

List One or List More:

Incentives of Host Expansion in Peer-to-peer Accommodation Sharing Services

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Abstract

Despite the prevalence of peer-to-peer accommodation-sharing platforms, what incentivizes individual hosts to expand their listings on platforms such as Airbnb remains unknown. This study investigates the economic/financial, social, and community incentive of hosts to expand listings and the interplay among these incentives in driving the listing expansion. Using large-scale but granular field data collected from an emerging accommodation-sharing platform in Beijing, China, we found that economic/financial, social, and community incentives significantly affect listing expansion in accommodation-sharing services. In addition, while the economic/financial and social incentives jointly motivate hosts to expand, such effects are both mitigated as the hosts' experiences of accommodation sharing increases. This study adds to the extant literature a unique but less studied perspective of host expansion and provides important implications on incentivizing and regulating hosts for a healthy and viable accommodation sharing community.

Keywords: Peer-to-peer accommodation sharing, sharing economy, host expansion, host incentives, data analytics

INTRODUCTION

The expansion of the sharing economy, particularly peer-to-peer accommodation businesses, has drawn considerable attention from both the industry and academia (Botsman & Rogers, 2011; Colby & Bell, 2016; Parker, Alstyne, & Choudary, 2016; Wang & Nicolau, 2017; Wladawsky-Berger, 2016). A PricewaterhouseCoopers study estimated that peer-to-peer accommodation is among the five prominent sharing economy sectors in Europe that generated nearly €4 billion revenues combined and facilitated €28 billion of transactions in 2015, and these five sectors could generate \$335 billion revenues globally by 2025 (Vaughan & Daverio, 2016). The success of the sharing accommodation businesses is attributed to many macro factors, such as the sluggish economy (Botsman & Rogers, 2011; Parker et al., 2016), a widespread adoption of technology, social networks and mobile devices (Guttentag, 2015; Parker et al., 2016; Zervas et al., 2015b; Hamari, Sjöklint, & Ukkonen, 2016), and increased awareness of community and trust among consumers. Among the most pronounced factors was arguably the 2008 financial crisis that led to a drastic shrink of people's income and wealth, and thus making the best use of their spare resources became critical for hosts.

While sharing accommodation businesses have been compared with traditional hotels in meeting people's accommodation needs (Nguyen, 2014; Pairolo, 2016; Zervas et al., 2015b; Zervas et al., 2016), they differ fundamentally in terms of how to grow and expand. Compared to hotels which increase supply through huge capital investment and various types of integrations, the supply of sharing accommodation relies on the listing behavior of numerous grassroots hosts with a vast geographical reach (Parker et al., 2016). Therefore, the expansion of sharing accommodation at the aggregate level is manifested by the incentives of a mass of individual hosts who are willing to list their properties on the accommodation platform in the first place. Because of the massive number of hosts, the expansion of the sharing accommodation does not follow a linear but exponential growth pattern, which traditional hotels are not able to match with. For instance, it is reported that an increase of 30,000 rooms would take an international hotel giant one year, but only two weeks for Airbnb to reach the same capacity of supply (Capizzani, Kim, & Obersiebnig, 2015).

The past decade has seen a growing body of research from a wide range of disciplines attempting to understand the supply and demand of various sharing businesses (Edelman & Luca, 2014; Edelman, Luca, & Svirsky, 2015; Guttentag, 2015; Ikkala & Lampinen, 2015; Pairolo, 2016; Parker et al., 2016; Quattrone et al., 2016). Despite the pivotal role that hosts play in propelling the supply of the sharing accommodation, little research has yet done to focus on host behavior in peer-to-peer accommodation.

The literature also lacks empirical evidence to corroborate a few arguments in previous research particularly regarding what drives hosts to engage in sharing accommodation businesses and spur interactions with customers on the sharing platforms (Ikkala, 2014; Ikkala & Lampinen, 2015; Zervas et al., 2015a). We aim to adopt a data analytics approach to examining host expansion in peer-to-peer accommodation sharing. Our research question is twofold. First, what are the effects of a wide range of incentives, such as monetary returns and social incentives, on hosts' listing expansion? Second, how are these benefits interacted with each other to determine the listing expansion of hosts?

LITERATURE REVIEW

Sharing Accommodation Expansion and Financial Incentives

The practices of sharing resources have long been documented prior to the widespread use of the Internet (Botsman & Rogers, 2011). Yet the advent of the sharing economy featured by people listing their spare resources on online platforms is attributed to the economic benefits that sharing can bring about to users in difficult economic times (Botsman & Rogers, 2011; Montgomery et al., 2015). The quest for financial incentives was accelerated in the aftermath of the 2008 financial crisis, which deteriorated economic situations of many households. Soared unemployment rates and a drastic shrink of income forced people to make alternative use of their spare resources, particularly houses and apartments, to offset the economic losses (Montgomery et al., 2015). Instead of renting a house on a long-term basis in the real estate market, people choose either to rent out their temporarily unused houses or even to replace their long-term rentals with several short-term rentals to accommodate tourists (Jefferson-Jones, 2015; Litvak, 2016; Pairolo, 2016). According to Jefferson-Jones (2015), such short-term rental rearrangements help preserve property values through generating additional income to homeowners, which can be used to offset mortgage and maintenance costs.

