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A Comparative Analysis between Airbnb and Hotel Industry: The Investigation from China

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A Comparative Analysis between Airbnb and Hotel Industry: The Investigation from China

(Full Paper)

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ABSTRACT

This paper constructs a comparative analysis to investigate the impact of sharing economy on the traditional hotel industry, using data collected from Airbnb and their hotel counterparts CTrip in ten major cities in China. Comparative static analysis and a multivariate regression model are used to draw the following conclusions: firstly, there exists a weakly negative impact of sharing accommodation rental on the traditional hotel industry. Airbnb's listing price and hotel price are weakly negatively associated. Moreover, the overall occupancy rate and rating of Airbnb listings do not significantly influence hotel price. Hotel price is mainly affected by hotel ratings and the average local income. The main findings offer managerial insights to managers in Airbnb and hotels.

Keywords: Sharing economy, Airbnb, hotel industry, quantitative analysis.

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INTRODUCTION

Sharing economy is a new business model to share or to rent the right to use products or services to other individuals in a peer-to-peer fashion (Wikipedia, 2020). The emerging unicorn companies, e.g., Airbnb, Uber, and Mobike, in sharing economy have deeply involved into our daily lives and significantly changed people consumption behaviors. It is reported that the revenue of sharing economy will exceed US $335 billion by 2025 (Rose, 2019). Given such emerging phenomenon, there are increasing discussions about the impacts of sharing economy on traditional economy.

By gathering a large number of unused resources, products or services provided in the online sharing platforms could compete directly to traditional enterprises offering similar products and services. For instance, Airbnb, the sharing accommodations service provider, could operate at a much lower cost since an Airbnb listing can be rent repeatedly anytime the owner wants, which grants considerable flexibility in the supply side of room offering. On the other hand, the supply increase from hotels may lead to a high vacancy rate during the off-season, leading to unacceptable losses. Besides, the housing vacancy rate has been over 25% in China (Blazyte, 2018) in the hotel market. Thus, the sharing accommodation holds a competitive advantage over the traditional hotel industry. Traditional housing rental suppliers will inevitably be impacted by entries of newcomers like Airbnb. Similarly, in mobility, Uber and Didi have caused a catastrophic blow on the traditional taxi market (Nie, 2017).

Yet discussions regarding to the impacts of sharing economy on traditional economy have not lead to consistency in existing literature (Choi *et al.*, 2015; Dogru, Mody, & Suess, 2019). On one hand, Dogru, Mody, and Suess (2019) found that sharing accommodation rental would compete with hotels. On the other hand, Choi *et al.* (2015) found there does not exist significant impacts between Airbnb and local hotels. Even in the hotel market, prior study has found that the impact of room sharing on the traditional hotel industry is different among different countries and different cities (Blal, Singal, & Templin, 2018; Guttentag & Smith, 2017; Xie & Kwok, 2017).

Given such confusion, this study aims to better understand the impact of sharing economy on the traditional economy in accommodation industry, at least adding evidence or empirical support from China perspective. More specifically, we investigate the accommodation rental sector of the tourism and hospitality industry and try to examine the impact of Airbnb on the hotel industry in major cities in China. Given the heterogeneity among different locations, we collect data from Airbnb and hotel listings' prices, reviews, addresses in multiple cities and regions at the same time. We first compare data among different regions for static analysis and then run regression analysis to examine the impact of room sharing on traditional hotels. Based on these analyses, this article makes corresponding suggestions for decision-makers of both Airbnb and the traditional hotel industry. Our finding could help to better understand how sharing economy like Airbnb would influence traditional hotel industry in China.

LITERATURE REVIEW

As a new emerging business phenomenon, sharing economy has entered into various industries, such as Airbnb in accommodation, Uber and Didi in mobility and Mobike in sharing bikes. As an echo of such business trend in academia, researchers have tried to examine the effect of sharing economy on traditional industries.

The effect of sharing economy has been investigated from perspectives of low-end vs high-end. Dogru, Mody, and Suess (2019) and Zervas, Proserpio, and Byers (2017) have shown the effects of sharing accommodation rental on hotels are twofold: in the low-end accommodation market, Airbnb would compete with hotels, while in the high-end accommodation market, hotels are less affected by the sharing economy.

