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Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings

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ABSTRACT

This paper examines the impact of a variety of variables on the rates published for Airbnb listings in five large metropolitan areas in Canada. The researchers applied a hedonic pricing model to 15,716 Airbnb listings. As expected, the results show that physical characteristics, location, and host characteristics significantly impact price. Interestingly, more reviews are associated with a drop in price. This information is useful to hosts who are forming a pricing strategy for their listings as well as for Airbnb, who needs to support them. The paper raises important questions about pricing in the sharing economy and suggests avenues for future research in this area.

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Introduction

Since launching in 2008, Airbnb has grown to become one of the largest single tourism accommodation distribution platforms in the world, with 2,000,000 listings and 60,000,000 guests (Airbnb, 2016a). This exponential growth means that hosts are increasingly facing greater competition and their marketing practices therefore require more systematic and informed approaches. Due to the unique characteristic of perishability within the accommodations business (i.e. a room cannot be stored away for a future sale, but rather must be sold each given night), pricing is an important and well researched topic. Indeed, pricing and revenue management have been identified as two of the most frequently researched subjects in hospitality marketing (Yoo, Lee, & Bai, 2011). Understanding of pricing is critical from practical as well as theoretical perspectives, as the pricing for hotel room rentals drives consumer decision making and hotel profitability. The growth in the use of the Internet for travel planning and purchasing has increased the importance of strategic pricing because it has made pricing more transparent, as consumers can easily price-shop multiple accommodation options with the click of the mouse.

Recognizing the importance of pricing to the overall accommodations industry, it could be argued that pricing is one of the most important business practices for Airbnb hosts to master. However, the uniqueness of the accommodation services offered on Airbnb makes it very difficult to set prices optimally. Hill (2015) described hosts as being confounded when prompted by the platform to set a price and not being able to determine the real market value of their offerings. Airbnb has recognized the significant problem it faces due to inefficient pricing by hosts and has consequently introduced a "price tips" feature in specific markets to support hosts in their pricing decisions (Airbnb, 2015). The specific algorithm behind the tool considers a large number of factors when suggesting prices, but lacks transparency.

Understanding Airbnb prices not only provides insights of practical importance to hosts but also to researchers trying to understand the sharing economy accommodation phenomenon. While commercial accommodation providers are generally strategic and deliberate in their pricing, and can typically rely on operational as well as market data and staff expertise when making pricing decisions, it is not clear how Airbnb hosts set their prices and how perceptions of consumers' willingness to pay for specific accommodation attributes potentially influence their pricing decisions.

The existing literature does not currently provide a comprehensive answer to the question of whether hosts systematically link their prices to the attributes of their offering. Although previous sharing economy research has identified the importance of trust

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between buyer and seller (Belk, 2014; Botsman & Rogers, 2010), it has not addressed price. The work of Li, Moreno, and Zhang (2015) identified a difference in performance for professional hosts who manage two or more properties versus hosts who manage a single listing, but did not address the specific factors that affect price. Lee et al. (2015) investigated the impact of social factors like the number of reviews on Airbnb sales, but again not price. Ikkala and Lampinen (2014) used qualitative methods to identify how hosts may price their listings below market in order to be able to choose their exchange partners, but the research does not address the factors that affect price. Hill (2015) discussed the pricing tip tool offered by Airbnb, but did not provide a comprehensive list of the factors that affect price. Ert, Fleischer, and Magen (2016) looked at factors affecting Airbnb prices, but only considered a small number of independent variables related to trust. Therefore, the research to date related to pricing and Airbnb does little to explain the variables that make up the price of a listing.

Based on Airbnb listings in five major Canadian urban markets and their publicly visible attribute information, this paper uses the hedonic price method to examine if and how different listing attributes are reflected in the price. Hedonic models have been widely used in real estate, tourism, and hotels. While the pricing model employed in this research includes traditional accommodation attributes such as location, physical components, and amenities, our analysis also looks at listing management, social factors, and host characteristics. As such, the research builds on existing pricing literature but uses a model that takes into account the unique features of the Airbnb platform and the practices of hosts participating in the sharing economy.

Literature review

Airbnb

Airbnb is a disruptive innovation in the sharing economy whose business model focuses on tourist accommodation, and this accommodation has a unique appeal to tourists (Guttentag, 2015). Airbnb has quickly grown to become a popular alternative form of accommodation with global implications, and this growth has also led to increased scholarly inquiry into the phenomenon. Recent articles about Airbnb have addressed issues related to regulation (Jefferson-Jones, 2014), discrimination (Edelman & Luca, 2014), impacts on the hotel industry (Zervas, Proserpio, & Byers, 2015b) and branding (Yannopoulou, Moufahim, & Bian, 2013).

Given the importance of reputation management in the sharing economy, consumer reviews have also become a popular focus of analyses related to Airbnb. Zervas, Proserpio and Byers (2015a) found reviews on Airbnb are dramatically more positive than on established electronic word-of-mouth platforms, but similar to ratings of vacation rental properties listed on TripAdvisor. Lee et al. (2015) used sales data from 4178 Airbnb listings to determine that the number of reviews, membership seniority, count of "Wish lists", and host responsiveness are social factors significantly associated with sales. In the same research, conventional features such as overall rating were not significantly associated with sales. Based on a sample of Airbnb listings in Stockholm, Sweden, Ert et al. (2016) found that the perceived trustworthiness of the host, as inferred from the host's photo, is a better indicator of price and demand than review scores. These findings by Lee et al. (2015) and Ert et al. (2016) are somewhat counterintuitive to findings from the hotel sector, where Anderson (2012) used hotel performance data and online reviews to demonstrate that a 1% increase in review scores leads to a 1.42% increase in revenue per available room.

