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Pricing strategies on Airbnb: Are multi-unit hosts revenue pros?

Linchi Kwok[a,*], Karen L. Xie[b]

[a] The Collins College of Hospitality Management, Cal Poly Pomona, 3801 West Temple Avenue, Pomona, CA, 91768, USA
[b] Daniels College of Business, University of Denver, 2044 E Evans Avenue Suite 331, Denver, CO, 80208, USA

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ABSTRACT

This study examined the effects of pricing strategies, including price positioning and dynamic pricing, on an Airbnb listing's revenue with a particular interest on the performance difference between multi-unit and single-unit hosts. A series of econometric analyses were performed using a dataset of 320,243 listings managed by 216,058 hosts in 10 major U.S. markets across a longitudinal period from October 2014 to July 2017. The results suggest while price positioning and dynamic pricing have positive impacts on an Airbnb listing's revenue performance, a multi-listing host performs better than a single-listing host in driving a listing's revenue, through (a) positioning a listing at a higher price than the average listing price in a neighborhood and (b) adopting less dynamic pricing strategies. Our study fills the void of pricing research in room-sharing economy literature and generates important insights about the pricing strategies and the consequent performance outcome between two different host types.

1. Introduction

Sharing economy is built on the ideology that people share their underutilized recourses with peers or other consumers in the market (Botsman and Rogers, 2011). When more people are able to use the underutilized resources, additional value can be created (Koopman et al., 2015). For individual consumers, such additional value created by "sharing" the idling resources often means extra sources of incomes, which encourages more individual consumers who possesses extra space to become an entrepreneur (host) running a room-sharing business and further fuels the phenomenal growth of peer-to-peer (P2P) short-term residential rentals in the cyber marketplace (Guttentag, 2015; Karlsson et al., 2017). The dominant room-sharing platform – Airbnb, for example, which was established just a decade ago in 2008, has already recruited over 640,000 hosts who provide more than four million listings in 65,000 cities around 191 countries (Smith, 2017).

Despite the fact that more individual consumers are now renting out extra space on room-sharing platforms for extra sources of incomes, many of them lack professional training or experience in adopting the right pricing strategies for the listing(s) they manage, as what a revenue manager does in the hotel industry. Hotel professionals, for example, are equipped with industry benchmarking reports and technical tools for revenue management, whereas Airbnb hosts have insufficient revenue management training and support of pricing resources (Gibbs et al., 2018b). Airbnb hosts have repeatedly been reported that they are inefficient in setting the "right" listing price (Learnairbnb.com, 2015) or confused when trying to set up the price to maximize a listing's revenue performance (Hill, 2015).

Recently, Airbnb has developed a variety of tools to assist hosts in pricing (e.g., "smart pricing" option[1]) but still leaves the final decisions to individual hosts of how much they want to charge a listing against others in the same neighborhood (i.e., price positioning) and whether or not they want to adjust listing price according to the fluctuated demands by the travelers (i.e., dynamic pricing). A premise of revenue management is that service firms are selling perishable products with fixed capacities, which requires operation managers to maximize revenue through price manipulations (e.g., changing price to influence demands) (Gallego and Hu, 2014). Price positioning, which was described as the gap of the relative prices between a lodging product and its competitors (Enz et al., 2009; Xie and Kwok, 2017; Lee, 2015), has become a key pricing strategy adopted by hotel revenue managers (Noone et al., 2013). In an analogous fashion, dynamic pricing, defined and measured as the price variation or fluctuations of a product over a period time (e.g., Abrate et al., 2012; Melis and Piga, 2017), is another frequently used revenue management technique among hotels (Abrate and Viglia, 2016; Viglia et al., 2016). As hosts are also trying to maximize their revenue through the management of a perishable product – Airbnb listings, strategies such as price positioning and dynamic pricing

* Corresponding author.
E-mail addresses: lkwok@cpp.edu (L. Kwok), Karen.Xie@du.edu (K.L. Xie).

[1] Source: https://blog.atairbnb.com/smart-pricing/

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can be very helpful and particularly relevant to those entrepreneurs running a short-term residential rental business on a room-sharing website.

While the extent of literature began paying attention to pricing strategies adopted by Airbnb hosts (e.g., Benítez-Aurioles, 2018; Gibbs et al., 2018a, b; Magno et al., 2018; Oskam et al., 2018; Xie and Kwok, 2017) or how price is determined on an Airbnb listing (e.g., Chen and Xie, 2017; Wang and Nicolau, 2017), it is unclear if such revenue management tactics as price positioning and dynamic pricing that have been frequently used by hotels would also work for P2P room-sharing services. In a review of studies about the sharing economy, Cheng (2016) advocated for more research efforts to identify the critical factors that contributed to the success of room-sharing services. Additionally, Gibbs et al. (2018b) and Oskam et al. (2018) also called for more research investigations on the pricing strategies adopted by hosts on room-sharing platforms. In response to the advocacy and calls, we aim to examine the effects of price positioning and dynamic pricing on an Airbnb listing's revenue performance. Our first research question is:

RQ1: How would the strategies of price positioning and dynamic pricing affect an Airbnb listing's revenue performance?