Other researchers have studied the sharing economy's impact on traditional industries in different locations. In accommodation industry, Airbnb's impact on hotels is different across different countries due to different economic environments and market structures in each country. Besides, supply, classification, and price of hotel markets in different countries are also very different. In US, Airbnb is identified as a significant disturbance factor for the local hotel market and the revenue of hotels has been affected by Airbnb (Xie & Kwok, 2017). It is found that Airbnb could serve as an imperfect alternative for hotels and constitutes a direct competitive relationship with hotels (Blal *et al.*, 2018; Guttentag & Smith, 2017). On the other hand, researchers find that Airbnb has not negatively affected the local hotel market in South Korea (Choi *et al.*, 2015) and Norway (Strømmen-Bakhtiar & Vinogradov, 2019). The relationship between Airbnb and local hotels is complementary rather than competitive because they have different target customer groups as well as pricing strategies. These studies believe that the increase in Airbnb listings will help improve the overall performance of the hotel market due to the elasticity of the Airbnb supply.

Airbnb has entered China for years. Both of the numbers of Airbnb's listings and the number of orders are growing at a fairly rapid rate. It has already become an important force in the Chinese accommodation market. Thus, this research quantitatively analyzes Airbnb's impacts on the Chinese hotel market. This paper aims at comparing and analyzing the hotel and accommodation rental in China, in order to figure out the relationship between the sharing economy and the hotel industry.

DATA COLLECTION AND DATA PROCESSING

The sample in this study is from ten major cities in China: namely Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin, Nanjing, Wuhan, Chengdu, Shenyang and Xiamen. The first four cities are the well-known tier 1 cities in China. The following five cities are the regional representative cities in China. The last city is one of the popular truism cities in China. Furthermore, among the ten cities, one is in the Northeast China, two are in the North China, two are in the East China, one is in the Southeast China, two are in the South China, one is in the Central China, and one is in the Southwest China. We choose these ten cities for two reasons: (1) these are the top performing cities in China in terms of hotel room supply and Airbnb supply; (2) these ten cities are located in various regions in China.

For data collection, we design and implement a web crawler in Python. The data in this study is collected from two sources: (1) the Airbnb listing data from Airbnb China's official website (www.airbnb.cn), and (2) the hotel listing data of the searched results in CTrip (www.Trip.com) under the hotel category. As the initial investigation, we plan to conduct the static comparative analysis, thus, all the data is collected from Mar 19, 2019 to Mar 20, 2019. This could avoid the effects form weekends and holidays. For instance, on vacations like traditional Chinese New Year or National Day, people are more likely to have family trips thus would spend more money on room bookings. As a result, on holiday seasons, room demand increases significantly and customers tend to be less sensitive in room prices, and thus the listing prices would increase significantly as well. Data would be collected in a longer period to include the weekend and holiday effects in future research. Besides, all data are crawled from both websites simultaneously to avoid any inconsistency from time effect.

Based on preliminary observations in Airbnb and Ctrip, and for the purpose of facilitating static comparative analysis between Airbnb and hotel listings in different regions, we crawl the following listing metadata from Airbnb: price, geographic location (both longitude and latitude), number of reviews, and star ratings. To avoid the effects of holidays and weekends, this paper queries the average price of Airbnb and hotel listings from March 24, 2019 to March 30, 2019. This average price within a week could approximately serve as the overall price level of the listing during data collection. The effects of holidays will be explored in the future.

Currently we have not got the three major performance indexes in the hotel industry: daily room average income (Revenue of Per the Available Room, RevPar), the daily average price (Average Daily Rate, ADR) and occupancy (Occupancy, OCC). Thus, this article adopts the average price (Hotel Listing Price) within a week as the measurement for daily average price. This is also for the purpose to compare with Airbnb, where the bookings data is not available neither. In the future research, we plan to extend the current research by getting RevPar, ADR and OCC to measure hotel performance.