With Airbnb hosts acting as sharing economy entrepreneurs, social media marketers, and hospitality providers, they occupy a very unique space in tourism. Hosts typically sell accommodation without any general business or specific hospitality knowledge. Through qualitative interviews, Ikkala and Lampinen (2014) found that some hosts listed their properties below market price to increase the number of requests, which affords them with more options to choose their guests. This finding suggests that price setting among hosts was driven by emotional considerations. Particularly focusing on the notion of hosts as entrepreneurs, Li et al. (2015) scraped 18 months of Airbnb data for Chicago to investigate operational differences between non-professional and professional hosts (hosts with two or more listings for entire places). The professional hosts achieved both higher daily revenue (+16.9%) and occupancy rates (+15.5%) than the non-professional or casual hosts (with only one listing). Both research projects suggest that there are pricing inefficiencies for non-professional hosts. Previous Airbnb-related research has started to highlight findings related to price but no research to date has done a systematic analysis of factors influencing the price of an Airbnb listing that would allow for a better understanding of host behaviors and perceptions.

Hedonic pricing and accommodation

Hedonic pricing theory states that the price of a product can be regarded as a function of the measureable, utility-affecting attributes or characteristics of the product (Rosen, 1974). An Airbnb accommodation listing, according to hedonic pricing theory, is therefore a bundle of elements that influence the quality of the overall product and provide consumers with value and satisfaction. Accordingly, a listing's price can be linked to the presence or absence of specific items; it is a price proposal that reflects the host's assumptions about implicit marginal prices of particular listing characteristics.

Hedonic pricing models use multiple regression analysis to estimate the characteristics which most influence the price of a heterogeneous product. The technique has been widely used in real estate (Goodman, 1978; Goodman & Thibodeau, 2003; Witte, Sumka, & Erekson, 1979) and price competitiveness of tourism packages (Aguiló, Riera, & Rosselló, 2005; Clewer, Pack, Sinclair, Johnson, & Thomas, 1992; Mangion, Durbarry, & Sinclair, 2005; Taylor, 1995). Within the accommodations sector, hedonic models have been widely used in the context of urban hotels (Chen & Rothschild, 2010; Thrane, 2007; Zhang, Ye, & Law, 2011), holiday area hotels (Abrate, Capriello, & Fraquelli, 2011; Coenders, Espinet, & Saez, 2003; Espinet, Saez, Coenders, & Fluvià, 2003; Fleischer, 2012), holiday apartments (Juaneda, Raya, & Sastre, 2011; Portolan, 2013; Saló & Garriga, 2011), and bed and breakfasts (Monty & Skidmore, 2003).

Across the many different forms of hedonic pricing models for accommodation, the most widely reported and significant factors are related to the physical characteristics of the offering. Saló and Garriga (2011) identified that the rental price of a holiday apartment was 10.9% less than that of a terraced house, a detached house was 13.8% higher than a terraced house, and an extra room generated an extra 13.8% in price. Similarly, Juaneda et al. (2011) identified that an additional room in an apartment increases the price by 20.6%. While apartment-based accommodation has shown to have different prices by type and capacity of accommodation, hotel-based accommodation price is largely influenced by star rating (Abrate et al., 2011; Fleischer, 2012; Israeli, 2002). Based on a study of hotel rooms listed on Booking.com in a holiday region of the Mediterranean, Fleischer (2012) found that some room categories drove a higher price than standard rooms, namely deluxe (11%), superior suite (15%), and villa (64%) respectively.

Another common factor within hedonic pricing models for accommodation is location. Amongst holiday-based accommodation, one of the main positive drivers for price is distance to the beach (Coenders et al., 2003; Espinet et al., 2003; Saló & Garriga, 2011). Amongst city-based hotels, conflicting results can be found in the literature. Thrane (2007) looked at 78 hotels located in Oslo, Norway, and determined that the closer the hotel was to the downtown train station the higher price. Counterintuitively, Chen and Rothschild (2010) looked at 73 hotels in Taiwan and determined that hotels located outside of downtown were more expensive than those in the city centre.

Depending upon the context and the situation, amenities also affect price. The most significant amenity affecting price is parking. Within city-based hotels, parking increased price anywhere from 7.4% to 19% (Coenders et al., 2003; Juaneda et al., 2011; Thrane, 2007). Other important amenities for hotels in city environments include pools and fitness centers. While the investigation into hotels located in Oslo found no effect of such amenities on room rates (Thrane, 2007), Chen and Rothschild (2010) found that hotels with fitness centers had prices that were 26.7% higher than those without.

