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Do Professional Hosts Matter?

Evidence from Multi-listing and Full-time Hosts in Airbnb

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Abstract

Professional hosts who operate more than one listing or in a full-time manner on peer-to-peer (P2P) accommodation sharing platforms are growing. This study investigates (1) the effect of customer evaluation on property performance through online traveler reviews, (2) the difference of property performance between host types, and (3) how the effect of customer evaluation on property performance varies by host types. A large-scale, longitudinal dataset of the entire State of California is used for econometric analyses. A property managed by a multi-listing host makes 27.8% more revenue per available night (RevPAN) than a property managed by a single-listing host in a month. In contrast, a property managed by a full-time host makes 23.8% less RevPAN than its counterpart managed by a part-time host. While customer evaluation positively affects listing performance, its effect is divergent between professional hosts, weaker for a multi-listing host but magnified for a full-time host.

Keywords: Multi-listing hosts, Full-time hosts, Airbnb, Peer-to-peer accommodation sharing

1. Introduction

The rapid growth of peer-to-peer (P2P) sharing platforms is changing the hospitality landscape by offering travelers new options for where to stay and eat, what to do, and how to travel around. Airbnb is a notable case to exhibit how P2P sharing platforms allow individuals to offer their extra living spaces to travelers around the world. As of June 2020, Airbnb has more than 7 million listings in over 100,000 cities across 191 countries (Airbnb, 2020), which are more than the combined numbers of the world's five largest hotel brands in inventory (Hartmans, 2017).

The massive popularity of Airbnb turns the spotlight on professional hosts working behind the scene. The most successful and valuable hosts on the site are a rapidly growing class of micro-entrepreneurs - multiple-unit operators and full-time hosts, accounting for around 71% of Airbnb's $14.1 billion revenue in its top 12 markets (Dogru et al., 2020). Multi-listing hosts are those who list more than one property through Airbnb, which constitutes one type of professional hosts (Li et al., 2017; Gunter & Önder, 2018). The other type of professional hosts is the full-time hosts, who rent out their listings for the full length of a month (e.g., 30 days or more) or year (e.g., 360 days or more) (O'Neil & Ouyang, 2016). In contrast, the part-time hosts list their units for the duration fewer than the full length of a month or year. According to a report released in late 2014 by the New York Attorney General, most Airbnb hosts (94%) rented out two units or fewer in New York City (New York State Office of the Attorney General, 2014). Similarly, a Penn State report shows that nearly 30% of hosts rented out their entire unit year-round and full-time operators generate a substantial amount of Airbnb's revenue in the New York City metropolitan area (O'Neil & Ouyang, 2016). Hoteliers contend that these professional hosts generate unfair competition because they turn housing stock into quasi-hotels and represent a threat to the hotel industry (Hickey & Cookney, 2016; Somerville & Levine, 2017). While Airbnb has become popular as an alternative to hotel accommodation, commercial homes like Airbnb are distinct from traditional hotels in that home element remains their central appeal, and thus they are often referred to as para-hotel businesses or quasi-hotels (Ye, Xiao, & Zhou, 2018).

Despite the fact that professional hosts are reaping the benefits of P2P accommodation sharing, hospitality scholars have only started to examine the role of professional hosts, and their findings are often inconclusive. A handful of studies have explored the professional and nonprofessional hosts and their performance difference (Li et al. 2017; O'Neil & Ouyang, 2016; Xie & Mao, 2017). For example, Li et al. (2017) found that Airbnb properties managed by professional hosts earn 16.9% more in daily revenue and have 15.5% higher occupancy rates compared with properties owned by nonprofessional hosts. In addition, O'Neil and Ouyang (2016) reported that full-time hosts represented only 3.5% of all Airbnb hosts in the nation but generated 26.0% of revenue, further demonstrating professional hosts' higher revenue generating capabilities and better performance. On the other hand, Xie and Mao (2017) showed that professional host (i.e., multi-listing hosts) underperform non-professional hosts (i.e., single-listing hosts) in profiting each listing with a sample of Airbnb hosts in Austin, Texas. Such inconclusive findings potentially produce a hurdle for practitioners to understand the performance success of professional hosts. Deboosere, et al (2019) suggested future research to examine the link between professionalization and increases in monthly profit.

To add evidence to the debate on the role of professional hosts, we investigate the performance difference between the professional and nonprofessional hosts and the moderating effect of customer evaluations on listing performance. Consumers consider observable quality signals, such as third-party certificates, customer reviews, and price, and numerous studies have investigated how those signals affect perceptions of quality and purchasing risk (O'Connor, 2010). There is abundant literature on quality signals (e.g., customer evaluation) as a predictor of performance because of its importance in the consumer's intention to purchase (e.g., Ballina, Valdés, & Del Valle 2020). Customer evaluation has been generally considered as an essential element that decides lodging performance (Casaló et al., 2015; Zhao et al., 2015) and is worth investigation, especially when evaluating professional host performance in P2P accommodation sharing. From the perspective of the signaling theory, this study explores the role of customer evaluation as a predictor of Airbnb's performance and whether host type moderate the signaling effects of customer evaluation on revenue performance.

Our research questions are three-fold: (1) What is the relationship between customer evaluations and revenue performance of Airbnb properties? (2) How do the professional hosts (multi-listing and full-time hosts) affect the revenue performance of Airbnb properties, compared to their counterparts (single-listing and part-time hosts)? (3) How would multi-listing and full-time hosts moderate the effect of customer evaluations on revenue performance, respectively? Consistent with prior literature (Li et al., 2017; O'Neil & Ouyang, 2016), we segment professional hosts into multi-listing hosts and full-time hosts for a finer understanding of their performance difference. Customer evaluation is measured by the average rating of online reviews and revenue per available night (i.e., *RevPAN*) is used to measure the revenue of Airbnb listings of all of the available nights, which has been widely adopted in Airbnb research as performance evaluation (e.g., Xie et al., 2019).