In general, there are two types of Airbnb hosts, namely multi-unit and single-unit operators, and the way they operate the P2P room-sharing business could vary dramatically (Li et al., 2016; O'Neill and Ouyang, 2016). While single-unit hosts, who only manage one listing on Airbnb, account for the majority of the host base (Guttentag, 2015; Guttentag and Smith, 2017), multi-lilting hosts, who manage more than one listing at a given time, have grown substantially in numbers lately because the sharing economy model significantly lowers the start-up costs and the standards for people to enter the cyber marketplace as an entrepreneur (Cheng, 2016). It is plausible that multi-unit hosts, as compared to single-unit hosts, would devote more time and attention into the operations of their room-sharing business and thus become more proficient in serving guests and manipulating the price for the listings they managed, which would further lead to higher revenue performance for the listings they managed (Oskam et al., 2018). Single-unit hosts, however, could arguably outperform multi-unit hosts too. Unlike multi-unit hosts who are less likely to stay with or even interact with guests while managing multiple listings, single-unit hosts are more focused in running only one listing, creating intimate hospitality and social interactions with every guest, thus potentially leading to higher revenue performance for the listing they managed. While recent research has begun to pay attention to the differences between multi-unit and single-unit hosts in room-sharing businesses (e.g., Xie and Mao, 2017; Wegmann and Jiao, 2017), the results remain mixed, and the question of whether host type has a significant impact on an Airbnb listing's revenue performance deserves more research attention. Our second research question is:

RQ2: How would host type (multi-unit vs. single-unit hosts) affect an Airbnb listing's revenue performance?

Meanwhile, depending on host type, it is likely that pricing strategies adopted by individual hosts would have different impacts on an Airbnb listing's revenue performance. Recent research has reported that the host type may affect the adoption of using the dynamic pricing strategy (Gibbs et al., 2018b; Li et al., 2016). For example, a multi-unit host usually deals with more transactions occurring at multiple listings on a daily basis than a single-unit host does. Therefore, a multi-unit host may be able to learn from her/his experience quickly and can price a listing more effectively according to the fluctuating demands in the market to maximize a listing's revenue performance. Recent studies have reported that hosts with greater experience use the dynamic pricing strategy more frequently (Gibbs et al., 2018b) and multi-unit hosts are more proficient in using the dynamic pricing strategy than the single-unit hosts, leading to a higher RevPAR (revenue per available room) performance of an Airbnb listing (Oskam et al., 2018). We are interested in examining the differences in pricing strategies, as well as the consequent revenue performance, between multi-unit and single-unit hosts. Our third research question is:

RQ3: Would the effects of pricing strategies (price positioning and dynamic pricing) on an Airbnb listing's revenue performance vary by host type (multi-unit vs. single-unit hosts)?

By answering these three research questions, our study adds new theoretical insights to the room-sharing literature about the effects of price positioning and dynamic pricing on an Airbnb listing's revenue performance and how such effects differ between multi-unit and single-unit hosts, responding to the call for research in the field (e.g., Cheng, 2016; Gibbs et al., 2018a; and 2018b; Oskam et al., 2018). Practically, our findings provide entrepreneurial hosts as well as the room-sharing platforms with useful suggestions on what pricing strategies are helpful in driving a listing's revenue performance. With a better understanding of what pricing strategies work well (or not as well) in room-sharing businesses, hoteliers may also be able to find better approaches to conquer the threat created by this counterpart.

2. Literature review and hypotheses

2.1. Price positioning and dynamic pricing

Because price is often used as a manipulated variable in competition among similar lodging products (Choi, 1991), price competition is particularly significant among hotels within a ten-mile radius (Lee, 2015). Being able to set the right price at the right time hence becomes a critical revenue management technique for service companies to maximize incomes (Gallego and Hu, 2014). Hotels, for example, can closely monitor the price against what the close competitors offer and then strategically place their products' price point to a level that is higher, equivalent, or lower than that of the close competitors over time, a frequently-used revenue management tactic – price positioning (Noone et al., 2013; Xie and Kwok, 2017). In addition, hotels have also widely adopted the dynamic pricing strategy in operations, where they adjust the room prices in corresponding to the real-time moving number of available rooms, the level of room inventory, the prices of close competitors, as well as other indicators in the market (Viglia et al., 2016).

According to the relevant literature in hospitality and revenue management, a hotel's price positioning can be assessed with "price difference," which is defined as the gap between the price of a lodging product and the price of its competitors (Enz et al., 2009 and 2015; Lee, 2015); Dynamic pricing, also known as "price dispersion" or "price variation," signals the variation of a lodging product's price points in a period (Kim et al., 2014; Noone et al., 2013). In the context of P2P room-sharing services — the settings of this investigation, we define price positioning, or price difference, as the variable that measures the gap between the price of an Airbnb listing and the average price of other Airbnb listings in the market; and we use dynamic pricing, or price dispersion/variation, to illustrate the level of deviation in price of the same Airbnb listing in a given time.

Noone et al. (2013) described price positioning (price difference) and dynamic pricing (price variation) as two key dimensions of a lodging product's strategic pricing strategy. Through an analysis of 6998 hotels in a period of 11 years, Noone et al. (2013) concluded that hotels would have stronger revenue performance than others if they have a high price positioning strategy (higher positive value in price difference) and are able to maintain a relatively stable high-price strategy (lower value in dynamic pricing or fewer price variation). Likewise, Enz et al. (2015) also found from a sample of European hotels that properties with a high price positioning could achieve higher RevPAR performance.