Although not a hedonic price analysis, Lee et al. (2015) found that amenities have very little impact on the sales of rooms on Airbnb. While it could be argued that the sales of rooms are not related to price, sales are still a relevant business indicator. Hosts who responded to guests faster received more bookings. Interestingly, this same study found that the number of reviews had a greater influence than the rating of the reviews. These findings suggest that management of a listing matters. Using the listings of 1022 holiday rentals in Spain, Saló and Garriga (2011) found that listings booked through a wholesaler were 28.9% more expensive than when booked through other intermediaries on the Internet. This would suggest that professional travel retailers sell for higher prices, reinforcing again the notion that Airbnb hosts who lack professional skills engage in "inefficient" pricing strategies.

Given the difference between traditional hotel and Airbnb accommodation products, providers, and distribution platforms, this research identified the need to revisit some of the known factors and identify potential new factors reflected in the prices of Airbnb accommodation listings. The goal of the research presented in this paper was therefore to build a hedonic price model for Airbnb listings that can inform our understanding of hosts' perceptions of consumers' willingness to pay for certain listing characteristics.

Methodology

Data and model

The market chosen for this research was Canada because Airbnb considers it to be one of its top markets and because it exhibited a steep increase in listings in past years (Serebrin, 2014). To conduct this research, we used software to scrape data about Airbnb listings in five large urban destinations in Canada – Montreal, Calgary, Toronto, Ottawa, and Vancouver. The five destinations within the country were selected because they represented the five most populated metropolitan areas in Canada in the most recent population census (Statistics Canada, 2016). The use of five markets within one country provides a data set which has similarities in currency, Airbnb legislation (at the time the data was pulled), and travel seasonality. Data was collected for June 2016. The scrape was set up to collect only active listings and to eliminate listings with conflicting information. In total, 15,716 listings located in the five large urban areas were scraped (Calgary = 791, Montreal = 5713, Ottawa = 783, Toronto = 5262, and Vancouver = 3167). According to Chau and Chin (2003), most hedonic models suffer from some level of misspecification but biases due to missing variables are negligible and the selection of a small number of key variables is common practice. A major limitation of the hedonic pricing method is that it offers limited theoretical guidelines for selecting these key variables (Anderson, 2000). What made the selection of variables especially difficult for the current research was the unique nature of Airbnb in relation to existing hedonic pricing literature in tourism and hospitality. In some cases, Airbnb could be deemed similar to a hotel (guests interested in location and amenities), a bed and breakfast (private room in a house), or a vacation apartment rental (renting an entire place). Abrate et al. (2011) indicated that most hedonic pricing studies related to tourist accommodation take into account price, accommodation physical attributes, quality signals (including reputation-based quality signals such as ratings and reviews), and site-specific attributes (generally location, measured as distance from the city centre or major attraction or transport hub). However, sharing economy and Airbnb-specific characteristics, such as whether the listing offers "Instant booking", are not taken into account by studies on traditional accommodations. For this reason, the mix of variables selected for this research focused on the levels of progressive search criteria Airbnb offers, suggesting that these are deemed especially important for sharing economy accommodation and therefore highlighted by the platform.

In level one of the Airbnb consumer search process, consumers enter the location, dates, and number of guests. The presence of the number-of-guests field at this level makes the capacity of an Airbnb listing a primary attribute. In level two, consumers are presented with the ability to filter for room type (private, shared, or entire home) and price. A map on the side of the search interface also allows for filtering based on location.

The third and final stage of consumer search via the Airbnb platform presents the ability to use filters about very specific traveler needs. Categories offered by this third level of search allow the consumer to filter for size (number of bedrooms, washrooms, and beds), booking options ("Instant book" and host's "Superhost" status), neighborhoods, amenities (wireless Internet, kitchen, pool, etc.), property type (apartment, house, etc.), and host language. Number of beds was not included in the model due to its strong link with number of bedrooms. The neighborhoods variable had to be neglected to specify the model across different urban markets. Nonetheless, geography was taken into account with a "distance" variable indicating the distance between each listing and its respective city's City Hall, which is a method commonly used in hedonic pricing models for accommodation (Abrate et al., 2011). With more than 30 potential amenities to select from, we used frequency and existing literature to select the most appropriate variables to test for. First, variables that were either in almost all rentals (e.g. wireless Internet and air conditioning) or variables that were not listed for many rentals (e.g. hangers, shampoo, and breakfast) were eliminated. From the narrowed list of variables, three were chosen (parking, pool, and gym) based on their presence in previous hotel hedonic pricing literature (Juaneda et al., 2011; Thrane, 2007; White & Mulligan, 2002) and relative importance and discriminatory power within the data. Property type was transformed into a single variable to isolate the effect of whether the listing represented an independent property (e.g. house) or a multi-unit dwelling (e.g. apartment). Boat, treehouse, dorm, tent, and camper/recreational vehicle (RV) accommodation types were not included due to their irrelevance for city tourism. Also, the bed and breakfast category was not included as it describes a type of service rather than a type of property. Host language was not considered as it encompasses over 25 different languages with varying importance across the five selected markets.