Monetary Returns and the Expansion of Sharing Accommodation

The concept of monetary network hospitality suggests the motivation of hosts to list their properties is to obtain monetary benefits through harnessing the network effects generated by these platforms (Ikkala, 2014; Ikkala & Lampinen, 2015; Jung et al., 2016). Hosts are willing to engage in such sharing accommodation businesses because they are able to recoup monetary benefits by utilizing sharing platforms (Ikkala, 2014; Ikkala & Lampinen, 2015). Due to technology advancement, hosts can easily match their properties and consumers, and turn these relationships into economic benefits (Botsman &

Rogers, 2011; Parker et al., 2016). Research on the effect of online rating found that Airbnb hosts with high ratings from guests can charge higher prices for their listings, which ultimately contribute to better financial performance of their listings. For instance, studies have shown that Airbnb can charge higher price premiums than hotels when their listings are highly rated by guests (Zervas et al., 2015a).

Empirical studies have also shown that engaging in sharing accommodation can be more profitable than traditional hotel and real estate businesses. For instance, Zervas et al. (2016) found that Airbnb in Austin drove down the revenues of hotels by 8–10% on average, particularly low-priced hotels and those not catering to business travelers. Zervas et al. (2016) found that by using what is called supply to scale, a differentiating feature of peer-to-peer platforms, Airbnb significantly stunted the hotel industry's ability to raise prices in peak demand period. In the real estate market, Jefferson-Jones (2015) argues that despite short-term housing prohibitions in many countries, Airbnb-based transactions can actually help preserve property values by providing income to homeowners. Thus, the economic burdens of the ownership can be shared between owners and users on a temporary and continuous basis (Jefferson-Jones, 2015).

Social Benefits, Monetary Returns, and the Expansion of Sharing Accommodation

A lot of studies have underscored the role of social interactions in motivating hosts to engage in sharing accommodation businesses (Ert et al., 2016; Ikkala, 2014; Ikkala & Lampinen, 2015; Jefferson-Jones, 2016; Lee et al., 2015; Zervas et al., 2015a). Ikkala's (2014) interview with Airbnb hosts in Greater Helsinki area, Finland revealed that engaging in social interactions with guests remains one of the pivotal motivations for hosts to participate in sharing accommodation businesses. These social benefits would not only affect guests in meeting their needs but also motivate hosts to engage in short-term instead of long-term rentals. Given the importance of social benefits, hosts who are willing to accumulate more social benefits would not only choose to participate in sharing accommodation businesses but also are more likely to expand its listings provided they have spare houses or properties.

A line of research on online rating systems implies that social benefits can motivate hosts to be more involved in sharing businesses (Ikkala, 2014; Ikkala & Lampinen, 2014, 2015). Social benefits derived from higher ratings, for example, can be translated into economic benefits for hosts, thereby contributing to the expansion of Airbnb listings (Ikkala & Lampinen, 2015). Ikkala and Lampinen's (2015) study suggested that monetary benefits are critical for sharing accommodation businesses to function because these benefits can encourage hosts continuously devote efforts to achieving desired sociability through selecting their preferred guests and controlling demand volume and type. Ikkala and Lampinen's (2014)

study also showed that some hosts intentionally price their properties lower than the market price to enlarge their consumer base, thereby increasing the probability of zeroing in on their preferred exchange partners. In this case, social benefits derived from a larger consumer bases overweigh monetary gains by charging higher prices. Ikkala (2014) emphasized that it is money obtained by hosts that lays a foundation to trigger, rather than impede, social interactions.

Host Characteristics and the Expansion of Sharing Accommodation

Previous research has suggested that a wide range of host characteristics, such as race, can affect the operation of sharing accommodation businesses, particularly pricing behavior (Edelman & Luca, 2014; Ikkala & Lampinen, 2015; Kakar et al., 2016; Lee et al., 2015). Kakar et al. (2016) found in San Francisco that white hosts have a nearly 10% higher listing price on average than that of their Hispanic and Asian counterparts after controlling for the effects of other factors. Similar results were documented in New York City, where non-black hosts charge approximately 12% more than black hosts for equivalent rentals (Edelman & Luca, 2014). Li et al. (2015) argues that hosts are less likely to change room rates when the demand suddenly changes during major holidays and conventions, resulting in lower daily revenues and occupancy rates, as well as a higher chance of exiting the market. This argument was supported by Hill's (2015) focus group observation, where hosts normally were stumped when setting a price for their listings due to a lack of relevant knowledge and expertise.

