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Are Neighbors Friends or Foes? Assessing Airbnb Listings' Agglomeration Effect in New York City

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Abstract

This study investigates the agglomeration effect of Airbnb listings in New York City (NYC) and answers two research questions: (a) Does agglomeration benefit or hurt the performance of individual Airbnb listings? (b) How does the effect of agglomeration vary by hosts regarding their operational experience (measured by their capacity and tenure on Airbnb)? A series of econometric analyses using large-scale data of Airbnb in NYC reveal that agglomeration positively affects the revenue performance of each Airbnb listing. In addition, such an effect is strengthened as host tenure spans but mitigated as host capacity expands, indicating a nonsymmetric agglomeration effect across service providers. This research contributes an important but less researched perspective to the home-sharing literature. Managerial implications on leveraging agglomeration for improved revenue performance are provided to Airbnb and its hosts, as well as the hotel chains that want to combat Airbnb's negative impacts or have already entered the short-term residential rental market to compete head-to-head with Airbnb.

Keywords

home sharing; agglomeration; Airbnb; host capacity; host tenure; revenue performance

Introduction

Location is an essential attribute of a lodging product and can significantly affect a hotel's performance (Balaguer & Pernías, 2013). Hoteliers perceive spatial location as one of the top five factors that affect their decisions on a development project (Yang et al., 2012). Geographic proximity has also become a critical criterion when hotels define their competitors in the market (Lee, 2015).

Although proximity in location for businesses providing similar services or products (i.e., homogeneous suppliers) is often associated with competition and therefore potentially harmful to their revenue performance (Chung & Kalnins, 2001), economists also argue that agglomeration of homogeneous suppliers may allow their businesses to profit from the positive externalities in the market (Marshall, 1890). The entry of incumbents, for example, will increase the intensity of competition (McCann & Vroom, 2010), but at the same time, homogeneous suppliers located in the same neighborhood or market can gain substantial financial as well as operational benefits through heightened or spillover demands (Lee & Jang, 2015) and strategic price positioning in the marketplace (Canina et al., 2005; Enz et al., 2008; McCann & Vroom, 2010).

Despite the debatable effects of agglomeration on a lodging product's performance, research about agglomeration of hotels has received limited attention (Yang et al., 2014). In addition, Airbnb and the broader home-sharing businesses represent a new form of lodging products and add extra complexity to the debate. Founded in 2008, Airbnb is now the dominant cyber marketplace for home-sharing or short-term residential rental businesses (Xie & Mao, 2018). Although Airbnb has recently encountered a lot of criticism, in some cases even lawsuits, such as driving up the housing prices in the residential real-estate market (W. Chen et al., 2019; Horn & Merante, 2017), discriminating against travelers on the basis of ethnicity (Kwok & Xie, 2018), and creating political conflicts with cities and local communities (Davidson & Infranca, 2016; Rauch & Schleicher, 2015), the company, along with other platforms for short-term residential rentals, continues to experience phenomenal growth in the lodging sector (Kwok & Xie, 2019; Wu et al., 2017).

Interestingly, Airbnb listings are often found agglomerated in popular locations such as tourist attractions and

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points of interest (Blal et al., 2018; Heo & Blengini, 2019; Wegmann & Jiao, 2017) because short-term residential rental businesses heavily rely on the nearby amenities in which the lodging facility offers (Davidson & Infranca, 2016). Meanwhile, Airbnb listings remain highly decentralized in operation and management by individual hosts rather than centralized corporate decision-makers (Kwok & Xie, 2019), allowing small entrepreneurs to realize sizable returns (Chark, 2019). Furthermore, some research has shown that Airbnb hosts (service providers) with more experience, either through operating multiple listings simultaneously or through running the home-sharing business for a more extended period, can be more efficient in manipulating the listing price for a better revenue performance than those with less experience (Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018; Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018; Magno et al., 2018). The questions of whether agglomeration generates a positive impact on individual Airbnb listings and how such an agglomeration effect may vary across different types of hosts—with respect to their capacity and tenure—remain unexplored in the existing literature.

In this study, we aim to bridge the research gap by investigating the agglomeration effect in the home-sharing market. Through a review of the agglomeration theory and the relevant literature (e.g., Gutiérrez et al., 2017; Yang et al., 2014), we raised two research questions in our inquiry:

Research Question 1 (RQ1): Would Airbnb listings benefit from agglomeration?

Research Question 2 (RQ2): Would such an agglomeration effect vary based on the service provider's experience? That is, is the agglomeration effect uniform across the hosts managing one or more listings and the hosts with various lengths of tenure?

We focus on the granular-level markets of zip codes in New York City (NYC), the city with the most extensive presence of Airbnb in the United States. Through quantifying the number of Airbnb listings in each zip code, we identify the level of Airbnb agglomeration. We further obtain unique data of the Airbnb listings' revenue performance and host characteristics to investigate the agglomeration effect and how host experience (capacity and tenure) moderates such an effect. We make a first attempt in the hospitality literature to empirically show that the advantages of proximity in location would surpass the drawbacks of competition among Airbnb listings agglomerated in a market. Practically, our findings shed light on the difference of Airbnb hosts in leveraging the agglomeration effect, providing actionable recommendations for the entrepreneurs as well as the hotel chains that recently entered the home-sharing market to improve the financial performance.