After crawling, all records with missing values and duplicate values are removed. Rooms without reviews in Airbnb are usually the ones have not been booked previously. We then remove outliers by observing the scatter plots of data separately. We also remove data including prices not consistent with common sense.

Originally, we crawled 46477 records of hotel data from CTrip and 2055 records from Airbnb for ten cities in the specific time period. The data size from Airbnb is significantly smaller than that from CTrip is because usually only around 200 listings are shown in Airbnb for a given region (sometimes even less depending on the region's popularities). We could crawl more data from cities like Beijing, Shanghai, Guangzhou, Shenzhen, Chengdu, Shenyang but less data from cities like Tianjin, Nanjing, Xiamen, which is consistent with our common sense, since the former are cities with stronger economic performance and higher accommodation needs. In this study, our dataset including 46477 records from CTrip and 2055 records from Airbnb, with attributes like prices, locations, number of reviews, star rating.

In this preliminary study, we would like to statically compare the impact of Airbnb on CTrip, thus, we need to identify rooms in Airbnb and hotels in CTrip in the same region. Due to the strict privacy policy in Airbnb, the location of all listings on its website is intentionally obscured. The exact location of listings cannot be obtained before booking. According to the fuzzy addresses of Airbnb listings, we could derive the geographic location (both latitude and longitude) of listings. The distance (in kilometers) between each listing and the geographic center of the city could be calculated to measure the listing location. Finally, we establish a dataset with 187 region-level records for ten cities.

DATA ANALYSIS

In this section, we would first present the descriptive analysis for our data collection, and then describe the dependent variable, independent variables and regression results.

Preliminary Analysis

	Average Price/RMB	Average Distance/KM	Average Rating
Airbnb	233.839337	6.12115102	4.8968
Hotel	226.269921	8.26378175	4.2726

The preliminary analysis shows generally the average price in Airbnb is higher than that in CTrip, and rooms in Airbnb are closer to the geographical center of the city. This pattern is consistent in all 10 different major cities. Furthermore, quality (ratings from consumers) of rooms in Airbnb is generally higher than that in traditional hotels.

Although luxury hotels are much more expensive than rooms in Airbnb in most cities, the median hotel price in each city is significantly lower than the average price, leading to that most hotels are budget-oriented. On the other hand, Airbnb is family, vacation, and leisure-oriented, offers a large number of large-sized, well-equipped and comfortable homes. Thus, the price is relatively higher than that of hotels.

Rooms listed in Airbnb are generally closer to the city center compared to hotels. This maybe because most budget hotels locate far away from downtown. In contrast, tourism and leisure-oriented Airbnb listings are usually well located for convenience, and they are often closer to downtown. Besides, another explanation may be that the collected Airbnb listing are high-quality listings selected by Airbnb, so they are generally well located. Furthermore, the average rating is higher in Airbnb than that in CTrip.

Explanatory Variables, Dependent Variables and Control Variables

This research chooses the average hotel price (HPrice) as an indicator in the hotel market. There exist thousands of hotels in Ctrip and rooms in Airbnb, leading to an almost perfectly competitive market. Thus, price could serve as the indicator whether Airbnb's supply will positively or negatively impact the hotels' prices.

We first average the price, rating, and occupancy for all Airbnb listings with the same address. Then, to match the hotel located in the same region, we choose to map hotels to the nearest Airbnb listing in fuzzy geographical location. That is, every hotel is matched to the nearest Airbnb listing. Overall, this article obtained a sample of 187 addresses from 10 cities across the country and recalculated the distance from each listing location in each city to downtown of the city respectively. Since the actual bookings is not displayed in Airbnb website, this paper chooses the count of reviews in Airbnb website as the proxy to measure listing occupancy. Similar approach has been used in existing literature (Zervas, Proserpio, & Byers, 2017).

China is a vast country and hug difference exists among different cities, especially in economy performance. We consider the heterogeneity in market environment among cities by introducing the following control variables: regional average house price/yuan (district level), annual average income/yuan (city level), population / million (city level). Average house price in certain regions is closely related to prices of room offerings in the supply side in this region. On the other hand, average income and population are closely related to the demand side in hotel industry. This research uses the average house price in April 2019 from http://www.cityhouse.cn/city.html, and population and the average income reported in the end of 2017 from National Bureau of Statistics of China (http://data.stats.gov.cn).

