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Use of dynamic pricing strategies by Airbnb hosts

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Abstract

Purpose – The purpose of this paper is to provide a comprehensive analysis of dynamic pricing by Airbnb hosts.

Design/methodology/approach – This study uses attribute and sales information from 39,837 Airbnb listings and hotel data from 1,025 hotels across five markets to test different hypotheses which explore the extent to which Airbnb hosts use dynamic pricing and how their pricing strategies compare to those of hotels.

Findings – Airbnb is a unique and complex platform in terms of dynamic pricing where hosts make limited use of dynamic pricing strategies, especially as compared to hotels. Notwithstanding their limited use, hosts who own listings in high-demand leisure markets, manage entire places, manage more listings and have more experience vary prices the most.

Practical implications – This study identified a great need for Airbnb to encourage dynamic pricing among its hosts, but also warned of the potential perils of dynamic pricing in the sharing economy context. The findings also demonstrated challenges for hotel managers interested in actionable information related to Airbnb as a competitor.

Originality/value – This is the first Airbnb study to use a comprehensive set of data over a continuous period in multiple markets to look at a number of listing and host factors and determine their relation with dynamic pricing strategies.

Keywords Hotels, Dynamic pricing, Sharing economy, Revenue management, Airbnb

Paper type Research paper

1. Introduction

Airbnb has emerged as one of the stars of the sharing economy. In 2016, Airbnb was estimated to be valued at $30bn (Newcomer, 2016), and in markets like the New York City (Fox, 2016) and Toronto (Gibbs, 2016), Airbnb has been reported to represent 5 per cent of the tourism accommodation revenue. Despite such business success, Airbnb has struggled to optimize pricing by its hosts, potentially missing out on large financial gains. Pricing has been identified as one of the Airbnb's biggest challenges, and it has been estimated that Airbnb hosts forfeit up to 46 per cent of additional revenues because of inefficient pricing (LearnAirbnb.com, 2015). According to focus groups conducted by Airbnb, hosts become

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confused when trying to set their prices (Hill, 2015). Unlike the hotel business, which has trained professionals, industry benchmarking reports and technical tools to help set pricing for rooms, Airbnb units are generally managed by regular people with very limited support of pricing tools.

Although Airbnb has been building pricing tools for hosts since 2012, these tools have been very basic and only focused on simple factors related to characteristics of the property, such as number of rooms, neighboring properties and amenities like parking (Hill, 2015). After years of working on a pricing algorithm, Airbnb recently selectively released a new pricing tool that takes both property characteristics and demand into account (Hill, 2015). The pricing of Airbnb listings is unusually complex because, in addition to traditional demand factors such as seasonal changes, local events and location, each Airbnb listing exhibits unique characteristics and hosts often adopt extra roles, such as concierge, cook and tour guide (Hill, 2015). Airbnb's new pricing algorithm tool therefore uses machine learning to provide hosts with a new pricing suggestion for each date in the future that the host makes the listing available. Once the hosts receive a pricing tip, they can either choose to go higher, lower or do nothing. Thus, unlike many other sharing economy platforms, like Lyft and Uber, where an algorithm controls prices, Airbnb allows its individual hosts to decide whether they want to act on the tool's advice or not. This individual host control over pricing decisions creates a situation whereby the hosts' characteristics and skills are as important as the listing and market characteristics in determining the price.

Wang *et al.* (2015) identified a literature gap regarding the understanding of revenue management and specifically dynamic pricing beyond their application in the airline, hotel and car rental sectors. Sharing economy accommodation represents an especially interesting context for dynamic pricing research, as it challenges many of the fundamental assumptions of the dynamic pricing theory, most importantly the unchanging/limited capacity and profit maximization goals (McAfee and te Velde, 2006). The setting of prices in a traditional hotel context is typically motivated by the economic need for a business to generate profit. Managers have detailed information about their competitors' pricing, future supply of new hotels and demand generators that allow them to manage prices for optimal economic gain. Within Airbnb, the supply of accommodation is controlled by hosts who are motivated by both economic and social reasons (Gutt and Herrmann, 2015; Lampinen and Cheshire, 2016). Karlsson and Dolnicar (2016) show that even hosts motivated by economic gains are often not on Airbnb to make large profits but, rather, use the platform to cover fixed costs, while other hosts are in desperate need of money to pay their bills and price to sell. Also, Airbnb supply is unpredictable. Unlike hotels, which cost millions of dollars and take years to build, someone can become an Airbnb host with the click of a mouse. Further, Airbnb hosts can make their spaces unavailable for dates they do not want paying visitors. It has been reported that the median number of annual nights booked in the New York City per listing was 42, with 84 per cent of listings available fewer than 120 days per year (Fox, 2016). There is also high turnover, with many hosts dropping out completely over time. Li *et al.* (2015) calculated a turnover rate of 49 per cent by pinging the URLs of Airbnb listings one and half years later. Therefore, while hotels represent a mature industry with relatively stable management of supply, demand and pricing, Airbnb represents a new business model with nonprofessional management, instability regarding supply and potentially very inconsistent pricing.

Recent studies related to pricing and Airbnb have looked at a number of factors, including the reputational impact on pricing (Gutt and Herrmann, 2015), social features and room sales (Lee *et al.*, 2015), racial discrimination and pricing (Edelman and Luca, 2014), functional characteristics (Chen and Xie, 2017; Gibbs *et al.*, 2017), host experience (Chen and Xie, 2017; Wu, 2016) and the difference between hosts managing multiple listings and nonprofessional hosts in terms of pricing efficiencies (Li *et al.*, 2015). However, although there is a growing body of research related to Airbnb and pricing, it is typically focused on one market or a very specific factor related to price, or uses a limited time series of data. This present study seeks to overcome these limitations by providing a comprehensive look at the Airbnb pricing across five different markets, over a 12-month period and compared to hotel pricing strategies. It specifically focuses on dynamic pricing because of its importance for the accommodation sector and the dearth of research on it in the sharing economy context. The key questions it seeks to answer are to what extent Airbnb hosts engage in dynamic pricing, how their pricing fluctuations compare to those of hotels and whether greater price variation can be associated with certain host and listing characteristics.

2. Literature review

Dynamic pricing is a strategic revenue management tool used by businesses to maximize profit by continuously adjusting prices in response to fluctuations in demand (McGuire, 2015). Dynamic pricing is based on analytical, fact-driven decision-making to replace a "gut feeling" approach to pricing (Bodea and Ferguson, 2014). It involves changing the price charged for a product or service either over time (Fernandez *et al.*, 2015), across consumers, or across products/services (Kannan and Kopalle, 2001). Originally developed by airlines (Chiang *et al.*, 2006), it has spread to car rentals and hotels, which now heavily rely on it. These sectors share numerous characteristics that make them ideal application areas for dynamic pricing – perishability, fixed capacity, demand volatility, advance booking by customers, wide swings regarding the balance of supply and demand, microsegmentation of the market, lower cost competition and high fixed costs relative to variable costs (Ivanov and Zhechev, 2012). The implementation of dynamic pricing is an expensive proposition in terms of both technical and human cost. From a technical perspective, companies spend millions of dollars developing systems which can collect data, analyze results and recommend pricing in real time. Although the analytic engines used for dynamic pricing attempt to instantaneously update pricing, in many cases they still require human intervention to approve the recommendation (Bodea and Ferguson, 2014). Consequently, the implementation of dynamic pricing usually requires specially trained people. Interestingly, the hiring and training of specially trained revenue managers has been identified as one of the hotel industries biggest challenges today (Wang *et al.*, 2015).