While previous research has attributed hosts' participation in sharing accommodation to financial gains and social benefits (Botsman & Rogers, 2011; Guttentag, 2015; Ikkala, 2014; Ikkala & Lampinen, 2015; Jefferson-Jones, 2016; Montgomery et al., 2015), there is a lack of empirical evidence to corroborate these arguments. Research on host behavior so far has centered on pricing behavior, race discrimination, and their choice between long-term and short-term rental arrangements (Edelman & Luca, 2014; Hill, 2015; Jefferson-Jones, 2015; Kakar et al., 2016; Wang & Nicolau, 2017). There is no empirical research on what makes new entrants choose to list their properties in the first place and, for incumbent hosts, what determines their decision of listing one property versus many on the sharing platform. Given the growth of professional hosts and multiple listings on the platform (Slee, 2016), understanding multiple listing behavior can not only help understand the tradeoff of listing one versus many but also help articulate the underlying reasons of the expansion of sharing accommodation.

METHODOLOGY

Data and Measures

We used a Python¹-enabled software procedure to scrape publicly available information from Xiaozhu (xiao-zhu.com). Established in August 2008, Xiaozhu is a leading peer-to-peer accommodation platform in China. As of March 2017, Xiaozhu offers 80,000 listings in more than 250 domestic destinations of China (Xiaozhu, 2017). Xiaozhu displays a unique host profile page in which we can observe the release date of each listing managed by a host as well as the host characteristics (Figure 1). By collecting the release date information of listings managed by each host, we were able to track the expansion activities of the host over time. We focused on hosts who had more than one listing (i.e., hosts with listing expansion activities) upon the data collection of this study in Beijing, the largest peer-to-peer accommodation market in China. Our sample includes 3,199 observations of 815 listings managed by 252 multi-listing hosts from September 2012 to October 2016 (49 months). Our unit of analysis is host-month.

Figure 1

Table 1 presents the variable definition and summary statistics. Our dependent variable is *NumExpand*, which measures the number of listings that a host has expanded and is a function of host incentives to expand, including *EcoIncent*, *SocIncent*, and *ComIncent*. Specifically, *EcoIncent* measures the economic gains from listing investment indicated by the cumulative number of transactions that a host has gained in peer-to-peer accommodation sharing; *SocIncent* measures the online social interactions of a host being actively replying to the renter reviews online in the peer-to-peer accommodation sharing community; and *ComIncent* measures the length of membership of a host since he/she joins the peer-to-peer accommodation sharing platform. We also control the host characteristics that would influence the listing expansion of a host, including *ReplyRate*, *ConfirmTime*, *AcceptRate*, *CreditScore*, *Gender*, *Age*, *Education*, and *Employment*. Table 2 presents the Pearson correlation coefficients which measure the linear dependence between each pair of two independent variables. The values of correlation among these variables are below 0.8 (Katz, 2006), indicating that our estimation is unlikely to be biased by collinearity.

Table 1

Table 2

¹ Python is a widely used high-level programming language for general-purpose programming. It is usually used as a powerful tool for web scraping, often called web crawling or web spidering, to programmatically go over a collection of web pages and extract data.

Figure 1 presents the distributions of listings per host. Nearly half of the hosts (49.55%) were single-listing hosts without expansion. The remaining hosts (50.45%) were multi-listing hosts who had expanded on the sharing platform with more than one listing. In particular, we observed a long tail in the distribution of the hosts. A large number of listings (6–10 listings) managed by the hosts occurred far from the center of the distribution, with a slight jump in the number of hosts who managed 9 listings (1.09%) and 10 listings (1.91%).

Figure 2

Model Specifications

For each host i in month t , we model the accumulative listings he/she has expanded on the peer-to-peer accommodation sharing platform ($NumExpand$) as a function of his/her economic, social, and community incentives ($EcoIncent$, $SocIncent$, and $ComIncent$) as well as a wide range of host characteristics. The resulting equation is

$$NumExpand_{it} = \alpha + \delta' INCENTIVE_{it-1} + \gamma' HOST_i + \varepsilon_{it}, \quad (1)$$

where $INCENTIVE_{it-1}$ is a vector of covariates representing the economic, social, and community incentives and their interaction terms. We use the lagged rather than contemporaneous incentive variables for two reasons. First, investigating the lagged effects mitigates the endogeneity issue caused by the potential reverse causality between host incentives and listing expansion if both variables estimated in the same period. Second, estimating the lagged effects of host incentives on listing expansion in the subsequent month is appropriate because the estimation uses the most relevant and recent information about the hosts in last month. We are interested in estimating the parameter, δ' , which measures the effects of three incentives and their three interaction terms on hosts' listing expansion. Besides the primary variables, we use a vector, $HOST_i$ to represent the host characteristics controls, including *ReplyRate*, *ConfirmTime*, *AcceptRate*, *CreditScore*, *Gender*, *Age*, *Education*, and *Employment*. The parameter, γ , measures the effects of these controls on the listing expansion of a host. ε_{ijt} is random errors.

