Consumer valuation of Airbnb listings: a hedonic pricing approach

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Received 28 October 2016
Revised 21 January 2017
6 March 2017
Accepted 23 March 2017

Abstract

Purpose – This paper aims to identify a wide array of utility-based attributes of Airbnb listings and measures the effects of these attributes on consumers' valuation of Airbnb listings.

Design/methodology/approach – A hedonic price model was developed to test the effects of a group of utility-based attributes on the price of Airbnb listings, including the characteristics of Airbnb listings, attributes of hosts, reputation of listings and market competition. The authors examined attributes as they relate to the price of Airbnb listings and, therefore, estimated consumers' willingness to pay for the specific attributes. The model was tested by using a dataset of 5,779 Airbnb listings managed by 4,602 hosts in 41 census tracts of Austin, Texas in the USA over a period from Airbnb's launch in Texas up until November 2015.

Findings – The authors found that the functional characteristics of Airbnb listings were significantly associated to the price of the listings, and that three of five behavioral attributes of hosts were statistically significant. However, the effect of reputation of listings on the price of Airbnb listings was weak.

Originality/value – This study inspires what they call a factor-endowment valuation of Airbnb listings. It shows that the intrinsic attributes that an Airbnb listing endows are the primary source of consumer utilities, and thus consumer valuation of the listing is grounded on its functionality as an accommodation. This conclusion can shed light on the examination of competition between Airbnb and hotel accommodations that are built on the same or similar intrinsic attributes.

Keywords Hedonic price, Sharing economy, Price model, Airbnb listings, Customer valuation

Paper type Research paper

1. Introduction

The sharing economy businesses in the hospitality industry, such as Airbnb, represent an alternative business model that shares the accommodation function with traditional hotel businesses (Guttentag, 2015; Pairolero, 2016). The basic accommodation functionality drives the growth of the sharing economy in two ways. On the one hand, it meets the escalating needs of consumers searching for affordable accommodations, and on the other hand, it monetizes house ownership for owners through sharing their spare resources (Jefferson-Jones, 2015). The boom of the sharing economy is driven by technology, through which the functionality is augmented on both the supply and demand sides to connect a massive number of hosts and guests (Guttentag, 2015; Zervas *et al.*, 2015b). Airbnb also represents a novel business model, having distinct consumer appeals, such as cost savings for both hosts and guests, and a wide variety of household amenities and local experiences for guests (Guttentag, 2015).

International Journal of Contemporary Hospitality Management
Vol. 29 No. 9, 2017
pp. 2405-2424

0959-6119
DOI 10.1108/IJCHM-10-2016-0606

While the sharing economy has drawn considerable attention in recent years (Cannon and Summers, 2014; Edelman *et al.*, 2015; Horton and Zeckhauser, 2016; Quattrone *et al.*, 2016; Zervas *et al.*, 2015a), there is little research on what attributes may affect consumers' valuation of Airbnb listings (Gutt and Herrmann, 2015; Wang and Nicolau, 2017). The difficulty of measuring consumer valuation of Airbnb listings lies in its functional complexity. Not only are Airbnb listings heterogeneous in a huge number of utility-bearing attributes, but some of these attributes also overlap with those of established accommodation businesses, particularly hotels. The heterogeneity of these attributes can be attributed to distinct hosts and their properties, which provide more amenities to guests, yet cause difficulties for consumers to sort out the attributes that matter to their consumption (Ikkala and Lampinen, 2015; Lee *et al.*, 2015). Therefore, the pricing of Airbnb listings entails the examination of which attributes, and to what extent, matter to consumers.

The present study aims to identify a wide array of utility-bearing attributes of Airbnb listings and measure the effects of these attributes on consumers' valuation of Airbnb listings. We begin with exploring a variety of attributes that are most likely to affect consumers' choices and reflect their valuation of Airbnb listings. The criteria for selecting these attributes are grounded on their theoretical importance in affecting the demand of Airbnb accommodation (Edelman and Luca, 2014; Fradkin *et al.*, 2016; Gutt and Herrmann, 2015; Wang and Nicolau, 2017; Zervas *et al.*, 2015b, 2016). We apply the hedonic pricing approach to estimate the contribution of each utility-bearing attribute to consumer valuation of Airbnb listings. We adopt a hedonic pricing approach to estimate the implicit prices of the attributes of Airbnb listings that are valued by consumers in their decision-making. Given the competition between Airbnb and hotels (Nguyen, 2014; Pairolero, 2016; Zervas *et al.*, 2015b, 2016), we also look whether and to what extent competition would alter consumer valuation on Airbnb attributes. Yet, this point has been disregarded by recent studies attempting to examine the price determinants of Airbnb listings (Gutt and Herrmann, 2015; Wang and Nicolau, 2017).

We organized the paper as follows. Section 2 reviews the related studies on the hedonic price approach and its application in tourism and hospitality. In particular, we underscore the theoretical relevance of the hedonic price model to the demand for Airbnb listings. Section 3 describes the model specification and methods of the study. Section 4 discusses the results. We conclude this study in Section 5 by highlighting the theoretical and practical implications and spotting the limitations.

2. Literature review

2.1 Hedonic price and the demand for tourism and hospitality

The theoretical foundation of consumer valuation of a product is the characteristics theory (Lancaster, 1966a, 1966b), which has been extensively used for price estimation of heterogeneous products (Feenstra, 1995; Goodman, 1978; Rosen, 1974). It assumes an implicit market that exists for the characteristics of a good, where each characteristic can be priced to reflect consumers' willingness to pay for that characteristic (Lancaster, 1966a, 1966b; Rosen, 1974). Applications of the hedonic demand theory in tourism and hospitality have caught much attention because the tourism product, in general, or hotel rooms, in particular, are heterogeneous, which entail a precise valuation of a range of elements that the tourism product incorporates (Sinclair *et al.*, 1990). Therefore, empirical studies have primarily been devoted to tourist destination choices and pricing strategies for various tourism products and services, ranging from hotels to package tours (Espinet *et al.*, 2003; Falk, 2008; Monty and Skidmore, 2003; Morley, 1992; Papatheodorou, 2001; Rugg, 1973; Thrane, 2005).