In another study, Kim et al. (2016) acknowledged that dynamic pricing was a common practice by hotels and examined dynamic pricing's effects on hotels' revenue performance. They concluded in their analysis of the hotels in Houston between 2005 and 2014 that certain types of price movements (e.g., those cannot be explained in price positioning or market influence) might seem to be helpful in enhancing a hotel's short-term revenue performance but could bring in an adverse effect on a hotel's long-term revenue performance. More specifically, Oskam et al. (2018) found that Airbnb hosts who adjusted the listing price more frequently could outperform the others in a listing's RevPAR performance through an analysis of over 11 million daily observations from 32,815 Airbnb listings.

While the topic of pricing strategies has not yet been widely discussed in the room-sharing literature, it is commonly believed that Airbnb listings are a new form of lodging products in the market with a perishable nature. Listings on Airbnb, like hotel rooms, need to be priced appropriately to maximize revenue (Guttentag and Smith, 2017; Wang and Nicolau, 2017). Referring to the relevant literature about the traditional lodging products, we make an analogous proposition about Airbnb listings and hypothesize:

H1a. Price positioning positively affects an Airbnb listing's revenue performance.

H1b. Dynamic pricing positively affects an Airbnb listing's revenue performance.

2.2. Host type: multi-unit vs. single-unit hosts

While the original intents of sharing economy were to encourage people to share their idling or underutilized resources in the market (Botsman and Rogers, 2011; Guttentag, 2015), there is a trend showing more Airbnb hosts are now turning their part-time room-sharing business into a full-time job as they manage multiple listings at the same time (O'Neill and Ouyang, 2016). Hosts who operate multiple Airbnb listings as a full-time job, as compared to those who rent out a single listing as a part-timer, would very likely be more driven by revenue and become more experienced in operations. As multi-unit hosts would devote more time and attention in managing the Airbnb business, they may also become more eager to learn the best practices of maximizing their revenues, the knowledge needed for identifying the effective pricing strategies. Over time, when multi-unit hosts become more experienced and invest more efforts in managing the P2P room-sharing business, they could charge for a premium price for an Airbnb listing (Gibbs et al., 2018b), resulting in higher revenues for the listing than the ones operated by a single-unit host.

Empirical evidence has supported the superior performance of multi-unit hosts than single-unit hosts. For example, Wegmann and Jiao (2017) found that the total revenues of a destination that were contributed by multi-unit hosts were proportionally much larger than those contributed by single-unit hosts, where multi-unit hosts only manage 30–44 percent of the total listings in the markets being observed, yet they contributed between 47–59 percent of the total revenues to the markets. Magno et al. (2018), for example, reported that listings managed by multi-unit hosts (as compared to single-unit hosts) or those who have a longer membership on Airbnb could have a higher rate than other listings. Along the same stream, Oskam et al. (2018) found that as the number of properties that a host manages increases, a listing's RevPAR performance will also surge through negative price changes (adjusting the price that is lower than usual); such effect from positive price changes (adjusting the price that is higher than usual) varies depending on the frequency of positive price changes. Given the discussions above, we hypothesize:

H2. An Airbnb listing managed by a multi-unit host has a higher revenue performance than the one managed by a single-unit host.

2.3. The differential effects of pricing strategies by host type

Recent research has discussed the differences between multi-unit and single-unit hosts in operating the room-sharing business. For example, Li et al. (2016) found that listings managed by multi-unit hosts earn 16.9% more in daily revenue than the ones run by single-unit hosts; more importantly, such performance differences between these two host types can be partially explained by pricing inefficiencies. Xie and Mao (2017) assessed the impacts of Airbnb hosts' quality and quantity attributes on a listing's sales performance, revealing that the positive performance effects from the host's quality attributes (e.g., response rate, being a "super host," and etc.) would become less salient as the number of listings that a host manages increase. In the same vein, we argue that, when analyzing the effects of price positioning and dynamic pricing on an Airbnb listing's revenue performance, host type may also play an influential role. That is, the effects of price positioning and dynamic pricing on an Airbnb listing's revenue performance can be moderated by host type and thus deserve additional research attention.

Multi-unit hosts, for example, may be able to achieve higher revenue performance as they quickly gain more experience through their operations of multiple listings at the same time. They may become more concerned when some properties in their multi-unit portfolio are not occupied, resulting in a loss of revenue (Gibbs et al., 2018b). Multi-unit hosts might hence become more active in manipulating and adjusting the listing price since they would closely monitor the demands of the market to avoid the uncaptured revenue from un-occupied listings. In fact, empirical evidence has also confirmed that greater price variation (through dynamic pricing) can have a positive impact on an Airbnb listing's RevPAR performance (Oskam et al., 2018). Likewise, in a general business setting, research has reported that experienced managers tend to have a deeper understanding of the issues facing operations, allowing them to identify more options in solving a problem (Schaltenbrand et al., 2016). Experienced revenue managers in hotels can also apply their past experiences to the results of their quantitative analyses and make the necessary adjustments accordingly (Schwartz and Cohen, 2004). Therefore, when it comes to adopting the right pricing strategy as a means to increase an Airbnb listing's revenue performance, it is likely that multi-unit hosts are more capable and effective than single-unit hosts in practicing the price positioning and dynamic pricing strategies. Hence, we hypothesize:

H3a. The positive effect of price positioning on an Airbnb listing's revenue performance is more salient for a multi-unit host than for a single-unit host.