We first examine the impact of customer evaluations on performance in general. We then investigate the interaction between customer evaluation (evident in guest reviews) and host type in order to explore which type of professional hosts would magnify (or suppress) the performance effect of customer evaluations in accommodation sharing.

The findings can help us better understand the role of professional hosts and their relative effectiveness in affecting revenue performance and moderating the customer evaluations, which can provide implications on how to enhance the performance across various types of hosts.

2. Literature Review

2.1 Overview of the Home Sharing Literature

There is a growing body of literature on P2P sharing platforms. Several researchers have tried to understand the unique characteristics of the P2P transactions (e.g., Chandna & Salimath, 2018; Gunter, 2018; Ert et al., 2016). Others have focused on this new trend of sharing in hospitality (e.g., Dogru et al., 2020; Heo, 2016), the impact of P2P accommodation-sharing platforms on the incumbent hotel industry (e.g., Heo et al., 2019; Xie & Kwok, 2017; Zervas et al., 2017; Sainaghi & Baggio, 2020), travelers' trust formation and indicators (e.g., Ert & Fleischer, 2029; Mao et al., 2020), travelers' motivations (e.g., Guttentag et al., 2018; Mao & Lyu, 2017), hosts' trust formation (e.g., Wang et al., 2020) and motivations (e.g., Liang et al., 2019), and macroeconomic and social issues (e.g., Farmaki & Kiladou, 2020; Heo & Blengini, 2019; Dogru et al., 2020; Zhu, 2020).

Given the growing volume of research on P2P sharing platforms, several studies focused on a systematic and holistic review of the literature to summarize the main research topics and to uncover the theoretical foundations. For example, Cheng (2016)'s study revealed three broad areas of focus on sharing economy research in general (i.e., business models and its impacts, nature, sustainability development) and two areas in tourism and hospitality specifically (i.e., the impacts on destinations and tourism services and the impacts on tourists). Additionally, Prayag and Ozanne's (2018) systematic review of P2P accommodation sharing suggested seven main themes, including: "conceptual development; regulation; macro-level impacts; regime response; host behavior; guest/host experience; and marketing issues". Moreover, Altinay and Taheri (2019) identified overarching theories and several emerging themes by synthesizing recent studies in the sharing economy literature. Lastly, based on 118 articles on Airbnb between 2013 and 2018, Dann, Teubner, and Weinhardt (2019) concluded that research on Airbnb is highly diverse in terms of domains, research methods, and scope; motives for using Airbnb are wide-ranging (e.g., financial, social and environmental); trust and reputation are found to be crucial.

In particular, a critical challenge for Airbnb is the formation of trust between the guest and the host. Review scores and the number of positive reviews are mainly identified as strong trust-enhancing signals, influential for shaping consumers' booking decisions (e.g., Abramova et al., 2017). Therefore, several studies use customer evaluation as a proxy for a listing's popularity and hence its performance (Lee et al., 2015; Ke, 2017; Liang et al., 2017).

2.2 The Literature on Home Sharing Hosts

Our study is most relevant to the literature on home sharing hosts. Some P2P accommodation-sharing research is performed from the host's perspective, with many focusing on pricing issues (e.g., Chen & Xie, 2017; Gibbs et al., 2017). For example, Gibbs et al. (2017) and Chen and Xie (2017) found that listing characteristics and host characteristics significantly impact price using a hedonic pricing approach. In addition, scholars began to delve into the effects of host characteristics (photo, gender and host status, etc.) on operational performance or traveler evaluation under the framework of signaling effects (Edelman et al., 2017; Mauri et al., 2018). On the other hand, Kwok, Tang, and Yu (2020) compared Airbnb's 7 Ps marketing mix among the listings managed by different types of hosts found that multi-unit and single-unit hosts deliver similar services with a small noticeable difference; whereas Superhosts and the normal hosts offer different services. Other researchers focused on the spatial patterns of Airbnb listing. Gutiérrez et al. (2017) analyzed a close spatial relationship between Airbnb and hotels in Barcelona and discovered that the factors explaining location are also different for hotels and Airbnb. While Airbnb listings prevail around the city's main hotel axis, hotels predominate in some peripheral areas of the city (Gutiérrez et al., 2017). Xie, Kwok, and Heo (2020) interested in co-location dynamics and agglomeration effects. Agglomeration effect refers to the benefits the businesses can receive from the clustering (Yang, Wong, & Wang, 2012). Xie et al. (2020) found that agglomeration positively affects the revenue performance of each Airbnb listing in New York City, and such an effect is strengthened as host tenure spans but mitigated as host capacity expands. On the other hand, Yang and Mao (2020) apply the Hausman-Taylor model to estimate the effects of location factors and found that co-location has little influence on revenue performance among hotels and Airbnb listings.

While the professionalization of Airbnb becomes an emergent topic recently (e.g., Dogru et al., 2020; Gil & Sequera, 2020), only a few empirical papers discuss professional and nonprofessional hosts, including Li et al. (2017) and Xie and Mao (2017). They compared the difference in operational performance between multi-listing and single-listing hosts but attributed such difference to different mechanisms. Specifically, Li et al. (2017) showed that the pricing strategies and familiarity with the market of multi-listing hosts differentiate themselves from amateur hosts, leading to a competitive advantage in listing performance. Xie and Mao (2017), in contrast, advocated that the unavoidable tradeoff between quality and quantity due to an individual’s limited resources (time, attention, etc.) is a disadvantage of hosts when operating multiple listings, which hurdles the listing performance for multi-listing hosts.

