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Effect of commercial neighbors on the online popularity of peer-to-peer accommodation sharing properties

1. Jianwei Liu
School of Management, Harbin Institute of Technology, No. 92 Xidazhi Street, Harbin, 150001, China. Email: jianweiliu@hit.edu.cn; Tel: 86-151-2457-2304

2. Jinah Park
School of Hotel and Tourism Management, The Hong Kong Polytechnic University, 17 Science Museum Road, TST East, Kowloon, Hong Kong SAR, China. Email: jinah.park@polyu.edu.hk

3. Karen Xie
Daniels College of Business, University of Denver, 2044 E Evans Avenue Suite 331, Denver, CO 80208 U.S.A. Email: Karen.Xie@du.edu; Tel: 1-303-871-4275

4. Haiyan Song
School of Hotel and Tourism Management, The Hong Kong Polytechnic University, 17 Science Museum Road, TST East, Kowloon, Hong Kong SAR, China. E-mail: haiyan.song@polyu.edu.hk

5. Wei Chen
Department of Management Information Systems, Eller College of Management, University of Arizona, Tucson, AZ 85721 U.S.A. Email: weichen@email.arizona.edu

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Effect of Commercial Neighbors on the Online Popularity of Peer-to-Peer Accommodation Sharing Properties

ABSTRACT

Commercial hosts are becoming increasingly common in peer-to-peer accommodation sharing, but the interplay between commercial and individual hosts is less identified. This study investigates the effect of properties managed by commercial hosts on the individual hosts in the neighborhood. Specifically, we hypothesize that an increase in commercial properties, which have competitive advantages, would penetrate neighborhood markets and cannibalize the online popularity of individual properties. We test these hypotheses using a large-scale and longitudinal dataset collected from a leading peer-to-peer accommodation sharing platform in Beijing. The findings show that an increase of commercial properties is associated with a decrease in the popularity of individual properties in the neighborhood. However, the negative effect of commercial properties is weakened where there is a higher price difference between two ownership types and a higher density of tourist attractions. The implications on service operations, pricing, and locational strategies for peer-to-peer accommodation sharing businesses are discussed.

KEYWORDS: peer-to-peer accommodation sharing; commercial property; individual property; online popularity of properties; China

INTRODUCTION

Internet services facilitate the sharing of information and goods. The tourism marketplace has been changed by the emergence of the sharing economy and collaborative consumption (Heo, 2016). Peer-to-peer (P2P) accommodation sharing services have accelerated market growth in tourism (Pizam, 2014) and cater to the specialized needs of travelers who seek authentic destination experiences that involve "living like a local" (Guttentag, 2015). The largest P2P accommodation sharing platform, Airbnb, has 4 million properties listed across 65,000 cities in 191 countries (Airbnb, 2017). P2P accommodation sharing has expanded to destinations around the world. For example, due to the rapid growth of China's travel market and the diverse needs of Chinese tourists, *Tujia*, China's largest P2P accommodation sharing website, had 600,000 properties across 345 Chinese domestic and 1,037 overseas destinations as of 2017 (Tujia, 2018).

Scholars and practitioners have observed an emerging trend of institutionalization on P2P accommodation sharing platforms (Adamiak, 2018; Hardy & Dolnicar, 2017), in which commercial hosts who operate multiple properties as business entities are growing, while the majority of the hosts are individuals making some extra income by renting out their spare space. Compared to properties shared with individual hosts, commercial properties focus on providing standardized, "cookie-cutter" services. These commercial properties may attract travelers who prefer professional services or prefer to stay alone rather than with their local hosts (Hardy & Dolnicar, 2017). A handful of studies have explored the pricing (Wang & Nicolau, 2017; Xie & Kwok, 2017) and location

(Abdar & Yen, 2017) strategies of commercial hosts. For example, commercial hosts tend to offer competitive lower prices and target popular tourist attractions for performance maximization, operating their business with multiple listings (Ke, 2017). In contrast, properties operated by individual hosts may not be systematically located near tourist attractions and in general have a wider range of prices at the hosts discretion.

Although both types of operation (and host) coexist in the P2P accommodation sharing market, empirical research investigating accommodation sharing hosts still lags in three critical aspects. First, despite the coexistence of commercial and individual hosts in the P2P accommodation sharing market, limited research sheds light on how these two types of host interplay and interact (competition or complementarity). Second, while research on the disruption of P2P sharing (e.g., Uber and Airbnb) to external incumbents that provide similar services (e.g., taxis, hotels, and long-term rentals) is widely published (e.g., Gutierrez, Garcia-Palomares, Romanillos, & Salas-Olmedo, 2017; Xie & Kwok, 2017; Zervas, Proserpoi, & Byers, 2017), the internal competition of players inside P2P accommodation sharing is less researched. If the interactions are competitive rather than complementary, it is worth investigating whether commercial hosts penetrate the performance share of individual hosts through pricing and location decisions. Lastly, most of the literature on P2P accommodation sharing focuses on Western destinations (e.g., Wang & Nicolau, 2017; Xie & Kwok, 2017; Chen & Xie, 2017); research on P2P accommodation sharing from an international perspective and a focus on emerging destinations is still lacking.

To bridge the research gaps, we investigate the effect of properties managed by commercial hosts (commercial properties thereafter) on the online popularity of properties operated by individual hosts (individual properties hereafter) using P2P

accommodation sharing data from China. Our research questions are: (1) What is the effect of commercial neighbors on the online popularity of individual properties? (2) How would such an effect change as the pricing difference between the commercial neighbors and an individual property increases? (3) Would such an effect become more salient as the density of tourist attractions in the neighborhood increases? We use online popularity, or online guest reviews, as a performance measure of P2P accommodation sharing properties because it reflects the volume of guest discussions (Chen & Xie, 2008; Duan, Gu, & Whinston, 2008), signals brand awareness of a product/service (Zhu & Zhang, 2010), and is directly related to the bottom line of business performance (Aria, 2015; Xie, Chen, & Wu, 2016). Our scope of observation is neighborhoods in which commercial and individual properties are co-located and concentrated for similar market demand. Contextualizing the research in China, an emerging tourist destination and a booming P2P accommodation sharing market, we find important implications to P2P accommodation sharing participants in international markets and provide a cross-cultural perspective to the P2P accommodation sharing literature.