After consumers have used the filters, they are presented with images with short snippets of information about listings that meet the criteria of their search filters. New variables within the search hierarchy introduced at this stage of the information search are review quality, review quantity, and pictures. Reviews have been frequently used in previous hedonic pricing literature (Abrate et al., 2011; Coenders et al., 2003; Juaneda et al., 2011; Saló & Garriga, 2011; Zhang et al., 2011) and have generally produced significant findings in relation to price. Ert et al. (2016)

also pointed out the importance of reputation-based variables in the Airbnb context and called for more research on the impact of reviews in sharing economy contexts. Airbnb listings exhibit a star rating, up to five stars, based on ratings from previous guests. However, 28.5% of the listings had no star rating, as Airbnb does not publish aggregate star ratings for a listing until it has been reviewed by at least three guests (Airbnb, 2016b). The researchers experimented with transforming star ratings into an ordinal variable to accommodate this issue, but abandoned this approach due to questionable results suggesting a negative relation between star rating and price. To better account for this complication, the researchers excluded all listings with no star rating from the primary models, and then ran a separate model to identify the impact of having a star rating (regardless of the rating number). Also, while listing pictures have not been used in previous hedonic literature, it has been reported that pictures are an important factor for hosts to consider (Grothaus, 2015) and Airbnb informs hosts that more pictures are better.

Only one variable was neither in the hedonic literature nor emphasized through the booking process – a host's "professional" status. The management of more than one listing by a host is a contentious issue related to Airbnb. It could be argued that professional hosts are more experienced and invested in the management of the Airbnb experience and would thus be able to charge a premium price. Since uncovering the pricing strategies of Airbnb hosts was the focus of this paper, deriving a variable capturing host activity/professionalism on the platform was deemed important. Also, guests can see whether a host manages multiple listings by looking at a host's Airbnb profile, and it is possible some guests will prefer hosts perceived to manage their listings as a more professional enterprise. Hosts were designated as professional hosts if they had two or more active listings.

Table 1 lists and defines all of the variables entered into an ordinary least squares (OLS) regression model, with PRICE as the dependent variable. In addition to the base price that Airbnb listings charge, many listings also have a relatively substantial one-time cleaning fee.

Table 1. Description of study variables.

Variable	Description
PRICE	Price per night (including 20% of cleaning fee), log transformed
General characteristics	
PRIVATE[a]	A "private room" (vs. an "entire place")
SHARED[a]	A "shared room" (vs. an "entire place")
INDEPENDENT[a]	An independent property (vs. a multi-unit dwelling)
CAPACITY	Guest capacity
BEDROOMS	Number of bedrooms
BATHROOMS	Number of bathrooms
DISTANCE	Distance (km) to local City Hall
Amenities	
PARKING[a]	Free parking available
POOL[a]	Swimming pool available
GYM[a]	Gym available
Management features	
INSTABOOK[a]	Instant booking available
PICTURES	Number of pictures
Review quantity and quality	
REVIEWS	Number of reviews
STAR	Average star rating
Host characteristics	
PROFESSIONAL[a]	Professional host (i.e. at least two listings) (vs. casual hosts)
SUPERHOST[a]	Superhost status

[a] Indicates a binary variable (yes = 1). "Independent properties" consist of houses, townhouses, cottages, bungalows, and villas, whereas "multi-unit dwellings" consist of apartments, condominiums, and lofts. "Instant booking" signifies that guests can place a reservation without explicit approval from the host. "Superhost" status is a badge awarded to hosts who fulfill certain criteria (e.g. frequent hosting, quick response rate, and high ratings).

Airbnb has indicated that its guests stay an average of 4.5 nights (Lu, 2015), so this duration was rounded up to five, and one-fifth of each listing's cleaning fee was added to the base price in order to produce a more accurate total nightly price. This total price was then logarithmically transformed to create the PRICE variable, as is customary in the hedonic pricing literature.

The semilogarithmic OLS model was applied to all of the five separate Canadian urban markets – Calgary, Montreal, Ottawa, Toronto, and Vancouver – separately and in aggregate. The aggregate model is intended to offer an overall picture of the influence of different listing characteristics on prices throughout the five urban markets, while the individual city models highlight the shared and unique patterns defining each city. The OLS model can be expressed as follows:

$$
\begin{aligned}
&LnPRICEi = \beta 0 + \beta 1PRIVATEi + \beta 2SHAREDi + \beta 3INDEPENDENTi + \beta 4CAPACITYi + \\
&\beta 5BEDROOMSi + \beta 6BATHROOMSi + \beta 7DISTANCEi + \beta 8PARKINGi + \beta 9POOLi + \beta 10GYMi + \\
&\beta 11INSTABOOKi + \beta 12PICTURESi + \beta 13REVIEWSi + \beta 14STARi + \beta 15PROFESSIONALi + \\
&\beta 16SUPERHOSTi + u_i
\end{aligned}
$$

Based on hedonic pricing theory, the general assumption was that because the privacy, comfort, capacity, centrality, amenities, convenience, star rating, host professionalism/excellence, and other quality signals represented by these variables provide value to consumers, hosts should adjust their prices according to the absence or presence of the attributes. PRIVATE, SHARED, and DISTANCE were expected to negatively influence the price of a listing, while the rest of the variables were expected to contribute in positive ways to listing price.

Results

Descriptive statistics for each of the variables are presented in Table 2, and it is worth highlighting some especially noteworthy characteristics of the Airbnb inventory in the five cities. To begin with, there is a huge variation in the listed nightly prices within each city, as indicated by the large standard deviations for all five cities. The clear majority of listings (58.0%, ranging from 51.3% in Calgary to 68.3% in Vancouver) involve entire places, with shared rooms representing only a marginal share (1.5%, ranging from 0.5% in Montreal to 2.2% in Vancouver) of the total accommodations. Likewise, the standard deviations suggest wide variation in the centrality, number of reviews, and number of pictures characterizing different listings. Also, with an overall average of 4.7 (out of five), it is clear that star ratings tend to be exceptionally high. Finally, hosts classified as professional operators maintain 37.3% of the total listings (ranging from 33.9% in Montreal to 43.7% in Ottawa).