Relevant Literature

The Agglomeration Theory

The agglomeration effects have long been acknowledged by economists (Canina et al., 2005; Tsang & Yip, 2009). First introduced by Marshall (1890), the agglomeration theory provides two explanations to illustrate why some competitors choose to colocate in the same market, including production enhancements (Tsang & Yip, 2009) and increased demands (Canina et al., 2005). More recently, Yang et al. (2014) conducted a comprehensive retrospective analysis of the contemporary literature regarding hotel location; they concluded that relevant research was usually framed under four theoretical models, including tourist-historic city model, mono-centric model, agglomeration model, and a multidimensional model. Different from the other three models, the agglomeration model/theory allows researchers to evaluate both the negative and positive effects from agglomeration, and it can be used to analyze hotel locations in various scales, ranging from intra-metropolitan to inter-regional areas (Balaguer & Pernías, 2013; Yang et al., 2014). The agglomeration theory provides a strong theoretical foundation in explaining why lodging products usually agglomerate in certain geographic locations (Lee & Jang, 2015).

It was not until the 21st century, however, that the agglomeration theory/model became a more commonly adopted framework in analyzing hotel locations (Yang et al., 2014). Balaguer and Pernías (2013), as well as Tsang and Yip (2009), for example, used agglomeration models to estimate the effects of agglomeration on hotels' performance in an intra-metropolitan area. Specifically, Balaguer and Pernías (2013) identified the negative effects of clustering by location on hotel prices in the market of Madrid, Spain, where higher density would lead to a lower average daily rate and less price dispersion of a hotel although such impacts would become weaker on weekends. Tsang and Yip (2009) examined the agglomeration effects in Beijing, China, and concluded that the high star-ranking joint-venture hotels primarily contribute the benefits of the heightened demand while all hotels were able to gain such benefits from agglomeration. In another study by Marco-Lajara et al. (2014), agglomeration model was used in analyzing how the density of tourist companies (including hotels, restaurants, and cafés) at a tourist destination may affect the profitability of those hotels located in the same market, revealing a negative relationship between a hotel's profitability and the degree of agglomeration.

The above literature suggests that the agglomeration theory, being a relatively new framework in hotel location research, can provide researchers with a strong theoretical foundation and the flexibility in assessing either the positive or negative effects of the agglomeration in a market of various scales. Home-sharing listings, representing the possibly fastest growing sector in the lodging industry, may also be a great context to validate the agglomeration theory. The current research, however, tends to focus on the agglomeration effect in the hotel industry (e.g., Yang et al., 2014) and remains silent on whether such an effect applies to the home-sharing markets. The agglomeration effect of home sharing has not yet been reported in empirical studies in hospitality management, which motivates this research.

Home-Sharing Services

The collaborative trends among tourists, such as couchsurfing and home-swapping, are not new, but the advance of information technology has significantly accelerated the growth of the home-sharing phenomenon (Forno & Garibaldi, 2015). Home-sharing websites, for example, enable everyone with extra living space to run a home-sharing business as a lodging operator in the cyber marketplace (Xie & Kwok, 2017). Listings on home-sharing websites added a tremendous amount of supply to the lodging industry (Heo, 2016; Kwok & Xie, 2018). Today, Airbnb alone has already had over 6 million unique listings in more than 100,000 cities and 191 countries (Airbnb, 2019). By comparison, Marriott International, the world's largest hotel chain, currently operates over 1.25 million rooms in 130 countries and territories (Marriott, n.d.; Statista, 2018).

Home-sharing business is perceived as the disruptive incumbents to the traditional lodging products (Guttentag & Smith, 2017; Kwok & Xie, 2018). It is not surprising to see research about the home-sharing phenomenon has sparked significant interest among researchers in recent years (Cheng, 2016). Current literature about home-sharing business has covered a wide range of topics, including but not limited to the following: home-sharing business' economic impacts on the lodging market (e.g., Blal et al., 2018; Brochado et al., 2017; Fang et al., 2016; Heo et al., 2019; Williams & Horodnic, 2017; Xie & Kwok, 2017; Zervas et al., 2017), effects on the residential rental markets (W. Chen et al., 2019; Horn & Merante, 2017), travelers' experience of home-sharing products (e.g., Guttentag & Smith, 2017; Ju et al., 2019; J. L. Liang et al., 2018; Tussyadiah, 2016; Tussyadiah & Pesonen, 2016, 2018), customers' trust and loyalty attitudes/behaviors toward home-sharing products (e.g., S. Liang et al., 2017; Mao & Lyu, 2017; Wu et al., 2017; Xie, Kwok, & Wu, 2019; Xie, Kwok, Wu, & Chen, 2019), the pricing or booking strategies adopted by the hosts (e.g., Chark, 2019; Y. Chen & Xie, 2017; Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018; Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018; Kwok & Xie, 2019; Magno et al., 2018; Oskam et al., 2018), and legal compliance issues of the key players in the sharing economy (Davidson & Infranca, 2016; Rauch & Schleicher, 2015).

It is not until very recently that Zhang and Chen (2019) sought to understand Airbnb's geographic dynamics with the convenience theory. Using the data from NYC, Los Angeles, and Chicago, they confirmed that Airbnb listings are often centered in such popular locations as tourist attractions and points of interest, agreeing to what was reported in the current literature (e.g., Blal et al., 2018; Heo & Blengini, 2019; Wegmann & Jiao, 2017). Although they revealed some significant correlations between residents' certain demographic variables (e.g., age, race, and income) and Airbnb supply in one or more of the three cities being analyzed, they concluded that Airbnb supply has no impact on rents for all three cities, contradictory to W. Chen et al. (2019) and Horn and Merante (2017). We take a different angle in this study by applying the agglomeration theory to analyze the possible effects of the clustering of home-sharing services on an individual listing's performance while also carefully controlling for the possible impacts from the characteristics of the neighborhoods, and more importantly the traditional lodging products—hotels, which directly compete with Airbnb in the same market. In the next section, we introduce the hypotheses that we propose for statistical analysis through a review of the agglomeration theory and relevant literature about home sharing.

