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Travelers' reactions toward recommendations from neighboring rooms: Spillover effect on room bookings

Abstract

This research aims to test the potential spillover effect among room rentals using the context of room-sharing platforms. The spillover effect generally refers to the influence of related units' outcomes on a unit's outcome. On this basis, we hypothesize that the number of bookings of targeted neighboring rooms influences the number of bookings of a recommended room. Given our sample of nearly 20,000 observations, the empirical application results show that with the increase in the bookings of targeted neighboring rooms, the bookings of a recommended room rise in line with the hypothesized spillover effect. Moreover, the similarity between the recommended room and its neighboring rooms targeted at the room search stage and the quality of the recommended room further strengthen the spillover effect. Overall, this research contributes to the literature by providing novel perspectives to the boundary conditions of spillover effects and presents relevant managerial implications for hosts and operators of room-sharing platforms.

Keywords: room sharing; spillover effect; neighboring rooms; room similarity; room quality.

1. Introduction

Online platforms usually recommend related products on the bases of customers' current social media activities or browsing history. Many studies have shown that this personalized recommendation can increase customer loyalty and encourage additional purchases by making customers feel being treated exclusively and increasing their decision efficiency (Zhang et al., 2011; Assiouras et al., 2019). An effective personalized recommendation can be beneficial for the operation of room-sharing platforms as it can assist travelers in determining the appropriate products with suitable quality and convenient location (Robert & Tribe, 2008). However, only a few studies have examined how such recommendation influences small businesses that share competitive relationships on online platforms. Specific to this context, a relevant question is to uncover travelers' reactions when they observe recommendations for other rooms and the potential spillover effect thereof.

From an economic perspective, a spillover effect suggests that a unit's outcome is a function of other related units' outcomes (Ellison et al., 2007). In recent years, scholars applied this construct to analyze pressing issues related to marketing communications (Ahluwalia et al., 2011), location advantages among room rentals (Yang & Mao, 2020), and the benefit of the entry of accommodation sharing (Song et al., 2020). In our study, the spillover effect refers to the influence that neighboring rooms (the rooms that the customer searches at the booking process) may have on the recommended room (the room that the customer eventually books after the search) owing to the design of personalized recommendations on a room-sharing platform. During a customer's booking process, he/she will first search for a targeted room (e.g., Room B). For a targeted room, rooms recommended by platforms share similar features, such as neighboring locations. When travelers are appealed by

a targeted room (Room B, which is one of Room A's neighboring rooms), they will notice the recommendation. They may browse the recommended room (Room A), increasing the possibility that Room A receives bookings. Thus, we may infer that the bookings of neighboring rooms (targeted rooms) will have a spillover effect on the recommended room as these bookings suggest the popularity of neighboring rooms. With high popularity, targeted neighboring rooms will receive additional online visits, which may spill over to the recommended room, increasing the probability of the recommended room being booked. This situation is especially prominent if these rooms share similar features and the recommended room has high quality. The reason is that spillover effects are sometimes associated with a wide range of factors, including similarity (Cao et al., 2017) and the recommended product quality (Janakiraman et al., 2006).

On the basis of the above discussions, this study intends to address two research questions: a) Does the number of bookings of targeted neighboring rooms have a spillover effect on that of the recommended room? b) Does the similarity between neighboring rooms and the recommended room and the quality of the recommended room positively influence this spillover effect?

2. Data and Methodology

We obtained our data from one of the largest room-sharing platforms in China (Mayi.com).[1] Mayi.com is one of the most popular Chinese room-sharing platforms (founded in 2011), which provides services in more than 300 cities around the country. We specifically chose this platform as its website displays the actual number of bookings for each room. The platform also has three ways to post reviews: reviews with comments and numerical ratings posted by consumers after experiencing the service, reviews with only numerical ratings by the consumers after the service, and default positive rating if consumers do not provide any comments. Thus, the combination of these three parts of reviews can indicate the actual number of bookings. We collected our room data from Shenzhen as it is one of the largest and most popular cities in China and provides information on more than 10,000 room rentals. We gathered data using a Java-based web crawler in July 2019, retrieving information over the two previous years, i.e., July 2017–June 2019. However, we only retained the sample observations with at least one booking in the latest two years and have rooms recommended by the website. The neighboring room should also have at least one booking in the latest two years. Our final data sample included 1,631 rooms.

[1] We collected the data in July 2019 through a personal computer channel. However, the website is currently only available as a mobile application.