2.1 Dynamic pricing in the hospitality industry

Much of the literature related to hotel pricing has aimed at understanding the different tangible, reputational or contextual variables that makeup the price of an accommodation (Abrate and Viglia, 2016), but there is a distinct lack of literature on dynamic pricing by hotels. Hotels are increasingly adopting dynamic pricing methods (Aziz *et al.*, 2011), but the bulk of research available is focused on the airline industry. What has been established is that hotels use price as a lever to manipulate demand, attract specific market segments, drive bookings and build market share (McGuire, 2015). Further, hotels base their dynamic pricing strategies on a number of factors, including advance purchase, length of stay, group size, seasonality, special events, day of week (weekdays and weekends), customer characteristics (e.g. corporate or leisure traveler, hotel rewards member), segments (e.g. transient, group and contract) and distribution channels (Marriott International, 2014). One of the challenges with studying dynamic pricing is that the forecasting models are the property of the hotel chain or a software developer, making it difficult to conduct empirical research (Ivanov and Zhechev, 2012). Recognizing this challenge, researchers have used information publicly available on the internet to understand hotels' use of dynamic pricing. Abrate *et al.* (2012) collected data from the online travel agency Venere to identify evidence of dynamic pricing strategies. The results indicated that more than 90 per cent of the price changes that occurred during the time of the study could be attributed to the type of the customer (business vs leisure) and the hotel star rating. Fernandez *et al.* (2015) scraped pricing data for hotels in Bilbao from Booking.com to identify price change patterns in advance of a future date and also found that 5-star hotels varied their prices more often than any other star category. Other dynamic pricing research related to hotels has built models for recommending hotel prices (Aziz *et al.*, 2011; Bayoumi *et al.*, 2013). Although these models identify different ways for a pricing algorithm to calculate the optimal price, they do not speak to the strategic implementation of dynamic pricing.

2.2 Dynamic pricing in the sharing economy

Price is a core competitive advantage for the sharing economy. Cost has been identified as a major factor influencing decisions on travel products and services, for traditional sectors such as hotels (Chu and Choi, 2000), car rentals (Katzev, 2003), but also in the context of peer-to-peer accommodations (Guttentag, 2015). Guttentag (2015) identified Airbnb accommodation as a disruptive product. Disruptive products generally perform less well than prevailing products, but they are often cheaper and introduce some new benefits. Airbnb, as a disruptive innovation, lacks some of the attributes which are important to tourists' hotel decisions, such as service quality, staff friendliness and security (Dolnicar and Otter, 2003), but Airbnb accommodation is generally cheaper than traditional services and travelers have the opportunity to stay with and live like a local (Guttentag, 2015). In comparison with hotels, prices on Airbnb are relatively low, partially because Airbnb hosts have already covered the main fixed costs such as rent and electricity, and also because there are minimal labor costs and often no taxes charged (Guttentag, 2015).

Dynamic pricing has been adopted by some of the leading sharing economy firms and has become an integral part of the sharing economy culture. Uber provides a mobile application to match riders with nearby drivers. Riders open the Uber mobile application to request a ride with their credit card information pre-saved in the app to guarantee the reservation. If a request is accepted and fulfilled, the application calculates the fare based on the distance and the time of travel and charges the rider electronically, thereby completely taking the monetary transaction out of the relationship between the rider and the Uber driver (Chen *et al.*, 2015; Hall *et al.*, 2015). Importantly, Uber uses a "surge pricing" algorithm which uses a "multiplier" to increase the standard fare during times of high demand (Hall *et al.*, 2015). This dynamic pricing practice was justified by Uber as allocating rides to people who value them most, benefiting both riders (by reducing waiting times) and drivers (by increasing profits) (Gurley, 2014). Chen and Sheldon (2015) verified that the dynamic pricing by Uber significantly increases the efficiency of the ride-sharing market. However, there are also concerns about the fairness of dynamic prices (Chen *et al.*, 2015; Roggenkamp, 2015). For example, in Sydney, Uber charged New Year's Eve passengers eight times the normal rates for a ride home, which led to a flood of complaints from passengers (Han and Robertson, 2016; Robertson and Fisher, 2016).

In terms of pricing, Airbnb occupies a unique position in the sharing economy. Unlike drivers on Uber and Lyft, who have no choice in setting their prices, Airbnb hosts can set daily, weekly and monthly room rates and control prices over time. There is a growing body of literature on pricing in the context of Airbnb, and it usually considers listing and host attributes as potential drivers of price (Chen and Xie, 2017; Gibbs *et al.*, 2017). The listing attributes considered include type of accommodation (entire home or apartment, private room and shared room), number of rooms, size, location, view amenities and facilities, whereas the host attributes deemed as important include the level of professionalism, years of experience, degree of trustworthiness and responsiveness (Ert *et al.*, 2016; Li *et al.*, 2015; Wu, 2016).

There is currently not much research available on hosts' price-setting strategies. Using data from two dates in the fall of 2014 for 14,000 listings in the New York City, Gutt and Herrmann (2015) found that hosts increase prices by an average of €2.69 after the rating for a listing becomes visible (i.e. when the listing has at least three reviews). Wu (2016) analyzed data sourced from 17,129 available Airbnb listings in Rio De Janeiro and found that professional hosts had a lower mean price per night than nonprofessional hosts. Furthermore, Li *et al.* (2015) investigated listing data from December 1, 2012 to March 31, 2013 in the Chicago area and found that professionally managed spaces realized 16.9 per cent higher average daily revenue and 15.5 per cent higher occupancy rate. Professional hosts also were found to be 13.9 per cent less likely to stop being hosts. Li *et al.* (2015) explain that these discrepancies can be partially attributed to pricing inefficiencies of nonprofessional hosts, such as failing to respond to surges in demand. Wu (2016) further examined whether host learning would impact price setting and identified that hosts with fewer than six months of experience charged higher prices than experienced hosts. Ikkala and Lampinen (2014) conducted qualitative interviews with 11 hosts in Finland and identified that some hosts lower their prices to increase the number of booking enquiries to have a wider pool of potential guests to choose from. They also found that hosts increase property prices as their "reputational capital" increases. Racial differences also seem to play a role in host pricing. Edelman and Luca (2014) investigated host photos collected from 3,752 listings in the New York City and found that there is a racial gap in host pricing for Airbnb. Nonblack hosts charge 12 per cent more for a similar listing with similar ratings and photos relative to black hosts. Lampinen and Cheshire (2016) interviewed participants from San Francisco and found that one of the drivers of increasing price was the number of requests to rent the place, showing that demand is positively associated with price. Although these studies supply important insights, they are usually limited to one market, a short time period and one or two host or listing characteristics. This study seeks to overcome these limitations to provide a comprehensive view of dynamic pricing adoption by Airbnb hosts.

3. Conceptual framework

Previous literature has stressed the informal nature of Airbnb (Guttentag, 2015) and hinted at the limited and inefficient strategies used by many hosts to price their spaces (Li *et al.*, 2015). As discussed earlier, Airbnb hosts can be motivated by a variety of reasons (Karlsson and Dolnicar, 2016), and optimizing revenue might not be at the forefront when making decisions regarding their listing. Just the act of setting an initial price for a listing can be overwhelming to unprofessional hosts (Hill, 2015) rendering it very unlikely that they will frequently change their listing price. Even for professional hosts with multiple listings, minimizing time investments in the management of individual listings could be important. Also, as suggested in the literature review, in contrast with other sharing economy platforms, dynamic pricing has not traditionally been a key aspect of Airbnb and hosts have until very recently not had the tools to help them implement dynamic pricing. We therefore propose the following hypothesis:

H1. Airbnb hosts make limited use of dynamic pricing strategies.

