LOVE THE NEIGHBOR?

AGGLOMERATION EFFECT ON HOME-SHARING BUSINESS

Karen L. Xie Daniels College of Business University of Denver

Linchi Kwok Collins College of Hospitality Management California State Polytechnic University Pomona

and

Cindy Y. Heo
Ecole hôtelière de Lausanne
HES-SO//University of Applied Sciences

Abstract

This study addresses two research questions: (1) Does agglomeration benefit home-sharing business? and (2) How host capacity and host experience moderate such agglomeration effect? A series of econometric analyses using large-scale data of Airbnb in New York City were employed. The findings suggest a positive agglomeration effect on a room-sharing listing's performance. Such effect is mitigated as host capacity increases but remains strengthened as host experience expands. Theoretical and practical implications are highlighted.

Keywords: Home sharing, agglomeration, revenue performance, Airbnb, New York City

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Introduction and the Research Questions

Location is an essential attribute of a lodging product and can significantly affect a hotel's performance (Balaguer & Pernías, 2013). It has now become an industry standard that a hotel defines its competitive set based on the competitors' geographic proximity in the market (Lee, 2015). Although proximity in location for suppliers who provide similar services or products (e.g., homogenous suppliers) is often associated with competition and may hence hurt a business' performance (Chung & Kalnins, 2001), agglomeration of homogenous suppliers may also benefit the business through amplifying the positive externality (Marshall, 2009). The entry of incumbents, for example, increases the intensity of competitions (McCann & Vroom, 2010), but homogenous suppliers located in the same neighborhood may also gain substantial financial and operational benefits through heightened or spillover demands (Lee & Jang, 2015) and strategic price positioning in the market (McCann & Vroom, 2010).

Despite the essential role that location plays in a lodging product's performance, research about hotel locations still received limited attention; in particular, analyses with the agglomeration models were not employed until 2000 (Yang et al., 2014). In this study, we add evidence to location research in the lodging industry by investigating the agglomeration effect on the performance of Airbnb listings, a new and alternative lodging product that recently disrupts the incumbent hotel business and receives extensive research spotlight (Guttentag & Smith, 2017). Our research questions include: (a) Whether Airbnb listings would benefit from agglomeration (proximity in location with other Airbnb listings in the same zip code)? (b) Would such agglomeration effect vary according to the operation characteristics of the hosts in terms of capacity (number of Airbnb listings operated) and experience (length of experience in operating Airbnb listings)? Drawing upon the theory of agglomeration, we provide valuable empirical evidence of whether the advantage of proximity in location would surpass the drawback of competitions when a group of Airbnb listings clusters in the same neighborhood. Practically, our findings provide managerial implications on what operational characteristics (host capacity

and/or experience) would help hosts address or leverage the agglomeration effect. Figure 1 presents a visual diagram of the key measures and their proposed relationships.

Methodology and Findings

We collected a large-scale and unique dataset from AirDNA that consisted of the entire population of 84,036 listings managed by 61,707 hosts in 201 zip codes of New York City from May 2015 to April 2016 (a total of 12 months). We examined the agglomeration effect among Airbnb listings and how it varies according to host capacity and experience while controlling listing characteristics, the potential influence of hotels, and the neighborhood demographics. Table 1 provides the definitions and the descriptive statistics of the aforementioned variables from the data source. We operated the analyses on a stepwise basis. We first estimated the baseline model with primary variables of the research interest only. We then included the groups of control variables to sequentially expand the richness of information.

The estimation results are presented in Table 2. As suggested in Column (1) – the main model, we identified a significantly positive effect of agglomeration on a listing's performance (0.127***). That is, for each 10% increase of Airbnb supply in the neighborhood, a listing's revenue per available night would increase by 1.27%. We further estimated if such positive effect of agglomeration would be moderated by host capacity and experience. The results suggest that the positive effect of agglomeration decreases as the host manages more listings simultaneously (-0.001**). In contrast, experienced hosts would be able to leverage the positive effect of agglomeration to enhance the listing performance, as shown in the moderation effect of host experience (0.002***). The R-square of the baseline model is 47.2%, which indicates that almost half of the variance in the listing performance is explained by the agglomeration effect and host operational characteristics. By including groups of control variables in Columns (2)-(4), the R-square increases from 47.2% to 69.6%. Among all the controls, listing characteristics explain a majority of the performance, followed by neighborhood and hotel controls.