Table 1 describes all variables.

Table 1: Variable Description

Variable	Description
HPrice	Average hotel price in RMB
APrice	Average price of Airbnb in RMB
ARating	Airbnb average score (out of 5)
AReview	Average number of Airbnb reviews
Distance	Distance from the geographic center of the region in kilometer
HRating	Average hotel rating (out of 5)
HousePrice	Average house price in district, in RMB
Income	Average urban income, in RMB
Population	Urban population, in 10 thousand

Table 2 shows descriptive analysis in the dataset.

Table 2: Descriptive Analysis

	HPrice	APrice	ARating	AReview	Distance	HRating	HousePrice	Income	Population
count	187	187	187	187	187	187	187	187	187
mean	226.27	233.84	4.90	30.27	6.12	4.27	46039.56	97883.73	926.04
std	67.62	66.54	0.13	24.24	5.28	0.10	24980.11	20921.12	406.82
min	135.09	67.00	4.00	4.00	0.34	4.08	6769.00	74181.00	231.03
25%	179.83	192.37	4.84	15.08	2.30	4.20	22411.00	79292.00	680.67
50%	205.13	225.81	4.93	25.35	5.00	4.26	46745.00	98612.00	897.87
75%	253.41	274.12	5.00	39.04	8.37	4.34	55317.00	101502.00	1359.20
max	533.25	458.00	5.00	190.00	43.71	4.52	132971.00	134994.00	1455.13

The correlation analysis show there exists a high correlation among variables, leading to the issue of multiple collinearities. More specifically, there exists a strong linear relationship among hotel prices, house price and income ($|r| > 0.7$). There is a moderate linear relationship among hotel prices, hotel ratings and population ($|r| > 0.3$). A weak linear relationship exists between hotel price and geographical location (distance) ($0.1 < |r| < 0.3$).

Tables 3 shows the correlation analysis of the data sample. The titles in the table represent:

Table 3: Correlation Analysis

	HPrice	APrice	ARating	AReview	Distance	HRating	HousePrice	Income	Population
HPrice	1.000								
APrice	-0.050	1.000							
ARating	0.047	0.151	1.000						
AReview	0.070	0.098	-0.080	1.000					
Distance	0.160	-0.019	0.030	-0.002	1.000				
HRating	-0.316	0.311	0.041	0.071	-0.122	1.000			
HousePrice	0.753	-0.022	0.110	0.044	-0.058	-0.265	1.000		
Income	0.844	0.106	0.034	0.081	0.153	-0.485	0.707	1.000	
Population	0.369	-0.157	-0.135	0.083	-0.004	-0.201	0.033	0.509	1.000

Regression Analysis

We build a logarithmic linear regression model as follows:

$$\ln HPrice_i = c + \alpha \ln APrice_i + \beta \ln ARating_i + \lambda \ln AReview_i + \delta \ln Distance_i + \upsilon \ln HRating_i + \eta \ln HousePrice_i + \theta \ln Income_i + \varepsilon \ln Population_i \quad (1)$$

where $HPrice_i$ is the average hotel price in region *i*, $APrice_i$ is the average price in Airbnb in region *i*, $ARating_i$ indicates the average rating in Airbnb in region *i*, $AReview_i$ is Aribnb listing's the average count of reviews in the region *i*, $Distance_i$ is the distance from region *i* to the geographic center of the city (in kilometer), $HRating_i$ indicates the average hotel rating in region *i*, $HousePrice_i$ is the average house price (in RMB) of region *i*, $Income_i$ indicates the average income (in RMB) in the city where region *i* belongs to, and $Population_i$ indicates the population in the city where region *i* belongs to (in 10,000).

To downplay the impact caused by multicollinearity among variables, we use the stepwise regression to isolate and filter out insignificant explanatory variables. During analysis, this paper adopts the backward stepwise regression analysis. The explanatory variables Airbnb rating ($p = 0.7863$), Airbnb average number of Reviews (used to represent the occupancy of the listing) ($p = 0.6429$), and population ($p = 0.3410$) were eliminated.