2.2 Hotel pricing, revenue management and consumer evaluation

Consumer valuation of hotels is determined by a wide range of hotel-specific attributes, including hotel star ratings, room attributes, location, cleanliness and amenities (Hung *et al.*, 2010; Lee and Jang, 2011; Schamel, 2012; Zhang *et al.*, 2011). Location is among the most important attributes that affect hotel prices (Lee and Jang, 2011; Zhang *et al.*, 2011). For instance, Lee and Jang (2011) found that airport hotels can obtain a price premium, which highly depends on their proximity to the airport and central business districts. Besides these hotel-specific attributes, many studies indicated the effect of what is called transactional attributes on hotel room rates, including types of distribution channels, cancellation polices and hotel ratings (Chen *et al.*, 2011; Noone and Mattila, 2009; Öğüt and Taş, 2012; Schamel, 2012; Tso and Law, 2005).

A second aspect of transactional attributes that affects hotel pricing is the lead times (Chen and Schwartz, 2008b; Schamel, 2012; Schwartz, 2000, 2006, 2008). A line of research has shown that lead times affect both consumer valuation of a hotel deal and how a hotel can implement price discrimination on booking time (Chen and Schwartz, 2008b; Schwartz, 2000). Schwartz (2000) showed that the willingness to pay of consumers at the time of booking increases as the arrival day is near, regardless of the market segments of business versus leisure travelers. In the internet-based marketplace, consumers can easily observe the change of room rates, and this has been found to influence their likelihood to book (Chen and Schwartz, 2008a). As Chen and Schwartz (2008a) demonstrated, the change patterns of such internal reference prices from hotels can affect the room rate expectations of consumers as well as their subsequent booking behavior. Abrate *et al.* (2012) found that the extent to which the lead times are used by hoteliers to implement dynamic pricing also depends on the star rating of hotels, the types of consumers and the number of hotels in the market.

2.3 Determinants of customer evaluation of Airbnb

2.3.1 Characteristics of Airbnb listings and the demand. Given the complexity of Airbnb listing attributes, studies have shown that many individual attributes of Airbnb listings collectively have tremendous effects on the sales and demand of Airbnb accommodation. For example, Lee *et al.* (2015) found that two types of attributes were strongly associated to room sales of Airbnb listings. One was room-specific attributes, including the price of the listing, minimum stay and household amenities. The other was social features that are specific to Airbnb listings, including the responsiveness of hosts to a guest request, number of reviews and length of membership of the hosts (Lee *et al.*, 2015). Guttentag (2015) argued that Airbnb's distinct attributes, namely, cost-saving, household amenities and an opportunity for the guests to acquire an authentic local experience, can affect the demand from mainstream consumers and acquire them from hotel establishments. Among these most cited attributes of Airbnb listings are customer reviews that can help hosts obtain a price premium for their listings (Ert *et al.*, 2016; Ikkala and Lampinen, 2015; Lee *et al.*, 2015).

2.3.2 Sociability and the attributes of hosts. Despite functional similarities between Airbnb listings and hotels, Airbnb differs from hotels by the existence of the peer-to-peer communication between hosts and guests. Airbnb is a transactional intermediary, through which guests can interact with hosts and build social relationships, which cannot be found in traditional hotel accommodations (Jefferson-Jones, 2016). Ikkala (2014) saw Airbnb as a monetary hospitality network in which interactions with customers are the major source of economic benefits for hosts. Besides obtaining financial benefits, Airbnb hosts can be rewarded with social benefits through sharing their accommodation (Ikkala, 2014; Ikkala and Lampinen, 2015). This means that, on the one hand, hosts can realize the financial value of their properties through social equity built upon Airbnb; on the other hand, the financial benefits can motivate hosts to further engage in interactions with guests in future transactions (Ikkala, 2014).

2.3.3 Customer reviews and reputation of Airbnb listings. Airbnb is a marketplace deeply rooted in a trusted community that incorporates both hosts and guests linked by customer reviews (Ert *et al.*, 2016; Zervas *et al.*, 2015a). Zervas *et al.*'s (2015a) study showed that Airbnb listings generated disproportionately more and higher positive ratings than that of hotels listed online, indicating that ratings change not because of the property itself but because of the platform on which the property is listed. It has been acknowledged that online reviews play a critical role for hotels to improve customer satisfaction (Anderson and Han, 2016). Customer reviews can also affect guests' purchase decisions, especially for the first time users (Panda *et al.*, 2015). However, customer reviews can be biased or misleading because customers who submitted reviews are not compensated for their effort and, therefore, may selectively choose some information to submit (Fradkin *et al.*, 2016). The fact that customer reviews on Airbnb are overwhelmingly positive and skewed to maximum scores might be because non-reviewers are likely to have worse experiences and choose not to report them (Fradkin *et al.*, 2016).

When it comes to the effect of customer reviews, it is argued that hospitality network businesses help increase host revenues, which are at least partially generated from the social nature of the sharing economy businesses (Ert *et al.*, 2016; Ikkala, 2014; Ikkala and Lampinen, 2015; Yannopoulou *et al.*, 2013). Ikkala and Lampinen (2015) argued that, on the one hand, hosts have incentives to monetize their properties for both financial and social benefits and, on the other hand, the generated benefits can encourage them to exert more effort to receive customer reviews by properly selecting guests and controlling the volume and type of demand. Lee *et al.*'s (2015) study identified some social attributes that can affect room sales, such as host responsiveness, number of reviews, count of Wish List and membership seniority, while others, such as overall rating and number of references, are not statistically significant in predicting sales.

2.3.4 Competition and market conditions. When it comes to market competition, Airbnb is seen as a competitor to hotels (Nguyen, 2014; Pairolero, 2016; Zervas *et al.*, 2015b). Empirical studies have emerged to examine the impacts of Airbnb on the incumbent hotel industry, concluding that not only can Airbnb compete with the traditional hotel industry but also can differentiate from it, thereby affecting the hotel industry's competitiveness, which includes decreasing hotels' pricing power and driving down their revenues (Zervas *et al.*, 2015b, 2016). For example, Zervas *et al.* (2016) found that Airbnb in Austin drove down the revenues of hotels by 8-10 per cent on average, particularly low-priced hotels as well as the ones not focusing on business travelers. Zervas *et al.* (2016) found that through leveraging supply to scale, which is a differentiator of peer-to-peer platforms, Airbnb significantly stunted hotels' ability to raise prices in peak demand periods.