While both studies provided unique evidence about the performance difference between professional and nonprofessional hosts, a few aspects still lag and motivate our study. First, full-time hosts as the other type of professional operators of accommodation sharing (O’Neil & Ouyang, 2016) are not examined. Different from prior studies that focus solely on multi-listing hosts, we consider both segments (i.e., multi-listing and full-time hosts) of professional hosts and provide a holistic perspective of their performance implications. Second, the operational performance of lodging businesses is reportedly driven by customer evaluation (Ye et al., 2009), which should be included as an influential factor along with the host type. Our study differs from prior literature by not only adding the perspective of customer evaluations into performance estimation but also examining how the effect of customer evaluations would differ by host types. Such an effort is helpful for providing implications on performance drivers for different types of hosts. Lastly, prior research on Airbnb hosts focuses on a specific city (e.g., Chicago in Li et al. 2017 and Beijing in Xie & Mao, 2017). A broader market beyond a specific city would make the findings more generalizable to the accommodation-sharing businesses. Our data cover the listing performance and host information for the entire state of California, which is valuable for research generalizability.

3. Hypothesis Development

3.1. Signaling theory: Customer Evaluations and Listing Performance

Signaling theory, situated within the broader realm of agency theory (Bergen et al., 1992), offers a basic framework for understanding how two parties (i.e., a buyer and a seller) address asymmetries of information in a contractual relationship (Spence, 1973). Signaling theory underscores the importance of quality signals, which has important management implications for P2P accommodation-sharing platforms from an uncertainty reduction theory perspective. To overcome this information asymmetry problem, potential guests will try to gain information about Airbnb hosts/listings and discern signals, such as the hosts' profile photos and Superhost badge, to reduce uncertainty or risk arising from the P2P transaction (Yao et al., 2019). Likewise, other host characteristics (e.g., length of host membership), product information (e.g., list's picture), and reputation attributes (i.e., average customer rating scores) also serve as reference points and quality signals for potential guests to assess a host's trustworthiness and a list's quality (Teubner et al., 2017). Xie and Mao (2018) investigated the effects of host's quality attributes on listing performance under the signaling theory. Their findings revealed that certain host's quality attributes, such as being a Superhost, having longer operating performance and a higher response rate, affect the listing performance in a positive way.

Particularly, online traveler reviews are one of the important information sources. With the proliferation of digital platform-based business models, online reviews have risen to prominence as reflections of customers' consumption experiences (Moe & Trusov, 2011) and are commonly taken as a proxy of service quality by consumers. The average rating of online reviews posted by travelers is regarded as informative, current, and reliable than information from travel service providers (Schuckert et al., 2015). The online traveler reviews' rating reflects the genuine attitude towards products and services by previous users with high reliability and creditability, which can help reduce information asymmetry and make informed decisions (Ho-Dac et al., 2013). Consumers consider customer evaluation more trustworthy and useful when they perceive an agreement between the review and their own opinion (Xia & Bechwati, 2008).

Online customer reviews become more crucial in P2P accommodation sharing as compared to traditional hospitality e-commerce. First, hosts are diverse and non-conventional peer individuals who, unlike hotel organizations, do not have a brand and reputation for building trust (Li et al., 2017). Hosts mainly have to rely on online customer reviews to establish their online presence and legitimacy. Second, for reference reviews about the products, services, and feelings derived from using the listing in P2P platforms, consumers feel more connected and confident in making a purchase decision because they place more value on the social influence of the reference group (Mao & Lyu, 2017). As a result, customer evaluation can increase the likelihood of sales and foster a healthy online platform. Further, the perceived effectiveness and reliability of the average rating reduce search costs and thus provide additional value for future consumers (Pavlou & Dimoka, 2006). In light of the salient effect of online traveler reviews as a signal of perceived quality and satisfaction in enhancing the transactions on P2P accommodation-sharing platforms, we hypothesize:

H1: The revenue performance per night of a listing that receives high customer evaluation through online reviews is higher than that of other listings.

3.2. Performance Difference between Multi-listing and Single-listing Hosts

While single-listing hosts can focus on one property, multi-listing hosts manage multiple properties at the same time. We conjecture that multi-listing hosts would outperform single-listing hosts per listing. Multi-listing hosts gain competitive advantages by operating multiple units with information resources. They observe more demand information in a given period and, therefore, better understand the local short-term rental market (Li et al., 2017). Additionally, multi-listing hosts can spread fixed costs (such as equipment and overhead) and gain more experience with their lists. They become more cost effective and skillful in managing their lists than their single-listing counterparts due to economies of scale. As a result, they become more strategically resourceful and gain additional benefits to manage multiple listings in that they can take good advantage of resources and chances, optimize pricing strategies, increase synergy and cross-sale across the listings, escalate productivity and efficiency, and eventually improve operational performance. In contrast, single-listing hosts often suffer pricing inefficiencies, such as less frequent price adjustments and inadequate response to surges in demand, resulting in inferior performance (Li et al., 2017). As such, we propose:

H2: The revenue performance per night of a listing operated by a multi-listing host is higher than that of a single-listing host.

3.3. Performance Difference between Full-time and Part-time Hosts

Full-time hosts offer their properties for a full-length month, while part-time hosts are opening up their listing only when they do not use it. The literature on full-time vs. part-time host comparison is quite sparse and, in fact, almost non-existent. The variety of part-time hosts and the unknown host identity may hinder our ability to further distinguish and compare the differences among part-time hosts for their motivations and reasons to rent out properties on selective occasions. While there are occasions when part-time hosts face constraints as to when and whether to rent out their listings, we still conjecture that part-time hosts would perform better than full-time hosts for a listing on an available night basis for their efficient utilization of accommodation as a perishable good. Part-time hosts are selective as to when to open the listings relative to full-time hosts. When the demand is high with constrained lodging supply, part-time hosts are more likely to list their properties so that they can charge high rates. In other words, part-time hosts react better during a demand change from major events. Major events (e.g., cultural festivals and sport events) tend to increase Airbnb listings in the market. According to the STR report on Airbnb & Hotel Performance (2019), the largest increases in Airbnb supply and demand occur during major events. For example, there was a large spike in Airbnb supply during the Super Bowl in East Rutherford, New Jersey, in 2014, and there were 76% more Airbnb units available during the Boston Marathon in 2015.