H3b. The positive effect of dynamic pricing on an Airbnb listing's revenue performance is more salient for a multi-unit host than for a single-unit host.

In summary, Fig. 1 illustrates the hypothesized relationships among the variables of our interests in this investigation. The hypotheses proposed for statistical analyses are also labeled in the model for easy reference.

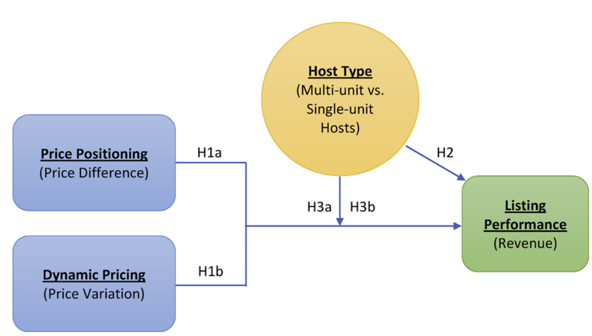

Fig. 1. A Proposed Model.

Table 1
Descriptions of the Ten Major Airbnb Markets.

Rank	Airbnb Market	Population[a]	GDP[b] ($)	Listings	Hosts
1	New York-Newark-Jersey City, NY-NJ-PA Metro Area	8,537,673	1,602,705	148,113	102,893
2	Los Angeles-Long Beach-Anaheim, CA Metro Area	3,976,322	930,817	48,358	29,444
3	San Francisco-Oakland-Hayward, CA Metro Area	870,887	431,704	30,025	20,713
4	San Diego-Carlsbad, CA Metro Area	1,406,630	220,573	19,466	12,123
5	Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	681,170	491,042	19,844	13,653
6	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	1,567,872	411,161	15,900	11,868
7	Seattle-Tacoma-Bellevue, WA Metro Area	704,352	313,654	14,626	9,512
8	Portland-Vancouver-Hillsboro, OR-WA Metro Area	639,863	158,770	10,228	7,087
9	Boston-Cambridge-Newton, MA-NH Metro Area	673,184	396,549	7,457	4,560
10	San Jose-Sunnyvale-Santa Clara, CA Metro Area	1,025,350	235,222	6,226	4,205
Total				**320,243**	**216,058**

[a] Source: United States Census Bureau, Population Division. Retrieved October 4, 2017 from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk.
[b] Source: US Department of Commerce, Bureau of Economic. Retrieved October 4. 2017 from www.bea.gov.

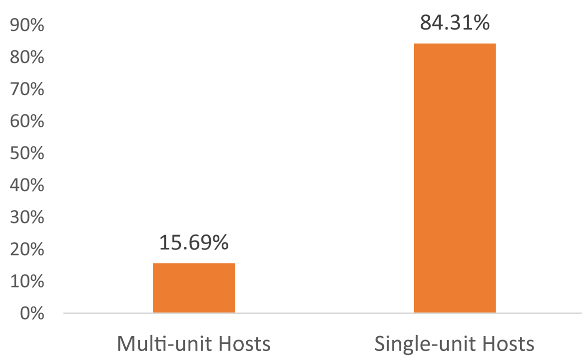

Fig. 2. A Comparison between Multi-unit and Single-unit Hosts.

3. Methodology

To test the proposed hypotheses, we obtained the data from Airdna (www.airdna.co), a research company that provides trusted data and analytics services about Airbnb[2]. The data services of Airdna have been used and endorsed by major hospitality institutions such as CBRE Hotels, American Hotel & Lodging Association (AH&LA), and Discover Los Angeles. Our data includes the monthly revenue performance of the listings, as well as the characteristics of both the hosts (e.g., host type) and the listings (e.g., price) in 10 major Airbnb markets in the U.S., which are also the top metropolitan statistics areas with largest populations and gross domestic products (GDPs) in the nation. Table 1 presents a summary of these Airbnb markets, in the rank order by the number of Airbnb listings. Our data is large-scale, yet granular, consisting of 320,243 properties managed by 216,058 hosts over a total of 34 months from October 2014 to July 2017. Fig. 2 displays the ratios of multi-unit (15.69%) and single-listing hosts (84.31%) to the total number of hosts in our dataset.

The unit of analysis in our data is *Listing - Month*, which enables us to repeatedly observe the effects of pricing strategies on an Airbnb listing's revenue performance over time in a longitudinal fashion. We studied each listing with consideration of its location in a specific neighborhood. Neighborhoods are defined by Airbnb as a way to help travelers make informed decisions about where to stay when planning a trip[3]. Our dependent variable is *Revenue,* a key performance indicator widely used in the hospitality industry.

Our primary independent variables are categorized into five dimensions: (1) host type (*Multi*), a dummy variable representing whether a host is a multi-unit host (*Multi* = 1) or a single-unit host (*Multi = 0)*; (2) pricing strategies in terms of the difference between the price of a subject listing and the average price of other counterpart listings in a neighborhood (*PriceDiff*) and the price variation of the subject listing itself (*PriceVari*). Besides these primary independent variables introduced in (1) and (2), we also control (3) the supply of Airbnb listings in a neighborhood for the competition measure (*Supply*), (4) listing characteristics such as number of online customer reviews received (*NumReview*), average rating (*AveRating*), number of bedrooms (*Bed*), number of bathrooms (*Bath*), whether a listing is an entire home, shared room, and private room (*Type*), and how many days in a month a listing is made available by a host (*Availability*), and (5) host service related to the management of a listing, including response rate (*ResRate*), response time (*ResTime*), and whether a host is recognized as a "super host" (*SuperHost*) as an indicator of his/her excellence in service. All these controls are very likely to influence a listing's revenue performance and should be controlled in the regressions.