Unlike hotel accommodation providers which are solely motivated by profits and dominated by hotel management companies with trained professionals who use sophisticated pricing tools, Airbnb hosts lack motivation and skills associated with dynamic pricing. Most importantly, they also lack information critical to implementing dynamic pricing. Hotels have extensive data on past demand and market dynamics. In his article about Airbnb's pricing algorithm, Hill (2015) indicated that Airbnb had implemented several pricing tools in the past, but none had taken into account issues related to demand in the marketplace. Without knowledge of fluctuations in demand, hosts have little on which to base their dynamic pricing decisions. Consequently, we thus assume the following:

H2a. Airbnb listing prices will fluctuate less overall than hotel prices.

H2b. Airbnb listing prices will fluctuate less in accordance with demand than hotel prices.

Prior research has identified substantial variation in the listed nightly prices across different Airbnb markets (Gibbs *et al.*, 2017). We assume that owing to their lack of knowledge, skills and tools, hosts have to largely rely on heuristics when setting prices. Markets differ in their variability of demand. They also differ in the extent to which they cater to the leisure market. Airbnb is dominated by leisure travelers looking for a place to stay at a good price. According to Airbnb, only 10 per cent of its guests are using Airbnb for business travel (The Economist, 2015). We contend that hosts in larger, high-demand leisure markets will have more inquiries for bookings and thus change pricing more than hosts in smaller markets:

H3. Airbnb price fluctuations will be more prominent in high-demand leisure markets.

Although pricing of a hotel as a form of accommodation is characterized by similar types of rooms managed by professionals, Airbnb units are unique places made available by individual hosts. They involve both shared and private accommodation. This variation in types of places offered on Airbnb will lead to different levels of price variability. Anticipating demand for a unique shared room with a unique host is extremely difficult. On the other hand, researchers have observed that guests pay a premium for privacy and that hosts who manage entire places have a need to meet financing or lease obligations (Gibbs *et al.*, 2017). Hosts managing entire places are more likely to change prices to keep their space filled than hosts who are sharing the space they live in. Thus, we propose the following hypothesis:

H4. Airbnb price fluctuations will be greater for entire spaces than for shared accommodation.

From a hotel perspective, O'Connor (2003) observed that hotels with lower prices are more likely to offer consistent rates across all distribution channels, whereas luxury hotels will vary their rates on different channels, suggesting that dynamic pricing increases with higher levels of professionalization and resources and more profit at stake. Prior research related to Airbnb suggests that different hosts will implement dynamic pricing more than others. Li *et al.* (2015) concluded that nonprofessional hosts (those managing only one listing) have less frequent price adjustments and inadequate responses to instances of high demand. Similarly, Wu (2016) found that prices for hosts managing one listing were much less dispersed than those of hosts managing multiple listings. Based on these findings, the following hypothesis is formulated:

H5. Airbnb price fluctuations will be greater for hosts that manage multiple listings.

Although the topic of professional Airbnb hosts has received much attention, a growing body of evidence also suggests that prices will vary based on the learned experience of the host. This corresponds to the research on hotels managers' experience and their pricing decisions (Lee, 2016). Wu (2016) suggests that hosts with less experience are at a disadvantage in terms of knowledge and dynamic pricing skills. Ikkala and Lampinen (2015) found that host pricing is a learned experience whereby hosts start changing prices after having received a certain number of bookings. However, no research to date has specifically looked at experience-based variables (superhost status, occupancy rate and length of time as an Airbnb member) as factors influencing dynamic pricing:

H6. Airbnb price fluctuations will be greater for hosts with greater experience (as evidenced by their superhost status, higher occupancy rates and longer Airbnb membership).

4. Methodology

Most Airbnb pricing research to date is limited to one market; for this reason, five cities in Canada were chosen for this research. Canada was chosen because it is ranked by the World Economic Forum (2015) as one of the top 10 most tourism-ready economies and is considered a top market for Airbnb because of a steep increase of listings in past years (Serebrin, 2014). The selection of multiple cities in Canada was also supported by a common currency, similar legislation for Airbnb and access to reliable datasets for both hotels and Airbnb.

4.1 Data collection

Data for the research were obtained from Smith Travel Research (STR), a leading provider of hotel performance data, and AirDNA, a data analytics company that services vacation rental entrepreneurs and investors. The dataset from AirDNA had 56,469 Canadian Airbnb listings with detailed host information and daily supply, demand and pricing data for the months of April 2015 to March 2016. From the AirDNA dataset, the researchers identified listings for five major Canadian metropolitan areas: Montreal, Toronto, Vancouver, Calgary and Ottawa (the total number of listings across these five markets was 39,837). To allow for comparisons with hotels, the researchers obtained monthly market report information from STR for these five markets, representing 1,025 hotels.

Before the key indicators used in the study could be calculated for Airbnb, the researchers needed to convert prices from US dollars to Canadian dollars. With Airbnb operating in 180 countries around the world, it converts prices to the local guest's country of origin based on the address of the computer searching for information, which in the case of AirDNA's data scraping effort is the USA. To convert the currency back to Canadian dollars, the researchers used OANDA (2016), the daily exchange service used by Airbnb.

To obtain the hotel key performance indicators (KPI) for the study period, 12-month averages (from April 2015 to March 2016) were calculated based on the monthly STR hotel indicators for each market. The AirDNA dataset provided daily availability, rental information and price for each listing for each day during the 12-month time period. The 12-month occupancy, as well as weekend (Friday plus Saturday) and weekday occupancy numbers, were calculated by taking the count of reserved listings and dividing it by the total number of available listings for each market. The average rates were calculated by adding up the prices for all reserved listings and dividing the sum by the total number of reserved listings. A summary of the KPIs used in the research can be found in Table I.

Accommodation key performance indicators	Calgary	Montreal	Ottawa	Toronto	Vancouver
Hotels					
Number of hotels	121	332	81	251	240
Number of hotel rooms	15,361	26,049	10,057	36,891	26,520
Occupancy (%)	60.94	70.38	72.76	72.61	75.92
Average daily rate($)	153.22	153.51	151.85	156.82	164.63
Weekend occupancy	62.33	72.32	73.38	73.57	79.52
Weekday occupancy	60.38	69.62	72.51	72.22	74.48
Weekend average daily rate	132.79	154.09	144.24	149.51	164.82
Weekday average daily rate	161.59	153.27	154.91	159.77	164.55
Airbnb					
Number of listings	2,224	14,679	1,910	12,479	8,545
Occupancy (%)	17.77	29.24	23.39	26.03	38.87
Average daily rate ($)	85.57	100.92	90.90	116.51	125.48
Weekend occupancy	19.53	32.54	26.21	30.10	42.41
Weekday occupancy	17.08	27.95	22.27	24.40	37.45
Weekend average daily rate	87.73	106.27	94.33	121.99	129.32
Weekday average daily rate	84.59	98.47	89.29	113.81	123.74

Source: All data based on results from Smith Travel Research (Hotels) and AirDNA (Airbnb) from April 2015 to March 2016

Table I.
Key performance indicator summary

4.2 Data analysis

The first data analysis stage focused on assessing the degree to which Airbnb hosts use dynamic pricing strategies. This stage strictly considered rates paid for booked Airbnb listings to parallel average rate figures for hotels. The analysis involved two parts, with the first focusing solely on Airbnb and the second comparing Airbnb price fluctuations with those of hotels. The portion of the analysis focusing solely on Airbnb involved comparing average daily rates (ADR) by day of the week and by season, which represent two well-established forms of basic dynamic pricing for accommodations (Revenuematters.com, 2015). Seasonality was considered by categorizing the months as follows: winter (December through February), spring (March through May), summer (June through August) and fall (September through November). Box plots were used to visualize the price differences, and one-way ANOVA tests were used to identify statistically significant differences between days of the week and season. When statistical significance was found, Games–Howell and Tukey HSD post hoc tests were used to better identify the differences, with the former used in cases of a lack of homogeneity of variance (Field, 2013).