Hypothesis Development

Effects of Agglomeration on Home-Sharing Performance

Companies selling similar products are pushed to locate far apart from one another due to the fear of direct competition (Baum & Haveman, 1997). The more commonalities these companies share, the more intense the competition will become because very likely they operate the business with similar resources and serve similar customers (Tsang & Yip, 2009). Hence, proximity in location for homogeneous suppliers is often associated with direct competition and may hurt their revenue performance (Chung & Kalnins, 2001). Such competition may become even more significant in the service sector because consumers often want to purchase some specific services in a particular geographic location (Silva, 2016).

Interestingly, geographic agglomeration of homogeneous suppliers, where companies selling similar products choose to colocate in proximity to one another, turns out to be a common phenomenon in many industries because of the agglomeration effects created by firm colocation (Canina et al., 2005). According to the agglomeration theory (Marshall, 1890), agglomeration can provide a wide range of benefits to companies. From the perspective of production and operation, clustering by location may help companies gain knowledge and resource spillover, as well as easier access to specialized labor and resources (Chung & Kalnins, 2001; Kalnins & Chung, 2004; McCann & Vroom, 2010). A good case in point is that many tech firms choose to colocate in Silicon Valley. Likewise, many financial firms are located in Manhattan. From the marketing perspective, the agglomeration effects are contributed primarily by the heightened and spillover customer demands as well as the reduction in search costs for the consumers (Canina et al., 2005; Lee & Jang, 2015). For example, travelers may want to stay in a neighborhood with an abundance of alternatives. When a place is fully booked, travelers can easily find a nearby alternative without starting a new search in a less familiar neighborhood.

Relevant research has reported both the negative and positive agglomeration effects of clustering for the lodging products (e.g., Balaguer & Pernías, 2013). For example, using the data from the tourist districts located in the Spanish Mediterranean Coast, Marco-Lajara et al. (2016) identified a U-shaped relationship between a lodging company's growth and the degree of agglomeration, where profits will decrease with more competition at the beginning but will go up after the agglomeration levels reach a certain point. When seasonal demands are taken into consideration, however, Silva (2016) reported that agglomeration could have a significantly positive impact on a hotel's room rate during the peak season among the hotels in the 74 cities in Spain. Likewise, Lee and Jang (2015) examined the effect of hotel agglomeration, such as the heightened demand and demand spillover, under the conditions of high versus low market demand. Their analysis using the data from the Texas lodging market reveals that the positive effects of agglomeration on hotels' revenue-per-available-room (RevPAR) performance are greater for hotels with similar attributes during the high seasons, but such positive effects appear to be greater for differentiated hotels during the low seasons. When the effects of clustering among different hotel segments (e.g., luxury, upper-upscale, and others) were further analyzed, it was found that the positive agglomeration effects may vary depending on the segment where a hotel belongs (Canina et al., 2005; Enz et al., 2008; Kalnins & Chung, 2004).

Airbnb listings added a tremendous amount of supply to the lodging industry since its induction to the market (Kwok & Xie, 2018), especially in the metropolitan markets (Blal et al., 2018; Heo et al., 2019; Wegmann & Jiao, 2017). Empirical studies about the home-sharing economy have recognized the fact that Airbnb listings generally compete in the urban market and used the Airbnb sample from major metropolitan areas in their analyses (e.g., Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018). There are also a couple of studies looking at Airbnb listings' location patterns (Coles et al., 2017; Gutiérrez et al., 2017). Gutiérrez et al. (2017), for example, compared the special patterns of hotels and Airbnb listings in Barcelona, Spain. They concluded that Airbnb listings colocated mainly in the areas with well-defined characteristics, such as the city center, places close to the tourist attractions, and the residential areas, whereas hotels mostly located in the offices and land that was dedicated for hospitality, leisure, and entertainment purposes. The possible agglomeration effect on home-sharing business has not yet been reported. We proposed the following hypothesis for statistical analysis:

> **Hypothesis 1 (H1):** The level of agglomeration is positively associated with an Airbnb listing's revenue per available night (RevPAN).

Moderations of Host Experience (as in Host Capacity and Host Tenure) on the Agglomeration Effect

Airbnb's original business idea was to build a cyber marketplace where people could rent out their underutilized accommodation space to other consumers/travelers in need, such as an extra bedroom or a sofa bed (Guttentag, 2015). It did not take long, however, for people to take advantage of the entrepreneurial opportunities offered by Airbnb. There are a growing number of hosts who are now managing more than one Airbnb listing as a full-time professional operator (Kwok & Xie, 2019). Multiunit hosts—those who manage more than one Airbnb listing—can outperform the single-unit hosts—those who manage only one Airbnb listing—in a variety of ways. Wegmann and Jiao (2017), for example, analyzed the Airbnb data in five U.S. cities and reported that multiunit hosts gained proportionally much higher revenues than single-unit hosts. As far as the listing price is concerned, the units managed by multiunit hosts or the hosts with a longer tenure on Airbnb are also reported to have a higher price point than others (Magno et al., 2018). Gibbs, Guttentag, Gretzel, Yao, and Morton (2018) argued that multiunit hosts would be able to gain higher revenue than single-unit hosts by charging travelers a higher price because they were able to gain more experience through the operations of numerous listings, and they invested more effort into the short-term rental business. Hoteliers and policymakers are hence highly recommended to distinguish between the impacts of the multiunit "commercial" hosts and the single-unit "mom-and-pop" hosts (Kwok & Xie, 2019; Wegmann & Jiao, 2017).