Table 2 presents the definitions and summary statistics of each variable discussed above. Table 3 shows the correlation matrix among the regressor variables. The values of correlation are consistently below 0.8 (Katz, 2006), indicating that our estimation is unlikely to be biased by collinearity.

To estimate the effects of the two pricing strategies on an Airbnb listing's revenue performance and how such effects vary by host type, we propose that, for a listing i in month t, its revenue performance is,

$$Revenue_{it} = \alpha + \beta\, Multi_{it} + \gamma' H_{it} + \eta' Multi_{it} \times H_{it} + \iota' Z_i + \mu_i + \nu_t + \varepsilon_{it}$$

where $Multi_{it}$ indicates host type with values of 1 = a multi-unit host and 0 = a single-unit host, H_i represents a vector of pricing strategies used by a host in managing a listing (i.e., price positioning and dynamic pricing). Another vector Z_i denotes a set of controls, including the neighborhood supply, as well as the characteristics of both listings and hosts that would likely influence an Airbnb listing's revenue performance. To control the heterogeneity of the neighborhood where a listing is located, a listing itself, and the time trends, we also include two sets of dummies at the listing and month levels, μ_i, and ν_t respectively, in the regressions. Finally, ε_{ijt} is the idiosyncratic error. Our focus in the regressions is to estimate the parameter η', which captures the differential effects of the two pricing strategies on an Airbnb listing's revenue performance between a multi-unit and a single-unit host. STATA 14 is used to implement the econometric estimations.

[2] The algorithms and methodologies used by Airdna to track and analyze Airbnb performance can be found at https://www.airdna.co/methodology. Although it is possible that the data offered by Airdna is not free from errors, it is the best data we can possibly collected for this research project.

[3] According to Airbnb, "the neighborhoods boundaries are based on research with locals and city experts. A cartographer helps make sure these boundaries are accurate and up-to-date. Source: https://www.airbnb.com/help/article/420/what-are-neighborhoods)

Table 2
Variable Definition and Summary Statistics.

Dimensions	Variable	Definition	Mean	Std. Dev.	Min	Max
Listing Performance	*Revenue*	Revenue received from booking a listing in a given month	879.12	1,913.27	0	250,000
Host Identity	*Multi*	Dummy variable of host identity with values of 1 = multi-listing host and 0 = single-listing host	0.40	0.49	0	1
Host Pricing	*PriceDiff*	Difference of the ADR of a listing and the average ADR of the other listings in a neighborhood (in dollars)	131.44	775.11	−1452.11	999934.1
	PriceVari	Standard deviation of the listing price in a given month	9.53	57.18	0	45228.36
Supply Control	*Supply*	Number of other Airbnb listings in a neighborhood in a given month	1,587.17	1,888.58	1	7,830
Listing Control	*NumReview*	Cumulative number of all-time online customer reviews	21.15	40.15	0	659
	AveRating	Average all-time customer review rating on a scale of 1 to 5, with values of 1 = Terrible, 2 = Poor, 3 = Average, 4 = Very good, and 5 = Excellent	4.64	0.44	1	5
	Bed	Number of bedrooms	1.25	0.84	0	14
	Bath	Number of bathrooms	1.23	0.58	0	15.5
	Type	Categorical variable of listing type with values of 1 = entire home, 2 = private room, and 3 = shared room	1.46	0.57	1	3
	Availability	Number of days in a month a listing is made available by a host for booking	11.79	12.59	0	31
Host Control	*ResRate*	Percentage of new booking inquiries and reservation requests a host respond to (by either accepting/pre-approving or declining) within 24 hours in a given month	89.69	22.20	0	100
	ResTime	Average number of minutes it takes a host to respond to new booking inquiries	323.43	443.40	0.01	1,440
	SuperHost[*]	Dummy variable indicating whether a host is recognized by the Airbnb platform as a super host,[a] with values of 1 = Super host, 0 = Regular host	0.14	0.35	0	1

[*]Super host is recognized by the Airbnb platform based on certain criteria in aspects of service quality. Source: https://www.airbnb.com/superhost.

Table 3
Correlation Matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*Multi*	1.00												
(2)	*PriceDiff*	−0.02	1.00											
(3)	*PriceVari*	0.01	0.12	1.00										
(4)	*Supply*	0.00	−0.03	0.00	1.00									
(5)	*NumReview*	0.11	−0.04	0.01	−0.07	1.00								
(6)	*AveRating*	−0.12	0.03	0.00	−0.06	0.06	1.00							
(7)	*Bed*	0.05	0.16	0.03	−0.08	−0.05	0.01	1.00						
(8)	*Bath*	0.07	0.14	0.03	−0.09	−0.05	0.01	0.57	1.00					
(9)	*Type*	0.16	−0.08	−0.02	0.07	−0.02	−0.07	−0.23	−0.08	1.00				
(10)	*Availability*	0.10	0.01	0.01	−0.02	−0.12	−0.09	0.01	0.04	0.12	1.00			
(11)	*ResRate*	0.07	−0.03	0.00	−0.06	0.16	0.11	0.02	0.01	−0.04	−0.15	1.00		
(12)	*ResTime*	−0.15	0.03	−0.01	0.07	−0.21	−0.05	−0.02	−0.02	0.01	0.11	−0.74	1.00	
(13)	*SuperHost*	0.10	−0.03	0.01	−0.10	0.33	0.21	0.01	0.00	−0.02	−0.05	0.18	−0.20	1.00

