.280*** 0.129*** 2.158*** -0.001** 0.840*** 0.239* 0.053*	. ,	(3.124)	(11.078)	(4.149)	(-0.047)	(-0.047)
Rom (-0.965) (-0.523) (0.689) (-1.194) Rom -0.104** 0.095*** -0.477 -0.030** Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448*** 0.405*** 7.993*** -0.035 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** 0.276*** 3.473*** -0.121*** Week -0.228*** 0.276*** 3.473*** -0.121*** Available -0.228*** 0.276*** 3.473*** -0.121*** Available -0.228*** -0.357*** -4.623*** 0.095*** Cancel 0.366*** (-22.7731) (-6.629) (4.143) Available -0.127*** -0.154*** -0.892*** 0.035*** Cancel 0.366*** 0.297*** 1.207*** -0.041*** Photo 0.280*** 0.129*** 2.158*** -0.001 Describe 0.239* 0.053* -0.766 0.009	ntrol variables	,	, ,	, ,	, ,	` ,
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Bed 0.160*** 0.021*** -0.077 0.003 Extra 0.448*** 0.405*** 7.993*** -0.035 Month 0.232*** 0.276*** 3.473*** -0.121*** Month 0.232*** 0.276*** 3.473*** -0.121*** Week -0.228*** -0.357*** -4.623*** 0.095*** Available -0.127*** -0.154*** -0.892*** 0.035*** (-6.245) (-32.795) (-6.127) (4.934) Cancel 0.366*** 0.297*** 1.207*** -0.041*** Photo 0.280*** 0.129*** 1.207*** -0.001** Describe 0.239* 0.053* -0.766 0.009 Rule 0.685*** 0.849*** 6.277*** 0.174*** Time 0.400*** 0.338*** 3.368*** -0.005 (13.557) (90.982) (16.067) (-0.660)		(-2.059)	(13.41)	(-1.345)	(-2.129)	(-2.119)
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Note. Coefficients are shown in the table; z and t (column 3,4,5) values are shown in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

According to our results, although the designation of "Superhost" truly improves the hosts' review volume and ratings, this designation is not without criticism. One of its challenges is the huge amount of effort required for hosts to keep this badge. One aspect is the daunting task of communicating with guests and the effort this entails. Discussing the specifics about the upcoming booking arrangement can generate numerous email exchanges between hosts and potential guests. Especially for "Superhosts" and those who aspire to be "Superhosts," there may well be an even greater need to spend more time chatting with guests to ensure a higher response rate as well as positive evaluations. It is difficult for hosts to manage such large quantities of messages, which always include many answers for lots of repeated questions. Accordingly, in order to reply to this criticism, Airbnb has recently started to offer the service of "Saved Messages," which significantly reduces the manual work of hosts as well as the difficulty of earning and keeping the "Superhost" badge (All About Airbnb, 2016a). By contrast, in recent days Airbnb has also attempted to motivate more "Superhosts" by gradually presenting activities designed to improve the benefits of this designation. Specifically, Airbnb wants real-estate owners to list their spaces and then allow them to be managed by experienced "Superhosts." In this way, "Superhosts" can earn additional revenue by serving as property managers since they have more experience managing properties (All About Airbnb, 2016b). All of these strategies from Airbnb further highlight the effect of the "Superhost" badge on hosts' revenues.

6.2. Theoretical and practical implications

This study offers two main contributions to the literature. First, it contributes to the tourism management literature by considering a very important research topic in a popular and emerging subindustry of the tourism industry – the vacation-rental industry, also called small-tourism business (Wang & Hung, 2015). The topic is how to influence the review volume and valence (rating) of accommodations. As we have noted both in the introduction and literature review, these two features of online reviews are very important and can have a direct effect on the online sales of a company. Related topics attract academic attention in many different areas, such as tourism, marketing, and management information systems (Ye et al., 2009; Zhu & Zhang, 2010). However, the vacationrental industry is an emerging one promoted by a new phenomenon called the sharing economy. Due to limitations of the new industry's still limited development and low-review volume, to the best of our knowledge, this study is one of the first to focus on this important topic in this industry and will thus be a useful starting point for further work in this area. In addition, we focused on this research topic because this sub-industry of the tourism industry has its own particularities and is different from traditional aspects of the tourism industry such as the hotel industry. First, the form of residence and guests' selection criteria for rental accommodations are different from those of standard hotels. To select a hotel, guests focus mainly