In addition, part-time hosts would offer listings only when the perceived monetary benefits may at least exceed the opportunity cost of their hosting activities, according to the rational agent theory (Osborne & Rubinstein, 2001). This opportunistic (maximize the return on their time and effort) and selective listing practice favor part-time hosts for better performance. Consequently, the surge price as the evidence of the power of scaling instantaneous supplies by Airbnb may have helped part-time hosts make great earning within a limited time, which essentially boosts the performance of a listing for its available nights. Thus, the following hypothesis is proposed:

H3: The revenue performance per night of a listing operated by a full-time host is lower than that of a part-time host.

3.4. Moderation Effects of Multi-listing Hosts or Full-time Hosts

As the expertise of multi-listing hosts is in place, the impact of customer evaluation on listing performance is lessened. Multi-listing hosts themselves have inherent creditability and are conceived as more legitimate business operators. Gibbs et al. (2017) argued that multiunit hosts invested more effort into the short-term rental business and would be able to gain higher revenue than single-unit hosts. Indeed, several studies found that Airbnb host with more experience, either through being a multiunit host or a host with a longer tenure on Airbnb, can be more efficient in managing the listing price (e.g., Gibbs et al. 2017; Magno et al., 2018; Xie et al. 2020).

Moreover, they have more review volumes because they simply rent out properties more often. Thus, a multi-unit business operation tends to decrease the overall degree of uncertainty for travelers. Travelers can rely less on customer ratings when making transactions with multi-listing hosts as compared to single-listing hosts. This implies a less important role of customer evaluation for multi-listing hosts in influencing potential performance impact. In contrast, single-listing hosts have fewer resources, volumes, and experience to influence performance, in which they are more likely to care more about customer ratings. That is, customer evaluation plays a more important role for single-listing hosts as compared to multi-listing hosts in listing performance. Therefore, we propose the following hypothesis:

H4a: The positive effect of customer evaluation on the listing performance per night is mitigated if the host is a multi-listing host.

Further, the positive impact of customer evaluations will be moderated by host type. This is because full-time hosts would put more effort into attracting and retaining guests given they have higher levels of commitment. Full-time hosts value customer ratings more than part-time hosts as they believe in broad influence by customer ratings on their dedicated listing operation over time. Customer rating as a powerful reputation signal requires steady accumulation over a period. Long time operation commitment for full-time hosts can help establish good ratings in a timely manner. Good ratings can also assist full-time hosts for better performance. In that sense, a synergy between full-time hosts and customer evaluation is fostered. On the contrary, the selective nature of part-time hosts (e.g., on-and-off operation) indicates their less dedication to hosting activities and associated factors such as customer ratings. Compared to part-time hosts, hosts who are committed to a full-time business operation would likely consider customer evaluation more important. As a result, customer evaluation is more influential to a listing operated by a full-time host as compared to the listing managed by a part-time host. We propose the following hypotheses:

H4b: The positive effect of customer evaluation on the listing performance per night is magnified if the host is a full-time host.

Figure 1 summarizes the hypothesized relationships in a research framework, which illustrates the effects of customer evaluations on the listing performance and the moderating effects of host types on such effects. Following the research framework, we empirically test the hypothesized effects and discuss our findings in the following sections.

(Please insert Figure 1 here)

4. Methodology

4.1. Data and Measures

We obtained data from Airbnb, the largest accommodation-sharing platform in the world, through AirDNA, a research company that provides trusted data and analytics services about Airbnb for industry practitioners. These industry practitioners include Las Vegas Tourism & Convention Board, CBRE Hotels, Bank of America Merrill Lynch, Vacasa, Black Rock, Quartz, etc. The data set is at the property by month level (i.e., our unit of analysis) and contains proprietary information on monthly revenue performance, host characteristics, as well as property attributes. Our data consist of 61,868 listings managed by 41,827 hosts across 407 cities in the entire state of California. We chose the state of California as our research setting because it is the birthplace of Airbnb and one of the largest Airbnb markets in the U.S. Our observation period is between May 2015 and April 2016, which covers 12 months of longitudinal changes in listing performance and host characteristics.

Table 1 shows the Top 10 Airbnb cities in California that have the largest number of listings and hosts. The cities that enjoy both the highest number of hosts and listings include Los Angeles, San Francisco, San Diego, Oakland, Venice, Santa Monica, Berkeley, San Jose, and Palm Springs. Among these cities, the supply of listings surpasses the supply of hosts, indicating the popularity of multi-listing.

(Please insert Table 1 here)

The hosts are further categorized as multi-listing hosts and full-time hosts. We follow previous literature to define that multi-listing hosts are those who manage more than one property in a given month (Li et al., 2017), while full-time hosts are those whose listings are available on Airbnb - no matter the listings are booked or not –for a full-length month. Among 41,827 hosts in California, 65.78% of the hosts rent out at least one of their properties on a long-term, full-time basis for an entire month, whereas 18.21% are multi-listing hosts who have managed at least two or more properties over the study period. It is evident that the phenomena of full-time management and multi-listing operation of Airbnb in California are non-trivial. It is possible that a host can operate multiple listings on a full-time basis. Such dual-type hosts are the overlap between full-time and multi-listing hosts and denoted as dual-type hosts. The dual-type hosts who operate more than one property on a full-time basis account for 16.6% of the hosts in California.

Our panel dataset is organized by listing and month (i.e., the unit of analysis), which allows us to observe the effects of average rating and host type on listing performance over time in a longitudinal fashion. Our dependent variable is *RevPAN,* which is a synonym to the widely used performance metric - average revenue per available rooms (or *RevPAR*) - in the hotel industry. Because each Airbnb listing is sold as one unit and its status can only be "booked" or "not booked" for each night, revenue per available room (RevPAR) is not applicable in the context of Airbnb. Instead of using RevPAR, we follow the literature (e.g., Xie et al., 2019) to use *RevPAN* to measure the revenue of Airbnb listings of all of the available nights. In fact, *RevPAN* has been increasingly adopted in Airbnb research for performance evaluation.