Because multiunit hosts are managing multiple listings at the same time, they are more likely to deal with more transactions than single-unit hosts do in a given period. Likewise, the hosts who have signed up to be a service provider on Airbnb for a longer period are also more likely to deal with more transactions than those hosts who signed up recently. In a more general business setting, managers with longer tenure are usually found to have a deeper understanding of the operations and hence can identify more

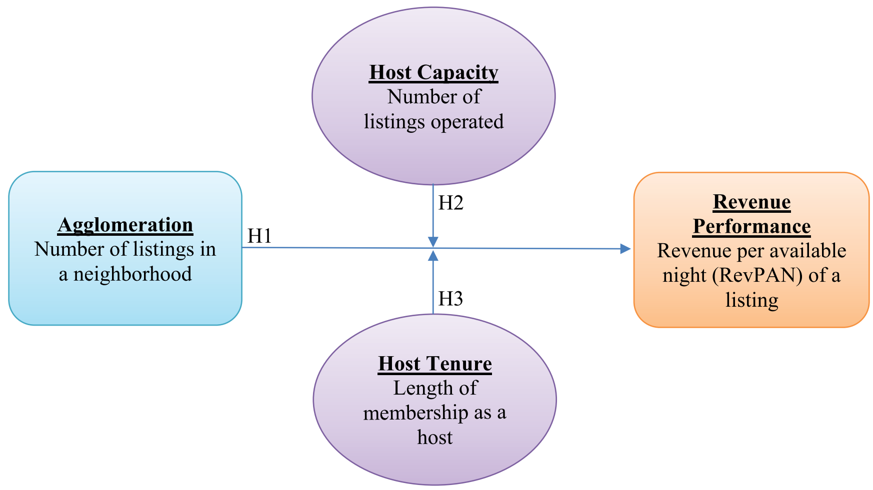

Figure 1.
A Proposed Model.

alternatives to solve new challenges (Schaltenbrand et al., 2018). Therefore, multiunit hosts or hosts who have been running the short-term residential business on Airbnb for a more extended period of time, as compared with the single-unit hosts and those who recently entered the market respectively, will probably find it easier to acquire the skills and knowledge for smoother operations through their own operation experience, allowing them to take better advantage of the agglomeration benefits through co-location.

According to the agglomeration theory, there are two types of benefits from agglomeration: production advantages and demand-based advantages (Canina et al., 2005). On one hand, businesses may gain production enhancements through information/knowledge flows and exchanges within the agglomeration cluster (Tsang & Yip, 2009). On the other hand, the effect of agglomeration can be created through increased demand, lower search costs, and demand spillover (Lee & Jang, 2015). It is possible that hosts with more experience, either through being a multiunit host or a host with a longer tenure on Airbnb, would have a better business sense in selecting the right location for a new listing, where they can fully utilize the agglomeration benefits while minimizing the negative impact from the competition created by colocation.

In fact, the differences between multiunit and single-unit hosts, as well as the differences between hosts with various tenure, have also been reported in the literature. For example, multiunit hosts (e.g., Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018; Kwok & Xie, 2019) and hosts with longer tenure (Magno et al., 2018) can be more effective in manipulating the listing price for a better revenue performance than their counterparts. Aligning with our main hypothesis, we argue that the agglomeration effects on home-sharing business may also vary according to the host experience in terms of capacity (number of listings operated) and tenure (length of membership as an Airbnb host). We propose the following two hypotheses:

Hypothesis 2 (H2): The effect of agglomeration on an Airbnb listing's RevPAN is larger for multiunit hosts than single-unit hosts.

Hypothesis 3 (H3): The effect of agglomeration on an Airbnb listing's RevPAN is larger for hosts with a longer tenure than those with shorter tenure.

Figure 1 presents the conceptual model that visualizes the relationships among the constructs of interest in this investigation. The main effect and the moderation effects among the constructs of interests are labeled with the appropriate hypotheses.

The Data

The Data and the Measures

We examined the agglomeration effect of Airbnb and how it varied by host capacity and tenure while controlling for the possible impacts from the listing characteristics, the potential influence of hotels in the same neighborhood, and the neighborhood social demographics. Accordingly, we collected the following data from three sources:

Performance of Airbnb properties. We obtained data on the monthly performance of the entire Airbnb listings in 201 zip codes of NYC from May 2015 to April 2016 (a total of 12 months) when legal restrictions had not yet been put on short-term residential rentals in the city. NYC was selected because it is the top tourist destination in the United States. The total number of travelers to NYC grew from 45.6 million in 2009 to 62.8 million in 2017, of which 1.6 million guests stayed in an Airbnb listing in 2016 alone (Center for an Urban Future, 2018). The data were provided by AirDNA, a third-party company that specializes in Airbnb data collection and market analysis. Although several limitations have been reported regarding the investigations using the Airbnb data provided by AirDNA (Agarwal et al., 2018), especially when they are compared against the STR (Smith Travel Research) data that are widely used in the hotel industry, considering the fact that our primary research focus is how Airbnb listings affect other Airbnb listings' revenue performance located in the same neighborhood, such a data set is the best source available for our analysis. We focused on Airbnb in NYC for two reasons. First, it is the largest metropolitan city, as well as the largest Airbnb market in the United States. Second, our findings can be added to the emerging literature, which also examines Airbnb-related issues in NYC (e.g., Coles et al., 2017).