2.4 Research objectives

Compared to a wide range of sophisticated revenue management tools adopted by hotels (Abrate *et al.*, 2012; Chen and Schwartz, 2008a, 2008b; Hung *et al.*, 2010; Schwartz, 2000, 2006, 2008), the price of Airbnb listings is largely affected by hosts' unprofessional pricing behavior (Hill, 2015; Li *et al.*, 2016). For instance, Li *et al.* (2016) argued that hosts are less likely to change room rates when the demand suddenly changes during major holidays and conventions, resulting in lower daily revenues and occupancy rates as well as a higher chance of exiting the market. This argument was supported by Hill's (2015) focus group observation, where hosts normally were stumped when setting a price for their listings due to a lack of relevant knowledge and expertise.

Difficulties in pricing Airbnb listings can be attributed to the complexity of Airbnb listings that consists not only of a wide range of functional attributes but also of social interactions between hosts and guests. While some studies have identified a set of price determinants of Airbnb listings, ranging from host attributes, property characteristics to amenities (Gutt and Herrmann, 2015; Li *et al.*, 2016; Wang and Nicolau, 2017), consumer valuation of these characteristics is largely underexplored. Also, the effect of the complexity of these attributes on price of Airbnb may depend not only on social interactions but also on the external market conditions, such as the competition between Airbnb and hotels. We aim to examine the contribution of each of these attributes on the price of Airbnb listings. By using the hedonic pricing approach, the implicit price of each attribute can be estimated to reflect consumers' willingness to pay for that particular attribute.

3. Methodology

3.1 Model specifications

We developed a hedonic price model (Baltas and Freeman, 2001; Hartman, 1989) to test the effects of a group of utility-bearing attributes on Airbnb listing price. We looked at which attributes can explain the price of Airbnb listings, and therefore estimated consumers' valuation for specific attributes. With regard of the demand, the hedonic price model is a solution to the problem of which characteristics embedded in a product, and to what extent, are valued by consumers under the constraints of consumption technology and income (Lancaster, 1966a, 1966b). As characteristics derive utility and lay a foundation for consumers to act when the attributes are presented, the market price of an Airbnb listing is a function of the implicit prices of listing characteristics. The hedonic price function originally given by Rosen (1974) is written as:

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

where P is the observed price of an Airbnb listing, z is a vector of characteristics derived from the listing, and ε is the residual term. Hence, the implicit marginal price of each characteristic of the listing could be obtained by calculating the derivative of P with respect to z:

$$p_z = \frac{\partial P}{\partial z} = \frac{\partial P(z, \varepsilon)}{\partial z} \tag{2}$$

where p_z refers to the marginal price of each characteristic, which is unobservable, yet represents consumers' willingness to pay for characteristic z at the margin, as well as the relative importance of the characteristic in consumers' purchase decisions.

Because the specification of the hedonic price model cannot be grounded in theories (Falk, 2008; Rasmussen and Zuehlke, 1990; Stanley and Tschirhart, 1991), previous research has suggested a number of model specifications, which are based on empirical performance and explanatory power of the models (Rasmussen and Zuehlke, 1990). In our study, we adopted the quadratic semi-log model proposed by Rasmussen and Zuehlke (1990) for two reasons. First, the quadratic semi-log specification performs better than the linear Box–Cox specification in explanatory power while maintaining its ability in interpreting the coefficient estimates (Rasmussen and Zuehlke, 1990). Second, this specification provides an effective alternative to linear specifications when it comes to policy applications (Rasmussen and Zuehlke, 1990). Therefore, we specify the hedonic price function of Airbnb listings as follows:

$$\ln P_i^{(\lambda)} = \alpha_0 + \sum \alpha_i X_i^{(\gamma)} \tag{3}$$

where ln P_i represents the natural log of Airbnb property i's market price, X_i represents a vector of property variables that include listing functionalities, host attributes, customer reviews as well as the market condition in the accommodation market.

3.2 Data and measures

We tested the hedonic price model using a data set of 5,779 Airbnb listings managed by 4,602 hosts in 41 census tracts (i.e. zip codes) of Austin, TX of the USA as of November 2015. Currently, there were more than two million properties worldwide and 60 million users on Airbnb[1]. We chose Austin as our study setting for two reasons. First, it is a major metropolitan area with a boom of vacation rentals in recent years (Dinges and Novak, 2013). Second, emerging studies have investigated various issues of Airbnb in Austin (Zervas *et al.*, 2016) due to data transparency and availability in Austin, making the city of most empirical relevance. Table I presents the distribution of Airbnb listings in these census tracts.

We assembled the data from a variety of sources. First, we developed a software procedure to scrape a wide range of information of Airbnb listings, which included:

- prices (daily, weekly and monthly rental rates);
- functionalities of listings (types of property, number of bedrooms, bathrooms, beds, etc.);
- customer reviews of listings (number of renter reviews and review scores, etc.);
- listing policy (number of guests allowed, types of cancellation policies, and whether allow instant booking, etc.); and
- host behavior (response rates, acceptance rates, response time, whether host is a super host[2], years of membership, etc.).

Second, we collected information of external factors that may affect the price of Airbnb listings, such as the hotel density in the same zip codes in Austin from TripAdvisor.com and sociodemographic information in these census tracts from City-Data.com[3].