The primary independent variables include customer evaluation (which is measure by the average rating of online reviews) and host type (*Multi, Full, or Dual*). Particularly, although our primary focus of professional hosts is multi-listing hosts and full-time hosts, some hosts would have a dual role of being both multi-listing hosts and full-time hosts. We recognize this practical need by adding the dual-type hosts in parallel with the full-time hosts and multi-listing hosts. We also control for a set of listing characteristics (*NumBed, NumBath, NumReview, MaxGuest,* and *ListType*) and host characteristics (*ResTime, ResRate,* and *SuperHost*) that may also influence the listing performance. The use of control variables is consistent with previous Airbnb literature (Li et al., 2017; Xie & Mao, 2017). Table 2 presents the definitions and summary statistics of variables. Table 3 shows the correlation matrix of variables. The correlation coefficients are consistently small, indicating that estimations using these variables as regressors are unlikely to be biased by collinearity.

(Please insert Tables 2 and 3 here)

4.2. Model Specifications

For a listing *i* managed by the host *j* in month *t*, we model the RevPAN performance of a listing as a function of average review rating, host type, as well as their interaction terms, and host and listing characteristic controls. We take the logarithm of *RevPAN* due to its skewness towards large values. The resulting model is,

$$log(RevPAN_{it}) = \alpha + \beta_1\, Type_{jt} + \beta_2\, CusEval_i + \beta_3\, HostType_{jt} \times CusEval_i + \iota' X_{ijt} + \varepsilon_{ijt} \quad (1)$$

where we are primarily interested in investigating $\{\beta_1, \beta_2, \beta_3\}$, which are, respectively, the coefficients of the effects of host type, customer evaluation (average review rating), and their interactions on the RevPAN performance. We use the vector X_{ijt} to represent covariates of the listing and host characteristic controls (*NumBed, NumBath, NumReview, MaxGuest, ListType, ResTime, ResRate, and SuperHost)*.ε_{ijt} is the random error.

5. Results and Findings

When implementing the main estimation, we first run two separate models for each type of hosts sequentially. We also include a third model for dual-type hosts as an additional analysis and robustness check. Table 4 exhibits these analyses. For each model, we use clustered robust standard errors at the listing level to reduce heteroscedasticity concerns (Greenwood & Wattal, 2017). Because the observations are composed of repeated observations from the same property across multiple months, the specification of robust standard errors clustered at the property level appropriately accounts for the independence of observations across properties as well as correlation within each property over time.

(Please insert Table 4 here)

Estimations for Customer Evaluation: We begin by estimating the impact of customer evaluation on the listing performance. As suggested in H1, the effect of online traveler reviews is salient in facilitating transactions in the P2P accommodation-sharing business (Pavlou & Dimoka, 2006). We indeed observe the average rating positively affects the listing performance (0.195***) across Column 1 to 3 (regardless of various models), supporting H1. This finding extends the importance of online word-of-mouth from incumbent hotels to P2P accommodation sharing, confirming online reviews as an important facilitator of trust-building in peer-to-peer business.

Estimations for Multi-listing Hosts: Column (1) of Table 4 shows the estimation results for multi-listing hosts. Compared to a property managed by a single-listing host, a listing managed by a multi-listing host who operates more than one Airbnb listing achieves 27.8% more in the monthly revenue per available nights (0.278***). This result supports H2, indicating an evident advantage of multi-listing hosts in operating P2P accommodation sharing, plausibly because of their experience, productivity, and efficiency (Li et al., 2017).

However, the positive performance effect of the average rating is weakened for a multi-listing host's listing (-0.048***). That is, for a multi-listing host, the incremental improvement in monthly revenue is only 0.147 (=0.195-0.048) as the average review rating goes up by 1 unit. This finding is plausible as we anticipate that the positive signaling effect of customer evaluations becomes less influential if the properties are already in the safe hands of a competent multi-listing host, as suggested in H4a.

Estimations for Full-time Hosts: The estimates of full-time hosts are presented in Column (2) of Table 4. On average, a listing managed by a full-time host makes 23.8% less monthly revenue per available nights than its counterpart managed by a part-time host (-0.238***). This result confirms our conjecture in H3, showing that the operation of part-time hosts within a limited period in response to meet the demand could help them earn a higher revenue per available night than full-time hosts. Indeed, our evidence confirms the finding of Zervas et al. (2017), which documents Airbnb homes can be instantaneously scaled by part-time hosts to cover on-demand needs. Therefore, we are in support of H3.

We also find that the positive effect of average review ratings on listing performance becomes stronger for a full-time host' listing (0.035**), supporting H4b. That is, for a full-time host, the increment drop in the monthly revenue is mitigated to 0.203 (= -0.238+0.035) with a 1-unit increase in average review rating. It is plausible that customer evaluation, or reputation, plays an important role in weakening the host disadvantage in operating a full-time listing.

Additional Analysis for Dual-type Hosts: We further investigate the listing performance of a dual-type host who operates multiple listings on a full-time basis. As shown in Column (3) of Table 4, the dual-ownership of a host does not guarantee a positive performance of an Airbnb listing, with a dual-type host makes 29.9% less than its counterpart, who is not overly committed to operating multiple properties in a full-time fashion (-0.299***). Still, the positive effect of the average rating is magnified for a dual-type host's listing (0.067***). The findings lend great support to those in our previous estimation of two separate models and cross-validate the estimated effects of customer evaluation and host type (full-time and multi-listing) in determining listing performance, even in a combined model. The results of hypothesis testing are summarized in Table 5.

(Please insert Table 5 here)

6. Conclusions and Implications

6.1. Discussion

Anecdotal reports have discussed multi-listing and full-time hosts in their professional operation of Airbnb listings (Hickey & Cookney, 2016; Somerville & Levine, 2017).