Figure 1 Sample targeted room and its recommended rooms 1–6 and their locations on the map

Figure 2 Example of neighboring rooms 1–6 presented on the homepage of a targeted room

The dependent variable is the number of room bookings in each month ($RoomBookings_{it}$) represented by the number of room reviews of a recommended room i at time t. The main independent variable is the average number of bookings of targeted neighboring rooms that could link to room i through the recommendation ($AveNeighborBookings_{it}$). The neighboring rooms consist of two groups, including those posted as neighboring rooms in the room page of room I and those recommended room i as one of their neighboring rooms in the targeted room page. Figures 1 and 2 show an example of a targeted room webpage and its neighboring recommendations and the rooms' locations on the map. We also included two potential moderators: the similarity value between recommended room i and its targeted neighboring rooms ($Similarity_i$) and the room quality represented by the ratio of positive reviews of recommended room i ($PositiveReviews_i$). Regarding the similarity value, we adopted the following algorithm (1) to measure the similarity value between room i and neighboring room j. $Value_i$ and $Value_j$ represent different attributes of room i or one targeted neighbor room j. In addition, we include several room attributes to calculate the attribute similarity including room prices ($Similarity1_i$), the room capacity measured by the number of customers ($Similarity2_i$), and the ratio of positive room reviews ($Similarity3_i$). The smaller the value, the more similar the recommended room and the initial targeted neighboring rooms.

$$Similarity_{ij} = \left|Value_i - Value_j\right| / max\left(Value_i, Value_j\right). \quad (1)$$

Other time-varying factors may also affect the number of room bookings. These factors include

room bookings at time $t-1$ ($RoomBookings_{it-1}$), the average number of review words at time $t-1$ ($ReviewWords_{it-1}$), the number of hosts' replies at time $t-1$ ($ReplyNum_{it-1}$), the average number of words in hosts' replies at time $t-1$ ($ReplyWords_{it-1}$), and time fixed effect and room fixed effect.

We also adopted the fixed effect model to control the unobserved heterogeneity, obtaining the following research models:

$$RoomBookings_{it} = \alpha_i + \beta_1 AveNeighborBookings_{it} + \delta Controls + \varepsilon_{it}, \tag{2}$$

$$\begin{aligned} RoomBookings_{it} = {} & \alpha_i + \beta_1 AveNeighborBookings_{it} \\ & + \beta_2 AveNeighborBookings_{it} \times Similarity_i + \delta Controls + \varepsilon_{it} \end{aligned}, \tag{3}$$

$$\begin{aligned} RoomBookings_{it} = {} & \alpha_i + \beta_1 AveNeighborBookings_{it} \\ & + \beta_3 AveNeighborBookings_{it} \times PositiveReview_i + \delta Controls + \varepsilon_{it} \end{aligned}, \tag{4}$$

where i is the recommended room. t is the time, β and δ are the coefficients to be estimated, *Controls* are the control variables, α is the fixed room effect controlling the difference between rooms that are not varied over time, and ε is the random error.

3. Empirical Results

We used data from July 2017 to June 2019 to test our model and obtain empirical results. Table 1 presents the descriptive statistics of the main variables. We checked the correlations of our dependent and independent variables (Table 2). The largest value is approximately 0.7 and exists among the control variables. Therefore, we performed the value inflation factor (VIF) test, and the results show that the VIF values of the control variables (*ReviewWords*, *ReplyWords*, *ReplyNum*) are below 4. Following prior research (Zhang et al., 2020), we did not consider multicollinearity a serious concern in this study. Table 3 provides the estimation results. The coefficient of *AveNeighborBookings* is positive and significant (0.0372, $p < 0.05$). Thus, the existence of more bookings in targeted neighboring rooms leads to more bookings in the recommended room. For the moderation effect of similarity, the coefficients of room capacity (*Similarity2*) and the ratio of positive room reviews (*Similarity3*) are significant and negative (−0.0179, $p < 0.1$; −0.1304, $p < 0.001$). The results show that the more dissimilar the recommended room and its targeted neighboring rooms, the weaker the effect of targeted neighboring rooms' bookings on the recommended room's bookings. Lastly, the ratio of positive room reviews positively strengthens the effect of targeted neighboring rooms' bookings on the dependent variable (0.1717, $p < 0.001$).