There were obvious associations between some of the variables included in the regression models – for example, accommodation capacity and bedroom count should tend to increase together – which highlights the potential for multicollinearity problems. However, the highest correlation between any two predictor variables in any of the six models is 0.577, which is far below common thresholds (0.8–0.9); the largest variance inflation factor (VIF) among the variables in any of the six models was 2.114, which is far below the commonly used threshold of 10; and the lowest tolerance value was 0.473, which is well above common thresholds like 0.1 and 0.2 (Field, 2013; Hair, Black, Babin, & Anderson, 2014). Also, in consideration that star rating may be driven by other factors not included in the model, such as “Total satisfaction” ratings, it was tested for endogeneity concerns using the Durbin–Wu–Hausman (DWH) test for endogeneity on all six models. This DWH test assessed endogeneity between STAR and an Airbnb user’s “Total satisfaction” rating of the property. Endogeneity was detected in the aggregate model ($F(1, 11221) = 15.436$, $p < 0.001$), but this significant finding likely derives at least in part from the very large sample size. Indeed, for each of the five cities, the DWH tests failed to detect endogeneity (Calgary: $F(1, 545) = 1.160$, $p = 0.282$; Montreal: $F(1, 3704) = 0.117$, $p = 0.732$; Ottawa: $F(1, 577) = 0.665$, $p = 0.415$; Toronto: $F(1, 3892) = 1.058$, $p = 0.304$; Vancouver: $F(1,$

Table 2. Descriptive statistics of study variables.

	All		Calgary		Montreal		Ottawa		Toronto		Vancouver	
	(N = 11,239)		(N = 563)		(N = 3,722)		(N = 595)		(N = 3,910)		(N = 2,449)	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
PRICE	102.806	66.626	83.251	50.007	88.366	62.766	84.249	40.766	109.151	66.601	123.664	73.119
General characteristics												
PRIVATE[a]	0.404	0.491	0.467	0.499	0.410	0.492	0.463	0.499	0.450	0.498	0.295	0.456
SHARED[a]	0.015	0.122	0.020	0.139	0.005	0.073	0.017	0.128	0.019	0.135	0.022	0.148
INDEPENDENT[a]	0.207	0.405	0.476	0.500	0.054	0.226	0.392	0.489	0.233	0.423	0.293	0.455
CAPACITY	2.861	1.100	2.581	1.055	3.082	1.071	2.660	1.086	2.852	1.104	2.651	1.083
BEDROOMS	1.108	0.518	1.183	0.496	1.123	0.546	1.108	0.551	1.083	0.480	1.109	0.529
BATHROOMS	1.117	0.391	1.228	0.485	1.058	0.304	1.222	0.479	1.127	0.375	1.140	0.463
DISTANCE	3.936	3.578	5.378	4.706	3.703	2.807	4.807	5.926	4.448	4.247	2.928	1.475
Amenities												
PARKING[a]	0.442	0.497	0.796	0.404	0.283	0.450	0.660	0.474	0.404	0.491	0.608	0.488
POOL[a]	0.141	0.348	0.028	0.166	0.097	0.296	0.102	0.302	0.222	0.416	0.116	0.320
GYM[a]	0.250	0.433	0.192	0.394	0.114	0.318	0.158	0.365	0.377	0.485	0.288	0.453
Management features												
INSTABOOK[a]	0.139	0.346	0.160	0.367	0.180	0.384	0.135	0.342	0.113	0.317	0.115	0.319
PICTURES	13.617	9.955	13.140	10.925	13.185	9.190	12.682	7.220	13.392	10.913	14.971	9.692
Review quantity and quality												
REVIEWS	23.024	28.570	21.899	27.737	21.544	27.039	25.357	30.509	22.266	27.716	26.171	31.474
STAR	4.700	0.384	4.738	0.408	4.666	0.401	4.678	0.424	4.712	0.373	4.727	0.350
Host characteristics												
PROFESSIONAL[a]	0.373	0.484	0.375	0.484	0.339	0.473	0.437	0.496	0.391	0.488	0.382	0.486
SUPERHOST[a]	0.193	0.394	0.256	0.437	0.138	0.345	0.220	0.415	0.200	0.400	0.242	0.428

[a] Indicates a binary variable, and consequently the mean values signify the proportion of listings exhibiting the particular attribute. PRICE was log transformed for the regression model, but the original (non-transformed) data are presented in this table.

2431) = 0.053, p = 0.817). In addition, heteroskedasticity was assessed using the Breusch–Pagan test, and all six models were heteroskedastic (Aggregate: $\chi^2(16)$ = 1135.40, p < 0.001; Calgary: $\chi^2(16)$ = 47.45, p < 0.001; Montreal: $\chi^2(16)$ = 368.72, p < 0.001; Ottawa: $\chi^2(16)$ = 57.57, p < 0.001; Toronto: $\chi^2(16)$ = 538.91, p < 0.001; Vancouver: $\chi^2(16)$ = 90.32, p < 0.001). However, inspection of individual variable level to residual plots for all six models indicated that heteroskedasticity was primarily only visible for a few highly skewed count variables, such as review count and picture count. Further, research suggests that heteroskedasticity is often violated due to very large sample sizes rather than problematic modeling (Alexander, 2008).