Data set from the above sources were pooled at the individual listing level for analysis. The merged data set incorporates 5,764 listings in 41 zip codes of Austin over a period from September 2008 to November 2015. Table II shows the definitions and summary statistics of the variables. Our dependent variable, *lnPrice*, is a function of internal factors, including *Characteristics of Listings* (Internal Factor I) and *Attributes of Hosts* (Internal Factor II), and external factors such as *Reputation of Listings* (External Factor I) and *Competition in a Tract* (External Factor II). Specifically, to characterize listings, we measured *Bathrooms*, *Bedrooms*, *PropertyType*, *RoomType* and *Accommodates* of a listing. In addition, we included *AcceptanceRate*, *ResponseTime*, *CancellationPolicy*, *IsSuperHost* and *HostVerifications* to measure hosts who provide the listing services. In terms of reputation of listings, we focused on online customer review evaluation of different aspects of the listings and hosts, such as *ReviewAccuracy*, *ReviewCommunication*, *ReviewValue*, *ReviewCleanliness*, *ReviewCheckin*, *ReviewLocation* and *ReviewOverallRating*. Finally, *AirbnbTract*, *HotelTract* and *GrossRent* were used to measure the competition in a tract where a listing is located. Table III shows the correlation of variables, which was below 0.8, indicating that the estimation is unlikely to be biased by the collinearity of the variables (Katz, 2006).

Census tracts	No. of Airbnb listings	(%)
78701	143	2.47
78702	816	14.12
78703	413	7.15
78704	1,583	27.39
78705	250	4.33
78717	3	0.05
78721	84	1.45
78722	98	1.70
78723	172	2.98
78724	26	0.45
78725	14	0.24
78726	7	0.12
78727	29	0.50
78728	6	0.10
78729	28	0.48
78730	21	0.36
78731	103	1.78
78732	23	0.40
78733	28	0.48
78734	27	0.47
78735	26	0.45
78736	14	0.24
78737	20	0.35
78738	4	0.07
78739	12	0.21
78741	423	7.32
78744	66	1.14
78745	327	5.66
78746	163	2.82
78747	19	0.33
78748	63	1.09
78749	70	1.21
78750	21	0.36
78751	250	4.33
78752	85	1.47
78753	35	0.61
78754	19	0.33
78756	80	1.38
78757	108	1.87
78758	61	1.06
78759	39	0.67
Total	5,779	100

Table I. Airbnb listings in census tracts of Austin

3.3 Analysis scheme

The estimation of the hedonic price model is centered on two purposes. First, we examined the variance (i.e. R-squared) of the market price of the listings explained by each category of the independent variables. Second, we investigated the marginal effects (i.e. coefficients) of the independent variables on the market price of Airbnb listings. The goal was to formulate a hedonic price index using most relevant and explanatory internal and external factors of listings.

Accordingly, we developed a blend of multivariate regression models in a sequential fashion. Table IV presents the estimation results. We first estimated Internal Factor I in

Table II. Variable definitions and summary statistics

Category	Variable	Definition	Mean	SD	Minimum	Maximum
Listing price	*lnPrice*	Logarithm of price for a given listing	5.21	0.91	2.71	9.21
Internal factor I: *Characteristics of Listing* (listing functionality)	*Bathrooms*	Number of bathrooms for a given listing	1.48	0.77	0	8
	Bedrooms	Number of bedrooms for a given listing	1.74	1.13	0	10
	PropertyType	Categorical variable of property types for a given listing, with values of 1 = Apartment (the base group), 2 = House, and 3 = Others	1.75	0.58	1	3
	RoomType	Categorical variable of room types for a given listing, with values of 1 = Entire House/Apartment (the base group), 2 = Private Room, and 3 = Shared Room	1.33	0.51	1	3
	Accommodates	Number of guests accommodated by a given listing	4.38	2.68	1	16
Internal factor II: *Attributes of Hosts* (host effort)	*AcceptanceRate*	Number of acceptance to the number of reservation request for a given listing's host	86.13	22.17	0	100
	ResponseTime	Speed of response to renter's reservation requests for a given listing's host, with values of 1 = within an hour; 2 = within a few hours; 3 = within a day; 4 = a few days or more	1.75	0.82	1	4
	CancellationPolicy	Strictness of cancellation policy, with values of 1 = flexible (the base group), 2 = moderate and 3 = strict	2.03	0.88	1	3
	IsSuperHost	Dummy variable of whether a given listing's host is super host, 1 = super host and 0 = regular host	0.14	0.35	0	1
	HostVerifications	Number of verification options (email, phone, Facebook, Google, LinkedIn, etc.) disclosed online for a given listing's host	4.32	1.33	0	8
External factor I: *Reputation of Listings* (customer reviews)	*ReviewAccuracy*	Customer-generated review scores of the information accuracy for a given listing	9.65	0.75	2	10
	ReviewCommunication	Customer-generated review scores of the communication effectiveness for a given listing	9.84	0.56	2	10
	ReviewValue	Customer-generated review scores of the value for money for a given listing	9.42	0.89	2	10
	ReviewCleanliness	Customer-generated review scores of the cleanliness for a given listing	9.52	0.92	2	10
	ReviewCheckin	Customer-generated review scores of the check-in experience for a given listing	9.83	0.55	2	10
	ReviewLocation	Customer-generated review scores of the location for a given listing	9.47	0.83	4	10
	ReviewOverallRating	Customer-generated review scores of the overall ratings for a given listing	95.48	7.13	20	100
External factor II: *Competition in a Tract* (market conditions)	*AirbnbTract*	Number of other Airbnb listings located in the same census tract for a given listing	676.53	602.32	3	1583
	HotelTract	Number of hotels located in the same census tract for a given listing	7.69	4.93	1	22
	GrossRent	Median gross rent in the census tract for a given listing	996.46	178.2	805	2001