However, empirical hospitality literature examining multi-listing and full-time hosts is fairly scarce. This study represents an early attempt to examine professional hosts in P2P accommodation sharing. We adopted a data analytical approach to investigate the effect of customer evaluation on listing performance and how such an effect differs given the different types of professional hosts (multi-listing and full-time). Using large-scale Airbnb listing data in California, we first find a positive effect of customer evaluation on listing performance, demonstrating a positive signaling effect of customer reviews on the subsequent consumers' purchasing behaviors. The spatial and temporal separation of the online lodging markets creates information asymmetries and economic risks between guests and hosts. A possible solution to this information asymmetry and risk is to create information on the website to signal the quality of the hosts and their listings. Such information disclosure can reduce consumers' concern about the listings, enhance the trust between guests and hosts, and thus contributing to better listing performance. Good customer evaluation honestly induces effort-based trust for better listing performance, which is essential to the growth of both the Airbnb platform and the hosts. As such, customer evaluation acts as a quality signal and trust indicator in P2P accomodation sharing.

Additionally, while professional hosts are the subject of growing controversies in public, our empirical evidence reveals an intriguing difference in listing performance between two types of professional hosts. Specifically, a listing managed by a multi-listing host tends to receive more revenue per available nights than its single-listing counterpart, while a listing managed by a full-time host does not outperform a part-time host. Furthermore, in operating the Airbnb business, a multi-listing host would weaken the positive effect of customer evaluation on listing performance due to his/her already well-perceived credibility and seasoned experience, whereas a full-time host magnifies the effect of customer evaluation for a synergized effect. Our study contributes to emerging research on the professional hosts and their performance implications, which lay the groundwork for further understanding of and formulation policy for professional hosts.

6.2. Theoretical Implications

This study provides several theoretical contributions to the P2P accomodation literature through granular insight into professional host segments. It reveals that multi-listing hosts have high performance as compared to single-listing hosts. The insights provided in this study add to our understanding of why host segmentation is important in discussing professional hosts. By offering performance evidence of different types of hosts, this study draws the necessary attention of future scholars when evaluating professional hosts and the related performance takeaways from these hosts that hoteliers can incorporate in their operation. We advocate a finer-segmentation of professional hosts by differentiating multi-listing hosts and full-time hosts and understanding their performance in managing P2P accommodation sharing.

Furthermore, the study adds to the current sharing economy or P2P accommodation-sharing literature by focusing on the customer evaluation of the hosts. Customer evaluation is confirmed to act as a quality signal to influence the subsequent buyers according to the signaling theory. Moreover, it is clear that the positive effect of customer evaluation is likely to be discounted if a host is a multi-listing host but magnified if a host is a full-time host owing to different mechanisms. Through examining the moderation effect of host type on listing performance, this study suggests customer evaluation is critical to the P2P accommodation-sharing performance and draws the scholarly attention of its differential effect by host type.

Finally, the study differentiates itself from the majority of the hospitality literature by using a unique large-scale, secondary online observational business dataset and augmented by relatively less published analytics approaches. By repeatedly observing actual listing performance affected by host type and customer evaluation, we attempt to address the bottom line questions of P2P accommodation sharing with convincing real-world evidence. The analytic efforts we articulated in this study can complement existing research methods (primarily surveys, interviews, Qualtrics experiments, etc.) that have been widely used in the literature and offer additional evidence into how hosts perform in operating P2P accommodation-sharing services.

6.3. Practical Implications

This study generates important practical implications for P2P accommodation-sharing platforms and hoteliers. To the extent that disruptors such as Airbnb continue to grow on a global scale, our study provides cautionary evidence of the performance discrepancies among professional hosts. Such discrepancies should be fully understood for P2P accommodation-sharing platforms to support its listing suppliers (i.e., hosts) and for hoteliers to proactively differentiate from their emerging counterparts.

For Airbnb and the broader P2P accommodation-sharing platforms, although our findings suggest a performance advantage of multi-listing hosts, it is necessary for the platforms to incentivize these hosts to maintain high quality (positive customer evaluation) while reaping the benefit of the multi-listing operation. Xie and Mao (2017) provided a gentle warning that multi-listing hosts tend to face the trade-off between quality and quantity as they expand the accommodation-sharing businesses, which may compromise customer satisfaction and evaluation. It is therefore important for the P2P accommodation-sharing platform to monitor the quality performance of multi-listing hosts, spotting any act of listing expansion at the cost of declining customer evaluation.

Additionally, we have disclosed that part-time hosts seem well versed in meeting occasional demand and reaping better performance than full-time hosts. To support part-time hosts in providing services, especially during peak travel season, Airbnb should consider revenue management to encourage more part-time hosting activities in areas where guest demand is strong and city regulations on days of operation are strict[1]. Examples of this approach include the Calendar Updates[2] and Smart Pricing[3] tools that Airbnb is currently providing to its hosts to help them have an up-to-date calendar and market-driven price. These actions can help occasional hosts fill more heads into beds and are also likely to increase the profits of the platform. Such a customized revenue management approach for part-time hosts is also nicely aligned with the recent policy change of Airbnb restricting a host to offer tourist rentals on a short-term basis in housing-crunched cities.[4] By limiting the span of time and support the operation of part-time hosts, Airbnb will be able to address the concerns raised by regulators and the public without discounting revenue made by hosts.