Analytical Procedure

We test the listing expansion model in Table 3. We use a hierarchical and stepwise estimation approach through which the host characteristics controls, the primary incentive variables (economic, social, and community), and the interactions of the incentive variables are included sequentially in the multiple regression models (Models 1–3). The hierarchical and stepwise approach enables us to observe the increased expansionary power of each model to listing expansion, the outcome variable. For each model, we use a blend of econometric estimations with error specifications to cross-validate the robustness of the estimated effects. Specifically, we implement the estimation with standard errors in Column (a), followed by the estimations with the robust standard errors in Column (b) and the robust standard errors clustered at the host level in Column (c). Robust standard errors clustered at the host level are used to reduce heteroscedasticity concerns (Greenwood & Wattal, 2015).

RESULTS AND DISCUSSION

Effects of Host Characteristics on Listing Expansion

Model 1a presents the estimations of the effects of host controls on listing expansion (Table 3). The model explained 38.4% of the variance in listing expansions, indicating that the listing expansion can be attributed to host characteristics. In particular, we found that age and education were statistically significant in explaining hosts' listing behavior. Younger hosts were more likely to expand this listings and their expanding behavior tended to be gradually reinforced especially for those who were born between 1960 and 1969 (0.752*), 1970 and 1979 (1.080**), and 1980 and 1989 (1.619***). Those born between 1990 and 1999 was among the youngest, also having strikingly high listing expansion activities (1.222***). This might be because a majority of the hosts were the millennials whose behavior has largely been shaped by the Internet and ecommerce. In addition, it is intriguing that hosts who obtained high-school education outperformed those with bachelor degrees (the base group) in listing expansion (1.784***). We also found that hosts' behavioral characteristics, such as their reply rates and credits, affected their listing expansion behavior.

Table 3

We did not find evidence for the effects of gender and employment on listing expansion. We argue that the relationship between unemployment and listing expansion might be a context-specific issue. Since Xiaozhu was founded almost five years after the 2008 financial crisis, whether or not to list properties may not be seen as an alternative by Chinese hosts to tackle unemployment as it was for Airbnb and Uber

in 2008 and 2009. Also, since the Chinese economy was not affected by the financial crisis as much as the US and European economies, participating in sharing economy may not be seen by Chinese hosts as a solution to combat their deteriorated economic conditions.

Effects of Economic, Social, and Community Incentives on Listing Expansion

After controlling for the effects of host characteristics, we found that economic, social, and community incentives combined explained an additional 28.3% of variance in host listing expansion. This result suggests that listing expansion is driven by hosts' intention of acquiring economic, social and community benefits on the accommodation platform. Specifically, we found that economic incentive (0.002***), measured by the cumulative number of listing transactions received by a host in the previous month, positively affected the current listing expansion, indicating that listing expansion highly depends on the transaction volume in the preceding periods. While previous studies did not explicitly draw a linkage between economic benefits and listing expansion nor attempted to quantify such a positive relationship (Ikkala, 2014; Ikkala & Lampinen, 2015; Jung et al., 2016), our study showed that these benefits may not only encourage hosts to participate in sharing accommodation businesses in the first place as previous studies have suggested, but also reinforce their intentions to expand afterwards if they are able to fulfill sufficient transactions of after participation.

While social incentives, alongside economic benefits, have been underscored by previous studies in spurring the growth of sharing accommodation businesses (Ikkala, 2014; Ikkala & Lampinen, 2015; Jefferson-Jones, 2016), the positive effect of social incentive (0.135) on listing expansion was not supported by our study. We measured social incentives as the cumulative number of host replies divided by cumulative number of renter reviews in a given month to indicate not only the absolute number, but also the quality, of interactions between hosts and guests. This measurement implies that hosts need to devote a considerable amount of time to reviewing and responding to customer reviews in order to establish meaningful interactions. Thus, listing more properties means that it would become more difficult for a single host to establish these interactions. We conjecture that the desire to acquire social benefits through listing expansion can backfire, as it simultaneously decreases the effort and time required to establish social interactions for each single list.

We also found that the longer the hosts have operated on the sharing accommodation platform the more likely they would expand their listings. This result was verified by the positive relationship between community incentive (0.027***), measured by cumulative number of months elapsed since a host

registered the very first listing on xiaozhu.com in a given month, and hosts' likelihood of listing expansion. This result is comprehensible in two ways. First, it takes time for hosts to judge the success of its first or a previous listing before considering expansion, and therefore whether or not to expand their listings depends how long they have been operating on the sharing accommodation platform and how much experience they have accumulated. Second, for hosts, staying longer in the market suggests increased accumulation of economic benefits, which in turn drive hosts to expand their listings.

Interactions of Economic, Social, and Community Incentives on Listing Expansion

We further included the interaction terms of the three incentives into Model 3a, which explained a total of 73.6% of the variance in listing expansion, indicating the predictive power and validity of the model. The aforementioned effects estimated in Models 1a, 1b, and 1c were also in line with other two columns using different error specifications, indicating the robustness of the estimated effects. It is worth noting that social incentives were positively associated with listing expansion (0.181*) and such effect was magnified in conjunction with the economic incentive (-0.002*). This result shows that the return in listing investment and the social interactions with hosts jointly motivate a host to expand in peer-to-peer accommodation sharing. However, community incentives did not seem additive or complementary with economic incentives (-0.001***) and social incentives (-0.024*) in driving hosts' listing expansion. That is, as the membership and experience of a host with the peer-to-peer accommodation platform increase, the effects of economic and social incentives on listing expansion are mitigated.