The portion of the analysis comparing Airbnb's price fluctuations with those of hotels used average monthly rates for both Airbnb listings and hotels to gauge seasonal price fluctuations. A coefficient of variation was calculated for each of the two accommodation types, based on the 12 average monthly rates. The coefficient of variation represents the standard deviation divided by the mean, and it is preferable to use simply the standard deviation because it accounts for differences among the means. The coefficient of variation is commonly used in time series data analysis and as a measure of price dispersion (Sorensen, 2000), including in Abrate *et al.*'s (2012) study of dynamic pricing among European hotels. A paired sample *t*-test was used to compare the average coefficients of variation among the two accommodation types in the five different cities. Subsequently, correlation coefficients were used to compare Airbnb listings and hotels with regards to the relationship between monthly occupancy percentages and average rates.

The second analysis stage involved comparing different types of Airbnb listings to better identify which ones are more likely to have adopted dynamic pricing strategies. Six distinguishing variables were considered – city, type of accommodation, number of listings by host, superhost status, occupancy rate and amount of time as a member of Airbnb. Although Airbnb offers three types of accommodation – entire home, private room and shared room – this analysis combined the private room and shared room categories into a single “shared accommodation” category owing to the very small percentage of shared rooms. This stage of the analysis considered prices for all days on which a listing was available for rental, regardless of whether or not it was booked. Only listings that were available for rental for at least 14 days within the 12-month period considered were included in this stage of the analysis to prevent biases stemming from listings with just a handful of price data points (1,413 listings did not qualify, resulting in an actively listed sample of 38,424).

Two indicators of dynamic pricing were used. The first indicator was the coefficient of variation, on which the different types of Airbnb listings were compared using a Welch test, t-tests and correlation coefficients, depending on the nature of the variable. Although the coefficient of variation provides a useful continuous variable for statistical testing, it is not easily interpretable. Consequently, the frequency of price fluctuations was used as a second indicator of dynamic pricing, and the different types of Airbnb listings were compared using chi-square tests. To account for the different number of days for which listings were available, frequency was measured as the percentage of days on which prices fluctuated among all consecutive pairs of available days. However, the currency conversion of prices described earlier, combined with the fact that Airbnb prices are rounded to the nearest dollar, led to an abundance of very minor price fluctuations. Especially with inexpensive listings, a currency fluctuation leading to even a $1 price increase could misleadingly suggest a price fluctuation of several percentage points. Therefore, based on an examination of frequency distributions of percentage price changes for numerous days on which many price changes seemed influenced by currency fluctuations, only price changes of at least 3.5 per cent were counted.

5. Results

5.1 Key performance indicators: Hotels versus Airbnb listings

Table I presents a comprehensive list of KPIs for both Airbnb listings and hotels in the five markets based on annual averages. When reviewing the table, some noticeable differences are observed. One key difference between hotels and Airbnb is related to the ADR and occupancy percentage. The hotel ADR in different markets ranges from $151.85 to $164.63, whereas Airbnb ADR ranges from $85.57 to $125.48. This demonstrates that hotels achieve similar ADR from market to market, whereas Airbnb listings are different between markets. Similar differences can be seen when comparing the occupancy percentages from market to market. The hotel occupancy in different markets ranges from 60.94 per cent to 75.92 per cent, whereas Airbnb occupancy ranges from 17.77 per cent to 38.87 per cent. Except for Calgary, an economic market that is struggling with plummeting oil prices, hotel occupancy is relatively similar from market to market, in the 70 per cent range, whereas Airbnb occupancy varies substantially more.

Another observation related to the differences can be made by comparing weekend and weekday ADRs. Consistent across all five markets, Airbnb listings have higher occupancy and higher ADR on weekends versus weekdays. However, hotels’ ADRs are either similar or lower on weekends.

5.2 The extent of dynamic pricing among Airbnb listings

Figure 1 shows box plots of Airbnb ADRs for each day of the week for five different markets. It is visually apparent that in all cities, weekend (Friday and Saturday) rates tend to be higher than weekday rates, although this pattern is somewhat less pronounced in Calgary than in the other four cities. The outliers in the box plots tend to represent either summer dates or holiday periods at the end of the calendar year. One-way ANOVA and Welch tests detected significant differences between the ADRs in each of the five cities: Calgary (F[6, 359] = 4.175, $p < 0.001$), Montreal (F[6, 158.514] = 10.640, $p < 0.001$), Ottawa

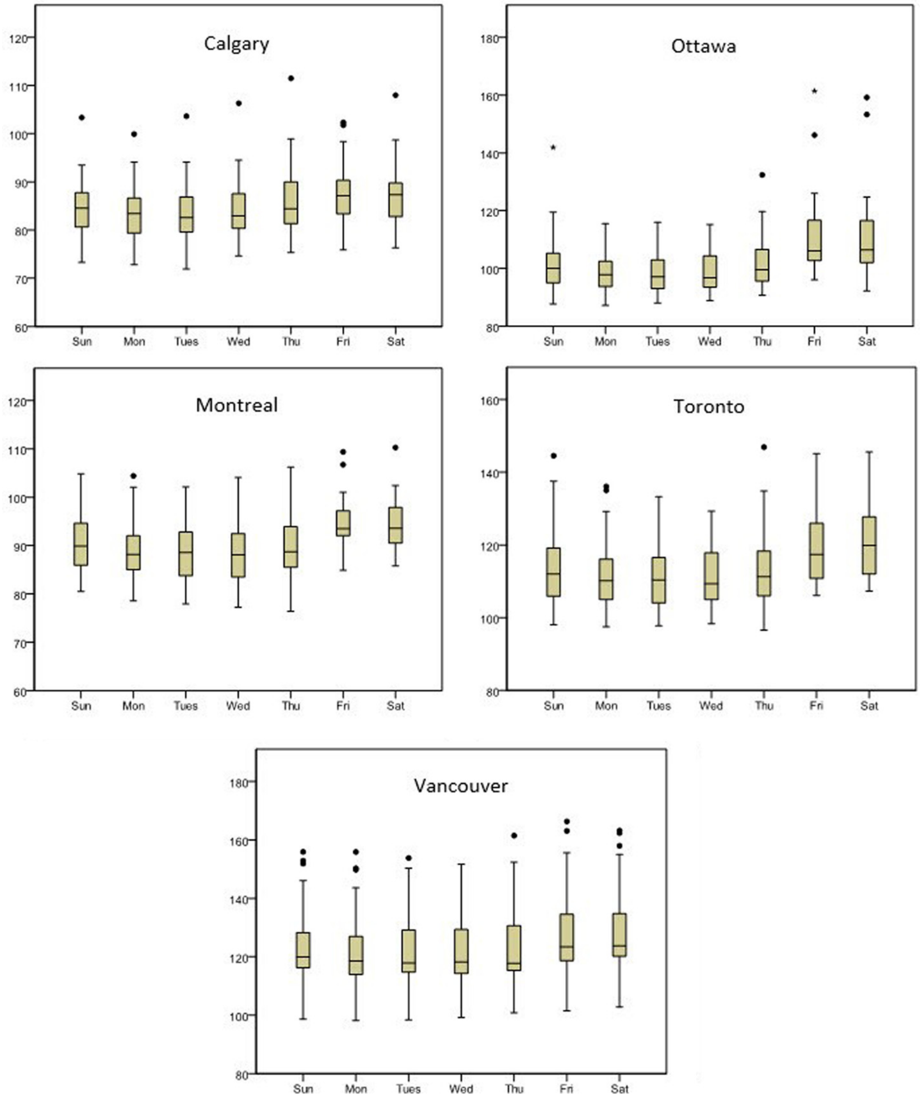

Figure 1.
Box plots with average daily rates ($) for Airbnb listings by day of week

(F[6, 359] = 10.324, p < 0.001), Toronto (F[6, 359] = 8.938, p < 0.001) and Vancouver (F[6, 359] = 2.310, p = 0.034). Tukey HSD post hoc tests distinguished the weekend rates from the weekday rates for both Ottawa and Toronto, and distinguished the Friday and Saturday rates from the Monday and Tuesday rates for Calgary. The same test failed to distinguish between any days in Vancouver. A Games–Howell post hoc test was used to examine Montreal rates owing to a lack of homogeneity of variance, and it also distinguished weekend rates from weekday rates in that city.