Our dependent variable is an Airbnb listing's *RevPAN*, a similar measure that is widely used to assess other lodging products' revenue performance (i.e., RevPAR). Our focal variables of interest include listing agglomeration (*NumList*) and host experience (measured in *Capacity* and *Tenure*) that are central to our research interest. Because the revenue performance of each Airbnb listing is likely influenced by its characteristics, we also include other control variables in our analysis, such as average listing price (*ADR*), the valence and volume of online traveler reviews (*VolReview* and *ValReview*), number of bedrooms (*Bed*), bathrooms (*Bath*), and online photos (*Photo*), and whether the listing is managed by a super host (*Super*).

Hotels in the neighborhoods. According to Zervas et al. (2017), Airbnb is penetrating the lodging market where hotels and Airbnb are competing locally for guests. Therefore, we also account for the potential influence of hotel competition by controlling the number of hotel rooms in the neighborhood (*HotelRoom*), volume and valence of traveler reviews for hotels (*HotelVolR* and *HotelValR*), and the nightly rack rate of these hotels (*HotelRack*). These variables are sourced from Expedia, a major online travel agent for hotel bookings in the United States.

Social demographics of the neighborhoods. The social demographics of the neighborhoods where Airbnb listings are agglomerated may also affect their revenue performance and hence should be included in our estimation. We collected the neighborhood information from the *American Community Surveys* by the Census Bureau of the United States, including *MedianAge, CollegeDegree, Unemployment, Population, NumHousehold*, and *MedianIncome*. The rich set of control variables effectively mitigates the missing variable bias that may confound listing performance apart from our focal variables of interest. Table 1 presents the definitions and summary statistics of the variables discussed above.

Descriptions of the Data

Figure 2 presents the growth trajectories of the listings and the hosts in NYC. By the 12th month of the study period (April 2016), the Airbnb supply reached 31,928, which represented an impressive 54.7% increase from May 2015. Although at a slower pace of growth, the number of hosts had also increased from 16,743 to 24,902 over the study period. Figure 3 shows the level of listing agglomeration by zip code over the study period. The agglomeration of Airbnb listings seemed quite salient, with the average listings per zip code increasing from 915 to 1,422 in just 12 months.

Table 2 presents the distribution of host capacity. Most hosts (80.6%) only managed one listing (vs. 19.4% multi-unit hosts). Table 3 shows the distribution of host tenure. A total of 67.7% hosts have a membership on Airbnb for a year or less (vs. 32.3% with longer tenure). Both tables show clear variations in host capacity and tenure, which is beneficial for our analysis. Because hosts with multiple units and longer tenure are not small portions of the host population, it is also evident that the issues of our research interest are nontrivial.

Table 4 presents the correlation matrix of the independent variables. The results of correlation coefficients (all below .8) suggest that our estimation is less likely to be biased due to the multicollinearity concern.

Estimation Results

We operated the analyses on a stepwise basis. We first estimated the baseline model with the primary variables only. We then included the groups of control variables to expand the richness of information sequentially. Such a stepwise estimation was useful for two reasons. First, it showed the incremental power of our independent variables in explaining the listing performance. Second, the models with incrementally increased controls could serve as robustness checks for the baseline model.

Table 5 presents the estimation results. In the baseline model, we estimated the effect of listing agglomeration, host experience/attributes, and their interactions. Column 1 suggests a significantly positive effect of agglomeration on the listing performance (0.127***). That is, for each 10% increase of Airbnb supply in the neighborhood, the *RevPAN* of a listing would increase by 1.27%, supporting H1. In addition, we identified the dyadic effects of the host experience/attributes on listing performance. On one hand, expanding the capacity of a host seems to negatively

Table 1.
Variable Definitions and Summary Statistics (Unit of Analysis: Listing–Month).

Variable	Definition	*M*	*SD*	Minimum	Maximum
Dependent variable					
RevPAN	Logarithm of the average revenue per available nights in a month[a] (in U.S. dollars)	4.88	0.63	0.00	9.21
Primary independent variables					
NumList	Logarithm of the number of listings agglomerated in a zip code where the focal listing is located	6.62	1.07	0.00	8.34
Capacity	Number of listings simultaneously managed by a host, including the focal listing	2.17	3.59	1.00	77.00
Tenure	Number of months elapsed since the focal listing's operator become an Airbnb host	20.34	15.69	0.00	94.00
Control variables (listing characteristics)					
ADR	Average daily rate	65.95	118.89	0.00	10,000.00
VolReview	Number of online guest reviews	18.81	33.41	0.00	478.00
ValReview	Average rating of online guest reviews, with values 1 = *terrible*, 2 = *poor*, 3 = *average*, 4 = *very good*, and 5 = *excellent*	4.58	0.46	1.00	5.00
Bed	Number of bedrooms	1.14	0.69	0.00	14.00
Bath	Number of bathrooms	1.12	0.40	0.00	15.50
Photo	Number of listing photos available on Airbnb	12.61	9.89	0.00	240.00
Super	Dummy variable indicating whether a host is recognized by Airbnb as a super host,[b] with values of 1 = *super host* and 0 = *otherwise*	1.08	0.28	1.00	2.00
Control variables (hotel characteristics)					
HotelRoom	Logarithm of the number of hotel rooms in a zip code where the focal listing is located	5.62	2.16	0.00	9.81
HotelVolR	Logarithm of the number of online guest reviews for the hotels in a zip code where the focal listing is located	7.43	2.38	0.00	11.96
HotelValR	Average rating of online guest reviews for the hotels in a zip code where the focal listing is located, with values 1 = *terrible*, 2 = *poor*, 3 = *average*, 4 = *very good*, and 5 = *excellent*	3.85	0.45	0.00	5.00
RoomRate	Logarithm of the average room rate of the hotels in a zip code where the focal listing is located	5.42	0.45	4.37	7.28
Control variables (neighborhood characteristics)					
MedianAge	Median age of the population in a zip code where the focal listing is located	34.01	3.24	27.90	47.50
CollegeDegree	Percentage of population with a college degree and above in a zip code where the focal listing is located	23.89	6.15	6.50	45.70
Unemployment	Unemployment rate in a zip code where the focal listing is located	8.00	3.54	1.30	17.60
Population	Population in a zip code where the focal listing is located (in thousands)	62.40	28.20	3.04	112.98
NumHousehold	Number of households in a zip code where the focal listing is located (in thousands)	25.05	9.99	1.57	43.46
MedianIncome	Median income of households in a zip code where the focal listing is located (in thousands of U.S. dollars)	70.32	28.66	23.76	234.96