The results of the hedonic regression analysis can be observed in Tables 3 and 4. The adjusted $R2$ values indicate that the five city-based models explain between 48.8% (Montreal) and 68.8% (Calgary) of the variance in Airbnb listing prices. The two tables also include the percentage change in accommodation price associated with the attributes that were found to be statistically significant. When assessing the influence of a dummy coded variable on a logarithmically transformed dependent variable, one must transform the coefficient by (e^{β} – 1), with β representing the coefficient and e representing the base of the natural logarithm (Halvorsen & Palmquist, 1980). For example, a hypothetical coefficient of 0.25 would signify that this attribute results in a 28.4% increase [exp. (0.25) – 1] in the price of an Airbnb listing.

Looking first at general characteristics of the listings, it is clear that room type has a very sizeable impact on a listing's price, and this pattern was consistent among all five of the cities. Private rooms were priced between 28.3% (Toronto) and 40.1% (Calgary) lower than entire homes, and shared spaces were priced between 50.8% (Toronto) and 61.6% (Montreal) lower than entire homes. Independent properties were somewhat cheaper than listings in multi-unit dwellings in Ottawa, Toronto, and Vancouver, but this attribute had no significant influence on price in the other two markets. Various attributes related to the size of the accommodation – capacity, bedroom count, and bathroom count – exhibited significant positive influences on price in all six models. Each (individual person) increase in capacity was associated with price increases ranging from 7.3% (Ottawa) to 16.3% (Toronto). Bedroom count also had a large influence on price, as each additional bedroom was associated with price increases ranging from 8.9% (Montreal) to 16.8% (Vancouver). Bathroom additionally exhibited a noteworthy influence on the listed price, and each additional bathroom was associated with price increases ranging from 3.3% (Toronto) to 14.4% (Montreal). Finally, centrality (distance from City Hall) was significant in all of the cities. The percentage increases listed in Tables 3 and 4 signify price changes associated with each additional kilometer a listing was located away from City Hall. The importance of centrality is therefore best appreciated by using a multiple such as five to

Table 3. Estimated results from the hedonic price model.

	All			Calgary			Montreal		
Variable	Coef.	S.E.	Diff (%)	Coef.	S.E.	Diff (%)	Coef.	S.E.	Diff (%)
General characteristics									
PRIVATE	−0.442***	0.009	−35.719	−0.513***	0.036	−40.111	−0.501***	0.015	−39.389
SHARED	−0.829***	0.031	−56.358	−0.919***	0.098	−60.090	−0.958***	0.093	−61.645
INDEPENDENT	0.017	0.011		−0.032	0.034		0.037	0.032	
CAPACITY	0.128***	0.004	12.817	0.085***	0.017	8.543	0.150***	0.007	14.967
BEDROOMS	0.095***	0.008	9.542	0.126***	0.034	12.595	0.089***	0.014	8.918
BATHROOMS	0.086***	0.010	8.551	0.113***	0.029	11.320	0.144***	0.023	14.378
DISTANCE	−0.033***	0.001	−3.328	−0.021***	0.003	−2.112	−0.041***	0.003	−4.147
Amenities									
PARKING	0.069***	0.008	7.171	−0.039	0.035		0.052**	0.016	5.374
POOL	0.051***	0.013	5.258	−0.068	0.082		0.044	0.028	
GYM	0.243***	0.011	27.564	0.066	0.035		0.228***	0.027	25.576
Management features									
INSTABOOK	−0.070***	0.011	−6.785	−0.084*	0.036	−8.023	−0.010	0.018	
PICTURES	0.002***	0.000	0.180	0.005***	0.001	0.528	0.003**	0.001	0.251
Review quantity and quality									
REVIEWS	−0.001***	0.000	−0.079	−0.002***	0.000	−0.187	−0.001***	0.000	−0.094
STAR	0.127***	0.010	13.561	0.091**	0.033	9.495	0.129***	0.018	13.716
Host characteristics									
PROFESSIONAL	0.023**	0.008	2.370	−0.030	0.028		0.035*	0.015	3.544
SUPERHOST	0.075***	0.010	7.794	−0.021	0.032		0.119***	0.021	12.615
CONSTANT	3.506***	0.051		3.744***	0.165		3.279***	0.091	
F-value	783.900			78.282			222.475		
Adjusted *R2*	0.527			0.688			0.488		

*p < 0.05; **p < 0.01, ***p < 0.001.

Table 4. Estimated results from the hedonic price model.