For hoteliers, our study makes it clear that multi-listing properties - or arguably the "illegal hotels" (CBRE, 2017) – enjoy the great listing performance. Thus, it is likely that hoteliers will soon face pressures of restoring competitiveness from this type of Airbnb particularly. In the context of P2P accommodation-sharing businesses, hosts are micro-entrepreneurs (Miners, 2013) and thus intrinsically motivated. This stands in contrast with traditional hotel employees who receive instructions on how to serve guests. It is, therefore, quite important for hoteliers to differentiate the product and service offerings to improve customer evaluation as well as financial outcomes of incumbent hotel rooms. Additionally, we conjecture that part-time hosts who occasionally rent out Airbnb properties may have developed insightful market observations and proactive response to demand, a practice that leverages their competition power against full-time counterparts. With the advent of Airbnb's disruption, its revenue management savvy hosts have represented a challenge for incumbent

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[1] This is the case in Canadian cities like Toronto and Vancouver; European cities such as Amsterdam, Paris, London, Berlin, and Milan; and the Asia Pacific, specifically Singapore, Hong Kong, and Sydney (O'Sullivan 2016).
[2] Source: https://blog.atairbnb.com/calendar-updates/
[3] Source: https://blog.atairbnb.com/smart-pricing/
[4] Source: https://www.2ndaddress.com/research/short-term-rental-laws/

full-time business entities such as hotels that are not yet fully utilizing revenue management systems. We advocate that data-informed decisions through advanced revenue management practice remain strong differentiators of hoteliers from individual Airbnb hosts who are of fewer resources compared to hotels. Hoteliers can identify areas where they are more likely to manage capacity and pricing for improved market performance.

For city managers and legislators, it is becoming increasingly true that professional hosts rise on the platform. Our study shows a strong performance superiority of these professional hosts over nonprofessional ones. Their dominance in certain markets may eventually crowd out smaller hosts and eradicate the grassroot nature of Airbnb in its early time. We advocate a strong regulatory stance over these professional hosts by re-evaluating the tax obligation, insurance requirements, safety, and inspection aspects of these professional hosts based on their participation on the platform. This is to ensure the welfare of all of the suppliers in a fair game of the P2P economy.

6.4. Limiations and Future Research

This study is not without its limitations. First, although we attempted to control as many variables that might affect listing performance as possible, it is likely certain confounding variables may not be included due to the data unavailability of data. For example, the offline host-renter interactions that may affect the listing performance are not observable online. It would be interesting for future scholars to supplement or even replicate the study by collecting granular data from the offline context. Using such data, researchers can find useful insights such as how professional hosts should serve and engage customers for increased customer evaluation and listing performance, which is important and relevant to the business practice.

Second, it is quite likely some hosts are in partnership and hiring professional companies to manage marketing, accommodation bookings, and maintenance on Airbnb.

Although we could not observe this partnership due to the data unavailability, it will be important for future researchers to study how such a special approach in listing operation would affect the role of professional hosts (companies, rather than individuals, in this case).

Third, our sample can be expanded to cover more recent time periods and a wider geographic region. The time period from May 2015 to April 2016 allows us to observe the Airbnb host segmentation and related performance data without being influenced by any market shocks such as the COVID-19. We encourage future researchers interested in examining the impact of market shocks on the Airbnb hosts to collect recent data in the P2p accommodation-sharing industry toward an understanding on how the host segments and their related performance are affected by the market shock. Similarly, our analysis restricts to Airbnb listings in the state of California. While California is the birthplace of Airbnb and the largest Airbnb market in the U.S., our findings may not be generalizable to other states or regions. Further research using Airbnb data in more recent time periods and other regions will be necessary to strengthen the generalizability of the findings.

Lastly, COVID-19 pandemic put a halt on all types of travel and change the mindset of travelers. Airbnb CEO Brian Chesky mentioned that the COVID 19 pandemic will change how people travel for years to come. People would prefer meaningful travel than mass travel and consider smaller communities than touristy areas (Abril, 2021). Travelers may have much concern about the hygiene standards of Airbnb accommodation, too. Therefore, we suggest future research to explore whether the revenue performance of a listing operated by professional hosts (e.g., full time, multi-listing hosts) is higher than that of non-professional hosts (e.g., part-time, single-listing hosts) in the post−COVID-19 era. As the P2P accommodation sharing continues to grow, we very much expect a steady stream of research joining our study for a better understanding of this fascinating phenomenon.

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Figure 1. Research Framework