Figure 2 presents seasonal box plots. Once again, seasonality effects on dynamic pricing are visually evident, particularly when comparing summer and winter rates. The winter outliers represent the holiday period at the end of the calendar year and the Valentine's Day period (in Toronto). There is no obvious pattern to the spring outliers in Montreal and Toronto. The summer outliers in both Montreal and Toronto represent July 31 to August 2, which was a public holiday weekend in Ontario. The fall outliers in Vancouver represent the Labor Day weekend. One-way ANOVA and Welch tests detected significant differences between ADRs for the different seasons in each of the five cities: Calgary (F[3, 197.571] = 26.914, p < 0.001), Montreal (F[3, 184.556] = 22.840, p < 0.001), Ottawa (F[3, 362] = 50.154, p < 0.001), Toronto (F[3, 190.622] = 91.351, p < 0.001) and Vancouver (F[3, 198.465] = 95.187, p < 0.001). For Calgary, a Games–Howell post hoc test distinguished summer from the other three seasons, while also distinguishing between spring and fall. For Montreal, the same test distinguished summer and fall from winter and spring. For Ottawa, a Tukey HSD post hoc test distinguished summer from all other seasons, and also distinguished fall from winter. For Toronto, a Games–Howell post hoc test distinguished between every pair of seasons, except for winter and spring. Finally, for Vancouver, a Games–Howell post hoc test distinguished between every possible pair of seasons.

To compare price fluctuations among Airbnb listings with that of hotels in each of the five cities, a coefficient of variation was calculated for using average monthly rates of Airbnb listings and hotels. In each city except for Toronto, the coefficient of variation was higher for hotels, ranging from 1.64 times higher in Calgary to 1.20 times higher in Montreal. (In Toronto, the coefficient of variation was 1.08 times higher for Airbnb.) Subsequently, the correlation coefficient between occupancy percentages and average monthly rates was calculated for both Airbnb listings and hotels in each of the five cities. In each city, the correlation between hotel occupancy percentages and average rates was higher than was detected among Airbnb listings: Calgary (hotels: r = 0.779, p = 0.003; Airbnb: r = 0.534, p = 0.074), Montreal (hotels: r = 0.905, p < 0.001; Airbnb: r = −0.153, p = 0.635), Ottawa (hotels: r = 0.607, p = 0.036; Airbnb: r = 0.515, p = 0.087), Toronto (hotels: r = 0.810, p = 0.001; Airbnb: r = 0.798, p = 0.002) and Vancouver (hotels: r = 0.945, p < 0.001; Airbnb: r = 0.235, p = 0.462). Moreover, when looking at the five cities in aggregate, the correlation between monthly occupancy percentages and average rates was far higher among the hotels than the Airbnb listings (hotels: r = 0.951, p < 0.001; Airbnb: 0.412, p = 0.183).

5.3 Dynamic pricing among different Airbnb listings

To determine whether certain types of Airbnb listings are more likely to use dynamic pricing strategies, several types of Airbnb listings were compared based on two dynamic pricing indicators – the coefficient of variation and the frequency of price fluctuations. The former provides a more statistically sound analysis, but the latter offers much easier interpretation.

Beginning with a comparison of the five cities, a Welch test detected a significant difference between cities with regards to the coefficient of variation of Airbnb rates (F [4, 8147.361] = 43.940, p < 0.001). The ranking of cities, from the highest to the lowest

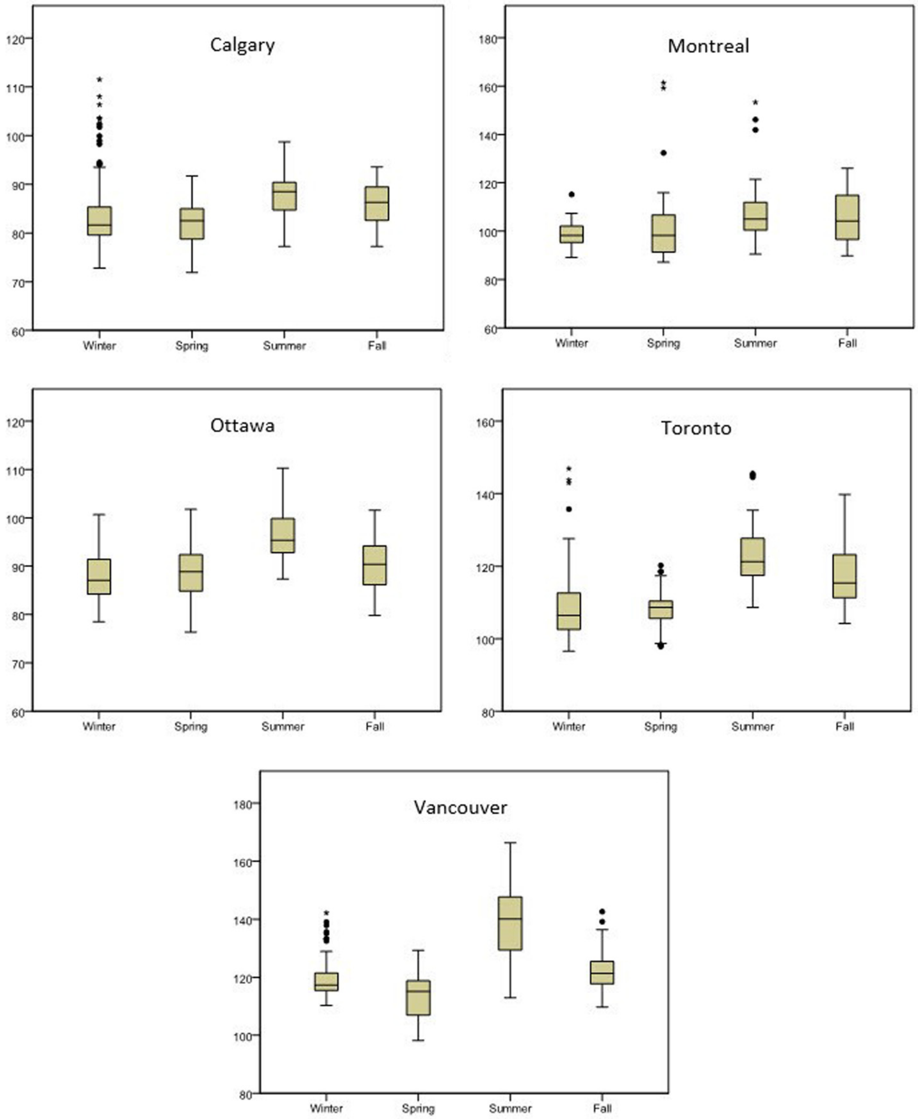

Figure 2.
Box plots with average daily rates ($) for Airbnb listings by season

coefficient of variation, was Vancouver, Toronto, Montreal, Calgary and then Ottawa. A Games–Howell post hoc test distinguished between every pair of cities except for Calgary and Ottawa. A *t*-test also detected a significant difference between the coefficient of variation for entire homes and shared accommodations ($t[32981.749] = 19.284$, $p < 0.001$), with the former exhibiting a higher mean coefficient of variation. Likewise, a *t*-test detected a significant difference between the coefficient of variation for listings that were and were not managed by superhosts ($t[38422] = 15.184$, $p < 0.001$), with superhosts exhibiting a higher mean coefficient of variation. Additionally, significant correlations were found between the coefficient of variation and number of listings owned by a host ($r = 0.146$, $p < 0.001$), occupancy percentage of the listing ($r = 0.134$, $p < 0.001$) and the amount of time a listing's host had been a member of Airbnb ($r = 0.044$, $p < 0.001$). However, it is worth acknowledging that the statistical significance of these correlations is partly driven by the very large sample size, and the correlation coefficients are relatively small, particularly regarding the membership duration variable.