CONCLUSION AND IMPLICATIONS

This study sheds light on the incentives of hosts to expand their listings in peer-to-peer accommodation-sharing services. The empirical findings show significant positive effects of economic/financial, social, and community incentives on listing expansion of the hosts. In addition, economic/financial and social incentives jointly motivate hosts to expand and scale their listings on the accommodation-sharing platform. However, as their membership or experience of accommodation-sharing increases, hosts are less likely to be incentivized by economic/financial and social incentives. The findings indicate that economic/financial, social, and community incentives may play important roles in the initial stage of host tenure with the peer-to-peer accommodation-sharing service. However, long-time hosts are less likely to expand more listings due to economic/financial and social incentives plausibly given personal constraints in time and energy of managing multiple listings.

Theoretical Implications

Research on the sharing economy has been largely devoted to examining the demand of sharing businesses. There is no exception in sharing accommodation research, where renters' motivations to use peer-to-peer sharing platforms have been exclusively studied (e.g., Tussyadiah, 2016; Tussyadiah & Pesonen, 2016ab; Tussyadiah & Zach, 2016). We contributed to the literature by evidencing the role of hosts in the expansion of sharing accommodation. While previous research has suggested that both economic and social benefits can explain the advent of the sharing economy as well as hosts' engagement in sharing accommodation businesses, most of the research was based on a couple of assumptions that are either qualitative or untestable (Botsman & Rogers, 2011; Ikkala, 2014; Ikkala & Lampinen, 2015). We advanced these studies by constructing a host behavioral model that examines whether and to what extent listing expansion can drive the growth of sharing accommodation at the aggregate level.

We also provided concrete empirical evidence for many arguments in explaining sharing economy. Current research mostly relied on customer intention-based survey data, without referring to actual activity or behavior data of hosts over time. We adopted a data analytics approach to mining actual host performance and expansion data that helped uncover hosts' expansion decisions. We also articulated the differences between engaging in sharing accommodation and list expansion. Previous qualitative research suggested that the advent of sharing economy might be a response of hosts to their deteriorated economic situations (Botsman & Rogers, 2011; Montgomery et al., 2015). Yet our study has shown that listing expansion is a behavioral indication of the economic benefits hosts have recouped in their sharing accommodation operations. This means that it is also possible to abandon sharing economy if hosts are not able to recoup sufficient economic or social benefits. Listing expansion can also be a forward-looking decision rather than an ex post response to unfavorable macroeconomic circumstances.

Practical Implications

This study reveals how the platforms, such as Airbnb and Xiaozhu, would incentive and motivate the hosts to scale the supply by actively expanding the listings. In particular, our findings suggest that platforms can provide host support such as facilitating the listing reservations and transaction process to increase the economic/financial return of the hosts on their listings. Furthermore, the platforms should continue to bridge the two-way communication between hosts and renters for effective online social interactions. Reward points or badges could be assigned to hosts who proactively reply to renters' reviews and address their concerns and complaints about the stay experience. Such rewarding practice would

motive the hosts to improve the service in peer-to-peer accommodation sharing by learning from the customer feedback as well as elevate the quality of the service providers in the peer-to-peer accommodation sharing community. Finally, host retention is important for the viability of the peer-to-peer accommodation sharing businesses, especially for those platforms such as Xiaozhu which is emerging and growing. Besides actively scaling the hosts and users to join the platforms, peer-to-peer accommodation sharing businesses should also engage hosts and minimize the dropout rates.

As city legislators and policy makers are debating how to regulate host expansion from one listing to multiple listings, this study suggests that the timing matters. Our study shows that hosts are less likely to be incentivized by economic/financial and social incentives to expand listings as their membership or experience of accommodation sharing increases. Thus, we would suggest the regulations such as “One Host, One Home,” a policy recently imposed by Airbnb to smoothen the relationship with legislators and policy makers in San Francisco and New York City (Kerr, 2017), should be effective if implemented in the initial stage of the host tenure. For hosts that have been in service of peer-to-peer accommodation sharing for a relatively long time, financial and social incentives are less likely to motivate hosts to expand any way. Relevant regulations or policies that discourage host expansion would want to pull plug on multi-listing hosts in the earlier stage, for example, at the time the host is registering with the platform and posting listings.

Limitations

First, there might be unobservable factors online that would affect host expansion. For example, the income and household demographics of the hosts are plausibly associated with the listing expansion of hosts. Future studies taking a survey approach would best capture such information from the hosts and thus can extend our current with more interesting findings. Second, hosts on peer-to-peer accommodation sharing platforms such as Airbnb reportedly have multiple fake accounts, one per listing (SubletSpy, 2016). If it is the case in the host data collected from Xiaozhu, we may be subject to the measurement errors. Future studies may need to address such data biases if investigating host-related activities in the peer-to-peer accommodation sharing platforms. Finally, this study is instantiated in a research context in Beijing, China. Although this study provides unique cross-cultural implications of peer-to-peer accommodation sharing from an emerging market, its findings may not be generalized to other markets.