Source. https://www.airbnb.com/superhost.
[a]Available nights in a month are the nights a host does not block a listing but makes it available for booking (regardless of whether the listing ends up being booked or not). b. Super host is recognized by the Airbnb platform based on certain criteria in aspects of service quality.

influence a listing's RevPAN (−0.025***), whereas the increase in host tenure will benefit a listing's RevPAN (0.005***).

We further estimated whether the positive effect of listing agglomeration would be moderated by host capacity and host tenure. Column 1 continues to show that the positive effect of agglomeration would decrease as a host manages more listings (−0.001**), contradictory to H2, although still at a significant level. The results also indicate that hosts with longer tenure can further strengthen the positive effect of agglomeration on a listing's revenue performance, as shown in the moderation effect of host tenure (0.002***). The result supports H3. Table 6 summarizes the major findings of hypothesis testing.

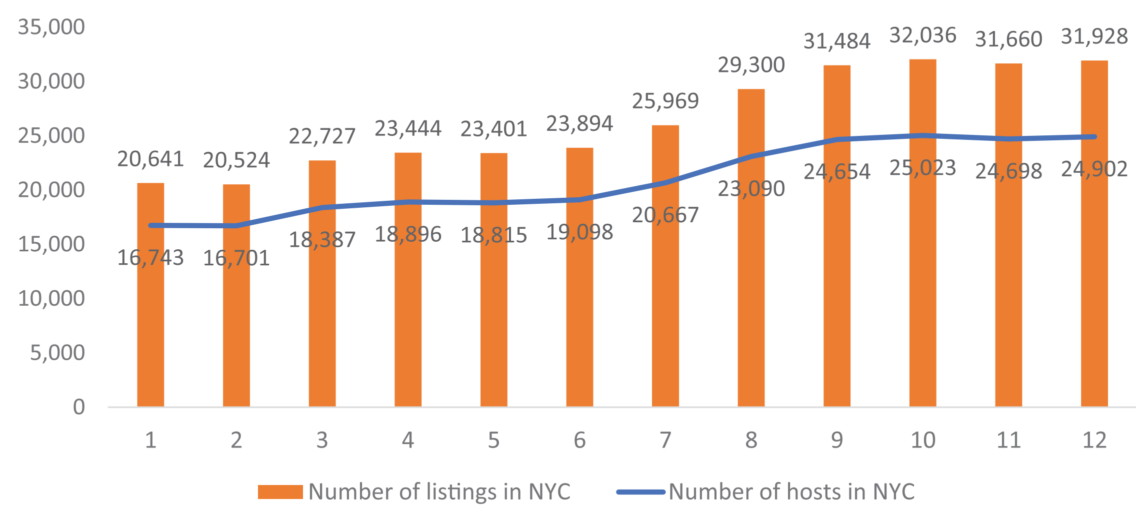

Figure 2.
The Growth of Listings and Hosts in the NYC From May 2015 to April 2016.
Note. NYC = New York City.

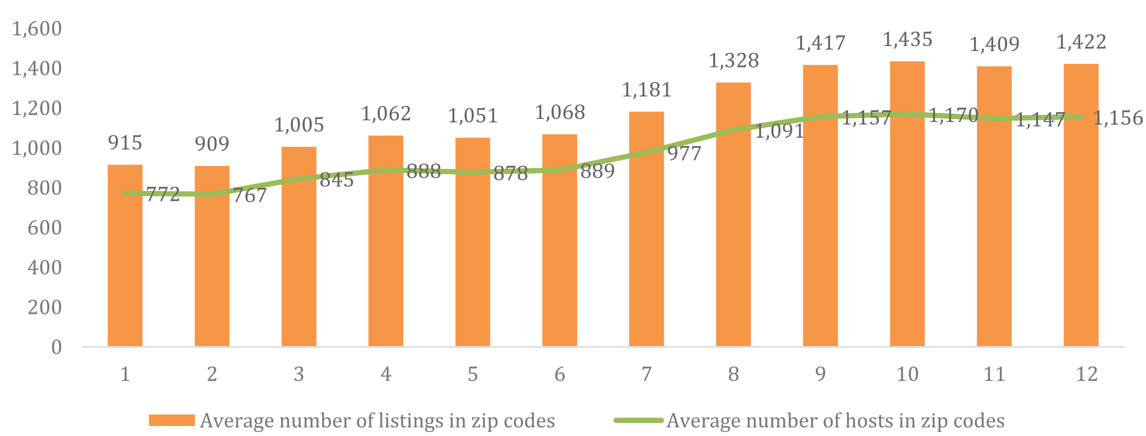

Figure 3.
Average Number of Listings and Hosts in a Zip Code From May 2015 to April 2016.

Table 2.
Distribution of Host Capacity.