Table II displays these same patterns in a more interpretable fashion by categorizing listings according to percentage of days on which their prices changed (by at least 3.5 per cent). As can be observed, chi-square tests detected significant differences between the groups for each variable. However, once again, the actual percentage differences between the groups distinguished by year in which they joined Airbnb were quite minimal.

5.4 Summary of results and discussion

The findings indicate that Airbnb listing prices overall fluctuate according to seasons and day of week, and there is additional evidence of some special holidays taken into account.

Listing characteristics	Percentage of days with price fluctuations > 3.5%				Chi-square test results		
Variable	0.000-5.000(%)	5.001 - 10.000(%)	10.001 - 25.000(%)	25.001% or more	df	χ^2	p
City							
Calgary	62.1	11.5	16.7	9.7	12	430.524	<0.001
Montreal	52.7	11.8	14.5	21.0			
Ottawa	52.6	14.0	18.1	15.3			
Toronto	51.8	11.2	17.5	19.5			
Vancouver	49.3	13.8	21.4	15.5			
Type of accommodation							
Shared accommodation	56.6	13.0	15.2	15.1	3	268.031	<0.001
Entire place	49.8	11.6	18.4	20.3			
Number of listings by host							
1	59.1	12.0	14.8	14.1	6	1,516.557	<0.001
2-5	44.9	12.6	20.5	22.0			
6+	34.6	11.6	21.9	31.9			
Superhost status							
Nonsuperhost	53.9	11.9	16.4	17.8	3	799.277	<0.001
Superhost	23.9	16.3	31.7	28.2			
Occupancy (%)							
0.000%	79.7	4.3	3.8	12.2	9	5,922.533	<0.001
0.001-10.000(%)	64.0	9.9	10.1	16.0			
10.001 - 40.000(%)	40.2	17.5	22.8	19.5			
40.001% or higher	33.8	14.9	27.4	23.9			
Year joined Airbnb							
2008-2013	50.7	13.1	18.4	17.7	6	48.560	<0.001
2014	49.9	12.3	19.1	18.7			
2015-2016	53.2	11.9	16.5	18.5			

Table II. The percentage of days with price fluctuations among different types of Airbnb listings ($N = 38,424$)

However, the results also show that across all markets, over half (52.2 per cent) of the listings basically do not change in price. Only 18.4 per cent of listings have different prices on over 25 per cent of the active listing days, thus supporting *H1*. Further, in support of *H2a* and *H2b*, the results confirm that Airbnb rates vary less than hotel rates and, in contrast to hotel rates, exhibit much less association with occupancy rates. Interestingly, Airbnb listings also seem to vary prices in the opposite direction from hotels, increasing their prices on weekend days. Importantly, while Airbnb represents one corporate entity and one brand, the company has limited control over hosts' pricing decisions, which creates significant variations from market to market. Distinct market patterns are already apparent from the ADR differences across markets presented in Table I, which are much more pronounced than those for hotels. In terms of dynamic pricing, evidence such as the presented box plots and market-based findings presented in Table II highlight unique characteristics of each market in terms of price variations. Price variations are greatest in Vancouver, Toronto and Montreal, supporting *H3* regarding more incentives to change prices and also more obvious demand change cues in these high-demand leisure markets.

Interesting findings were presented regarding host and listing characteristics. In support of *H4*, listings for entire homes versus shared accommodation exhibited more frequent price variations. This confirms the explanation provided by researchers that hosts who manage entire place listings have a greater need to meet financing and lease obligations and therefore price more aggressively than hosts that manage shared listings (Gibbs *et al.*, 2017). The findings about professional hosts versus nonprofessional hosts are consistent with prior studies about variation in pricing across these two types of hosts (Li *et al.*, 2015; Wu, 2016). Moreover, hosts who manage multiple listings vary their prices more than hosts who manage only one listing, which is in accordance with the professionalization and resources argument made in *H5*. Factors related to the experience of the host (superhost, occupancy and year joined) were also tested. The findings are consistent with the learning argument presented by Wu (2016) and Ikkala and Lampinen (2015) and, thus, support *H6*, with differences being more pronounced for superhost and occupancy than for year joined.

6. Conclusions

Despite the importance of dynamic pricing for accommodations and widespread use by hotels, the study finds that it is not uniformly adopted by Airbnb hosts and identifies market, listing and host characteristics as important drivers of this heterogeneity. As such, it draws attention to differences in potential host motivations and abilities to financially benefit from the platform.

6.1 Theoretical implications

Using a comprehensive, multiple market dataset and daily pricing information, this study confirmed and extended previous literature on pricing by Airbnb hosts. Prior studies about Airbnb had highlighted limited price changes by hosts and the impact of isolated host characteristics (Gutt and Herrmann, 2015; Li *et al.*, 2015; Wu, 2016), but this is the first study to use comprehensive data over a continuous period in multiple markets, looking at a number of listing attributes and host factors. Most importantly, by directly comparing Airbnb price variations with those of hotels in the same markets, it was possible to draw a vivid picture of the Airbnb platform uniqueness in terms of pricing dynamics. While most pricing research deals with maximizing revenue (McAfee and te Velde, 2006), the limited use of dynamic pricing and unique Airbnb host characteristics suggest that the sharing economy may require a new theory development. It thus calls for the formulation of a sharing economy-specific theory of dynamic pricing. The study also highlights the complexity of dynamic pricing and adds to the literature emphasizing knowledge requirements, learning curves and barriers to dynamic pricing tool adoption.

6.2 Practical implications

This research confirms that a large majority of Airbnb hosts are not engaged in dynamic pricing, suggesting that these hosts are foregoing revenue opportunities and not effectively competing with hotels and other Airbnb listings. With calculated turnover rates of 49 per cent (Li *et al.*, 2015) and occupancy rates in the 17-39 per cent range, hosts may get frustrated with a lack of bookings and delist their accommodation. This presents a challenge for Airbnb as it needs engaged hosts motivated to rent space at competitive prices to grow its business. With inefficiency in pricing by most hosts, simple improvements could represent significant increases in occupancy and revenues. The lack of dynamic pricing strategies can be explained by motivations of the host (Lampinen and Cheshire, 2016), lack of professionalism/experience and also limited availability of an Airbnb pricing tool that takes into account demand generators (Hill, 2015). The great need for host support is evidenced by the large number of online forums and consulting companies dedicated to helping hosts set their prices along with occupancy rates in the 17-39 per cent range as highlighted in Table I. Airbnb needs to play an important role in providing data, tools, training and incentives for hosts to adopt dynamic pricing. However, dynamic pricing does not come without perils: While consumers are nowadays more used to and accepting of dynamic pricing, especially in the context of travel and hospitality (Knowledge@Wharton, 2016), they might become more sensitive to price and more prone to bargain hunting. A shift in attention towards price will likely also mean less emphasis on the uniqueness of accommodation in the consumer's mind. In addition, dramatic price variations might create a conflict with Airbnb's branding of its sharing economy entrepreneurs as "hosts". Dynamic pricing may portray the host as a profit-maximizing provider. This might not only collide with noneconomic host motivations but also Airbnb consumers' desire for a stay and a relationship with the host that is built on more than just an economic transaction. In this sense, it might be better for Airbnb to follow the ride-sharing platforms and take the pricing out of the hosts' hands to avoid these conflicts, as rate hikes would then be attributed to Airbnb rather than the individual hosts. Airbnb could then also impose caps and consistently communicate the reasons for rate changes to avoid the negative image problems Uber currently faces because of its surge pricing policy (Dholakia, 2015).