Table III. Pearson correlation of variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Bathrooms (1)	1.000																			
Bedrooms (2)	0.655	1.000																		
PropertyType (3)	0.183	0.227	1.000																	
RoomType (4)	−0.288	−0.414	0.023	1.000																
Accommodates (5)	0.664	0.706	0.186	−0.473	1.000															
AcceptanceRate (6)	0.005	−0.001	0.000	−0.012	−0.004	1.000														
ResponseTime (7)	0.066	0.068	−0.001	−0.057	0.038	0.006	1.000													
IsSuperHost (8)	0.003	0.002	−0.005	0.001	0.004	0.106	−0.006	1.000												
HostVerifications (9)	0.015	0.027	−0.019	−0.037	0.008	0.031	0.088	0.217	1.000											
CancellationPolicy(10)	0.170	0.231	0.122	−0.239	0.254	0.019	−0.034	−0.007	−0.054	1.000										
ReviewAccuracy(11)	0.012	−0.002	0.025	−0.040	−0.017	0.018	−0.029	−0.009	−0.077	0.009	1.000									
ReviewCommunication(12)	−0.016	−0.016	0.014	−0.056	−0.009	0.006	−0.034	0.014	−0.022	−0.029	0.490	1.000								
ReviewValue(13)	−0.018	−0.023	0.061	0.035	−0.048	−0.014	−0.056	0.007	−0.091	−0.041	0.549	0.452	1.000							
ReviewCleanliness(14)	0.062	0.052	0.063	−0.080	0.026	0.054	−0.028	0.009	−0.080	0.075	0.578	0.434	0.536	1.000						
ReviewCheckin(15)	−0.028	−0.002	0.043	−0.031	−0.013	−0.002	−0.036	0.021	−0.035	−0.011	0.470	0.632	0.446	0.418	1.000					
ReviewLocation(16)	−0.001	−0.029	−0.010	−0.062	−0.029	−0.002	−0.031	−0.024	−0.063	0.005	0.364	0.278	0.438	0.323	0.237	1.000				
ReviewOverallRating(17)	0.056	0.035	0.077	−0.055	0.007	0.005	−0.023	−0.014	−0.066	0.006	0.625	0.566	0.650	0.676	0.524	0.407	1.000			
AirbnbTract(18)	−0.004	0.037	−0.025	−0.196	0.076	−0.037	0.033	0.005	0.044	0.138	0.040	0.022	−0.019	0.039	0.042	0.147	0.042	1.000		
HotelTract(19)	−0.053	−0.063	−0.171	−0.003	−0.050	0.052	0.018	0.038	−0.027	−0.009	−0.010	0.000	0.007	0.030	0.004	0.129	0.016	0.163	1.000	
GrossRent(20)	0.052	0.011	−0.067	−0.020	0.009	0.010	−0.001	−0.064	−0.003	−0.007	−0.033	−0.007	−0.006	−0.002	−0.046	0.185	−0.010	−0.222	0.327	1.000

Table IV.
Estimation of hedonic pricing models

	lnPrice					
		Internal Factor I			*Internal Factors I & II*	
Independent variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Characteristics of listings (listing functionalities)						
Bathrooms	0.320*** (0.000)	0.320*** (0.000)	0.320*** (0.000)	0.292*** (0.000)	0.292*** (0.000)	0.292*** (0.000)
Bedrooms	0.172*** (0.000)	0.172*** (0.000)	0.172*** (0.000)	0.172*** (0.000)	0.172*** (0.000)	0.172*** (0.000)
PropertyType						
House	−0.027 (0.174)	−0.027 (0.248)	−0.027 (0.248)	0.047* (0.060)	0.047* (0.059)	0.047* (0.059)
Others	−0.144*** (0.000)	−0.144*** (0.000)	−0.144*** (0.000)	0.086** (0.026)	0.086** (0.029)	0.086** (0.029)
RoomType						
Private room	−0.643*** (0.000)	−0.643*** (0.000)	−0.643*** (0.000)	−0.583*** (0.000)	−0.583*** (0.000)	−0.583*** (0.000)
Shared room	−1.093*** (0.000)	−1.093*** (0.000)	−1.093*** (0.000)	−1.113*** (0.000)	−1.113*** (0.000)	−1.113*** (0.000)
Accommodates	0.027*** (0.000)	0.027*** (0.002)	0.027*** (0.002)	0.042*** (0.000)	0.042*** (0.000)	0.042*** (0.000)
Attributes of hosts (host effort)						
AcceptanceRate				0.001 (0.175)	0.001 (0.161)	0.001 (0.161)
ResponseTime				0.040*** (0.001)	0.040*** (0.001)	0.040*** (0.001)
IsSuperHost				−0.002 (0.935)	−0.002 (0.934)	−0.002 (0.934)
HostVerifications				0.015* (0.094)	0.015* (0.069)	0.015* (0.069)
CancellationPolicy						
Moderate				−0.104*** (0.000)	−0.104*** (0.000)	−0.104*** (0.000)
Strict				0.024 (0.330)	0.024 (0.350)	0.024 (0.350)
Reputation of listings (customer reviews)						
ReviewAccuracy						
ReviewCommunication						
ReviewValue						
ReviewCleanliness						
ReviewCheckin						
ReviewLocation						
ReviewOverallRating						
Competition in a tract (market conditions)						
AirbnbTract						
HotelTract						
GrossRent						
Constant	4.548*** (0.000)	4.548*** (0.000)	4.548*** (0.000)	4.118*** (0.000)	4.118*** (0.000)	4.118*** (0.000)
Observations	5,727	5,727	5,727	2,560	2,560	2,560
R-squared	0.538	0.538	0.538	0.673	0.673	0.673

Note: p-value in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$

(*continued*)

Table IV.