The results of regression analysis are reported in Table 4, Table 5 and Table 6 as follows:

Table 4: Coefficients of the Regression Model

Average Hotel Prices			
	coefficient	standard error	t test p-value
Intercept (c)	-9.735243915***	1.124582996	2.61304×10^{-15}
APrice (α)	-0.179328941***	0.030450878	1.85157×10^{-8}
Distance (δ)	0.03985593***	0.010336551	0.000160135
HRating (υ)	2.478374709***	0.456782387	1.83295×10^{-7}
HousePrice (*η*)	0.155346206***	0.020309919	1.15778×10^{-12}
Income (*θ*)	0.940598849***	0.069731228	3.74795×10^{-29}

Note: significance level: *** 1%, ** 5%

Table 5: Regression Statistics

Regression Statistics	
Multiple R	0.906116409
R Square	0.821046947
Adjusted R Square	0.816103493
Standard Error	0.116478604
Observations	187

Table 6: Analysis of Variance

ANOVA					
	DF	SS	MS	F	Significance F
Regression	5	11.26677875	2.25335575	166.0876918	1.16483×10^{-65}
Residual	181	2.455674989	0.013567265		

Note: DF stands for degrees of freedom, SS stands for sum of squares, MS stands for mean squared, R stands for regression, and Residual stands for residual error.

The adjusted R2 is 0.816103493 (see Table 5). According to regression results, the presence of Airbnb has significant impacts on hotel prices in the same region. This pattern is statistically significant. The analysis of variance (see Table 6) shows the F value is 166.088, and the p-value of the F test is 1.164483×10^{-65}, indicating the high confidence of this regression results.

According to the regression results, the regression model could be presented as:

$$\ln HPrice_i = -9.7352 - 0.1793 \times \ln APrice_i + 0.0398 \times \ln Distance_i + 2.4784 \times \ln HRating_i + 0.1553 \times \ln HousePrice_i + 0.9406 \times \ln Income_i \quad (2)$$

This model shows that, for hotel prices, there exist significant positive effects of listing distance, hotel room rating, house price in certain region and consumers' income on hotel room price. On the other hand, there exists significant negative effect of room price in Airbnb on in hotel. According to this model, the average hotel price would decrease if Airbnb's price in the same region increases, leading to a negative impact of sharing apartments on traditional hotels. Thus, in the accommodation rental sector, the sharing room may weakly negatively relate to prices of traditional hotels.

Model Extension

Some market factors would influence the hotel room price. Thus, to test the robustness of our model, we consider following control variables: Total Retail Sales of Consumer Goods (TRSCG) and Gross Domestic Product (GDP). The total retail sales of consumer goods refers to the amount of physical goods sold by enterprises, through transactions to individuals and social groups for non-production and non-business use, as well as the amount of income derived from the provision of catering services. This indicator only include commodities sold to individuals for daily consumption, which is a perfect measure of the region's consumption level. It can represent the willingness that people would like to spend their money. GDP, on the other hand, is an indicator of the region's overall production outcome. GDP reflects a region's overall economic status. It may represent the consumption intensity of citizens in certain regions. Since TRSCG and GDP are a reflection of region level consumption and overall economic situation, they are closely related to hotel prices.

The extension model is presented as follows:

$$\ln HPrice_i = c + \alpha \ln APrice_i + \beta \ln Distance_i + \lambda \ln HRating_i + \delta \ln HousePrice_i + \upsilon \ln Income_i + \eta \ln Retail_i + \theta \ln GDP_i \quad (3)$$

where $HPrice_i$ is the average hotel price in region *i*, $APrice_i$ is the average price in Airbnb in region *i*, $Distance_i$ is the distance from region *i* to the geographic center of the city (in kilometer), $HRating_i$ indicates the average hotel rating in region *i*, $HousePrice_i$ is the average house price (in RMB) of region *i*, $Income_i$ indicates the average income (in RMB) in the city where region *i* belongs to, $Retail_i$ indicates the total annual retail sales (in 100 million RMB) in the city region *i* belongs to, and GDP_i indicates the annual domestic production in the city region *i* belongs to (in 100 million RMB).