4. Results

Table 4 presents the estimation results. We use a family of econometric error specifications for effect cross-validation, including (1) robust standard errors for a baseline estimation, (2) robust standard errors clustered on the listing level and (3) and robust standard errors clustered on the neighborhood level for alternative models. Clustering robust standard errors at the property and neighborhood levels may be necessary because the listings observed in this study are co-located in neighborhoods, and their observations are independent across neighborhoods but likely correlated within neighborhoods.

We first discuss the result in Column (1) and then check whether results in other models remain consistent. We found positioning a listing at a price level higher than the average of neighborhood listings significantly drove the listing's revenue performance (0.892***), supporting H1a. Similarly, dynamic pricing seems an effective performance-driven strategy, supported by the evidence that an increased price variation would significantly drive the revenue up by ten dollars (10.239***). Therefore, H1b is supported.

The result also shows a significantly larger revenue performance of a listing managed by a multi-listing host compared to the one managed by a single-listing host (198.021***), supporting H2. What is intriguing is that a multi-listing host would magnify the positive effect of price positioning on revenue performance through pricing the listing at a higher price level compared to the average price of other counterparts in the neighborhood (0.474***), supporting H3a. However, such positive effect of dynamic pricing is weakened for a multi-listing host (-6.218**), not supporting H3b.

We further checked the results across other models using aforementioned error specifications (i.e., robust standard errors at the listing and neighborhood levels) in Columns (2) and (3). The estimations show an across-model consistency, validating the robustness of the estimated effects.

5. Discussion and implications

In responding to the calls for more research on the pricing strategies adopted by the entrepreneurs running a P2P room-sharing business (Cheng, 2016; Gibbs et al., 2018a; and 2018b; Xie and Kwok, 2017), we raised three hypotheses for a series of econometric analyses with a unique internet-enabled dataset of 320,243 Airbnb listings managed by 216,058 hosts in 10 major U.S. markets. Our research discovers a few crucial findings that enhance our understanding about the pricing strategies that would help entrepreneurs/hosts increase revenue performance in the room-sharing context and more importantly, the moderating role that host type (multi-unit vs. single unit hosts) play in this setting.

As Airbnb listings and hotel rooms are essentially fulfilling the same needs for travelers — accommodation, Airbnb has been widely recognized as an alternative option for hotels (e.g., Xie et al., 2018;

Table 4
Effect Estimation.

Hypothesis Testing		Revenue		
		Baseline Model	Robustness Checks	
		Robust Standard Errors	Robust Standard Errors Clustered on Listings	Robust Standard Errors Clustered on Neighborhoods
		(1)	(2)	(3)
	Primary Variables			
H1a	*PriceDiff*	0.892***	0.892***	0.892***
		(0.000)	(0.000)	(0.000)
H1b	*PriceVari*	10.239***	10.239***	10.239***
		(0.000)	(0.000)	(0.000)
H2	*Multi*	198.021***	198.021***	198.021***
		(0.000)	(0.000)	(0.000)
H3a	*Multi x PriceDiff*	0.474***	0.474*	0.474*
		(0.002)	(0.068)	(0.093)
H3b	*Multi x PriceVari*	−6.218**	−6.218**	−6.218**
		(0.013)	(0.017)	(0.037)
	Control Variables			
	Supply	−0.004***	−0.004***	−0.004*
		(0.000)	(0.000)	(0.077)
	NumReview	11.441***	11.441***	11.441***
		(0.000)	(0.000)	(0.000)
	AveRating	48.835***	48.835***	48.835**
		(0.000)	(0.000)	(0.012)
	Bed	360.090***	360.090***	360.090***
		(0.000)	(0.000)	(0.000)
	Bath	166.846***	166.846***	166.846***
		(0.000)	(0.000)	(0.000)
	Type			
	PrivateRoom	−620.431***	−620.431***	−620.431***
		(0.000)	(0.000)	(0.000)
	SharedRoom	−668.740***	−668.740***	−668.740***
		(0.000)	(0.000)	(0.000)
	Availability	−33.866***	−33.866***	−33.866***
		(0.000)	(0.000)	(0.000)
	ResRate	−3.767***	−3.767***	−3.767***
		(0.000)	(0.000)	(0.000)
	ResTime	−0.295***	−0.295***	−0.295***
		(0.000)	(0.000)	(0.000)
	SuperHost	263.018***	263.018***	263.018***
		(0.000)	(0.000)	(0.000)
	Listing Dummies	Y	Y	Y
Month Dummi-es	Listing Dummies	Y	Y	Y
	Month Dummies	Y	Y	Y
	Constant	1120.568***	1120.568***	1120.568***
		(0.000)	(0.000)	(0.000)
	VIF	1.36	1.36	1.36
	Observations	2,649,140	2,649,140	2,649,140
	R-squared	0.249	0.249	0.249

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Zervas et al., 2017)., Airbnb hosts, just like hotel managers, are also challenged to manage a service product that is perishable and with fixed capacities — a premise of revenue management (Gallego and Hu, 2014). Therefore, Airbnb hosts should also be able to leverage the power of price positioning and dynamic pricing to increase a listing's revenue performance, which has been identified as two effective pricing strategies in helping hotels increase revenues (Enz et al., 2015; Kim et al., 2014; Noone et al., 2013). Our results provide strong empirical evidence to support such proposition.