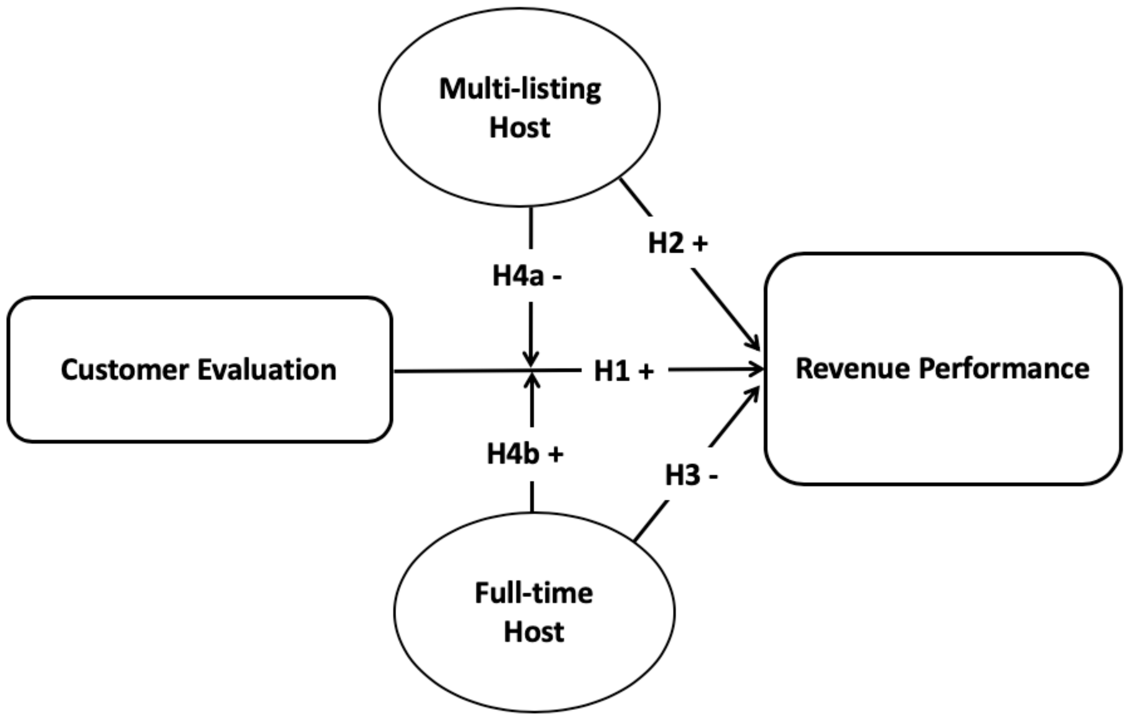

Table 1. Top Ten Cities in California by Airbnb Hosts and Listings

Ranking	Number of Hosts		Number of Listings	
1	Los Angeles	8970	Los Angeles	12724
2	San Francisco	7320	San Francisco	9711
3	San Diego	3420	San Diego	4939
4	Oakland	1376	Venice	1836
5	Venice	1231	Oakland	1678
6	Santa Monica	1119	Santa Monica	1455
7	Berkeley	1060	Berkeley	1450
8	San Jose	749	San Jose	1210
9	Palm Springs	598	Palm Springs	1182
10	West Hollywood	459	Big Bear Lake	1007

Table 2. Variable Definitions and Summary Statistics (Unit of Analysis: Property by Month)

Variable	Definition	Mean	Std. Dev.	Min	Max
Dependent Variable					
logRevPAN	Logarithm of revenue per available nights	4.18	0.98	0.03	9.23
Primary Independent Variables					
CusEval	Average rating of cumulative online reviews on a scale of 1 to 5, with values of 1 = terrible, 2 = poor, 3 = average, 4 = very good, and 5 = excellent	4.69	0.35	1	5
Multi	Dummy variable indicating whether a listing is managed by a host who operates more than one Airbnb listing, with values of 1 = a multi-listing host and 0 = a single-listing host	0.41	0.49	0	1
Full	Dummy variable indicating whether a listing is managed by a host whose listing(listings) is(are) available on Airbnb - no matter the listing(listings) is(are) booked or not – for a full-length month, with values of 1 = a full-time host and 0 = a part-time host	0.53	0.50	0	1
Control Variables					
NumBed	Number of bedrooms	1.44	1.04	0	19
NumBath	Number of bathrooms	1.38	0.77	0	8
NumReview	Cumulative number of online reviews	31.34	40.34	0	788
MaxGuest	Maximal number of guests allowed	3.69	2.66	1	50
ListType	Type of listing, with values of 1 = entire home/apartment, 2 = private room, and 3 = shared room	1.42	0.56	1	3
ResTime	Average number of minutes it takes a host to respond to new booking inquiries	193.60	317.81	.01	1440
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	93.30	13.79	5	100
SuperHost	Dummy variable indicating whether a host is recognized by Airbnb as a super host,[5] with values of 1 = a super host, 0 = a regular host	0.23	0.42	0	1

[5] A super host is recognized by Airbnb based on certain criteria in aspects of host services and commitment. For the criteria of deciding a super host, please refer to https://www.airbnb.com/superhost

Table 3. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11
1	*CusEval*	1.00										
2	*Multi*	-0.14	1.00									
3	*Full*	-0.14	0.36	1.00								
4	*NumBed*	0.01	0.06	0.01	1.00							
5	*NumBath*	0.00	0.10	0.06	0.70	1.00						
6	*NumReview*	0.08	0.05	0.04	-0.14	-0.14	1.00					
7	*MaxGuest*	-0.03	0.12	0.04	0.80	0.65	-0.09	1.00				
8	*ListType*	-0.02	0.11	0.08	-0.31	-0.14	-0.01	-0.41	1.00			
9	*ResTime*	-0.04	-0.16	-0.06	0.01	0.01	-0.17	-0.03	-0.02	1.00		
10	*ResRate*	0.11	0.09	0.00	0.00	-0.01	0.14	0.02	0.00	-0.78	1.00	
11	*SuperHost*	0.30	-0.03	-0.06	-0.05	-0.06	0.24	-0.05	0.01	-0.18	0.20	1.00

Table 4. Estimation Results

Dependent Variable: *logRevPAN*	(1) Multi-listing Hosts	(2) Full-time Hosts	(3) Dual-type Hosts
Primary Independent Variables			
CusEval	0.195***	0.120***	0.160***
	(0.013)	(0.012)	(0.014)
Multi	0.278***		
	(0.075)		
CusEval× Multi	-0.048***		
	(0.016)		
Full		-0.238***	
		(0.065)	
CusEval× Full		0.035**	
		(0.014)	
Dual			-0.299***
			(0.080)
CusEval× Dual			0.067***
			(0.017)
Control Variables			
NumBed	0.182***	0.177***	0.180***
	(0.006)	(0.006)	(0.006)
NumBath	0.082***	0.086***	0.085***
	(0.007)	(0.007)	(0.007)
NumReview	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
MaxGuest	-0.000	0.003	0.000
	(0.002)	(0.002)	(0.002)
ListType			
Private room	-0.759***	-0.747***	-0.757***
	(0.007)	(0.007)	(0.007)
Shared room	-1.407***	-1.367***	-1.393***
	(0.017)	(0.017)	(0.017)
ResTime	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)
ResRate	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
SuperHost	0.025***	0.019***	0.021***
	(0.007)	(0.007)	(0.007)
Observations	270,618	270,618	270,618
R-squared	0.336	0.337	0.339

*Notes: Robust standard errors clustered on properties in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 5. Hypothesis Testing Results

Hypothesis	Result
H1: The revenue performance per night of a listing that receives high customer evaluation through online reviews is higher than that of other listings.	Supported
H2: The revenue performance per night of a listing operated by a multi-listing host is higher than that of a single-listing host.	Supported
H3: The revenue performance per night of a listing operated by a full-time host is lower than that of a part-time host.	Supported
H4a: The positive effect of customer evaluation on the listing performance is mitigated if the host is a multi-listing host.	Supported
H4b: The positive effect of customer evaluation on the listing performance is magnified if the host is a full-time host.	Supported