on location, price, cleanliness, brand reputation, and other general aspects. However, prospective guests of rental accommodations can focus on more details, such as the style of decoration, the amenities, or even the personality of the owner. Second, the guest structure of these two sub-industries also differs. For example, some studies have reported that Airbnb users are more price conscious than hotel consumers (Guttentag, 2013; Zervas, Proserpio, & Byers, 2015). Finally, the characteristics of owners also differ from those of hotel managers since most of them own the accommodations. Their levels of expertise in online self-marketing and guest management are obviously much lower than those of professional hotel managers. In summary, due to the above differences, we expect that the findings of previous studies focusing on online reviews in the hotel industry cannot be applied to the vacation-rental industry, which highlights our theoretical contributions.

This study also has implications for the literature on gamification designs. Gamification is a common practice applied by many online communities. Previous studies have investigated the effect of users' intrinsic motivation to achieve a goal provided by gamification, such as obtaining a badge, through their online engagement (Cavusoglu et al., 2015; Li et al., 2012). This study differs from all the above studies by focusing on a badge system designed to reward service providers (accommodation owners) and estimating the effects of this system on guests' knowledge-sharing behavior and post-consumption evaluations. Accordingly, the current study may offer possible directions for future research in this area.

The practical contributions of the current study are also twofold. First, several previous studies reported that a portion of accommodation owners pursue their rental business just for fun or to meet people (Thomas, Shaw, & Page, 2011; Wang, Hung, & Bao, 2015). Thus, some owners lack the motivation as well as the ability to manage their accommodations professionally and to earn profits. The "Superhost" badge system used by Airbnb provides intrinsic motivation for owners to improve their accommodations in order to earn a badge and thus attract more guests. This badge represents a goal or a motivation for owners/hosts to improve or professionalize their services. The results of this study show that this badge system can provide not only a special identification for owners that confers higher status within the Airbnb community but also concrete benefits. First, the "Superhost" badge can attract more bookings and reviews and improve ratings. Second, the energy cost to earn and keep this badge can be compensated by raising the total rental price, as guests are willing to spend more money for accommodations with a "Superhost" badge. Accordingly, owners of accommodations on Airbnb who want to improve their review volume and ratings can devote efforts to satisfying the conditions of "Superhost" status.

Our main findings relating to the control variables also offer owners of rental accommodations many practical suggestions. In order to investigate the effect of our variables, we controlled many factors relating to accommodation characteristics. These findings can help owners understand how to attract more reviews and obtain higher ratings by improving the corresponding characteristics of their accommodations, and all these factors are within their control.

7. Conclusion and limitations

In this paper, we have focused on the "Superhost" badge system used by Airbnb and investigated its effect on review volume and ratings. We addressed the research question by proposing a set of detailed hypotheses concerning the relationship between the "Superhost" badge, rental price, and review volume (rating). To handle the different distributions of the independent variables, two different empirical models, the negative binomial model and the Tobit model, were constructed to investigate all Airbnb accommodations available in Hong Kong. Based on the results, we have

presented a number of important implications for the literature and for owners of rental accommodations.

Although this study provides meaningful contributions to both theory and practice, it has certain limitations. First, we have focused only on a single destination. Further studies should expand samples to include more cities and compare the results with ours to observe the impact of destination features and/or different guest groups. Second, in this study, we have investigated a research question and constructed empirical models at the accommodation level. Future studies should consider the research question at the guest level and incorporate guest-related variables in order to compare the results with our findings.

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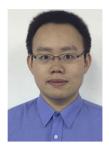
References