LITERATURE REVIEW AND HYPOTHESES

P2P Accommodation Sharing: Competition and the Chinese Market

Along with considerable interests in the society and academia, sharing economy is encouraging a wide-ranging debate about its effects, business models and logics (Acquier, Daudigeos, & Pinkse, 2017). In tourism and hospitality, P2P accommodation sharing also generates disruptive changes in existing social and economic structures. These dynamics encompass the demand and supply sides

from travel experience and consumption, host-guest interaction (Belarmino, Whalen, Koh, & Bowen, 2019), and sustainability (Leung, Xue, & Wen, 2019) to industries, public policy and environment sectors (Fang, Ye, & Law, 2016; Dolnicar, 2019). However, as Köseoglu, Okumus, Putra, Yildiz, and Dogan, (2019) indicate that lodging-context studies have been focused on the hotel business, and it restricted more various viewpoints of lodging sectors. Similarly, numerous studies on P2P accommodation sharing also address the new entrants' effect on the hotel industry, rather than its internal structure or development.

Although P2P accommodation sharing has experienced rapid growth in recent years, research on commercial hosts remains sparse. We identify several research subjects in the literature, summarized in Table 1, and discuss how our study addresses recent research gaps. First, previous studies of P2P accommodation sharing have primarily examined its competition with external players such as hotels and rental markets, neglecting the competition among players within the P2P accommodation sharing sector. For example, numerous studies have identified Airbnb's negative impact on hotels (Aznar, Sayeras, Galiana, & Rocafort, 2016; Belarmino et al., 2019; Mody, Suess, & Lehto, 2017; Xie & Kwok, 2017; Zervas et al., 2017) and increasing pressures on destination regions (Gutierrez et al., 2017). Although Chandna and Salimath (2018) have shown that business models with different operational and value complexities exist on P2P online platforms, few studies have discussed the P2P accommodation sharing sector's internal relations, such as the different performance of professional versus non-professional hosts (Li, Moreno, & Zhang, 2016), and guests' evaluations of the different performance and features of these categories (Tussyadiah & Zach, 2017; Xie & Mao, 2017). This study segments the players (commercial hosts versus individual hosts) within the P2P accommodation sharing sector and investigates the potential

competition among commercial and individual properties in neighborhoods. The results provide new insights into the competition between the two types of host and their properties.

Second, although a few studies discuss the differences between commercial hosts and individual hosts, their effects on each other and the mechanisms of these effects are less explored. For example, Li et al. (2016) define professional hosts as hosts with two or more listings on Airbnb and find substantial discrepancies in the financial and operational performances of professional and non-professional hosts. Previous studies define professional hosts as multi-listing hosts who provide a more proficient and standardized service. Similarly, the number of listings owned by a host has been identified as a critical element of service quality (Xie & Mao, 2017). Ke (2017) compares the characteristics of different groups of "multi-listers" using threshold numbers of owned listings to define categories of hosts.

In terms of internal competition, we further address the players in the arena. Recently incumbent firms are being menaced by the entry of sharing economy, and they have pushed for regulations that stifle new entrants. As Rauch and Schleicher (2015) describe the regulation is the key issue in "sharing wars," and securing legitimacy, obviously, is what accommodation sharing should look for (Ozdemir & Turker, 2019). Unlike previous studies, this study uses the *Tujia* classifications and identifies commercial hosts as those with a business license. Commercial hosts may achieve market legitimacy and neutralize the concerns of unfair competition that some have raised to sharing economy. Our study examines the effect of commercial properties on individual properties and the mechanisms (such as pricing and location) underlying these effects. Thus, we contribute to the literature by not only revealing the effect of commercial properties on individual properties but also explaining the mechanisms that drive this effect.

Finally, previous studies of P2P accommodation sharing are primarily focused on the Western context (e.g., Airbnb). For example, studies have been conducted using data from mature European destinations (Gutierrez et al., 2017) and major US cities (Belarmino et al., 2019; Kakar, Franco, Voelz, & Wu, 2016). Despite the growth of travel in emerging destinations such as China (Park et al., 2016), our understanding of Chinese travelers' use of P2P accommodation sharing is limited due to the lack of research (Yang & Marquis, 2014). A handful of studies have focused on P2P accommodation sharing in China. For example, Xiang and Dolnicar (2017) study the concept and business model of P2P accommodation sharing platforms in China. Wu, Ma, and Xie (2017a) discuss how the hosts' attributes affect Chinese renters' trust and decision to stay in a stranger's place. Wu, Zeng, and Xie (2017b) examine Chinese travelers' behavioral intentions toward accommodation sharing platforms. Our study differs from these studies in that we collect data from *Tujia* to examine different types of host on a Chinese P2P accommodation sharing platform and their competition with each other. As an exploratory empirical study, the goal of this research is to develop an initial understanding of the managerial applications of P2P accommodation sharing services in China. The results of this study may also contribute to the expansion of a Chinese market that has been relatively ignored in recent academic studies.

[Insert Table 1 about here]

Effect of Host Heterogeneity

According to competitive advantage theory (Porter, 1985), the basic types of competitive advantage are cost leadership and differentiation. More recent studies of competitive advantage consider how various sources of competitive power (Black, Hashimzade,

& Myles, 2017) create economic and societal benefits (Porter & Kramer, 2011). Numerous studies in the field of service and marketing have explored the role of competitive advantage in the hospitality and tourism industry (Hahn, Sparks, Wilkins, & Jin, 2017; Kim & Oh, 2004; Preble, Reichel, & Hoffman, 2000).

Service quality is a differentiation strategy that enables a firm to obtain a competitive advantage over its rivals (Porter, 2011). For example, Bharadwaj, Varadarajan, and Fahy (1993) emphasize that businesses in the service industry build a reputation for service quality to achieve a differentiation advantage. As the labeling of sharing economy has been diversified from a social-oriented goal to a business model, quality control is a critical issue for sharing economy business model (Muñoz & Cohen, 2017). In our discussion, the differences between commercial and individual hosts can be seen in the positional and structural differences in their services, such as the advantages of standardized professional service versus authentic experience and deeper interaction. The quality of service is discussed from the following two perspectives.

First, compared to individual hosts, commercial hosts can provide a more standardized, consistent, and professional service, as established commercial providers tend to standardize their products and services (Dolnicar, 2017). By offering systematic service quality within legitimate commercial operations, commercial hosts, especially in *Tujia*, can eliminate inferior or inconsistent service and provide customers with a sense of certainty and value for money during their stay in commercial properties.