Conclusions and Implications

Our findings confirm the agglomeration benefits among Airbnb listings. Moreover, the management of experienced hosts would magnify such effect while that of a multi-unit host would mitigate such effect. Our study makes several contributions to the literature. Firstly, our analysis was built on the theory of agglomeration and enriches the location research in the lodging industry with a sample of a new and disruptive lodging product in the market - Airbnb. Secondly, we answered the debate of the agglomeration effect in the context of home-sharing economy by adding new insights about listings' proximity in location. Additionally, our findings allow us to make specific recommendations to experienced hosts and multi-unit hosts. Experienced hosts, for example, may benefits from agglomeration through the spill-over effect from the positive externality. For the hosts who want to increase the capacity of managing multiple listings, proximity in locations may represent a peril as the agglomeration benefits turn to diminish.

Figure 1. Research model

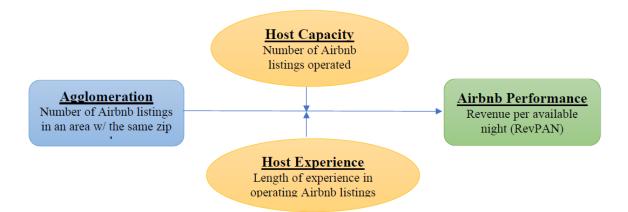


Table 1. Variable Definitions and the Descriptive Statistics

(Unit of Analysis: Listing–Month)

Variable	Definition	Mean	Std. Dev.	Min	Max
	iable (Airbnb; from AirDNA)				
RevPAN	Logarithm of the average revenue per available nights in a month ¹ (in US. Dollars), a performance metric similar to RevPAR used in the hotel industry	4.88	0.63	0.00	9.21
	endent 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
Experience	Number of months lapsed since the focal listing's operator become an Airbnb host	20.34	15.69	0.00	94.00
Control Variab	les (Listings)				
ADR	Average daily rate	65.95	118.89	0.00	10000.00
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 for view on Airbnb	12.61	9.89	0.00	240.00
Super	Dummy variable indicating whether a host is recognized by the Airbub platform as a super host,2 with	1.08	0.28	1.00	2.00
•	values of 1 = Super host, 0 = Regular host				
Control Variab	les (Hotels; from Expedia)				•
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 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 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
HotelRack	Logarithm of the average rack rate of hotels in a zip code where the focal listing is located	5.42	0.45	4.37	7.28
Control Variab	les (Neighborhoods; from Census Bureau of the United States)				
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 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	62.40	28.20	3.04	112.98
NumHousehold	Number of households in a zip code where the focal listing is located	25.05	9.99	1.57	43.46
MedianIncome	Median income of households in a zip code where the focal listing is located	70.32	28.66	23.76	234.96

¹ Available nights in a month are the nights a host does not block a listing but makes it available for booking (no matter the listing ends up being booked or not). Because Airbnb is sold one unit for each booking, the performance metric of RevPAN focus on available nights rather than available rooms/units.

² Super host is recognized by the Airbnb platform based on certain criteria in aspects of service quality. Source: https://www.airbnb.com/superhost

 Table 2. Effect Estimates

	(1)	(2)	(3)	(4)	
D.V.: RevPAN	Baseline	Robustness Checks			
Primary Variables					
NumList	0.127***(0.000)	0.071***(0.000)	0.042***(0.000)	0.023***(0.000)	
Capacity	-0.025***(0.000)	-0.014***(0.000)	-0.029***(0.000)	-0.016***(0.000)	
Experience	0.005***(0.000)	0.003***(0.000)	0.001***(0.010)	0.002***(0.000)	
NumList × Capacity	-0.001**(0.015)	-0.001***(0.000)	-0.001**(0.012)	-0.002***(0.000	
NumList × Experience	0.002***(0.000)	0.002***(0.000)	0.001**(0.020)	0.001**(0.032)	
Controls (Listing)		•			
ADR		0.004***(0.000)	0.003***(0.000)	0.003***(0.000)	
VolReview		0.001***(0.000)	0.001***(0.000)	0.001***(0.000)	
ValReview		0.032***(0.000)	0.038***(0.000)	0.066***(0.000)	
Bed		0.037***(0.000)	0.068***(0.000)	0.128***(0.000)	
Bath		-0.152***(0.000)	-0.110***(0.000)	-0.033***(0.000	
Photo		0.003***(0.000)	0.004***(0.000)	0.005***(0.000)	
Super		0.003(0.167)	0.019***(0.000)	0.031***(0.000)	
Controls (Hotels)					
HotelRoom			-0.003*(0.082)	-0.004(0.119)	
HotelVolR			0.044***(0.000)	0.006**(0.032)	
HotelValR			0.004(0.112)	0.051***(0.000)	
HotelRack			-0.132***(0.000)	-0.005(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***(0.000)	3.776***(0.000)	2.938***(0.000)	2.368***(0.000)	
Observations	249,576	212,303	148,568	66,637	
R-squared	0.472	0.615	0.636	0.696	

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