With price being one of the most important factors for the hotel business, pricing practices of Airbnb hosts present a unique challenge to the hospitality industry. Hotel managers are used to segmenting detailed competitive pricing information along with the predictable pricing patterns of economically motivated competitors. Airbnb represents a much more unique competitor. This research found that some Airbnb hosts change prices frequently in response to different market conditions, but most hosts do not change their prices much at all. Although this could represent a positive factor for hotels, it also represents a level of irrationality that is hard to build into revenue management systems. The process of acquiring the data for this research demonstrated a challenge in obtaining actionable information about Airbnb listings of relevance to hotel managers. Although there is a call for more use of big data in hotel pricing (van der Rest and Parsa, 2016; Wang *et al.*, 2015), hotel systems do not have a pipeline to obtain actionable Airbnb data for decision-making The variety of individual listings, inconsistent availability and complex nature of the data made it a cumbersome endeavor that hotel managers likely would not undertake. Furthermore, the segmentation (luxury, upscale, midscale, etc.) that hotels are prone to use for benchmarking purposes is not available from the source data about Airbnb listings.

Looking at the phenomenon from the host perspective, as Airbnb becomes more like a distribution platform (Duettoresearch.com, 2016; Oskam and Boswijk, 2016), direct competition with hotels will rise, and not adopting dynamic pricing will increasingly lead to less competitiveness for traditional, nonprofessional sharing economy hosts. The opposing strategies regarding weekend prices between hotels and Airbnb hosts might also lead to problems for Airbnb hosts, especially if traditional Airbnb listing and hotel prices become directly comparable via the platform.

6.3 Limitations and implications for future research

The research was not without limitations. Although the currency fluctuations limited precision with which price changes could be detected, the 3.5 per cent threshold provided a reasonable resolution. However, undoubtedly some price changes were misinterpreted as being either genuine or based on currency fluctuation. Another limitation is the use of the amount of time a host had been an Airbnb member as a measure of host experience. "Airbnb member since" dates do not perfectly represent the amount of time individuals have been an active host, as many probably start as guests. Further, the markets were limited to large Canadian cities. Whether the findings translate to other countries and host cultures and to markets with different demand characteristics should be investigated in future research. Lastly, the research only used economic modeling to explore a dataset and did not use other research methods to more deeply explore pricing in the Airbnb context.

Future research areas also emerge from the findings regarding inexperienced hosts. The inexperienced host is pricing inefficiently and not generating revenues similar to an experienced host. If this host is doing it more for social reasons, it is explainable and not an issue. However, if this host lists on Airbnb for economic reasons, his or her lack of success may lead to dropping out at some point. Research related to inexperienced hosts would be an important topic for Airbnb to avoid reductions in supply. Although the year joined relationship to price changes was not as strong as for other factors, research into newer hosts and pricing could also help better understand the needs of inexperienced hosts. More in-depth, qualitative research especially regarding social or psychological factors driving host decisions would certainly help shed further light on the phenomenon. In addition, although Airbnb recently introduced demand-based features within its pricing tool, the tool's adoption and usage by hosts is not known. If more hosts adopt the tool, Airbnb could gain more control over host pricing to stimulate demand. This suggests an opportunity for survey research capturing host attitudes and behaviors, as well as for longitudinal research examining whether the price tool introduction in certain markets leads to drastic changes in price variation. Although the research did not test for a relationship between residential real estate values and dynamic pricing for Airbnb, ranking the cities from the highest to the lowest coefficients of variation and ADRs happened to emulate residential real estate values. Cities with higher coefficients of variation and ADRs also happen to have higher residential real estate values. Examining real estate values as indicators of Airbnb listing prices within and beyond Canada could therefore also be a future research topic. Comparisons of different international markets could further inform the impact of market characteristics and regulatory environments on host pricing. Lastly, the results of this paper could be extended by further analyzing the data. With so many individual listings with unique characteristics, finding a way to classify them into competitive sets so that hotel managers can look at the results to form actionable responses to Airbnb pricing would certainly be beneficial for the hotel industry.

References

Abrate, G. and Viglia, G. (2016), "Strategic and tactical price decisions in hotel revenue management", *Tourism Management*, Vol. 55, pp. 123-132.

Abrate, G., Fraquelli, G. and Viglia, G. (2012), "Dynamic pricing strategies: evidence from European hotels", *International Journal of Hospitality Management*, Vol. 31 No. 1, pp. 160-168.

Aziz, H.A., Saleh, M., Rasmy, M.H. and ElShishiny, H. (2011), "Dynamic room pricing model for hotel revenue management systems", *Egyptian Informatics Journal*, Vol. 12 No. 3, pp. 177-183.

Bayoumi, A.E.M., Saleh, M., Atiya, A.F. and Aziz, H.A. (2013), "Dynamic pricing for hotel revenue management using price multipliers", *Journal of Revenue and Pricing Management*, Vol. 12 No. 3, pp. 271-285.

Bodea, T. and Ferguson, M. (2014), *Segmentation, Revenue Management and Pricing Analytics*, Routledge, New York, NY.

Chen, K.M. and Sheldon, M. (2015), *Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform*, Mimeo, UCLA, 11 December.

Chen, L., Mislove, A. and Wilson, C. (2015), "Peeking beneath the hood of Uber", *Proceedings of the 2015 ACM Conference on Internet Measurement Conference, ACM*, pp. 495-508.

Chen, Y. and Xie, K. (2017), "Consumer valuation of Airbnb listings: a hedonic pricing approach", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 9, pp. 2405-2424.

Chiang, W.C., Chen, J.C. and Xu, X. (2006), "An overview of research on revenue management: current issues and future research", *International Journal of Revenue Management*, Vol. 1 No. 1, pp. 97-128.

Chu, R.K. and Choi, T. (2000), "An importance-performance analysis of hotel selection factors in the Hong Kong hotel industry: a comparison of business and leisure travellers", *Tourism Management*, Vol. 21 No. 4, pp. 363-377.

Dholakia, U.M. (2015), "Everyone hates Uber's surge pricing – here's how to fix it", available at: https://hbr.org/2015/12/everyone-hates-ubers-surge-pricing-heres-how-to-fix-it (accessed 18 September 2016).

Dolnicar, S. and Otter, T. (2003), "Which hotel attributes matter? A review of previous and a framework for future research", in Griffin, T. and Harris, R. (Eds), *Proceedings of the 9th Annual Conference of the Asia Pacific Tourism Association (APTA), University of Technology Sydney*, pp. 176-188.

Duettoresearch.com (2016), "Despite pushback, Airbnb becomes viable sales channel", available at: http://duettoresearch.com/despite-pushback-airbnb-becomes-viable-sales-channel/ (accessed 15 September 2016).

Edelman, B.G. and Luca, M. (2014), "Digital discrimination: the case of Airbnb.com", Harvard Business School NOM Unit Working Paper No. 14-054, 10 January.

Ert, E., Fleischer, A. and Magen, N. (2016), "Trust and reputation in the sharing economy: the role of personal photos in Airbnb", *Tourism Management*, Vol. 55, pp. 62-73.

Fernandez, N.O., Gerrikagoitia, J.K. and Alzua-Sorzabal, A. (2015), "Dynamic pricing patterns on an Internet distribution channel: the case study of Bilbao's hotels in 2013", *Information and Communication Technologies in Tourism 2015 Proceedings of the international conference Lugano, Switzerland, Springer International Publishing*, pp. 735-747.

Field, A. (2013), *Discovering Statistics Using IBM SPSS Statistics*, Sage, Thousand Oaks, CA.