Second, commercial hosts with knowledge and professional abilities can enhance their competitive advantage over the regimented service and unified facilities of hotel firms. Compared to individual hosts, as discussed above, commercial properties are more professionally operated and more cost-effective, as most commercial hosts usually accumulate more than one listed property

(Hardy & Dolnicar, 2017). Previous studies in the business and service fields have proven that multi-unit firms are better equipped to achieve a competitive differentiation advantage over single-unit firms through the systematization and standardization of services (Bharadwaj et al., 1993). Similarly, commercial properties are more likely to obtain a "profitable and sustainable position" (Porter, 1985) within the P2P accommodation industry. As a differentiation factor, superior service quality can define the competitive advantage of commercial hosts. Therefore, we offer the following hypotheses:

Hypothesis 1_0 (Null): The proportion of commercial properties has no effect on the online popularity of properties for individual hosts in a neighborhood.

Hypothesis 1a (Alternative): As the proportion of commercial properties increases, the online popularity of properties for individual hosts in a neighborhood decreases.

Moderation Effect of Price and Location

Numerous studies have emphasized that price is a decisive element in service industries (Bharadwaj et al., 1993), especially in P2P accommodations (Li et al., 2016; Pappas, 2017; Wang & Nicolau, 2017; Xie & Kwok, 2017). According to Keaveney (1995), higher prices are one of the most critical motivations for customers' switching behaviors in the service industry. Customers compare competitors' prices in service industries (Chen, Gupta, & Rom, 1994), and price plays a moderating role in explaining customers' satisfaction and behaviors (Ryu & Han, 2010). Although the competitive strength of commercial hosts is very different from that of individual properties, a larger price difference weakens the advantage of commercial properties by minimizing the differentiation (i.e.,

service quality) of commercial hosts. In other words, a commercial supply threatens the online popularity of properties for neighboring service providers as long as the price positioning is similar. If the commercial hosts price their properties higher than the neighboring property, the threat is weakened, and customers are likely to switch from commercial properties to individual properties. Accordingly, we propose the following hypotheses.

Hypothesis 2_0 (Null): The effect of commercial properties on individual properties' online popularity will not be moderated by the price difference between them.

Hypothesis 2a (Alternative): The effect of commercial properties on individual properties' online popularity will be moderated by the price difference between them.

The location of the accommodation (distance to and density of tourist attractions) significantly affects customers' decision-making processes (Shoval, McKercher, Ng, & Birenboim, 2011). Location is a particularly valuable resource in the hotel and lodging sectors (Preble et al., 2000; Urtasun & Gutiérrez, 2006), as it is for the P2P accommodation sharing in terms of locational strategies (Xie & Mao, 2019). Tourists prefer accommodation that is near a variety of points of interest or attractions; specifically, they prefer centrally located areas (Fennell, 1996), downtowns, and airport strips (Wall, Dudycha, & Hutchinson, 1985). In the context of urban tourism, tourists select accommodation based on urban form and function in addition to distance to attractions (Wall et al., 1985).

As P2P accommodation sharing is associated with relatively scant tourism infrastructure and service facilities/amenities, location is vital for properties that are competing with hotels (Belarmino et al., 2019; Tussyadiah & Pesonen, 2016). For example, a high

density of attractions in a neighborhood increases the popularity of P2P accommodations (Gutierrez et al., 2017; Tussyadiah & Zach, 2017). Choosing accommodation near tourist attractions is an efficient way for tourists to save time and money.

A rational customer opts for the best service among the available choices. Tourists' willingness to increase expenditure for desired experiences is trending upward, and the effective expenditure of time and money at a destination is a critical issue for (rational) tourists. Thus, the location of accommodation, including the distance to and density of tourist attractions, plays a significant role in tourists' decision making (Shoval et al., 2011). An abundance of tourist attractions or interest points may appeal to various rational tourists, thus increasing the demand for accommodation. This increase in demand offers more opportunities for both commercial and individual hosts. Previous studies of accommodation selection (Aznar et al., 2016; Shoval et al., 2011) and tourist flow (Marrocu & Paci, 2013) have also identified that tourists are willing to pay for accommodations near attractions and tourist amenities.

For both time and monetary budgets (Sirakaya & Woodside, 2005), a property that is located in an area with a high density of tourist attractions is a competitive accommodation. Because it creates abundant demand and caters to a variety of preferences, a high density of tourist attractions inevitably moderates the impact of commercial supply on neighborhood properties and weakens the competitive relationship. Therefore, we propose the following hypotheses.

Hypothesis 3_0 (Null): The effect of commercial properties on individual properties' online popularity will not be moderated by the density of tourist attractions.

Hypothesis 3a (Alternative): The effect of commercial properties on individual properties' online popularity will be moderated by the density of tourist attractions.

This study draws out three hypotheses to explore how the supply of commercial properties in a certain area affects the individual properties' online popularity. Figure 1 presents the hypothesized relationships among the variables.

[Insert Figure 1 about here]

RESEARCH METHODS

Data Collection

Our data are primarily drawn from *Tujia* (www.tujia.com), a leading P2P accommodation sharing website in China. The properties on *Tujia* are owned and managed by both commercial and individual hosts. Commercial hosts have a business license, whereas individual hosts do not, allowing us to distinguish between the two types of host. Using a Python-based web crawler, we collected a dataset of 936 listings managed by 908 hosts near 933 tourist attractions in Beijing for the January 2013 to August 2017 period (56 months). As the capital city and the largest P2P accommodation sharing market in China, Beijing attracts more than 200 million visitors each year (Li et al., 2017), and the demand for P2P accommodation sharing is quite strong (Wu et al., 2017a). The longitudinal nature of the data allows us to construct a panel for econometric estimations in which we analyze each property by month. Figure 2 presents the distribution of the two types of property (commercial versus individual) during the study period. Overall, both

types of property have enjoyed continuous growth since January 2013. From December 2013 to late 2016, commercial properties showed a slightly higher growth ratio, but individual properties have greatly increased since late 2016.