- Airbnb. (2016a). *Superhost*. Retrieved from https://www.airbnb.com/superhost?
- Airbnb. (2016b). About us. Retrieved from https://www.airbnb.com/about/about-us.
 All About Airbnb. (2016a). Airbnb hosts put their guest communications on auto-pilot.
 Retrieved from http://all-about-airbnb.com/post/153300216291/aviva-iq-helps-hosts-automated-the-guest-communication.
- All About Airbnb. (2016b). Airbnb gets into the property management business by letting superhosts look after your place for you. Retrieved from http://all-about-airbnb.com/post/150019756336/experienced-superhosts-property-management-platform.
- Ayeh, J. K., Au, N., & Law, R. (2013). "Do we believe in TripAdvisor?" Examining credibility perceptions and online travelers' attitude toward using usergenerated content. *Journal of Travel Research*, 52(4), 437–452.
- Breen, R., & Goldthorpe, J. H. (1997). Explaining educational differentials towards a formal rational action theory. *Rationality and Society*, 9(3), 275–305.
- Brucks, M., Zeithaml, V. A., & Naylor, G. (2000). Price and brand name as indicators of quality dimensions for consumer durables. *Journal of the Academy of Marketing Science*, 28(3), 359–374.
- Cameron, A. C., & Trivedi, P. K. (1986). Econometric models based on count data: Comparisons and applications of some estimators and tests. *Journal of Applied Econometrics*, 1(1), 29–53.
- Cavusoglu, H., Li, Z., & Huang, K. W. (2015). Can gamification motivate voluntary contributions? The case of StackOverflow Q&A Community. In *The proceedings* of the 18th ACM conference companion on computer supported cooperative work & social computing (pp. 171–174). New York, NY: ACM.
- Census and Statistics Department. (2016). *Transport, communications and tourism.*Hong Kong, Retrieved from http://www.censtatd.gov.hk/hkstat/sub/so130.isp.
- Chao, P. (1989). The impact of country affiliation on the credibility of product attribute claims. *Journal of Advertising Research*, 29(2), 35–41.
- Chaves, M. S., Gomes, R., & Pedron, C. (2012). Analysing reviews in the Web 2.0: Small and medium hotels in Portugal. *Tourism Management*, 33(5), 1286–1287.
- Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(3), 345–354.
- Churchill, G. A., Jr., & Surprenant, C. (1982). An investigation into the determinants of customer satisfaction. *Journal of Marketing Research*, 19(4), 491–504.
- Deterding, S., Dixon, D., Khaled, R., & Nacke, L. E. (2011). From game design elements to gamefulness: Defining "gamification.". In *The proceedings of the 15th international academic MindTrek conference* (pp. 9–15). Tampere, Finland: ACM Press.
- Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, 28(3), 307–319.
- Erdem, T., Keane, M. P., & Sun, B. (2008). A dynamic model of brand choice when price and advertising signal product quality. *Marketing Science*, 27(6), 1111–1125.
- Erickson, G. M., & Johansson, J. K. (1985). The role of price in multi-attribute product evaluations. *Journal of Consumer Research*, 12(2), 195–199.
- Fang, B., Ye, Q., & Law, R. (2016). Effect of sharing economy on tourism industry employment. *Annals of Tourism Research*, 54, 264–267.
- Gallarza, M. G., & Saura, I. G. (2006). Value dimensions, perceived value, satisfaction and loyalty: An investigation of university students' travel behaviour. *Tourism Management*, 27(3), 437–452.
- Garbarino, E., & Strahilevitz, M. (2004). Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation. *Journal of Business Research*, 57(7), 768–775.
- Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science*, 55(10),