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Table 1. Variable Definitions and Summary Statistics

Category	Variable	Definition	Mean	Std. Dev.	Min	Max
Dependent Variable	<i>NumExpand</i>	Cumulative number of listings expanded by a host in a given month	2.27	1.90	1	10
Host Incentives	<i>EcoIncent</i>	Cumulative number of listing transactions received by a host in a given month	84.34	171.75	0	1,954
	<i>SocIncent</i>	Cumulative number of host replies divided by cumulative number of renter reviews in a given month	0.96	0.41	0	6.33
	<i>ComIncent</i>	Cumulative number of months elapsed since a host registered the very first listing on xiaozhu.com in a given month	10.13	8.09	0	49
Host Controls	<i>ReplyRate</i>	Number of host replies divided by number of online inquiries in a given month	0.95	0.09	0	1
	<i>ConfirmTime</i>	Number of minutes it takes a host to confirm a reservation request in a given month	5.17	4.35	0	71
	<i>AcceptRate</i>	Number of accepted reservations divided by number of reservation requests in a given month	0.86	0.13	0	1
	<i>CreditScore</i>	Zhima Credit Scores ² issued by a third-party company to evaluate host credibility online, with the score ranging from 350 to 950	727.00	45.50	579	812
	<i>Gender</i>	Dummy variable of host gender, with values of 1= male and 0= female	0.45	0.50	0	1
	<i>Age</i>	Categorical variable of host age measured in years of ten, with values of 40=born between 1940 and 1949, 50=born between 1950 and 1959, 60=born between 1960 and 1969, 70= born between 1970 – 1979, 80=born between 1980 and 1989, and 90=born between 1990 and 1999	76.08	9.23	40	90
	<i>Education</i>	Categorical variable of the highest level of host education, with values of 1= junior high school, 2= high school, 3= secondary vocational school, 4= specialist college diploma, 5=university bachelor degree, 6= master degree, and 7=doctoral degree	5.76	1.12	1	7
	<i>Employment</i>	Categorical variable of the host occupation, with values of 1= employed in the technology industry , 2= employed in the hospitality industry, 3= employed in industries other than technology and hospitality, 4= self-employed in accommodation sharing business, and 5= self-employed in industries other than accommodation sharing business	1.07	1.45	1	5

Table 2. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) <i>EcoIncent</i>	1.00										
(2) <i>SocIncent</i>	0.02	1.00									
(3) <i>ComIncent</i>	0.39	-0.03	1.00								
(4) <i>Gender</i>	-0.05	-0.01	0.02	1.00							
(5) <i>Age</i>	0.10	-0.02	-0.06	0.02	1.00						
(6) <i>Education</i>	-0.06	0.14	-0.03	0.06	-0.22	1.00					
(7) <i>Employment</i>	0.00	0.10	-0.02	-0.05	0.04	0.07	1.00				
(8) <i>CreditScore</i>	0.05	-0.02	0.07	-0.06	0.12	-0.03	-0.11	1.00			
(9) <i>ReplyRate</i>	0.10	0.18	-0.06	-0.07	0.06	0.02	-0.04	0.15	1.00		
(10) <i>ConfirmTime</i>	-0.07	-0.18	-0.02	0.03	-0.03	0.02	0.07	-0.08	-0.42	1.00	
(11) <i>AcceptRate</i>	0.13	0.18	-0.02	-0.03	-0.08	-0.02	-0.17	0.02	0.60	-0.45	1.00

² Zhima Credit Scores are issued by a third-party company named Alibaba Group, the largest eCommerce company in China, as a measure of online users' credibility based on their activity data on the Internet. Zhima Credit Scores have been used widely in online marketplace of China. Source: <https://zmxy.antgroup.com/index.htm>