Number of Listings	%
Single-unit capacity	
1 listing	80.6
Multi-unit capacity	
2 listings	12.7
3 to 4 listings	4.9
5 to 10 listings	1.6
More than 10 listings	0.2
Total	100

The R^2 of the baseline model is 47.2%, indicating almost half of the variance in the listing performance can be explained by the agglomeration effect and host attributes. We continued with the control variables of listing characteristics in Column 2. The R^2 showed a significant increase to 61.5%. We further added the competition controls of hotels into the estimation; the explanatory power of the model increased to 63.6%. It seems that, although hotels are documented to compete with Airbnb in the accommodation market (Zervas et al., 2017), Airbnb's influence is yet to manifest itself. Finally, we considered the neighborhood demographics that could also affect a listing's revenue

Table 3.
Distribution of Host Tenure.

Tenure (in months)	%
Less than 1 year	
0 month	10.6
1 to 6 months	40.2
7 to 12 months	16.9
More than a year	
13 to 24 months	17.2
25 to 36 months	8.2
37 to 48 months	4.4
49 to 60 months	1.7
61 to 72 months	0.6
More than 72 months	0.2
Total	100

performance. The result in Column 4 shows a 6% increase in R^2 from Column 3 to 69.6%. It is evident that among all of the controls, listing's characteristics explain the majority of its revenue performance, followed by the neighborhood and hotel controls.

Discussion

The sharing economy was born from the ideology where consumers share underutilized resources with their peers but has evolved into a business sector with a multibillion-dollar market value (Chark, 2019). Startups in the sharing economy, such as Uber, Lyft, Airbnb, and Task Rabbit, received enormous investments from venture capitals and other investment funds (Rauch & Schleicher, 2015). Unlike other segments of the sharing economy, such as Uber and Lyft in ride sharing, however, the growth of the home-sharing or short-term residential rental sector relies mainly on the location being close to the amenities available in an urban setting (Davidson & Infranca, 2016). It is therefore not surprising to see many Airbnb listings are colocated near city centers or tourist destinations (Coles et al., 2017; Gutiérrez et al., 2017). Moreover, while the nature of the ride-sharing services provided by Uber and Lyft requires that the service provider move from one place to another, a desirable and fixed location has always been a critical factor for any type of lodging product because once a site is selected, it becomes extremely difficult for a developer to move a lodging facility to a different place (Yang et al., 2012). The special focus of this study is to assess the agglomeration effects among the Airbnb listings in NYC.

With a focus on the granular-level data in 201 zip codes of NYC, the city with the most extensive presence of Airbnb in the United States, we successfully identified a significant positive agglomeration effect on an Airbnb listing's revenue performance, which possibly results from travelers' spillover demands for room-sharing listings in the same neighborhood. Such finding is consistent with H1, as well as the existing literature about hotel locations (e.g., Canina et al., 2005; Enz et al., 2008; Lee & Jang, 2015). When we further examined how such an agglomeration effect varies according to host experience as measured in capacity and tenure, our analysis reveals some intriguing findings. For example, while the positive agglomeration effect seems to be strengthened under the influence of host tenure, agreeing with H3, host capacity turned out to negatively moderate such an agglomeration effect. This result contradicts H2, which indicates that as the number of listings that a host manages increases, the positive effect of agglomeration on an Airbnb listing's revenue performance will become stronger due to the additional experience that the host might gain through the operations of multiple units (vs. through the operations of one unit only). It is plausible that when a host must dedicate his or her time and attention to multiple units on a day-to-day basis, it could become challenging for the host to maintain the same high quality of service across all listings being managed.

Inspired by the agglomeration theory, which provides two conceptual explanations for colocation of the lodging products, we assessed the agglomeration effect of a new form of lodging product—room-sharing listings. Our findings add new empirical evidence to two streams of literature, including location research in the lodging industry and the ever-growing research regarding the room-sharing business. For example, we made the first attempt in the hospitality literature to empirically show that the advantage of proximity in location would surpass the drawback of competitions among Airbnb listings.

Practically, we highly recommend the webmasters of room-sharing websites, the entrepreneurs who are running a short-term residential business, as well as the big hotel chains (e.g., Hyatt and Marriott) that also entered the short-term residential rental market recently, refer to our findings for critical business decisions regarding marketing and site/location selections. "Proximity in location," for instance, should be set as a crucial factor when a room-sharing website displays the alternative options to the travelers according to their searching/browsing history. The entrepreneurs who want to operate multiple units on a room-sharing website must pay close attention to such an agglomeration of production enhancements and spillover demands when they are choosing the "right" locations for their listings. We also encourage the hotel chains that have already gotten into the short-term residential rental market to use our analysis as a reference and see how they may take advantage of the knowledge- and resource-spillover effects as they recruit the hosts living in the same neighborhood of their existing lodging products. Last but not least, the moderation effects identified in our analysis also support other researchers' conclusions that policymakers should treat multiunit commercial hosts and single-unit