Table 1 Descriptive statistics of the main variables

Variables	Mean	Std. Dev.	Min	Max
RoomBookings	0.4031	1.0010	0	15
AveNeighborBookings	0.3704	0.8257	0	10
Similarity1	0.3073	0.2363	0	0.9836
Similarity2	0.2631	0.2372	0	0.8571
Similarity3	0.5136	0.4056	0	1
PositiveReviews	0.5875	0.4732	0	1
ReviewWords	19.7899	69.9926	0	1919
ReplyWords	8.8999	45.6679	0	1985
ReplyNum	0.1952	0.7033	0	13

Table 2 Correlations among the main variables

Variables	1	2	3	4	5	6	7	8
1 $RoomBookings_{it}$								
2 $AveNeighborBookings_{it}$	0.1816							
3 $Similarity1_i$	−0.0289	−0.0431						
4 $Similarity2_i$	−0.0065	−0.0023	0.5662					
5 $Similarity3_i$	−0.0785	−0.0729	−0.0431	−0.0555				
6 $PositiveReviews_i$	0.2113	0.1024	−0.0920	−0.0234	−0.0740			
7 $ReviewWords_{it-1}$	0.3633	0.1164	0.0075	0.0185	−0.0463	0.1569		
8 $ReplyWords_{it-1}$	0.2782	0.0802	0.0031	0.0137	−0.0324	0.1200	0.6022	
9 $ReplyNum_{it-1}$	0.3857	0.1243	-0.0028	0.0098	−0.0418	0.1604	0.7168	0.7327

To check the robustness of our empirical results, we introduced *Similarity4*, *Similarity5*, *Similarity6*, and *Similarity7*. *Similarity4* represents the similarity value calculated by the differences in room promotion (measured through a dummy variable that takes a value of 1 if promotion is used; otherwise, 0). *Similarity5* denotes the similarity value calculated by the differences in the number of beds. *Similarity6* refers to the similarity value calculated by the differences in the ratio of positive room reviews in room cleanliness. *Similarity7* is the similarity value calculated by the differences in the quality/cost between targeted neighboring rooms and the recommended room. *PositiveRreviews1*, *PositiveReviews2*, and *PositiveReviews3* are the ratio of positive room reviews in traffic, facilities, and host service. The results are presented in Table 4, which shows high consistency with the main results in Table 3. The coefficients of the interaction terms "$AveNeighborBookings_{it} \times Similarity$" are all negative and significant (−0.1374, $p < 0.01$; −0.1338, $p < 0.01$; −0.1322, $p < 0.01$; −0.1313, $p < 0.01$). By contrast, the coefficients of the interaction terms ($AveNeighborBookings_{it} \times PositiveReviews_i$) are all positive and significant (0.1747, $p < 0.01$; 0.1688, $p < 0.01$; 0.1684, $p < 0.01$).

Table 3 Estimation results

	Model 2	Model 3a	Model 3b	Model 3c	Model 4
$AveNeighborBookings_{it}$	0.0372**	0.0502*	0.0672***	0.0899***	−0.0846***
	(0.0148)	(0.0278)	(0.0246)	(0.0250)	(0.0100)
$AveNeighborBookings_{it}$ × $Similarity1_i$		-0.0487			
		(0.0956)			
$AveNeighborBookings_{it}$ × $Similarity2_i$			−0.1179*		
			(0.0711)		
$AveNeighborBookings_{it}$ × $Similarity3_i$				−0.1304***	
				(0.0328)	
$AveNeighborBookings_{it}$ × $PositiveReviews_i$					0.1717***
					(0.0203)
$RoomBookings_{it-1}$	0.1569***	0.1573***	0.1563***	0.1549***	0.1540***
	(0.0241)	(0.0241)	(0.0241)	(0.0238)	(0.0239)
$ReviewWords_{it-1}$	1.3E-04	1.3E-04	1.4E-04	1.4E-04	1.3E-04
	(3.4E-04)	(3.3E-04)	(3.4E-04)	(3.3E-04)	(3.3E-04)
$ReplyWords_{it-1}$	−5.1E-04	−5.1E-04	−5.1E-04	−5.0E-04	−5.1E-04
	(4.6E-04)	(4.6E-04)	(4.6E-04)	(4.7E-04)	(4.6E-04)
$ReplyNum_{it-1}$	0.1180***	0.1175***	0.1176***	0.1195***	0.1159***
	(0.0436)	(0.0436)	(0.0435)	(0.0432)	(0.0436)
Constant	0.5901***	0.5904***	0.5929***	0.5859***	0.5839***
	(0.0769)	(0.0769)	(0.0770)	(0.0769)	(0.0769)
Time fixed effect	Control	Control	Control	Control	Control
Room fixed effect	Control	Control	Control	Control	Control
Observations	19696	19696	19696	19696	19696
Within-R2	0.1754	0.1755	0.1760	0.1776	0.1804
Between-R2	0.5639	0.5629	0.5608	0.5640	0.5610
Overall-R2	0.2401	0.2402	0.2404	0.2441	0.2485
F	48.4800	46.8200	46.9500	47.5200	48.3500