[Insert Figure 2 about here]

Variables

Our research focuses on the effect of commercial properties on the online popularity of properties for individual hosts in the neighborhood. Our dependent variable is *Popularity*, measured by the volume of online reviews by verified customers for an individual accommodation sharing property in a given month (Moen, Havro, & Bjering, 2017; Xie et al., 2016). In e-commerce research, actual sales performance is not commonly available for empirical studies; therefore, most studies use online observational data (e.g., data collected from a website) to measure the popularity or performance of businesses. Marketing researchers have discussed the role of online reviews as a proxy for sales volume (Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010). In hospitality, the number of reviews is highly significant and has been proven to be closely associated with hotel or tourist attraction performance (Xie et al., 2016; Xie, Zhang, & Zhang, 2014; Yacouel & Fleischer, 2012). In particular, Liang, Schuckert, Law, and Chen (2017) and Ye, Law, and Gu (2009) have used online reviews as a proxy for sales in shared accommodations (e.g., Airbnb) and hotels, respectively. Customers tend to purchase products that have more online reviews because the products' quality has been experienced and evaluated by a large number of online peers (Godes & Mayzlin, 2004). On *Tujia*, customers can only post a review after completing their stay. Therefore, the online reviews reflect customers' post-purchase evaluation of a product or service (Moen et al., 2017). If we assume

that customers who have stayed at properties have a constant probability of posting reviews, the volume of online reviews should be a reasonable proxy for the online popularity of a property.

We define a 5 km radius around an individual property as its neighborhood, based on the urban design of Beijing (1,368 km^2) and tourists' urban mobility via public and alternative transportation (Xu et al., 2015; Zou, Yao, Zhao, Wei, & Ren, 2018). Although two similar studies of Barcelona (101.4 km^2) used a 1 km radius (Aznar et al., 2016; Gutierrez et al., 2017), we consider a 5 km radius more suitable for examining the spatial interactions (between accommodations and tourist attractions) and the competitive pressure from near substitutes of P2P accommodations in Beijing. Our independent variable, *ComRatio*, is the ratio of commercial properties (the number of commercial properties over the total number properties) in a 5 km radius of a given individual property in a given month. Instead of using an absolute number of commercial properties, we use the relative ratio of commercial properties to the total properties to avoid the bias created by comparisons without a reference point across neighborhoods.

Another research question is how different pricing and location strategies moderate the effect of commercial properties on the individual properties' online popularity. Our moderators include *PriceDiff* and *AttDen*. *PriceDiff* measures the pricing differentiation strategy by calculating the price difference between the average price of the commercial properties and the price of an individual property (Jayaswal & Jewkes, 2016). *AttDen* measures the location differentiation strategy by identifying different densities of tourist

attractions[1] (Vu, Li, Law, & Ye, 2015). By examining the moderation effects, we can evaluate the effect of heterogeneity in pricing and location.

We also control for the characteristics of the individual properties including *ListSupply*, *Room*, *Amenity*[2], *Age*, and *AveRating*. Although they are not our primary focus, these variables are likely to influence the online popularity of properties for individual hosts and are therefore included in the model. In addition, time trends and seasonality influence the online popularity of hospitality products (Chen, Li, Wu, & Shen, 2019; Zervas et al., 2017). We thus include monthly trend and seasonality fixed effects in our estimation. The former is a sequence of months (January 2013 to August 2017, a total of 56 months); the latter is a group of seasonality dummies.[3] Table 2 presents the definitions and statistics of the variables. The correlation matrix shown in Table 3 shows the results of a check for multicollinearity among the variables. As the correlation coefficients are all below 0.5, there is no collinear bias.

[Insert Table 2 and Table 3 about here]

Model Specification

[1] Tourist attractions are places of interest offering leisure and amusement that tourists visit, typically for their inherent or exhibited natural or cultural value, historical significance, or natural or built beauty. These attractions are recorded in a leading online travel agency website of China (Qunar.com).
[2] Amenity includes television, refrigerator, microwave oven, rice cooker, towel, slippers, washing machine, electric kettle, hanger, detergent, smart lock, air conditioner, induction cooker, tableware, WiFi, dental kit, cutter, body wash, heater, toilet paper, elevator, hot water, real shot by Tujia, bath towel, parcel collection, baggage deposit, free parking, and guards.
[3] Seasonality dummies denote whether a month is in spring (January–March), summer (April–June), fall (July–September), or winter (October–December).

To estimate the effect of commercial properties (*ComRatio*) on the online popularity of properties for an individual host (*Popularity*) and how this effect is moderated by pricing (*PriceDiff*) and location (*AttDen*), we construct a linear regression model in which the online popularity of an individual property *i* in month *t* is determined using the following function:

$$Popularity_{it} = \beta_0 + \beta_1 ComRatio_{it-1} + \beta_2 AttDen_{it-1} + \beta_3 PriceDiff_{it-1} + \beta_4 ComRatio_{it-1} \times AttDen_{it-1} + \beta_5\, ComRatio_{it-1} \times PriceDiff_{it-1} + \gamma' C_{it-1} + \theta' T_t + \varepsilon_{it} \quad (1)$$

where *Popularity* is the log transformation of the number of online guest reviews. *ComRatio* is the primary independent variable. *AttDen* and *PriceDiff* are the moderators. *C* is a vector of the covariates representing the control variables *ListSupply*, *Room*, *Amenity*, *Age*, and *AveRating*. *T* denotes a vector of monthly trend and seasonality dummies. ε is a random error.

To operationalize the estimation, we first include both moderation effects as the main estimation. To check the consistency of the estimated effects, we run separate models with each of the moderation effects. In this way, we validate the estimation consistency across models. For all of the model estimations, we use the OLS specification with robust standard errors clustered at the property level (Petersen, 2009).

DATA ANALYSIS AND RESULTS

Results

Table 4 presents the estimation results. The analysis of the time-related influences on accommodation products accounts for the monthly trend, seasonality, and both monthly trend and seasonality for each model estimation. Accordingly, Columns 1–3 are the estimation for the main model. Columns 4–6 are the estimation for Sub-model 1 (price difference moderation), and Columns 7–9 are the estimation for Sub-model 2 (density of tourist attractions moderation). For each model, we discuss the results in the first column, as the results of the other two estimations using different time specifications are similar.

In the main model, we find that *ComRatio* significantly affects the online popularity of a property for an individual host (-1.740**), supporting H1a, and the marginal negative effect is 6% in general which is calculated by the mean values of both moderators, according to Column 3. This result specifies the competitive effect of commercial properties on the individual properties' online popularity and confirms the competitive advantage of commercial hosts. As mentioned above, commercial hosts attain a competitive differentiation advantage by offering high-quality service; thus, a higher ratio of commercial properties has a negative effect on individual properties.