	lnPrice					
		Internal Factors I & II and External Factor I			Internal Factors I & II and External Factors I & II	
Independent variable	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Characteristics of listings (listing functionalities)						
Bathrooms	0.259*** (0.000)	0.259*** (0.000)	0.259*** (0.000)	0.279*** (0.000)	0.279*** (0.000)	0.279*** (0.000)
Bedrooms	0.168*** (0.000)	0.168*** (0.000)	0.168*** (0.000)	0.152*** (0.000)	0.152*** (0.000)	0.152*** (0.000)
PropertyType						
House	0.060** (0.018)	0.060** (0.017)	0.060** (0.017)	0.112*** (0.000)	0.112*** (0.000)	0.112*** (0.000)
Others	0.035 (0.390)	0.035 (0.395)	0.035 (0.395)	0.025 (0.559)	0.025 (0.566)	0.025 (0.566)
RoomType						
Private room	−0.578*** (0.000)	−0.578*** (0.000)	−0.578*** (0.000)	−0.527*** (0.000)	−0.527*** (0.000)	−0.527*** (0.000)
Shared room	−1.106*** (0.000)	−1.106*** (0.000)	−1.106*** (0.000)	−1.019*** (0.000)	−1.019*** (0.000)	−1.019*** (0.000)
Accommodates	0.043*** (0.000)	0.043*** (0.000)	0.043*** (0.000)	0.046*** (0.000)	0.046*** (0.000)	0.046*** (0.000)
Attributes of hosts (host effort)						
AcceptanceRate	−0.000 (0.781)	−0.000 (0.783)	−0.000 (0.783)	0.000 (0.776)	0.000 (0.785)	0.000 (0.785)
ResponseTime	0.038*** (0.003)	0.038*** (0.002)	0.038*** (0.002)	0.042*** (0.002)	0.042*** (0.001)	0.042*** (0.001)
IsSuperHost	0.024 (0.314)	0.024 (0.313)	0.024 (0.313)	0.023 (0.370)	0.023 (0.375)	0.023 (0.375)
HostVerifications	0.015* (0.082)	0.015* (0.057)	0.015* (0.057)	0.035*** (0.000)	0.035*** (0.000)	0.035*** (0.000)
CancellationPolicy						
Moderate	−0.101*** (0.000)	−0.101*** (0.000)	−0.101*** (0.000)	−0.102*** (0.001)	−0.102*** (0.001)	−0.102*** (0.001)
Strict	0.011 (0.678)	0.011 (0.701)	0.011 (0.701)	−0.015 (0.591)	−0.015 (0.617)	−0.015 (0.617)
Reputation of listings (customer reviews)						
ReviewAccuracy	−0.023 (0.246)	−0.023 (0.285)	−0.023 (0.285)	−0.018 (0.395)	−0.018 (0.438)	−0.018 (0.438)
ReviewCommunication	−0.014 (0.596)	−0.014 (0.682)	−0.014 (0.682)	−0.010 (0.713)	−0.010 (0.780)	−0.010 (0.780)
ReviewValue	−0.134*** (0.000)	−0.134*** (0.000)	−0.134*** (0.000)	−0.107*** (0.000)	−0.107*** (0.000)	−0.107*** (0.000)
ReviewCleanliness	0.048*** (0.003)	0.048** (0.023)	0.048** (0.023)	0.042** (0.014)	0.042* (0.070)	0.042* (0.070)
ReviewCheckin	−0.000 (0.985)	−0.000 (0.988)	−0.000 (0.988)	−0.007 (0.816)	−0.007 (0.858)	−0.007 (0.858)
ReviewLocation	0.080*** (0.000)	0.080*** (0.000)	0.080*** (0.000)	0.031** (0.047)	0.031* (0.065)	0.031* (0.065)
ReviewOverallRating	0.011*** (0.000)	0.011*** (0.000)	0.011*** (0.000)	0.010*** (0.000)	0.010*** (0.004)	0.010*** (0.004)
Competition in a tract (market conditions)						
AirbnbTract				0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
HotelTract				−0.004* (0.080)	−0.004* (0.064)	−0.004* (0.064)
GrossRent				0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Constant	3.532*** (0.000)	3.532*** (0.000)	3.532*** (0.000)	3.071*** (0.000)	3.071*** (0.000)	3.071*** (0.000)
Observations	1,989	1,989	1,989	1,647	1,647	1,647
R-squared	0.692	0.692	0.692	0.712	0.712	0.712

Models 1-3 to examine the explanatory power of the intrinsic characteristics of the listings. We then included Internal Factor I and II in Models 4-6 to estimate the effects of both the listing characteristics and attributes of hosts on the market price of the listings. We further estimated Internal Factor I and II and External Factor I in Models 7-9 for examining the explanatory power of the listing characteristics, host attributes and reputation of the listings. Finally, we included all internal and external factors, including the listing characteristics, host attributes, reputation of the listings and competition in a tract, in Models 10-12 to estimate the overall explanatory power of the hedonic price models. For each set of the aforementioned multivariate regression models, we cross-checked the robustness of the results using three estimation approaches, namely, ordinary least squares (OLS) with standard errors, OLS with robust standard errors and OLS with robust standard errors clustered on the listing level (Greene, 2012). While the first method was appropriate for our estimation purposes, the latter two methods were used to reduce heteroscedasticity concerns (Greenwood and Wattal, 2015). The above estimations were performed using Stata/SE 14.0.

4. Results and discussion

4.1 Performances of the models

We first examined the change of R-squared values in the four sets of models by entering the characteristics of listings, host effort, customer reviews and market conditions in sequence. Models 1-3 in Table IV show that in the basement model the intrinsic characteristics explained 53.8 per cent of the variance in the market price of Airbnb listings. By including host effort to the intrinsic characteristics, the predictive power of Models 4-6 in explaining the variance in price increased by nearly 14 percentage points to 67.3 per cent. Considering the constrained sample size of 2,650 for Models 4-6, which was less than half of the sample size for the basement model, we argue that the predictive power of host effort could be larger. By including the variables of customer reviews to intrinsic characteristics and host effort, we found that the predictive power of Models 7-9 only increased by 13 percentage points, while the sample sizes across the two categories of the models did not vary substantially. This indicates that customer reviews did not affect market price of Airbnb listings as noticeably as we would normally expect. In Models 10-12, we tested the effects of market conditions as well as the aforementioned three categories, including listing attributes, host effort and customer reviews, on the market price of Airbnb listings. The results show that the predictive power of the models increased two percentage points to 71.2 per cent.

As underscored by previous studies, one of the major differences between the sharing economy businesses and traditional hotels is that they provide extra benefits, primarily social interactions and connectedness, to both guests and hosts (Jefferson-Jones, 2016; Jung *et al.*, 2016; Ikkala, 2014; Ikkala and Lampinen, 2015). Not only have these social benefits been underscored by academic research referring to what is called monetary hospitality network (Ikkala, 2014; Ikkala and Lampinen, 2015), they are also advocated by industry supporters as a means to promote the sharing economy (Botsman, 2014). While our study did provide evidence in this regard, the effect might not be as large as they were claimed. The reason in that regarding the explanatory power of the models, the baseline model that built upon the listings' intrinsic attributes accounted for a substantially large proportion of variance in the market price. In other words, consumer valuation of Airbnb listings is predominant by the intrinsic functionality that the listings have as a prerequisite. The social attributes are secondary.