Note: Cluster-robust standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

We also adopted the average number of bookings of neighboring rooms at time $t - 1$ as the instrument variable ($AveNeighborBookings_{it-1}$). We used it to check for potential endogeneity derived from unobserved or ignored factors. The results are presented in Table 5, showing that the coefficient of *AveNeighborBookings* is significant and positive (0.1023, $p < 0.01$). $AveNeighborBookings_{it-1}$ also passes the weak instrument test ($F = 1359.4870$). Lastly, to deal with the potential influence of place, we adopted the room address (located in the same building, street, or nearby street) to match the rooms in our main model with the rooms without any neighboring recommendations on the website. We obtained 486 groups of matched data samples. We compared the average number of bookings per month in our data sample with that in the sample of matched rooms between July 2017 and June 2019. The results show that the rooms with the neighboring recommendations have more room bookings than those rooms without neighboring recommendations in the same place (0.3922 vs. 0.2751, $T = 6.419$, $p < 0.01$). Moreover, to control the effects of other room attributes, we process the regression with the dependent variable of average

number of bookings per month; independent variable of whether the room has neighboring recommendations; and the control variables including price, district, promotion, number of customers, and ratio of positive customer review. The coefficient of whether the room has neighboring recommendations is positive and significant (0.0451, $p < 0.05$), indicating the existence of spillover effect after controlling other room attributes.

Table 4 Estimation results with replaceable moderators

	Model 3d	Model 3e	Model 3f	Model 3g	Model 4a	Model 4b	Model 4c
$AveNeighborBookings_{it}$	0.0525***	0.0731***	0.0919***	0.0901***	−0.0861***	−0.0833***	−0.0833***
	(0.0165)	(0.0234)	(0.0257)	(0.0249)	(0.0100)	(0.0100)	(0.0101)
$AveNeighborBookings_{it}$	−0.1374***						
$\times Similarity4_i$	(0.0234)						
$AveNeighborBookings_{it}$		−0.1338***					
$\times Similarity5_i$		(0.0515)					
$AveNeighborBookings_{it}$			−0.1322***				
$\times Similarity6_i$			(0.0338)				
$AveNeighborBookings_{it}$				−0.1313***			
$\times Similarity7_i$				(0.0326)			
$AveNeighborBookings_{it}$					0.1747***		
$\times PositiveReviews1_i$					(0.0208)		
$AveNeighborBookings_{it}$						0.1688***	
$\times PositiveReviews2_i$						(0.0201)	
$AveNeighborBookings_{it}$							0.1684***
$\times PositiveReviews3_i$							(0.0199)
$RoomBookings_{it-1}$	0.1563***	0.1561***	0.1548***	0.1549***	0.1539***	0.1541***	0.1540***
	(0.0240)	(0.0239)	(0.0238)	(0.0238)	(0.0239)	(0.0239)	(0.0239)
$ReviewWords_{it-1}$	1.4E-04	1.4E-04	1.3E-04	1.4E-04	1.3E-04	1.3E-04	1.3E-04
	(3.3E-04)	(3.4E-04)	(3.3E-04)	(3.3E-04)	(3.3E-04)	(3.3E-04)	(3.3E-04)
$ReplyWords_{it-1}$	−4.9E-04	−5.0E-04	−5.0E-04	−5.0E-04	−5.1E-04	−5.1E-04	−5.1E-04
	(4.6E-04)	(4.6E-04)	(4.6E-04)	(4.7E-04)	(4.6E-04)	(4.6E-04)	(4.6E-04)
$ReplyNum_{it-1}$	0.1163***	0.1172***	0.1195***	0.1195***	0.1159***	0.1159***	0.1160***
	(0.0436)	(0.0435)	(0.0432)	(0.0432)	(0.0436)	(0.0436)	(0.0436)
Constant	0.5948***	0.5966***	0.5864***	0.5858***	0.5836***	0.5838***	0.5838***
	(0.0770)	(0.0772)	(0.0769)	(0.0769)	(0.0769)	(0.0770)	(0.0769)
Time fixed effect	Control	Control	Control	Control	Control	Control	Control
Room fixed effect	Control	Control	Control	Control	Control	Control	Control
Observations	19696	19696	19696	19696	19696	19696	19696
Within-R2	0.1769	0.1763	0.1776	0.1777	0.1805	0.1803	0.1803
Between-R2	0.5647	0.5601	0.5641	0.5639	0.5609	0.5610	0.5612
Overall-R2	0.2427	0.2408	0.2441	0.2441	0.2487	0.2484	0.2484
F	47.4400	46.9300	47.5400	47.5000	48.4200	48.3300	48.3200