We explore two mechanisms that explain this effect by introducing two moderators. We find that as the price difference between commercial properties and an individual property increases, the effect of *ComRatio* on the online popularity of a property is weakened (0.229*). The negative effect of commercial properties on the online popularity of individual properties is moderated by price difference, supporting H2a. This result suggests that commercial properties' competitive differentiation advantage based on quality service decreases if their price is higher than the price of the individual property. This result supports previous studies showing the

salient influence of price on business competitiveness (Chen et al., 1994; Ryu & Han, 2010; Wang & Nicolau, 2017) and convincingly demonstrates the applicability of this insight to micro-entrepreneurs in the P2P accommodation industry.

Similarly, the effect of *ComRatio* on the online popularity of a property is attenuated if the density of tourist attractions is higher (0.022**). The density of tourist attractions moderates the relationship between commercial and individual properties, thus supporting H3a. This finding illustrates the competitive clusters of tourist attractions and the rational tourists' decision-making processes. In other words, rational tourists prefer accommodation sites close to many attractions, and this increased market demand provides more business opportunities for both commercial and individual hosts. As the pie is bigger in an area with a high density of tourist attractions, the effect of commercial properties on individual properties is diluted by abundant demand and a variety of preferences.

[Insert Table 4 about here]

Robustness Checks

One concern in our estimation is that the individual properties' online popularity may be underestimated by the volume of online reviews, as online reviews are primarily written by consumers who have polarized experiences (either terrible or excellent); customers with neutral experiences tend not to write reviews. This polarized distribution of online review valence is the so-called "J-shaped" reviews effect (Hu, Pavlou, & Zhang, 2007). As the missing neutral reviews are not accounted for in measurements of the online popularity of a property based on online review volume, our estimation may be biased. Therefore, we create an alternative online popularity measure, *Scaled Popularity*, which is weighted by review valence (terrible or 1 star to excellent or 5 stars) as below:

$$Scaled\ Popularity = R \times \frac{S}{5} \quad (2)$$

where R is the volume of online reviews for an individual property in a given month and S is the rating of every online review for an individual property (with values of 1 being terrible and 5 being excellent). By assigning the volume of online reviews a weight (i.e., S/5), we are able to adjust the review volume for low-rated properties, which may have a higher volume of reviews because people are more likely to write critical reviews. Table 5 presents the estimation results, which serve as the robustness checks for the main models. The estimated effects are consistent with the ones reported in Table 4, lending supporting to the robustness of the results.

[Insert Table 5 about here]

CONCLUSION, IMPLICATIONS AND FUTURE LINES

Limitations and Future Directions

Several limitations to this research need to be acknowledged. First, the dataset represents the P2P accommodation sharing market in Beijing. The competitive advantage of commercial properties may differ in terms of geographic, economic, and cultural conditions. Therefore, the findings of this study may not be generalizable to other cities in China or the world. Future studies may expand the research to other cities. Second, we only explore the moderation effects of commercial properties' proliferation on the popularity of individual ones from two aspects including pricing and location differences in this study. However, there're still many other possible internal factors such as management style, scale of operation, characteristics of hosts, etc. We hope this paper will stimulate scholarly interest in P2P accommodation sharing to replicate our findings as well as explore many other angles. Finally,

some external variables that may affect the online popularity of a property have not been included in this study due to the unavailability of data. For example, the number of hotels is an important variable in accommodation supply and might have an impact on the online popularity of accommodation sharing (Zervas et al., 2017). With a broader dataset, future studies could examine in more detail the different competitive effects of hotels and commercial hosts on shared accommodations. We encourage future scholars to collect more generalizable and comprehensive data to cross-validate the estimated effects of commercial properties in the P2P accommodation sharing market.

Theoretical Implications

This study adds to the emerging literature on the P2P accommodation sharing economy. First, this study identifies an evolving institutionalized practice in P2P accommodation sharing: commercial hosts managing multiple properties as a single business entity that has the competitive advantage of high service quality. Despite the prevalence of commercial hosts, previous studies of P2P accommodation sharing have primarily focused on the competition between P2P accommodation sharing businesses and external hospitality players such as hotels (Aznar et al., 2016; Belarmino et al., 2019; Mody et al., 2017; Xie & Kwok, 2017; Zervas et al., 2017). Our study concentrates on internal competition within P2P accommodation sharing.

Second, the differentiation strategy of heterogeneous service providers within P2P accommodation sharing and their competitions are proved. The results demonstrate that the online popularity of properties for individual hosts is negatively affected by neighboring commercial hosts, but this effect is moderated by price and location. Specifically, price difference and density of tourist attractions

attenuate the negative effect of commercial neighbors. This finding is in accordance with previous studies that indicate the role of price and location in consumers' decision making on P2P accommodation sharing (Shoval et al., 2011; Wang & Nicolau, 2017). These findings not only provide a better understanding of the competitive advantages of commercial properties but also explain the heterogeneity of this effect in different pricing and location scenarios. Specifically, as price differences and density of tourist attractions increase, the negative effect of commercial hosts on individual hosts is weakened. Thus, we not only extend the differentiation strategy into the P2P accommodation sharing context but also explain the competitive advantages and the mechanisms (i.e., pricing and location) through which they work. Our findings can inspire future research exploring commercial hosts in the area of P2P accommodation sharing.

Third, this study attempts to address the lack of empirical evidence from Asian contexts. A few studies have suggested that the traditional perception of the "home" in East Asian cultures is quite different from that in Western cultures (Xiang & Dolnicar, 2017). The distinct spatial identification that defines a place as belonging to "us" or "them" makes Asians less interested in accommodation sharing. Despite the cultural restraints, there are several reasons that can explain the explosive market growth in P2P accommodation sharing in China. Our analysis indicates that one valid explanatory variable is the role of commercial hosts. Our exploratory study of Chinese P2P accommodation business models provides a deeper understanding of this new lodging market and its localization strategy in China. In particular, we consider the perception of commercial hosts in *Tujia* listings and their competitive effects in the market.