- 1605-1622.
- Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4), 545–560.
- Google. (2016). Google trends of "gamification.". Retrieved from http://www.google.com/trends/explore#q=Gamification.
- Grant, S., & Betts, B. (2013). Encouraging user behaviour with achievements: An empirical study. In the Proceedings of the 10th Working Conference on Mining Software Repositories, San Francisco, CA, pp. 65–68.
- Greene, W. H. (2011). Econometrics analysis (7th ed.). Upper Saddle River, NJ: Prentice Hall.
- Guttentag, D. (2013). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 18(2), 1–26.
- Gu, B., & Ye, Q. (2014). First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management*, 23(4), 570–582.
- Hamari, J. (2013). Transforming homo economicus into homo ludens: A field experiment on gamification in a utilitarian peer-to-peer trading service. *Electronic Commerce Research and Applications*, 12(4), 236–245.
- Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. In *The 47th Hawaii international conference on system sciences* (pp. 3025–3034). Hawaii, USA: IEEE Computer Society.
- Han, H., & Hyun, S. S. (2015). Customer retention in the medical tourism industry: Impact of quality, satisfaction, trust, and price reasonableness. *Tourism Management*, 46, 20–29.
- He, Y., & Song, H. (2009). A mediation model of tourists' repurchase intentions for packaged tour services. *Journal of Travel Research*, 47(3), 317–331.
- Hofferbert, S., Cahalane, M., & Finnegan, P. (2015). Gamification as an architecture of participation: An investigation of an innovation maker community. In *The twenty-third European conference on information systems (ECIS)* (pp. 1–10). Münster, Germany.
- Hudson, S., Roth, M. S., Madden, T. J., & Hudson, R. (2015). The effects of social media on emotions, brand relationship quality, and word of mouth: An empirical study of music festival attendees. *Tourism Management*, 47, 68–76.
- Jiang, P., & Rosenbloom, B. (2005). Customer intention to return online: Price perception, attribute-level performance, and satisfaction unfolding over time. European Journal of Marketing, 39(1–2), 150–174.
- European Journal of Marketing, 39(1–2), 150–174. Jung, J. H., Schneider, C., & Valacich, J. (2010). Enhancing the motivational affordance of information systems: The effects of real-time performance feedback and goal-setting in group collaboration environments. *Management Science*, 56(4), 724–742.
- Kwon, K. H., Halavais, A., & Havener, S. (2015). Tweeting badges: User motivations for displaying achievement in publicly networked environments. *Cyberpsychology, Behavior, and Social Networking*, 18(2), 93–100.
- Liang, S., Schuckert, M., & Law, R. (2016). Multilevel analysis of the relationship between type of travel, online ratings and management response: Empirical evidence from international upscale hotels. *Journal of Travel & Tourism Marketing*. http://dx.doi.org/10.1080/10548408.2016.1156613.
- Li, Z., Huang, K. W., & Cavusoglu, H. (2012). Quantifying the impact of badges on user engagement in online Q&A communities. In *The thirty-third international conference on information systems* (pp. 1–10). Orlando, FL.
- Li, G., Li, G., & Kambele, Z. (2012). Luxury fashion brand consumers in China: Perceived value, fashion lifestyle, and willingness to pay. *Journal of Business Research*, 65(10), 1516–1522.
- Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, 29(3), 458–468.
- Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management*, 47, 140–151.
- Liu, X., Schuckert, M., & Law, R. (2015). Can response management benefit hotels? Evidence from Hong Kong hotels. *Journal of Travel & Tourism Marketing*, 32(8), 1069–1080.
- Lu, X., Ba, S., Huang, L., & Feng, Y. (2013). Promotional marketing or word-of-mouth? Evidence from online restaurant reviews. *Information Systems Research*, 24(3), 596–612.
- Miyazaki, A. D., Grewal, D., & Goodstein, R. C. (2005). The effect of multiple extrinsic cues on quality perceptions: A matter of consistency. *Journal of Consumer Research*, 32(1), 146–153.
- Mudambi, S. M., & Schuff, D. (2010). What makes a helpful review? A study of customer reviews on Amazon.com. MIS Quarterly, 34(1), 185–200.
- Netemeyer, R. G., Krishnan, B., Pullig, C., Wang, G., Yagci, M., Dean, D., et al. (2004). Developing and validating measures of facets of customer-based brand equity. *Journal of Business Research*, 57(2), 209–224.
- Permalink. (2013). Airbnb vs hotels: A price comparison. Retrieved from http://priceonomics.com/hotels/.
- Phillips, P., Zigan, K., Silva, M. M. S., & Schegg, R. (2015). The interactive effects of online reviews on the determinants of swiss hotel performance: A neural network analysis. *Tourism Management*, 50, 130–141.
- Posselt, T., & Gerstner, E. (2005). Pre-sale vs. post-sale e-satisfaction: Impact on repurchase intention and overall satisfaction. *Journal of Interactive Marketing*, 19(4), 35–47.
- Schlagenhaufer, C., & Amberg, M. (2015). A descriptive literature review and classification framework for gamification in information systems. In *The twenty-third European conference on information systems (ECIS)* (pp. 1–15). Münster, Germany.
- Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and tourism online reviews:

- Recent trends and future directions. *Journal of Travel & Tourism Marketing*, 32(5), 608–621
- Seaborn, K., & Fels, D. I. (2015). Gamification in theory and action: A survey. *International Journal of Human-Computer Studies*, 74, 14–31.
- Severt, D., Wang, Y., Chen, P. J., & Breiter, D. (2007). Examining the motivation, perceived performance, and behavioral intentions of convention attendees: Evidence from a regional conference. *Tourism Management*, 28(2), 399–408.
- Sotiriadis, M. D., & van Zyl, C. (2013). Electronic word-of-mouth and online reviews in tourism services: The use of Twitter by tourists. *Electronic Commerce Research*, 13(1), 103–124.
- Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, 32(6), 1310–1323.
- Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research*, 49(5), 624–639.
- Stone, R. N., & Grønhaug, K. (1993). Perceived risk: Further considerations for the marketing discipline. *European Journal of Marketing*, *27*(3), 39–50. Tanford, S., Raab, C., & Kim, Y. S. (2012). Determinants of customer loyalty and
- Tanford, S., Raab, C., & Kim, Y. S. (2012). Determinants of customer loyalty and purchasing behavior for full-service and limited-service hotels. *International Journal of Hospitality Management*, 31(2), 319–328.
- Thomas, R., Shaw, G., & Page, S. J. (2011). Understanding small firms in tourism: A perspective on research trends and challenges. *Tourism Management*, 32(5), 963–976.
- Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: Journal of the Econometric Society*, *26*(1), 24–36.