	Ottawa			Toronto			Vancouver		
Variable	Coef.	S.E.	Diff (%)	Coef.	S.E.	Diff (%)	Coef.	S.E.	Diff (%)
General characteristics									
PRIVATE	−0.472***	0.034	−37.627	−0.332***	0.013	−28.254	−0.491***	0.019	−38.800
SHARED	−0.816***	0.095	−55.768	−0.709***	0.043	−50.801	−1.082***	0.048	−66.114
INDEPENDENT	−0.083**	0.031	−7.986	−0.064***	0.017	−6.233	−0.086***	0.019	−8.278
CAPACITY	0.073***	0.015	7.302	0.163***	0.006	16.258	0.074***	0.009	7.400
BEDROOMS	0.107***	0.027	10.659	0.097***	0.014	9.673	0.168***	0.016	16.789
BATHROOMS	0.083**	0.027	8.297	0.033*	0.016	3.309	0.098***	0.016	9.838
DISTANCE	−0.008***	0.002	−0.805	−0.036***	0.002	−3.643	−0.036***	0.005	−3.564
Amenities									
PARKING	−0.004	0.028		0.093***	0.013	9.703	−0.012	0.014	
POOL	−0.043	0.045		0.060***	0.017	6.133	0.066**	0.024	6.827
GYM	0.098*	0.039	10.314	0.131***	0.016	14.012	0.158***	0.018	17.093
Management features									
INSTABOOK	−0.018	0.035		−0.051**	0.018	−4.952	−0.046**	0.021	−4.521
PICTURES	0.012***	0.002	1.191	0.000	0.001		0.004***	0.001	0.393
Review quantity and quality									
REVIEWS	−0.001	0.000		−0.001***	0.000	−0.111	−0.001***	0.000	−0.080
STAR	0.012	0.030		0.139***	0.016	14.897	0.094***	0.021	9.852
Host characteristics									
PROFESSIONAL	0.015	0.025		0.010	0.013		−0.028	0.015	
SUPERHOST	0.097**	0.031	10.235	0.051**	0.016	5.222	0.026	0.017	
CONSTANT	3.996***	0.148		3.534***	0.082		3.962***	0.102	
F-value	64.553			326.466			251.969		
Adjusted *R*2	0.631			0.571			0.621		

*$p < 0.05$; **$p < 0.01$, ***$p < 0.001$.

indicate a somewhat more substantial distance having a stronger impact on price. Each additional five kilometers away from City Hall were associated with price decreases ranging from 4.0% (Ottawa) to 20.7% (Montreal).

Of the three amenities that were considered, the presence of a gym was associated with a significant increase in prices in each of the cities except for Calgary, ranging from 10.3% (Ottawa) to 25.6% (Montreal). The presence of a pool was comparably less important, despite the prices pertaining to listings offered in the summer, as it led to significant increases in prices only in Toronto (6.1%) and Vancouver (6.8%). Finally, parking only was associated with significant price increases in Montreal (5.4%) and Toronto (9.7%).

Looking next at management features, increases in the number of accommodation pictures were associated with price increases in all five cities except for Toronto. As with centrality, the importance of this variable is better appreciated by using a multiple such as five to indicate the price increases associated with adding an additional five photos. Each addition of five photos is associated with a price increase ranging from 1.3% (Montreal) to 6.0% (Ottawa). On the other hand, the availability of Instant booking was associated with significant decreases in prices in Calgary, Toronto, and Vancouver, ranging from −4.5% (Vancouver) to −8.0% (Calgary).

The number of reviews exhibited a significant negative influence on price in each city except for Ottawa. Nonetheless, the impact was relatively limited, as even when looking at the impact of an additional five reviews, the associated price decreases were no more than −1.0% in any of the cities. Likewise, star rating had a significant positive impact on price in every city except for Ottawa. Each single point increase in a listing's star rating was associated with a price increase ranging from 9.5% (Calgary) to 14.9% (Toronto). A host's professional status was only associated with a significant increase in prices in Montreal (3.5%). Lastly, Superhost status was associated with significant price increases in Montreal, Ottawa, and Toronto, ranging from 5.2% (Toronto) to 12.6% (Montreal).

Because these models only included Airbnb listings with a star rating (i.e. they had received at least three reviews), an additional aggregate model was run in which the review count (REVIEWS) and star rating (STAR) variables were excluded, and replaced with a binary categorical variable (RATING) indicating whether or not a listing had any star rating. This model (N = 15,716) was intended to assess how the presence of a visible star rating influenced price. As with the other models, multicollinearity was assessed by examining inter-item correlations, the variance inflation factor, and the tolerance values, and no issues were detected, although heteroskedasticity was again detected. The adjusted R^2 value for this model was 0.482. Most importantly, this analysis was interested in the RATING variable, which was highly significant ($p < 0.001$), with an unstandardized coefficient of

−0.043 and a standard error of 0.008. That coefficient signifies that having a star rating is associated with a −4.2% decrease in price.

Discussion and implications

The results confirm to a large extent the findings by previous studies regarding factors that influence price (see for example Abrate et al., 2011), suggesting that in many ways Airbnb accommodation occupies a similar space as hotel and bed and breakfast accommodation, which was also found by a recent comparison of online consumer reviews across accommodation types (Yao, 2015). Uniqueness and authenticity are heavily promoted by Airbnb but, overall, common traditional accommodation attributes like location and size clearly matter greatly, and are taken into account by Airbnb hosts when setting prices. Most importantly, the hedonic pricing models across all five cities indicate that hosts charge a huge premium for privacy. Fitness amenities are also important drivers of price (similar to the findings regarding hotels by Chen & Rothschild, 2010), and pools were seen as adding value by hosts in two of the biggest urban areas. Surprisingly, parking was only reflected in the prices of hosts in Montreal and Toronto, challenging the results found for hotel accommodation (Coenders et al., 2003). Also unexpected was the finding that hosts in Ottawa, Toronto, and Vancouver charge less for accommodation in independent dwellings, suggesting an important difference to traditional vacation rentals (Saló & Garriga, 2011).