Note: Cluster-robust standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 5 Estimation results of the 2SLS regression with the instrument variables

	$RoomBookings_{it}$		$AveNeighborBookings_{it}$
$AveNeighborBookings_{it}$	0.1023***	$AveNeighborBookings_{it-1}$	0.2445***
	(0.0303)		(0.0066)
$RoomBookings_{it-1}$	0.1577***	$RoomBookings_{it-1}$	0.0329***
	(0.0109)		(0.0096)
$ReviewWords_{it-1}$	9.2E-05	$ReviewWords_{it-1}$	−2.0E-04*
	(1.3E-04)		(1.2E-04)
$ReplyWords_{it-1}$	−4.1E-04*	$ReplyWords_{it-1}$	−1.7E-04
	(2.0E-04)		(1.8E-04)
$ReplyNum_{it-1}$	0.1242***	$ReplyNum_{it-1}$	−0.0084
	(0.0166)		(0.0148)
Constant	0.5381***	*Constant*	0.5521***
	(0.0541)		(0.0431)
Time fixed effect	Control	*Time fixed effect*	Control
Room fixed effect	Control	*Room fixed effect*	Control
Observations	19145	*Observations*	19145
Within-R2	0.1733	*Within-R2*	0.2318
Between-R2	0.5562	*Between-R2*	0.6215
Overall-R2	0.2382	*Overall-R2*	0.3016
Wald chi2	6603.2700	*F*	195.5200
Weak identification test (Cragg–Donald Wald F statistics)			1359.4870

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

4. Conclusion and Implications

Using a sample of nearly 20,000 observations collected from Mayi.com, we conducted fixed effect regressions and 2SLS regression with the instrument variables and obtained the following three key findings. First, the booking number of the recommended room increases with the increase in the booking number of targeted neighboring rooms. While prior research noted a positive role of personalized recommendations in making online platforms more attractive (Assiouras et al., 2019), this study further finds that personalized recommendations can also benefit room hosts when the neighboring rooms that could have been browsed and targeted by customers at the booking process have a large number of bookings. This benefit may arise because of a spillover effect. Although the spillover effect has been investigated in the accommodation industry (Yang & Mao, 2020; Song et al., 2020), this study explores how spillover effects may occur with the particular design of recommended neighboring rooms. Second, the similarity between the recommended room and its neighboring rooms that are targeted by customers further strengthens the spillover effect. Third, the quality of the recommended room plays a positive role in the spillover effect. Identifying the effect of room similarity and quality can complement the existing literature regarding the boundary conditions of the spillover effect.

The above findings provide theoretical implications that contribute to the literature on spillover effects. Existing studies mostly addressed the spatial spillover effect from a geographic perspective (Yang & Mao, 2020; Song et al., 2020). Our research enriches the understanding of spillover effects by identifying how the booking of a targeted room noticed at the booking stage could stimulate the

booking of a recommended room on the basis of recommendation design on a room-sharing platform. This novel perspective may add value to the existing spillover effect literature. Moreover, our findings yield implications for hosts and online digital management by room-sharing platforms. Positive spillover effects can motivate hosts who run neighboring rooms to cooperate and retain travelers within a specific geographic area. Once a targeted room draws travelers' attention, hosts' rooms with neighboring locations that are recommended may have a higher chance to be noticed and booked. The findings also suggest that room quality plays a determinant role in the spillover effect as rooms with good quality are likely to benefit from bookings of targeted neighboring rooms. Thus, hosts should put extra effort into increasing room quality through improved amenities or welcoming services. Our findings also offer implications for platform managers concerning online digital management. As travelers show an inclination toward rooms with high similarity in aspects, such as room size, platform operators can increase technological budgets to optimize the recommendation systems where travelers can find appropriate rooms more efficiently and show more loyalty to the platform. Finally, our findings highlight the importance of focusing on recommendation systems for other digital marketing platforms. The spillover effect is a broad concept that can happen in several contexts even without considering the spatial features.

This study also has some limitations. First, we collected our data only from the platform of Mayi.com and the city of Shenzhen. Future research can extend the analysis to other platforms and cities to validate our results and test the effect of other factors, such as trip purpose. For example, cities with beaches may appeal more to leisure travelers than business travelers, and their different preferences may influence the spillover effect. Second, we used the ratio of positive reviews of a recommended room to measure room quality. Follow-up studies may use a text-mining approach for travelers' evaluations and subsequently obtain other objective indicators for room quality.

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