Furthermore, we acknowledged that the market has a growing number of multi-unit hosts (O'Neill and Ouyang, 2016) even though they do not account for the majority of the host base (Guttentag, 2015; Guttentag and Smith, 2017). Researchers have begun paying attention to analyzing the possible different effects from two host types, including multi-unit and single-unit hosts, on the operations of P2P room-sharing services (e.g., Gibbs et al., 2018b; Li et al., 2016; Kwok and Xie, 2018; Xie and Mao, 2017). This study took part in this wave of research endeavors by examining not only host type's direct impact on an Airbnb listing's revenue performance but also host type's moderation effects on price positioning's and dynamic pricing's positive impacts on an Airbnb listing's revenue performance. After controlling other influential factors that may lead to a higher revenue performance for an Airbnb listing (e.g., average rating, number of bedrooms and bathrooms, response rate/time, having a "Super Host" status, and etc.), our analysis reveals that multi-unit hosts yield higher revenues for an Airbnb listing that they managed than single-unit hosts do. It is possible that many multi-unit hosts have become more experienced than single-unit hosts as they quickly learn from their operations of multiple listings at a given time. Multi-unit hosts with more experience can hence identify more solutions to the problems occurred in operations, as what experienced managers do in a general business setting (Schaltenbrand et al., 2016), leading to higher revenue performance for the Airbnb listings they managed. Such results also agree to the findings in Li et al. (2016) and Oskam et al. (2018). Accordingly, we also advocate hoteliers to pay close attention to multi-unit hosts in the market as they appear to be more threatening than single-unit hosts.

Interestingly, while the positive effect of price difference on an Airbnb listing's revenue performance would become even more salient for a multi-unit host than a single-unit host, as what we proposed in H3a, the positive effect of dynamic pricing on an Airbnb listing's revenue performance would diminish under the influence/operations of a multi-unit host, contradicting to what we suggested in H3b. It is plausible that multi-unit hosts are doing a better job in positioning their Airbnb listings at a higher price point than what the competitors are offered as they become more experienced in operating the room-sharing business. Yet, when multi-unit hosts have devoted their time and attention to multiple listings, they might not be able to pay the special attention needed to frequently adjust each of the individual listings that they managed — the tasks required in dynamic pricing. Our findings confirmed that even though greater price variation (dynamic pricing) are found among multi-unit hosts than among single-unit hosts (Gibbs et al., 2018b), it turns out the dynamic pricing strategy might not be able to help multi-unit hosts increase an Airbnb listing's revenue performance. To a large extent, such results echo what Noone et al. (2013) identified in their study about hotels' pricing strategies, where high price positioning with relatively stable high-price point (higher positive value in price difference plus fewer price variation) is helpful in increasing a hotel's revenue performance. Once again, since price positioning and dynamic pricing have similar effects on a lodging product for both the multi-unit hosts running a P2P room-sharing business and hotels competing in the traditional lodging industry, we strongly encourage hoteliers to carefully examine the behaviors of multi-unit hosts.

6. Conclusion and implications

This study identified a few significant relationships among price positioning, dynamic pricing, host type, and an Airbnb listing's revenue performance. Its theoretical and practical implications warrant a discussion.

6.1. Theoretical implications

First and foremost, this study conducted an in-depth analysis of the pricing strategies adopted by Airbnb hosts as entrepreneurs in the room-sharing context. The findings add complementary insights to current literature. It was advocated that more research attention be

Table 5
A Summary of the Detailed and Specific Practical Implications.

Audience	Pricing Strategy Recommendations	
	Price Positioning	Dynamic Pricing
Multi-unit Hosts	To maintain a relatively high price positioning in the market	To be very careful when using the dynamic pricing strategy to avoid its negative effects Particularly, do not lower the price so much that the listing would lose a high price positioning in the market
Single-unit Hosts	To maintain a relatively high price positioning in the market	To consistently monitor the market demand and fluctuate the listing price accordingly
Room-sharing Platforms	To use our study as a reference to conduct more analysis in other market for more insights To provide additional trainings on the topic of price positioning to better assist the hosts in setting up the initial price	To provide market insights for hosts, making suggestions to hosts in adjusting the listing price. To provide different trainings on dynamic pricing for multi-unit and single-unit hosts as they may need to adopt different dynamic pricing strategy
Hoteliers	To pay close attention to those listings with a relatively high price positioning in the market and see how those price points compared to the hotel's ADR	To pay close attention to the dynamic pricing strategy adopted by multi-unit hosts

needed to examine Airbnb hosts' pricing strategies (e.g., Benítez-Aurioles, 2018; Cheng, 2016; Gibbs et al., 2018a; and 2018b; Oskam et al., 2018; Xie and Kwok, 2017). The investigation taken in this study enables us to further establish the relationship between Airbnb hosts' pricing strategies, including price positioning and dynamic pricing, and an Airbnb listing's revenue performance.