4.2 Estimation of hedonic price functions

4.2.1 Effects of functionality of Airbnb listings. As presented in Models 1-3, we found that all variables that measured the functionality were statistically significant in association to the market price of the listings, with 53.8 per cent variance explained in price. Room types had the largest effect on the market price of listings. Airbnb listings featured by an entire house/apartment had a positive effect on the listing price, followed by a private room and the shared room. The results indicate that the basic accommodation that Airbnb listings provide largely determines the price of listings. Searching for functionality dominates consumer valuation of Airbnb listings, despite the fact that Airbnb provides extra social interaction opportunities to guests compared to traditional hotel establishments. When it comes to facilities at Airbnb listings, the numbers of bedrooms and bathrooms had considerable positive effects on the listing price, indicating that the basic amenities can determine its market price, and consumers would be more likely to pay for these amenities. We also found that property type can influence the listing price, showing that consumers are more likely to pay for a listing in an apartment than in a house or other types of properties. This might be because a listing in an apartment may be in a downtown area, which can provide more convenience to guests. Overall, we found that the estimated effects of listing functionalities were consistent across different estimations with error specifications of OLS (Models 1-3), supporting the robustness of the findings.

The predominance of the intrinsic attributes of Airbnb listings in predicting the market price indicates that functionality is the principal utility appreciated by guests. From a consumer's perspective, Airbnb is no more than a hotel or any other type of accommodation that should first and foremost satisfy basic accommodation needs. It is not surprising that consumers' valuation is largely determined by the functionality or amenities that Airbnb listings possess. As for hosts, the price premiums of Airbnb listings are determined by what and how many functional benefits they can provide to consumers (Wang and Nicolau, 2017). In this sense, there is indeed competition between Airbnb, hotels and even local real estate, all of which is built upon the existing intrinsic attributes of a property. This conclusion has been evidenced by some empirical studies in the USA, showing that Airbnb's intrusion has led to decreased revenues and market shares for hotels (Zervas *et al.*, 2015b, 2016).

4.2.2 Effects of host effort of Airbnb listings. We then controlled the effects of functionality and analyzed the effects of host attributes on the market price of the listings. The results show that host effort explained an additional 13.5 per cent of the variance in the listing price. Three of five behavioral indicators of hosts were statistically significant. We found that the speed of host response to guests' reservation requests had a positive effect on the listing price. Also, the more verification options available on the listing, the higher consumers would pay for the listing. The cancellation policy that a host adopts had a significant effect on the listing price. We only found that a moderate cancellation policy was significantly associated to the price of listings. We did not find evidence for the impact of a super host status on consumers' valuation of the listings. It seems that consumers are able to isolate the influence of host quality from committing the price they are willing to pay. As shown in estimations of OLS with different error specifications (Models 4-6), the findings on the effects of host effort on listing price remained consistent.

The effort exerted by hosts in serving guests can be seen as an extension of the functionality of Airbnb listings. This means that host effort, even before any transaction is being undertaken, can be seen as a service component of Airbnb-specific accommodation. While the intrinsic attributes of Airbnb listings do not vary across hosts, host behavior, specifically how much effort hosts are committed to serving guests, can add value to Airbnb listings. In this regard, the valuation of Airbnb listings can vary from one host to another even though the functionality of the property remains unchanged. Our study shows that both hosts' swift response to guest inquiries and relaxing cancellation policies increased the valuation of listings after controlling for the effect of functionality.

4.2.3 Effects of customer reviews of Airbnb listings. After controlling for both the effects of listing functionality and host effort, Models 7-9 explained an additional 2 per cent of the variance in the listing price. The results show that some variables of customer reviews had statistically significant effects on the listing price. Among the seven indicators measuring the reputation of the listings, we found that customer-generated review scores, which measured the value for money for Airbnb listings, had the largest effect on the price of the listings. Customer-generated review scores rating location also positively affected the listing price. It is thus obvious that travelers value a lot the accessibility and convenience of Airbnb listings to certain local attractions. In addition, customer-generated review scores that rated cleanliness positively affected the listing price, and customer-generated review scores that rated overall ratings of the listings positively affected the listing price. Such estimated effects persisted in the OLS estimation with different error specifications (Models 7-9), validating the robustness of the findings.

Customer reviews have been underscored by a number of studies in affecting demand (Panda *et al.*, 2015; Zervas *et al.*, 2015a). Our study has demonstrated that the effect of customer reviews in impacting the market price of Airbnb listings was weak, explaining an additional 2 per cent of variance in price. Two factors may help explain such a negligible effect. First, compared to intrinsic attributes of listings, social interactions are a post hoc measure of Airbnb performance, which cannot be anticipated by guests prior to their booking. While guests would expect that social interactions can become more intensive when staying at Airbnb listings, this expectation can only be fulfilled after the stay and, therefore, may exert an inconsequential effect on their valuation of Airbnb listings prior to booking. Second, an increasing proportion of professional hosts in the market that may have impeded the host–guest interactions (Slee, 2016). When social interactions are excessively commercialized aiming to accommodate mass tourists, the virtue of social interactions that Airbnb claimed at its inception stage may diminish.

4.2.4 Effects of competition of Airbnb listings. In Models 10-12, we controlled the effects of all variables that characterize an Airbnb listing, aiming at examining whether market competition could affect the market price. Table IV shows that the models explained an additional 2 per cent of variance in the price. By examining the density of Airbnb listings in a zip code, the density of hotels and median gross rents in the same census tract for a given listing, we found that the price of Airbnb listings was negatively affected by the number of hotels. This result suggests that the hotel supply can discount consumer valuation of Airbnb listings. This conclusion is consistent with prior studies, which concluded that Airbnb weakens the market performance of the hotel industry, especially the price competitiveness of economy hotels (Zervas *et al.*, 2015b, 2016).