Practical Implications

Our study has important implications for P2P accommodation sharing businesses and the public sector. First, this study identifies sustainable competitive strategies for commercial and individual hosts. The distinction between commercial and individual properties implies a competition within the platform. This study empirically demonstrates the differentiation of commercial hosts, its impact on the individual properties' online popularity in the same neighborhood, and the effect of price difference and density of tourist attractions on this interaction. At the same time, P2P accommodation sharing is being labeled as a deceptive and illegal business model by traditional competitors, and both landlords and tenants are expressing service and safety concerns. Thus, commercial hosts might be a new twist to the accommodation sharing market in terms of the legitimacy and standardized services. Our analysis has implications for individual hosts facing competition from neighboring commercial properties. To retain market competitiveness, individual hosts need to leverage price and location above their traditional strength in areas such as authenticity and deeper interaction with guests. In terms of location, the density of attraction is the issue. Individual hosts who cannot directly adapt the locational competitiveness may discover their local stories and cultural assets for enhancing attraction density to pull tourists.

Second, P2P accommodation sharing platforms not only embrace different types of host and support healthy competition but also monitor the balance between commercialization and authenticity. The platforms can satisfy specialized market needs in P2P accommodation sharing by offering professional and standardized service by commercial hosts. Furthermore, in the sharing economy, online platforms not only mediate economic exchanges between hosts and guests but also influence them both before and after purchase. It is also required that platforms as a facilitator guarantee the variation of spaces by various hosts to cater to guests'

experiences and expectations (Dolnicar, 2017). Therefore, platforms should offer a marketing mix that supports individual hosts by magnifying their unique features and helping them to compete with commercial hosts.

Third, regulatory guidelines through multilateral institutions are needed for monitoring and controlling the internal competition within P2P accommodation business, as well as congestion and distribution of P2P accommodations in the destination, especially in areas with a high density of attractions or residential districts. Our analysis finds that being located in areas with a high density of tourist attractions is an effective strategy for shared accommodation services (especially for individual hosts), but social and ecological concerns must be considered. In addition, this research discusses commercial hosts as licensed service providers in P2P accommodation sharing and stimulates the debate on regulatory interventions to ensure fair, legitimate competition between businesses in the sharing economy and traditional businesses, and within the sharing economy (Rauch & Schleicher, 2015).

Conclusion

In response to the increasing growth in commercial properties on P2P accommodation sharing platforms, we provide evidence that commercial properties obtain a competitive advantage through pricing and location. Responding to the main research question, the results show that commercial hosts negatively affect the online popularity of neighboring individual hosts. Furthermore, we find that the competitive effect of commercial properties is not uniform but heterogeneous, and depends on the price difference between the two types of property and the density of nearby tourist attractions. We quantify the impact of this advantage on individual properties in a 5 km radius. The results show that an increase in the ratio of commercial properties raises the likelihood that travelers

will choose a commercial property over an individual one. Furthermore, the price is a significant factor in tourists' choices of P2P accommodation sharing properties. As the price gap between commercial properties and individual properties increases, some price-sensitive customers compromise service quality and choose lower-priced properties, which is demonstrated by the significant moderation of price difference on the competition effect of commercial properties. Finally, being locating in a neighborhood with a higher density of tourist attractions mitigates the competition effect of commercial neighbors. The results not only provide evidence of the competitiveness of commercial hosts in terms of internal competition within P2P accommodation sharing, but also suggest how individual properties can respond to such competition through strategies in pricing (providing a lower price) and location (co-locating in a neighborhood with a higher density of attractions). The insights obtained from the findings can provide supporting evidence on the sustainable development of P2P accommodation sharing through competition and knowledge transfer of each business model within internal players.

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Table 1.

Review on P2P accommodation sharing studies for competition

Category	Author (Year)	Data and Research Context	Key Findings
Competition *between* accommodation sharing and hotel	Aznar et al. (2016)	54 hotels from Google Maps and nearby apartments on Airbnb; Change in revenues (ROE) from 2008 to 2013; Barcelona	New forms of supply (nearby apartment suppliers and Airbnb listings) have a negative effect on hotel profitability
	Belarmino et al. (2019)	400 Airbnb listings and 400 hotels (from TripAdvisor) reviews; New York, Los Angeles, Chicago, and Houston	Guests in P2P emphasize authentic and personal relationships with hosts when choosing a P2P accommodation over hotels.

	Gutierrez et al. (2017)	670 hotels and 14,500 Airbnb listings; Geolocated photographs (sightseeing hot spots) and population data; October 2015; Barcelona	Compared to hotels, Airbnb accommodations tend to (1) have much simpler and more regular spatial distribution; (2) be concentrated in city centers (near attractions); and (3) have a higher density in residential districts.
	Xie and Kwok (2017)	86 hotels and 63 Airbnb listings from 2008 to 2011; Austin	The supply of Airbnb listings potentially substitutes for the demand of nearby hotels and decreases their financial performance (RevPAR). As the price difference increases, the negative impact of Airbnb supply on hotel performance decreases significantly.
	Zervas et al. (2017)	Hotel's tax panel dataset and 5,994 hosts and 7,361 listings on Airbnb; 22,650 reviews by Airbnb guests between 2008 and 2013; Texas	As Airbnb listings increase, the hotel revenues significantly decrease. The impact of Airbnb differs substantially by hotel price segment: lower-priced hotels are negatively affected by Airbnb, whereas the effect on luxury hotels is not significant.
	Heo, Blal and Choi (2019)	Monthly average daily rate (ADR) and occupancy of 115,984 hotel rooms and 39,608 Airbnb listings from 2009 to 2015; Paris	Hotel occupancy rates have remained stable. Hotels ADR has decreased since the inception of Airbnb, but has been on the increase in the time series analysis. Different growth/seasonality/location of hotel and Airbnb were shown.
Competition *within* accommodation sharing	Li et al. (2016)	24,845 listings on Airbnb December 2012 to March 2013; Chicago	A property managed by a professional host has superior performance than a property managed by a nonprofessional host.
	Tussyadiah and Zach (2017)	41,560 reviews written in English only from 1,617 Airbnb listings; 12 May 2015; Portland	Listings with convenient locations (proximity to tourist attractions and good neighborhoods) are preferred by consumers.
	Xie and Mao (2017)	5,805 listings of 4,608 hosts on Airbnb; September 2008 to November 2015; Austin	Super hosts, who are hosts with a high response rate and experience, are considered superior to other hosts by consumers. There is no significant difference between local and non-local hosts' performance.