Additionally, this study examined the important role that multi-unit hosts play in the P2P room-sharing context. Not only host type (multi-unit vs. single-unit hosts) has a direct impact on an Airbnb listing's RevPAR performance, but it also moderates the main effects from a host's pricing strategies on an Airbnb listing's RevPAR performance. Our study confirms the importance of analyzing host type as a moderating factor in similar studies (e.g., Xie and Mao, 2017; Xie et al., 2018). We hence highly encourage future studies to further examine the moderation effects of host type in the analysis.

Generally, there are two distinguishing pricing models in the sharing economy. Some business platforms such as Uber and Lyft use the company's algorism to determine the price for each service request on behalf of the individual service providers. Other business platforms, including Airbnb, (sharing) food bank, crowdfunding, and (sharing) catering/tourism service, allow the service providers to adjust the sales price according to the market demands. The data analytic approach demonstrated in this study can provide a reference for other researchers as they investigate the pricing strategies on the sharing-economy sectors that adopt similar pricing models as what is currently used by the entrepreneurs in Airbnb.

6.2. Practical implications

Practically, we encourage entrepreneurs managing one or more room-sharing listings on room-sharing platforms, regardless if they are multi-unit or single-unit hosts, to adopt a relatively high-price position in the market. While a dynamic pricing strategy where hosts consistently adjust the listing price according to the fluctuating market demands can be beneficial in increasing a listing's revenue performance, multi-unit hosts are advised to be very careful when using the dynamic pricing strategy to avoid its adverse effects.

Meanwhile, Airbnb has made a few efforts in helping the hosts set the "right" price in the market. For instance, Airbnb not only offers guidelines for hosts in setting up the initial price (Xie and Kwok, 2017) but also provides price suggestions for hosts through the company's new pricing algorithm tools (Gibbs et al., 2018b). Accordingly, we encourage room-sharing platforms to look deeper into our findings regarding host type's moderation effects on price positioning's and dynamic pricing's positive effects on a listing's revenue performance. Multi-unit and single-unit hosts should receive different types of training because some strategies may work better in one group than in the other.

Last but not least, we recommend hoteliers to pay close attention to the multi-unit hosts, particularly on their price positioning and dynamic pricing strategies. We have found that multi-unit hosts are doing a much better job in managing the room-sharing business than single-unit hosts. More importantly, it appears that multi-unit hosts can better leverage the positive effect of price positioning and dynamic pricing strategies with the approach of maintaining a relatively stable yet high-price positioning, similar to what has been identified in Noone et al. (2013) for hotels. These findings indicate that listings managed by multi-unit hosts can be a real big threat to hotels and other traditional lodging products in the same neighborhood.

Table 5 provides a summary of the specific practical implications discussed above. We recommend a few specific tactics, which are organized by strategies (price positioning vs. dynamic pricing) and the key stakeholders of the room-sharing business (multi-unit hosts, single-unit hosts, room-sharing platforms, and hoteliers).

6.3. Limitations and future research

This study is not without limitations. First, despite the fact that our dataset captures each active listing in the 10 major U.S. Airbnb markets, it may not represent the markets in small cities, let alone the entire U.S. market. Also, given the rapid growth of Airbnb's overseas markets in Europe and Asia, our data has undoubtedly not captured the vibe of international markets. Therefore, the findings may not be generalized from this study to other contexts. Future research that uses a broader range of markets than that of this study can validate and extend our findings and thus is highly encouraged.

Second, this study is instantiated on the data purchased from Airdna. Although the data of Airdna is known as one of the best sources possible for academic research on Airbnb and used by leading hospitality institutions such as CBRE Hotels and AH&LA, it is unlikely that our dataset is entirely free from errors. We would hope to see more research investigating the pricing strategies of Airbnb hosts using different data sources other than Airdna — e.g., working with Airbnb directly if possible. Research from different data sources that address different but complementary research questions can often enhance our understanding of a complex phenomenon (Kwok, 2012).

Lastly, although this study has attempted to control as many variables as possible, it is possible that other market-related variables (price and supply of hotels and long-term rentals in each neighborhood) may also possibly influence the revenue performance of an Airbnb listing. Due to the unavailability of such data at a very granular level of neighborhood by month, we were unable to incorporate them into our analysis. Future research that has access to market-related data (e.g., price and supply of hotels and long-term rentals) is strongly encouraged. Overall, this study serves as a stepping stone for future room-sharing research in more depth and width. Through the collective efforts of researchers and industry supporters who are interested in sharing economy research, we believe this research stream can be further advanced.

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Linchi Kwok, Ph.D., is an associate professor in the Collins College of Hospitality Management at California State Polytechnic University Pomona (Cal Poly Pomona). He received an M.S. and a Ph.D. degree in Hospitality Administration at Texas Tech University, as well as an MBA at Syracuse University. His research interests include: information technology, social media, and service operations.

Karen Xie is an Assistant Professor of Hospitality Management at the Daniels College of Business, University of Denver. Her research interests focus on the IT-enabled business strategy. Her work relies primarily on econometrics and machine learning using large-scale, yet granular, business data. She holds a Ph.D. from Temple University Fox School of Business, an MPhil from the Hong Kong Polytechnic University, and a Bachelor of Management from Fudan University in Shanghai.