Table 3. Estimated Effects of Host Inventive on Listing Expansions

	<i>NumExpand</i>								
	Model 1			Model 2			Model 3		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
Primary Variables									
<i>EcoIncent</i>				0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.001)	0.008*** (0.000)	0.008*** (0.000)	0.008** (0.015)
<i>SocIncent</i>				0.135 (0.150)	0.135 (0.231)	0.135 (0.328)	0.181* (0.057)	0.181* (0.087)	0.181** (0.030)
<i>ComIncent</i>				0.027*** (0.000)	0.027*** (0.000)	0.027* (0.079)	0.041*** (0.001)	0.041** (0.034)	0.041** (0.027)
<i>EcoIncent</i> × <i>ComIncent</i>							-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.007)
<i>EcoIncent</i> × <i>SocIncent</i>							0.002* (0.088)	0.002** (0.014)	0.002* (0.051)
<i>SocIncent</i> × <i>ComIncent</i>							-0.024* (0.052)	-0.024** (0.021)	-0.024** (0.047)
Host Controls									
<i>Gender</i>	0.055 (0.780)	0.055 (0.714)	0.055 (0.180)	0.285* (0.092)	0.285** (0.022)	0.285*** (0.000)	0.108 (0.532)	0.108 (0.494)	0.108 (0.520)
<i>Age</i>									
<i>Born 1950 - 1959</i>	0.001 (0.453)	0.001 (0.400)	0.001 (0.479)	0.001 (0.312)	0.001 (0.334)	0.001 (0.330)	0.001 (0.733)	0.001 (0.740)	0.001 (0.797)
<i>Born 1960 - 1969</i>	0.752* (0.088)	0.752*** (0.000)	0.752 (0.140)	0.259 (0.467)	0.259** (0.049)	0.259 (0.459)	0.079 (0.816)	0.079 (0.563)	0.079 (0.797)
<i>Born 1970 - 1979</i>	1.080** (0.014)	1.080*** (0.000)	1.080** (0.039)	0.496 (0.160)	0.496*** (0.000)	0.496 (0.115)	0.240 (0.476)	0.240* (0.085)	0.240 (0.370)
<i>Born 1980 - 1989</i>	1.619*** (0.000)	1.619*** (0.000)	1.619*** (0.000)	0.725** (0.036)	0.725*** (0.000)	0.725*** (0.009)	0.487 (0.139)	0.487*** (0.000)	0.487* (0.050)
<i>Born 1990 - 1999</i>	1.222*** (0.006)	1.222*** (0.000)	1.222** (0.013)	0.584 (0.103)	0.584*** (0.000)	0.584 (0.129)	0.220 (0.521)	0.220 (0.186)	0.220 (0.568)
<i>Education</i>									
<i>Junior high school</i>	-0.251 (0.433)	-0.251 (0.246)	-0.251 (0.577)	-0.172 (0.504)	-0.172 (0.406)	-0.172 (0.688)	-0.152 (0.535)	-0.152 (0.459)	-0.152 (0.733)
<i>High school</i>	1.784*** (0.000)	1.784*** (0.000)	1.784** (0.021)	1.823*** (0.000)	1.823*** (0.000)	1.823*** (0.005)	1.809*** (0.000)	1.809*** (0.000)	1.809*** (0.000)
<i>Secondary vocational school</i>	-0.360 (0.245)	-0.360 (0.156)	-0.360 (0.543)	-0.144 (0.565)	-0.144 (0.441)	-0.144 (0.728)	-0.174 (0.465)	-0.174 (0.312)	-0.174 (0.644)
<i>Specialist college diploma</i>	0.165 (0.184)	0.165 (0.156)	0.165 (0.692)	-0.167* (0.100)	-0.167* (0.070)	-0.167 (0.496)	-0.295*** (0.003)	-0.295*** (0.001)	-0.295 (0.205)
<i>Master degree</i>	0.245	0.245* (0.000)	0.245	0.274** (0.000)	0.274*** (0.000)	0.274 (0.000)	0.184 (0.000)	0.184** (0.000)	0.184 (0.000)

	(0.101)	(0.085)	(0.601)	(0.024)	(0.007)	(0.341)	(0.111)	(0.050)	(0.432)
<i>Doctoral degree</i>	-0.844	-0.844***	-0.844**	-0.435	-0.435***	-0.435*	-0.255	-0.255**	-0.255
	(0.137)	(0.000)	(0.023)	(0.344)	(0.001)	(0.072)	(0.560)	(0.045)	(0.253)
<i>Employment</i>									
<i>Employed in the technology industry</i>	0.146	0.146	0.146	0.631	0.631**	0.631***	0.411	0.411	0.411*
	(0.779)	(0.577)	(0.461)	(0.157)	(0.013)	(0.002)	(0.335)	(0.102)	(0.091)
<i>Employed in the hospitality industry</i>	0.446	0.446	0.446**	0.630	0.630	0.630***	1.000**	1.000	1.000***
	(0.433)	(0.719)	(0.033)	(0.194)	(0.591)	(0.003)	(0.032)	(0.380)	(0.001)
<i>Employed in industries other than technology and hospitality</i>	-0.683	-0.683	-0.683***	-0.365	-0.365	-0.365**	-0.022	-0.022	-0.022
	(0.224)	(0.169)	(0.000)	(0.446)	(0.412)	(0.022)	(0.961)	(0.959)	(0.920)
<i>Self-employed in accommodation sharing business</i>	0.709	0.709**	0.709***	1.053***	1.053***	1.053***	0.604	0.604**	0.604***
	(0.133)	(0.037)	(0.000)	(0.009)	(0.000)	(0.000)	(0.118)	(0.016)	(0.003)
<i>CreditScore</i>	0.009**	0.009**	0.009***	0.012***	0.012***	0.012***	-0.010***	-0.010***	-0.010***
	(0.044)	(0.023)	(0.000)	(0.002)	(0.001)	(0.000)	(0.003)	(0.002)	(0.000)
<i>ReplyRate</i>	7.082***	7.082***	7.082***	6.632***	6.632***	6.632***	5.693***	5.693***	5.693***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
<i>ConfirmTime</i>	-0.085	-0.085***	-0.085***	-0.107*	-0.107***	-0.107***	-0.061	-0.061***	-0.061**
	(0.204)	(0.000)	(0.000)	(0.061)	(0.000)	(0.000)	(0.263)	(0.001)	(0.022)
<i>AcceptRate</i>	1.920	1.920***	1.920***	1.559	1.559***	1.559***	0.025	0.025	0.025
	(0.293)	(0.002)	(0.000)	(0.316)	(0.003)	(0.000)	(0.986)	(0.965)	(0.974)
<i>Constant</i>	-3.780	-3.780	-3.780**	-1.220	-1.220	-1.220	1.357	1.357	1.357
	(0.386)	(0.289)	(0.046)	(0.742)	(0.706)	(0.466)	(0.702)	(0.673)	(0.541)
Observations	3,199	3,199	3,199	3,199	3,199	3,199	3,199	3,199	3,199
R-squared	0.384	0.384	0.384	0.667	0.667	0.667	0.736	0.736	0.736
Mean VIF	4.47	4.47	4.47	5.04	5.04	5.04	6.43	6.43	6.43