Fox, J. (2016), "Airbnb: How the sharing economy is affecting New York City hotels", Hotel Management.net January, pp. 90-92.

Gibbs, C. (2016), "Airbnb and the impact on the Canadian hotel industry", available at: www.ryerson.ca/tedrogersschool/media-releases/2016-06-27_Airbnb.html (accessed 21 June 2016).

Gibbs, C., Guttentag, D., Gretzel, U., Morton, J. and Goodwill, A. (2017), "Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings", *Journal of Travel & Tourism Marketing*, pp. 1-11.

Gurley, B. (2014), "A deeper look at Uber's dynamic pricing model", available at: http://abovethecrowd.com/2014/03/11/a-deeper-look-at-ubers-dynamic-pricing-model/ (accessed 15 September 2016).

Gutt, D. and Herrmann, P. (2015), "Sharing means caring? Hosts' price reaction to rating visibility", ECIS 2015 Research-in-Progress Papers, Paper 54.

Guttentag, D. (2015), "Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector", *Current Issues in Tourism*, Vol. 18 No. 12, pp. 1192-1217.

Hall, J., Kendrick, C. and Nosko, C. (2015), *The Effects of Uber's Surge Pricing: A Case Study*, The University of Chicago Booth School of Business.

Han, E. and Robertson, J. (2016), "Uber says most New Year's Eve passengers not hit with massive surge pricing", available at: www.smh.com.au/nsw/uber-says-most-new-years-eve-passengers-not-hit-with-massive-surge-pricing-20160102-gly2v9.html (accessed 25 August 2016).

Hill, D. (2015), "How much is your spare room worth?", *IEEE Spectrum*, Vol. 52 No. 9, pp. 32-58.

Ikkala, T. and Lampinen, A. (2014), "Defining the price of hospitality: networked hospitality exchange via Airbnb", *Proceedings of the Companion Publication of the 17th ACM Conference on Computer Supported Cooperative Work and Social Computing*, *Baltimore, MD*, pp. 173-176.

Ikkala, T. and Lampinen, A. (2015), "Monetizing network hospitality: Hospitality and sociability in the context of Airbnb", *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing, Vancouver, BC*, pp. 1033-1044.

Ivanov, S. and Zhechev, V. (2012), "Hotel revenue management–a critical literature review", *Turizam: znanstveno-Stručni Časopis*, Vol. 60 No. 2, pp. 175-197.

Kannan, P.K. and Kopalle, P.K. (2001), "Dynamic pricing on the internet: Importance and implications for consumer behavior", *International Journal of Electronic Commerce*, Vol. 5 No. 3, pp. 63-83.

Karlsson, L. and Dolnicar, S. (2016), "Someone's been sleeping in my bed", *Annals of Tourism Research*, Vol. 58, pp. 159-162.

Katzev, R. (2003), "Car sharing: a new approach to urban transportation problems", *Analyses of Social Issues and Public Policy*, Vol. 3 No. 1, pp. 65-86.

Knowledge@Wharton (2016), "The promise and perils of dynamic pricing", available at: http://knowledge.wharton.upenn.edu/article/the-promise-and-perils-of-dynamic-pricing/ (accessed 15 September 2016).

Lampinen, A. and Cheshire, C. (2016), "Hosting via Airbnb: motivations and financial assurances in monetized network hospitality", *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, ACM*, pp. 1669-1680.

LearnAirbnb.com (2015), "Airbnb pricing strategy and tools", available at: http://learnairbnb.com/airbnb-pricing-strategy-tool/ (accessed 3 September 2016).

Lee, D., Hyun, W., Ryu, J., Lee, W.J., Rhee, W. and Suh, B. (2015), "An Analysis of Social Features Associated with Room Sales of Airbnb", *Proceedings of the 18th ACM Conference Companion on Computer Supported Cooperative Work and Social Computing, ACM*, pp. 219-222.

Lee, S.H. (2016), "How hotel managers decide to discount room rates: a conjoint analysis", *International Journal of Hospitality Management*, Vol. 52, pp. 68-77.

Li, J., Moreno, A. and Zhang, D.J. (2015), "Agent behavior in the sharing economy: evidence from Airbnb", Working paper, [1298] Ross School of Business, University of Michigan, Ann Arbor, MI.

McAfee, R.P. and Te Velde, V. (2006), "Dynamic pricing in the airline industry", in Hendershott, T. (Ed.), *Handbook on Economics and Information Systems*, Emerald, Bingley, pp. 527-570.

McGuire, K.A. (2015), *Hotel Pricing in a Social World: Driving Value in the Digital Economy*, John Wiley and Sons, Haboken, NJ.

Marriott International (2014), *Discover: Revenue Management (Marriott Extranet)*.

Newcomer, E. (2016), "Airbnb seeks new funding at $30 billion valuation", available at: www.bloomberg.com/news/articles/2016-06-28/airbnb-seeks-new-funding-at-30-billion-valuation (accessed 28 August 2016).

O'Connor, P. (2003), "On-line pricing: an analysis of hotel-company practices", *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 44 No. 1, pp. 88-96.

OANDA (2016), "Historical exchange rates report", available at: www.oanda.com/solutions-for-business/historical-rates/main.html (accessed 28 May 2016).

Oskam, J. and Boswijk, A. (2016), "Airbnb: the future of networked hospitality businesses", *Journal of Tourism Futures*, Vol. 2 No. 1, pp. 22-42.

Revenuematters.com (2015), "Emerging pricing trends in hospitality", available at: http://revenuematters.com/emerging-pricing-trends-in-hospitality/ (accessed 2 August 2016).

Robertson, J. and Fisher, J. (2016), "Sydney Uber prices surge by 800 per cent on New Year's Eve", available at: www.smh.com.au/nsw/sydney-uber-prices-surge-by-800-per-cent-on-new-years-eve-20160101-glxxv0.html (accessed 25 August 2016).

Roggenkamp, I. (2015), "What's mine is yours, but for a price: a model of fair pricing perceptions on willingness to engage in the collaborative economy – the case of Airbnb", Master's Thesis, Copenhagen Business School, available at: http://studenttheses.cbs.dk/bitstream/handle/10417/5672/isabelle_roggenkamp.pdf?sequence=1 (accessed 24 July 2016).

Serebrin, J. (2014). "Airbnb starts taking Canadian market seriously with physical presence" available at: https://techvibes.com/2014/11/04/airbnb-canada-2014-11-04 (accessed 24 January 2017).

Sorensen, A.T. (2000), "Equilibrium price dispersion in retail markets for prescription drugs", *Journal of Political Economy*, Vol. 108 No. 4, pp. 833-850.

The Economist (2015), "Business travellers are at last beginning to trust Airbnb", available at: www.economist.com/blogs/gulliver/2016/07/sharing-success (accessed 30 July 2016).

van der Rest, J.-P.I. and Parsa, P.G. (2016), "Pricing and revenue management in the international hospitality industry, (editorial)", *International Journal of Revenue Management*, Vol. 9 Nos 2/3, pp. 89-91.

Wang, X.L., Heo, C.Y., Schwartz, Z., Legohérel, P. and Specklin, F. (2015), "Revenue management: Progress, challenges and research prospects", *Journal of Travel & Tourism Marketing*, Vol. 32 No. 7, pp. 797-811.

World Economic Forum (2015), "The travel and tourism competitiveness report 2015", available at: www3.weforum.org/docs/TT15/WEF_Global_Travel&Tourism_Report_2015.pdf (accessed 24, January 2017).

Wu, E.A.A. (2016), "Learning in peer-to-peer markets: evidence from Airbnb", Masters thesis, Fundac to Gueulio Vargas, available from: http://sistema.bibliotecas.fgv.br/ (accessed 27 July 2016).

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