 Tse, D. K., & Wilton, P. C. (1988). Models of consumer satisfaction formation: An
- Tse, D. K., & Wilton, P. C. (1988). Models of consumer satisfaction formation: An extension. *Journal of Marketing Research*, 25(2), 204–212.
- Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, 30(1), 123–127.
- Völckner, F., & Hofmann, J. (2007). The price-perceived quality relationship: A metaanalytic review and assessment of its determinants. *Marketing Letters*, 18(3), 181–196.
- Völckner, F., & Sattler, H. (2005). Separating negative and positive effects of price with choice-based conjoint analyses. *Marketing JRM*, 1, 5–13.
- Wang, S., & Hung, K. (2015). Customer perceptions of critical success factors for guest houses. *International Journal of Hospitality Management*, 48, 92–101.
- Wang, S., Hung, K., & Bao, J. (2015). Is lifestyle tourism business in the age of commercialization just a dream? Challenges and remedies. *Journal of China Tourism Research*, 11(1), 19–34.
- Wang, M., Lu, Q., Chi, R. T., & Shi, W. (2015). How word-of-mouth moderates room price and hotel stars for online hotel booking an empirical investigation with Expedia data. *Journal of Electronic Commerce Research*, 16(1), 72–80.
- Winkelmann, R. (2013). Econometric analysis of count data. Berlin: Springer Science & Business Media.
- Xie, K., Chen, C. C., & Wu, S. Y. (2016). Online consumer review factors affecting the offline hotel popularity: Evidence from TripAdvisor. *Journal of Travel and Tourism Marketing*, 33(2), 211–223.
- Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, 43, 1–12.
- Yacouel, N., & Fleischer, A. (2012). The role of cybermediaries in reputation building and price premiums in the online hotel market. *Journal of Travel Research*, 51(2), 219–226.
- Ye, Q., Law, R., & Gu, B. (2009). The impact of online user reviews on hotel room sales. *International Journal of Hospitality Management*, 28(1), 180–182.
- Ye, Q., Li, H., Wang, Z., & Law, R. (2014). The influence of hotel price on perceived service quality and value in e-Tourism: An empirical investigation based on online traveler reviews. *Journal of Hospitality and Tourism Research*, 38(1), 23–39.
- Yeoh, E., Othman, K., & Ahmad, H. (2013). Understanding medical tourists: Word-of-mouth and viral marketing as potent marketing tools. *Tourism Management*, 34, 196—201
- Yoo, C. W., Kim, Y. J., & Sanders, G. L. (2015). The impact of interactivity of electronic word of mouth systems and e-quality on decision support in the context of the e-marketplace. *Information & Management*, 52(4), 496–505.
- Zeithaml, V. Å. (1988). Consumer perceptions of price, quality, and value: A meansend model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22.
- Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. Available online through http://papers.ssrn. com/sol3/papers.cfm?abstract_id=2554500.
- Zhang, Z., Ye, Q., & Law, R. (2011). Determinants of hotel room price: An exploration of travelers' hierarchy of accommodation needs. *International Journal of Contemporary Hospitality Management*, 23(7), 972–981.
- Zhang, Z., Ye, Q., Law, R., & Li, Y. (2010). The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, 29(4), 694–700.
- Zhang, Z., Zhang, Z., Wang, F., Law, R., & Li, D. (2013). Factors influencing the effectiveness of online group buying in the restaurant industry. *International Journal of Hospitality Management*, 35, 237–245.
- Zhou, L., Ye, S., Pearce, P. L., & Wu, M. Y. (2014). Refreshing hotel satisfaction studies by reconfiguring customer review data. *International Journal of Hospitality Management*, 38, 1–10.
- Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, 74(2), 133–148.



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