p-value in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

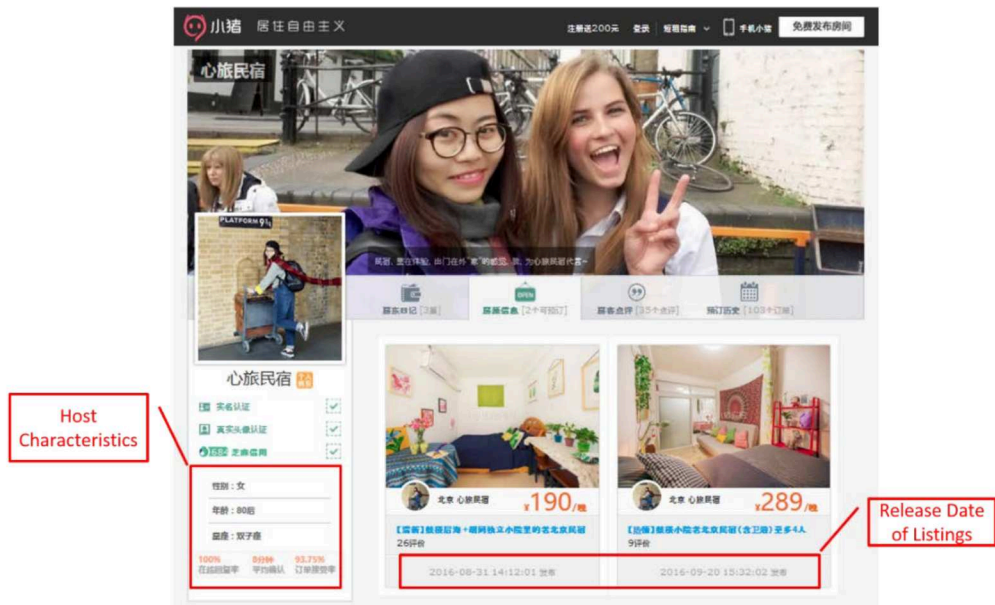


Figure 1. Example Host Profile Page with Release Date of Listings and Host Characteristics

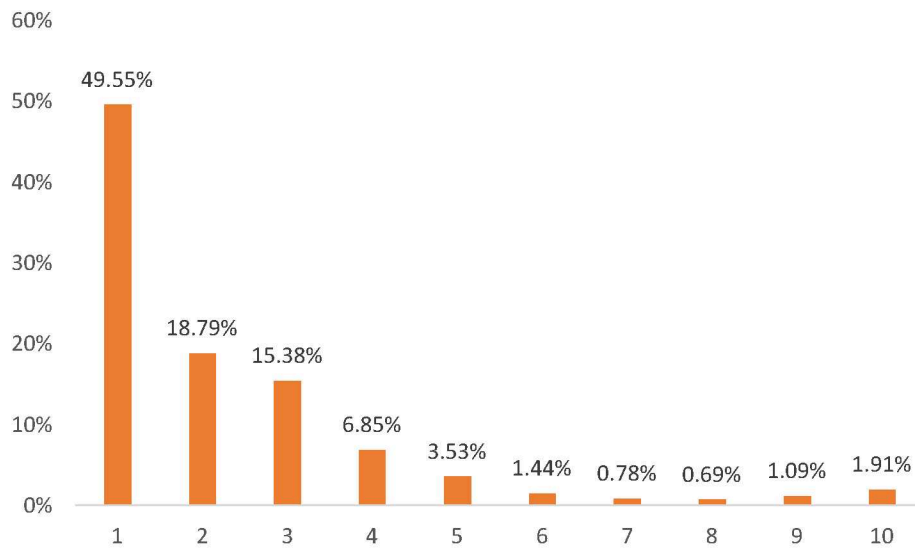


Figure 2. Distribution of Listings Per Host