Not surprisingly, higher star ratings are associated with higher prices, although given the preponderance of high ratings it is unclear just how significant a competitive advantage hosts receive from high ratings. Being a Superhost makes a difference in some cities, but its failure to influence price in Calgary or Vancouver suggests it may not be as important as some may expect. The findings further confirm that pictures are perceived to be important, as hosts who post more pictures charge more. More pictures could also be an indication of greater professionalism of the host.

What is perhaps most interesting is that there were unexpected negative coefficients associated with review count, the availability of Instant booking, and the presence of a star rating. While for review quantity this finding could be the result of demand factors, as more reviews may mean less information asymmetry and therefore less ability to overprice, or the reviews may simply reflect higher demand for low priced accommodation. Nevertheless, a more reasonable explanation can be derived from considering all three variables together. The story that emerges is one of hosts as real estate managers and their need to meet financing or lease obligations. Hosts who rent out their property frequently know that every night their property stays empty, they are not gaining any revenue. They are therefore likely to charge lower prices in order to "fill their beds". The lower prices charged by such frequent hosts create more demand and consequently more reviews. On the other hand, more casual sharing economy hosts need to carefully think about the risks and labors of hosting others in their property and need to make it worth their while. They thus elect to charge higher prices, more carefully vet guests and probably are more likely to reject reservation requests. Nonetheless, Airbnb claims that the number of reviews has a huge impact on price (Hill, 2015) and Lee et al. (2015) also found positive impacts of review count on sales but no influence of overall review scores. Together these findings suggest that more research is needed to better understand the influence of reviews in the context of Airbnb.

Overall, it is worth mentioning that the model had high explanatory power and delivered fairly consistent results across the five destinations as far as the major factors are concerned, but also identified unique patterns for the less prominent attributes, with Ottawa being the most distinct market. Whether that is because the hosts in Ottawa are different in terms of their pricing strategies and/or cater to a different consumer market cannot be answered with the data at hand, and should be the subject of future research. In general, the results suggest that hosts are not as consistent and strategic as Airbnb would probably like them to be in order to drive revenue for the platform.

By providing such a comprehensive look at factors that influence prices of Airbnb listings, this research provides hosts with insights as to potential strategies they could implement to increase their revenues. The findings could also be useful to Airbnb when suggesting prices to hosts, in addition to underscoring for Airbnb the need to further educate hosts. Both the descriptive and the hedonic pricing model results highlight some aspects of Airbnb that are alarming from a policy perspective given the large number of professional hosts, the identified pricing strategies hinting at long-term renting for financial gains, and the very small number of shared accommodations across the destinations. From a theoretical perspective, the paper makes an important contribution to the accommodation pricing literature by taking specific sharing economy related factors into account and providing an important perspective on sharing economy hosts and their pricing strategies.

The research has various limitations. To begin with, it used the listing price as the dependent variable rather than the actual realized price in the marketplace. While this is common practice in the hedonic pricing literature regarding accommodations (Abrate et al., 2011), it means that no statements can be made as to the correctness of the hosts' perceptions and the effectiveness of their pricing strategies. Further, the research only considered one price point in time and therefore was not able to capture seasonal differences in the importance of certain attributes (e.g. pools potentially being more important in the summer) or seasonal changes in visitor markets taken into account by hosts. We did, however, test for seasonal variation in the listing prices based on pilot data for one of the markets (Toronto) collected in December 2015 and found that the average price was almost identical (average price December 2015 = 122.60; average price June 2016 = 123.65) and that 49% of the listings had the exact same price between the two points in time. Given the lack of readily available data on average daily rates for listings, the data scraping effort involved in collecting data across multiple time periods for multiple markets, comparable examples of listing price used in existing literature, and the limited variation in prices over time found in the pilot test, one price point in time was deemed sufficient for the analysis.

Another limitation of the hedonic price model used in this research is its neglect of external factors such as competition in the market. While Airbnb takes demand factors into account when providing price tips to hosts (Hill, 2015), modeling competition is extremely complex in the Airbnb context given the large diversity in the types of accommodation listings. An extension of the hedonic price model to include competition was thus not possible. The current research can therefore not make statements on the extent to which hosts take competition into account when setting their prices. Another limitation of hedonic pricing research is the lack of segmentation (Chau & Chin, 2003). The model used assumes that Airbnb hosts cater to one uniform consumer market. A greater percentage of hosts catering to business travelers in Ottawa, for instance, could explain differences in the obtained results compared with other markets.

In conclusion, the current research provides important insights but also highlights the need for further research related to Airbnb hosts, the prices they list, and the bookings they receive. Specifically, more research is needed to inform the demand side – how consumers take the price of an Airbnb listing into account when making sharing economy accommodation decisions is not known. In addition, the findings suggest that more insights are needed as to how hosts determine prices (especially to what extent they implement dynamic pricing strategies) and what specific differences exist among professional and non-professional hosts in terms of knowledge of pricing and revenue goals.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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