Table 4.
Correlation Matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) NumList	1.00																			
(2) Capacity	−.07	1.00																		
(3) Tenure	.04	.07	1.00																	
(4) ADR	.05	.00	.09	1.00																
(5) VolReview	.01	.01	.34	.25	1.00															
(6) ValReview	.04	−.17	.02	.02	.02	1.00														
(7) Bed	−.01	.05	.06	.21	.02	−.03	1.00													
(8) Bath	.00	.07	−.01	.14	−.02	.00	.42	1.00												
(9) Photo	.00	.08	.23	.24	.29	.04	.23	.14	1.00											
(10) Super	−.02	.00	.08	.11	.25	.16	.03	.01	.14	1.00										
(11) HotelRoom	.26	.00	−.01	.13	.00	.01	−.04	.01	−.01	−.02	1.00									
(12) HotelVolR	.18	.01	−.02	.13	.00	.01	−.05	.00	−.02	−.02	.96	1.00								
(13) HotelValR	.00	.00	.01	.06	−.01	.04	−.01	−.02	.01	.01	.16	.18	1.00							
(14) HotelRack	−.07	−.02	−.01	.09	−.02	.03	−.05	−.03	−.02	−.01	.31	.32	.52	1.00						
(15) MedianAge	−.43	−.06	−.01	.04	−.02	.01	.00	−.02	−.01	.02	.14	.25	.07	.36	1.00					
(16) CollegeDegree	−.15	.03	−.05	.02	−.03	−.01	−.04	−.01	−.03	−.02	.26	.24	.19	.21	.12	1.00				
(17) Unemployment	−.05	.05	−.01	−.10	.04	−.09	.03	.06	.02	.01	−.41	−.50	−.32	−.55	−.32	−.07	1.00			
(18) Population	.37	.03	.00	−.10	.03	−.05	.01	.01	.00	−.01	−.22	−.31	−.42	−.71	−.30	−.30	.35	1.00		
(19) NumHousehold	.49	−.03	.01	−.06	.01	−.03	−.01	.00	−.01	−.01	−.05	−.10	−.37	−.57	−.13	−.25	.18	.94	1	
(20) MedianIncome	−.04	−.09	.00	.13	−.05	.08	−.04	−.03	−.02	−.01	.55	.64	.30	.73	.46	.09	−.72	−.61	−.40	1

Note. ADR = average daily rate.

Table 5.
Effect Estimations.

	(1)	(2)	(3)	(4)
DV: *RevPAN*	Baseline	Robustness Checks		
Primary variables				
NumList	0.127***	0.071***	0.042***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Capacity	−0.025***	−0.014***	−0.029***	−0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.005***	0.003***	0.001***	0.002***
	(0.000)	(0.000)	(0.010)	(0.000)
NumList × Capacity	−0.001**	−0.001***	−0.001**	−0.002***
	(0.015)	(0.000)	(0.012)	(0.000)
NumList × Tenure	0.002***	0.002***	0.001**	0.001**
	(0.000)	(0.000)	(0.020)	(0.032)
Controls (the listing)				
ADR		0.004***	0.003***	0.003***
		(0.000)	(0.000)	(0.000)
VolReview		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
ValReview		0.032***	0.038***	0.066***
		(0.000)	(0.000)	(0.000)
Bed		0.037***	0.068***	0.128***
		(0.000)	(0.000)	(0.000)
Bath		−0.152***	−0.110***	−0.033***
		(0.000)	(0.000)	(0.000)
Photo		0.003***	0.004***	0.005***
		(0.000)	(0.000)	(0.000)
Super		0.003	0.019***	0.031***
		(0.167)	(0.000)	(0.000)
Controls (hotels)				
HotelRoom			−0.003*	−0.004
			(0.082)	(0.119)
HotelVolR			0.044***	0.006**
			(0.000)	(0.032)
HotelValR			0.004	0.051***
			(0.112)	(0.000)
RoomRate			−0.132***	−0.005
			(0.000)	(0.480)
Controls (neighborhoods)				
MedianAge				−0.016***
				(0.000)
CollegeDegree				0.001***
				(0.000)
Unemployment				0.000
				(0.742)
Population				−0.004***
				(0.000)
NumHousehold				0.014***
				(0.000)
MedianIncome				0.001***
				(0.000)
Constant	4.038***	3.776***	2.938***	2.368***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	249,576	212,303	148,568	66,637
R^2	.472	.615	.636	.696

Note. DV = dependent variable; ADR = average daily rate.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6.
Summary of Hypothesis Testing.

Hypothesis		Result
H1	The level of agglomeration is positively associated with an Airbnb listing's revenue per available night (RevPAN).	Supported
H2	The effect of agglomeration on an Airbnb listing's RevPAN is stronger for multiunit hosts than single-unit hosts.	Not supported[a]
H3	The effect of agglomeration on an Airbnb listing's RevPAN is stronger for hosts with a longer tenure than for those with a shorter tenure.	Supported

[a] A significant negative moderation effect was identified, however.

"mom-and-pop" hosts differently (e.g., Kwok & Xie, 2019; Wegmann & Jiao, 2017). We echo their recommendations to the policymakers.

This study is not without limitations. First, we chose NYC as a unique context to address our research inquiry. The findings can only speak on the agglomeration effect specific to the city and may not be generalized to other cities or regions that have experienced Airbnb growth. Despite its limitation on generalizability, future research on the agglomeration effect of Airbnb can use this study as a reference point. Second, we have diligently collected data from multiple sources to carefully control the possible causes of impacts on our model estimations. Nevertheless, there might be other variables—such as the number of tourist attractions in the city, the attractiveness of each tourism attraction and/or the convenience of travel (e.g., access to public transportation system)—which should also be considered but are not yet available in our analysis. We encourage future research endeavors to replicate our analysis with a richer data set. Third, we studied the agglomeration effect during a limited time frame (12 months). Although we observed sufficient variations in Airbnb property activities and the associated agglomeration effect, this type of study would certainly benefit from a longer observation period to further validate the robustness of the results. Finally, we used zip codes–based neighborhoods in our analysis of the agglomeration effect. Alternatively, a neighborhood could also be defined by the size of areas (e.g., within 1 mile of each Airbnb listing). Although we do not expect our estimated impacts will change dramatically if we expand or shrink the scope of a neighborhood, we appreciate that researchers who have access to such data will conduct additional analyses as a complement to our study. Research that answers similar research questions with different methodologies can often provide a more comprehensive understanding of a complex phenomenon (Kwok, 2012).

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