Accommodation sharing in China	Wu et al. (2017a)	2,461 listings of 935 hosts on Xiaozhu.com; November 2015 to February 2016; Beijing	Hosts' trustworthy attributes (i.e., time of reservation confirmation, acceptance rate of renter reservations, number of listings owned, personal profile page, and gender of host) are important in renters' purchase decision making.
	Wu et al. (2017b)	445 surveys in 5 Chinese online travel communities (incl. Airbnb)	The motivations of Chinese room-sharing service users (incl. utilitarian and hedonic motivations) influence their behavioral intentions. Perceived trust in service platforms plays an essential role in behavioral intention.
	Xiang and Dolnicar (2017)	Review of Chinese media reports and 277 academic journal articles written by Chinese authors	Although traditional perceptions of "home" are different in the Chinese cultural context than in Western society, supply and demand are growing, and competition among P2P accommodation sharing platforms has been increased; Pricing, accommodation use habit, sense of safety, and service quality are the major challenges to demand growth.

Table 2.

Variable definitions and statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
Primary Variables					
Popularity	Number of online reviews for an individual property; a proxy for a property's online popularity in a given month	1.24	2.26	0	42
ComRatio	Ratio of commercial properties to the total number of properties within a 5-kilometer radius of a property in a given month	0.40	0.33	0	1
Moderators					
PriceDiff	Logarithm of the difference between the average price[4] of commercial properties within a 5-kilometer radius of a property and the price of the property in a given month	3.76	1.61	0	6.79
AttDen	Number of tourist attractions within a 5-kilometer radius of a property in a given month	37.13	47.52	0	168
Control Variables					
ListSupply	Number of total properties within a 5-kilometer radius of a property in a given month	31.48	37.30	0	256
Room	Number of bedrooms in a property	1.97	1.74	1	18
Amenity	Number of facilities in a property	20.00	4.71	3	29
Age	Operating period of a property (in months) till a given month[5]	8.60	9.30	0	55
AveRating	Average online review rating of a property	4.79	0.30	2	5

[4] Prices of properties are in Chinese Yuan (¥). As of January 2018, 1 USD is equal to 6.7 Chinese Yuan. Source: Bloomberg Market. January 13, 2018: https://www.bloomberg.com/quote/USDCNY:CUR

[5] We use the date of the first guest review to mark the starting date of a property.

Table 3.

Correlation matrix

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1)	*ComRatio*	1							
(2)	*PriceDiff*	-0.13	1						
(3)	*AttDen*	0.27	0.11	1					
(4)	*ListSupply*	-0.14	0.05	0.40	1				
(5)	*Room*	-0.25	-0.13	-0.35	-0.19	1			
(6)	*Amenity*	-0.11	-0.17	0.04	0.09	-0.04	1		
(7)	*Age*	0.27	0.00	0.14	0.39	-0.11	-0.13	1	
(8)	*AveRating*	-0.26	-0.08	-0.12	0.02	0.13	0.22	-0.25	1

Table 4.

Estimation results

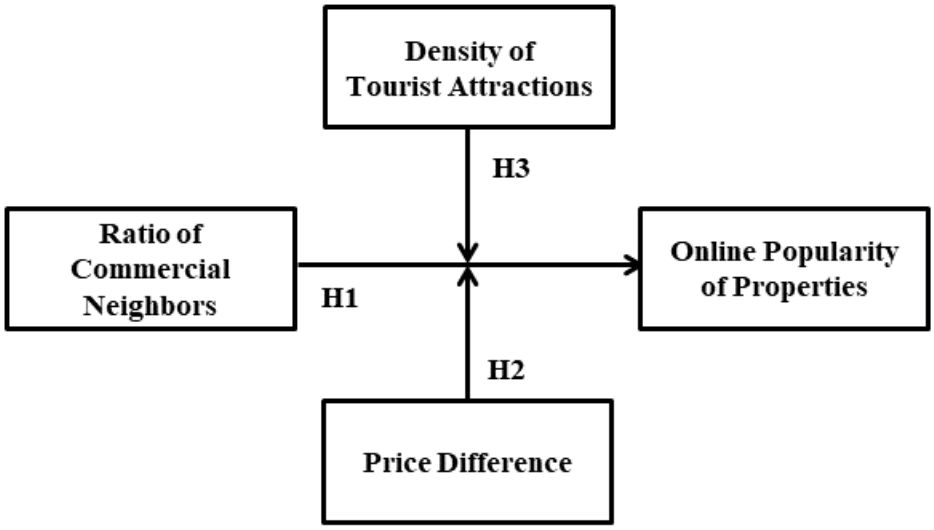
Hypothesis		*Online Popularity*								
		Main Model			Sub-model 1: Moderation of price difference			Sub-model 2: Moderation of density of tourist attractions		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Primary Variables									
H1	*ComRatio*	-1.736**	-1.796**	-1.740**	-1.340**	-0.967*	-1.377**	-0.564**	-0.464*	-0.586**
		(0.727)	(0.744)	(0.729)	(0.507)	(0.573)	(0.640)	(0.238)	(0.245)	(0.241)
	PriceDiff	-0.007	-0.009	-0.008	-0.006	-0.006	-0.009			
		(0.054)	(0.055)	(0.055)	(0.053)	(0.055)	(0.054)			
H2	*ComRatio × PriceDiff*	0.235*	0.226*	0.229*	0.343**	0.371**	0.339**			
		(0.125)	(0.123)	(0.125)	(0.147)	(0.157)	(0.148)			
	AttDen	-0.002	-0.000	-0.000				0.001	0.001	0.002
		(0.004)	(0.004)	(0.004)				(0.003)	(0.003)	(0.003)
H3	*ComRatio × AttDen*	0.023**	0.021**	0.022**				0.013**	0.013**	0.012*
		(0.008)	(0.009)	(0.009)				(0.006)	(0.006)	(0.006)
	Controls									
	ListSupply	-0.003	-0.005**	-0.005**	0.002	-0.001	0.000	-0.001	-0.003*	-0.002
		(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
	Room	0.043	0.046	0.047	0.025	0.037	0.028	0.028	0.030	0.029
		(0.098)	(0.100)	(0.100)	(0.095)	(0.096)	(0.096)	(0.041)	(0.041)	(0.041)
	Amenity	0.079***	0.078***	0.078***	0.090***	0.091***	0.089***	0.071***	0.071***	0.072***
		(0.016)	(0.016)	(0.016)	(0.019)	(0.020)	(0.019)	(0.013)	(0.013)	(0.013)
	Age	0.015	0.021	0.020	0.017	0.019	0.021	0.007	0.009	0.010
		(0.013)	(0.014)	(0.013)	(0.014)	(0.015)	(0.014)	(0.008)	(0.009)	(0.009)
	AveRating	0.340	0.409*	0.397*	0.116	0.060	0.157	0.273	0.272	0.297*
		(0.248)	(0.238)	(0.238)	(0.344)	(0.360)	(0.338)	(0.176)	(0.173)	(0.174)
	Trend and Seasonality									
	Month Trend	Y		Y	Y		Y	Y		Y
	Seasonality FE		Y	Y		Y	Y		Y	Y
	Observations	6391	6391	6391	6391	6391	6391	6391	6391	6391
	VIF[6]	4.78	4.21	4.27	4.36	3.84	3.85	2.90	2.59	2.75
	Adjusted R-squared	0.090	0.098	0.098	0.054	0.057	0.061	0.058	0.064	0.064

[6] The variance inflation factor (VIF) values of all of the models are lower than 10, indicating that there are no multi-collinearity issues in these models (Allison, 1999).