5. Conclusions

5.1 Conclusions

This study has provided evidence for what we call a factor-endowment valuation, suggesting that the intrinsic attributes of an Airbnb listing are the primary source of consumer utility. This result to some extend casts doubt on the views of those who have advocated the sharing economy that can dwarf traditional business modes and outperform well-established hospitality businesses (Botsman and Rogers, 2011; Ikkala, 2014; Ikkala and Lampinen, 2015). These views are that the sharing economy provides the benefits of social interactions and the like, which cannot be generated by traditional hospitality businesses, and therefore consumers tend to overweigh the benefits of social interactions (Ikkala, 2014; Ikkala and Lampinen, 2015). However, our study has shown that the basic functionality as an accommodation, which Airbnb and hotels have in common, is the deterministic factor of consumer's evaluation. This means that social interaction is secondary to functionality in determining consumer valuation of Airbnb listings.

5.2 Theoretical implications

This study can shed light on examining competition between Airbnb and established hotel accommodations which are built on same or similar intrinsic attributes. Prior studies have concluded that Airbnb undermines hotels' pricing power and drives down their revenues (Zervas *et al.*, 2015b, 2016). In particular, low-priced hotels and those catering leisure travelers are among the most affected in the hotel industry (Zervas *et al.*, 2016). We argue that the competition between the two would become fierce in the foreseeable future as Airbnb gradually expands to serve the business travel market. Another issue is that the competition between Airbnb as a short vacation rental and long-term real estate market can escalate, as they compete for the same properties. The success of sharing economy businesses, particularly Airbnb, lies at their interpersonal connections that address the needs of consumers for social interactions, thereby creating incremental consumer value. This argument, though compelling especially when compared with hotel establishments, was not supported by this study.

In addition to intrinsic attributes of Airbnb listings, we found that host effort is important in affecting listing price. This result has complemented by Wang and Nicolau (2017), who concluded that host attributes, including the superhost status, more listings and verified identities, are positively associated with price premiums that an Airbnb listing can command. In our study, host effort can be seen as an extension of the functionality of Airbnb listings, which generates utility to consumers and therefore contributes to increasing consumer valuation of Airbnb listings. Worth noting is that the two indicators measuring host effort are host response time and cancellation policies, which are presented before actual transactions. This means that consumers anticipate some sort of values prior to actual purchases and are willing to pay for the benefits. These anticipated benefits are in fact independent of the intrinsic attributes as they are solely tied to hosts.

5.3 Practical implications

The factor-endowment valuation of Airbnb listings has profound implications to hosts in formulating pricing policies. This is because whether a host wants to list his properties on Airbnb, first and foremost, he needs to well understand the intrinsic attributes of the properties that generate the values to consumers. This study suggests a couple of solutions for pricing Airbnb listings. First, consumer valuation of Airbnb listings is primarily tied to the intrinsic attributes of Airbnb listings, particularly types of rooms and properties. Airbnb hosts should scrutinize these utility-bearing attributes and base their pricing strategy on these attributes. Relying on social attributes in setting price can be misleading and risky as social benefits are a result of a dynamic process between hosts and guests, which are difficult to materialize on the consumer's side before making purchases. On the other hand, Airbnb supply dominated by professional hosts or hosts with multiple listings may have impeded host–guest interactions. The social benefits are post hoc gains to consumers and may not be fully fulfilled on site. In this regard, observing the change of hotel prices in the market, in particular when these intrinsic attributes are comparable to those of adjacent hotels, can help hosts set a right price to reflect the market value of these attributes.

Second, hosts should consider rewarding their effort of providing timely response or other customer service through price premiums. In other words, these *ex ante* efforts need to be monetized as they increase consumers' willingness to pay upon purchase. This is where the sharing economy in general can generate benefits to consumers and differentiate from hotel businesses. Wang and Nicolau (2017) showed that the super host status commands a price premium compared to similar Airbnb listings without such a status. Also, Gutt and Herrmann's (2015) study concluded that listings with star rating visibility can have an average price premium of nearly three euros compared to those without the rating visibility. Therefore, hosts should transform their role as an owner of the property to an operator of the network hospitality business and importantly charge a higher price to reflect their effort and reputation.

5.4 Limitation and future research

We are prudent on whether the findings of our study can be generalized to other cities and even other countries. In particular, the results from Austin may not apply to a less developed market where information provided by hosts might be more valuable to guests. Due to a lack of data, we did not distinguish between domestic travelers and international tourists. Compared to international tourists, domestic travelers may not value social benefits as much as their international counterparts do. Also, certain host attributes that may affect consumer valuation of Airbnb listings were not incorporated in the analysis. The hosts of sharing economy consists of both professional players and nonprofessional players (amateur) (Li *et al.*, 2016). Although it is not possible to observe whether a host is "amateur" or professional in our data, we believe the role of hosts ("amateur" versus "professional") is interesting and should be included in future study to advance our understanding of the sharing economy.

When it comes to consumer evaluation of hotels, the role of lead times in affecting hotel pricing and revenue management has been underscored in previous studies (Chen and Schwartz, 2008a, 2008b; Schwartz, 2000, 2006, 2008). As consumer's booking of Airbnb listings resembles hotel booking, this study would generate more meaningful results if we tested the effect of lead times in the Airbnb context. Nevertheless, due to the data limitation, this effect was unexplored in our study. We should be cautious about applying the results of Airbnb pricing to the hotel context, in which not only the lead times but also multiple types of distribution channels play pivotal roles in affecting hotel prices.

Notes

1. Source: www.airbnb.com/about/about-us
2. Being a Superhost refers to a host elite status. It is a reward recognizing those hosts who receive stellar reviews that reveal their exemplary hospitality skills. According to the Airbnb website, the Superhost status is characterized by a high rate of honoring reservations, a high percentage of 5-star reviews, a high response rate and a longer hosting experience, all of which clearly indicate a high standard of Superhosts over non-Superhosts (Airbnb, 2016).
3. City-Data.com is the most visited website in the nation with 22 million monthly visitors for public records of zip code specific data, such as population, rent, property assessments, sex offenders and copyrights. Source: http://city-data.com/contacts.html

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