Table 5.

Robustness checks

Hypothesis		*Scaled Online Popularity*								
		Complete Model			Sub-model 1: Moderation of price difference			Sub-model 2: Moderation of density of tourist attractions		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Primary Variables									
H1	*ComRatio*	-1.592**	-1.653**	-1.593**	-0.564**	-0.464*	-0.586**	-1.243**	-0.923*	-1.276**
		(0.652)	(0.663)	(0.654)	(0.238)	(0.245)	(0.241)	(0.571)	(0.525)	(0.582)
	PriceDiff	-0.011	-0.013	-0.013				-0.011	-0.011	-0.014
		(0.052)	(0.052)	(0.052)				(0.051)	(0.052)	(0.051)
H2	*ComRatio × PriceDiff*	0.218*	0.209*	0.212*				0.315**	0.339**	0.311**
		(0.114)	(0.112)	(0.113)				(0.132)	(0.140)	(0.132)
	AttDen	-0.001	0.000	-0.000	0.001	0.001	0.002			
		(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)			
H3	*ComRatio × AttDen*	0.020**	0.018**	0.019**	0.013**	0.013**	0.012*			
		(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)			
	Controls									
	ListSupply	-0.003	-0.004*	-0.005*	-0.001	-0.003*	-0.002	0.002	-0.001	0.000
		(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	Room	0.039	0.042	0.044	0.028	0.030	0.029	0.023	0.033	0.026
		(0.092)	(0.094)	(0.94)	(0.041)	(0.041)	(0.041)	(0.089)	(0.090)	(0.090)
	Amenity	0.075***	0.074***	0.074***	0.071***	0.071***	0.072***	0.084***	0.086***	0.084***
		(0.015)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.018)	(0.018)	(0.018)
	ListAge	0.012	0.018	0.017	0.007	0.009	0.010	0.014	0.016	0.018
		(0.012)	(0.013)	(0.012)	(0.008)	(0.009)	(0.009)	(0.013)	(0.014)	(0.013)
	AveRating	0.451**	0.515**	0.502**	0.273	0.272	0.297*	0.250	0.203	0.286
		(0.223)	(0.216)	(0.215)	(0.176)	(0.173)	(0.174)	(0.302)	(0.316)	(0.297)
	Trend and Seasonality									
	Time trend	Y		Y	Y		Y	Y		Y
	Seasonality FE		Y	Y		Y	Y		Y	Y
	Observations	6391	6391	6391	6391	6391	6391	6391	6391	6391
	VIF	4.78	4.21	4.27	2.90	2.59	2.75	4.36	3.84	3.85
	Adjusted R-squared	0.083	0.090	0.090	0.058	0.064	0.064	0.050	0.052	0.056



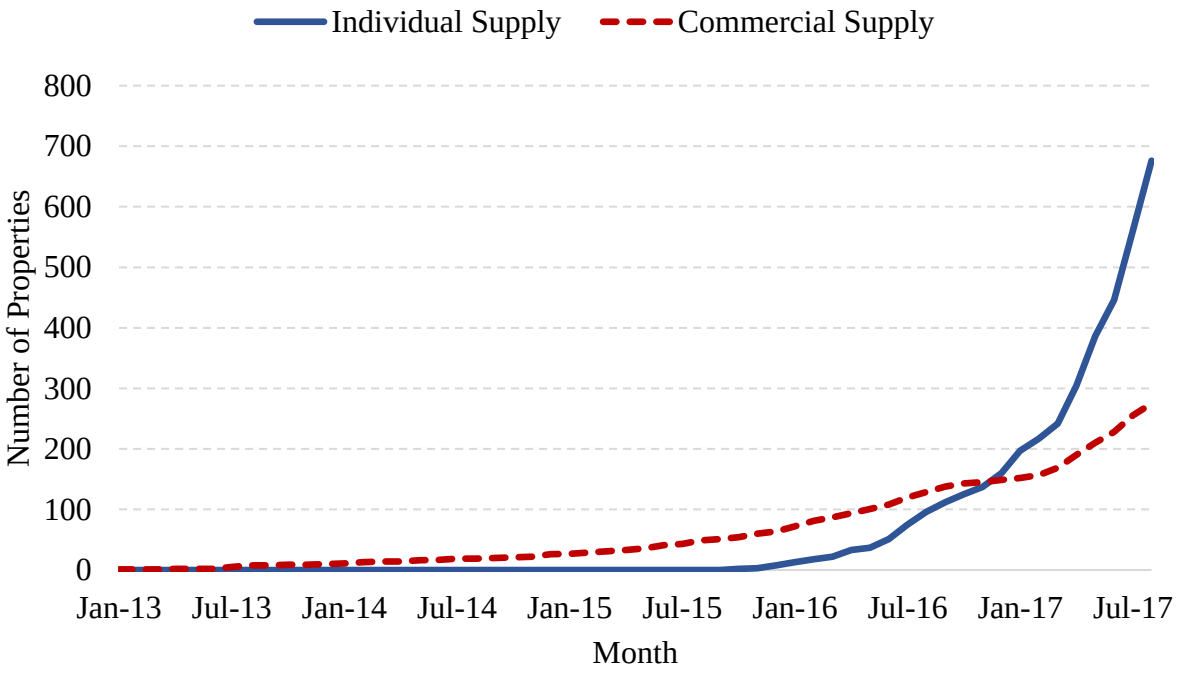


Figure 2. Distribution of Commercial Property Supply vs. Individual Property Supply over Time (January 2013 - August 2017).