Similarly, we adopt stepwise regression approach to reduce the effect of multicollinearity. Insignificant explanatory variables are removed using backward stepwise regression analysis.

Regression results of the extended model are presented in Table 7, Table 8 and Table 9:

Table 7: Coefficients of Model Extension

Average Hotel Prices			
	coefficient	standard error	t test p-value
Intercept (c)	-10.49846363***	1.223387458	4.39645×10^{-15}
APrice (α)	-0.246433167***	0.037530348	5.40718×10^{-10}
Distance (β)	0.048973906***	0.010331739	4.34069×10^{-6}
HRating (λ)	2.553221128***	0.444594336	3.92402×10^{-8}
HousePrice (δ)	0.196130744***	0.032823518	1.21271×10^{-8}
Income (υ)	1.052679315***	0.1421674	4.97358×10^{-12}
TRSCG (η)	0.174051323***	0.055270403	0.001919472
GDP (θ)	-0.231554991***	0.048236919	3.32961×10^{-6}

Note: significance level: *** 1%, ** 5%

Table 8: Regression Statistics of Model Extension

Regression Statistics	
Multiple R	0.917466312
R Square	0.841744433

Adjusted R Square	0.835555668
Standard Error	0.110146035
Observations	187

Table 9: Analysis of Variance in Model Extension

ANOVA					
	DF	SS	MS	F	Significance F
Regression	7	11.55079904	1.650114149	136.0116935	3.44203×10^{-68}
Residual	179	2.171654694	0.012132149		

Note: DF stands for degrees of freedom, SS stands for sum of squares, MS stands for mean squared, Regression stands for regression, and Residual stands for residual error.

The adjusted R2 is 0.84 (see Table 8). According to regression results, the influence of Airbnb on hotel prices in the same region is statistically significant. The analysis of variance (see Table 9) shows the F value is 136.0, and the p-value of the F test is close to 0, indicating the high confidence of our model.

According to regression results, the extended regression model could be presented as:

$$\ln HPrice_i = -10.49846363 - 0.246433167\ln APrice_i + 0.048973906\ln Distance_i + 2.553221128\ln HRating_i + 0.196130744\ln HousePrice_i + 1.052679315\ln Income_i + 0.174051323\ln Retail_i - 0.231554991\ln GDP_i \quad (4)$$

According to results of the extended model, it can be found that the impacts of TRSCG and GDP on hotel price are statistically significant. The coefficients of the original explanatory variables and control variables have not changed significantly. Therefore, Airbnb listings' price has a weak negative correlation with hotel prices. The main factors affecting hotel prices are hotel ratings and the region's average income.

Through this initial preliminary static comparative analysis, we find there might exist negative impact coming from Airbnb room offering on traditional hotel industry at least in Chinese market. This finding could help to add empirical support about the impact of room sharing on traditional accommodation industry and help to better understand the impact from sharing economy.

CONCLUSIONS AND DISCUSSIONS

With the rapid development of Internet Technology, business models and processes are significantly changing over time. With the support of IT infrastructure, the rights of using products and service could be rent to other individuals, this will inevitably have impacts on traditional industries. Increasing research attention has been given to the impact of such sharing economy on traditional economy. However, the existing literature has not drawn consistent conclusion, thus more empirical supports are urgently needed.

From the point of view in Chinese market, this study would like to empirically investigate this issue in hotel industry. More specifically, this research could fill the gaps in the current research on the impact of the sharing economy on the Chinese hotel industry and the relationship between them. Based on these analyses, this article could also make corresponding recommendations to decision makers in the sharing economy and the traditional hotel industry. We conduct a static comparative analysis and a regression analysis to examine the sharing economy’s impacts on local hotels according to samples in ten major cities in China. These ten cities are representative since 4 tier-1 cities, 5 regional center cities and one truism city are included. We crawl data from two sources: Airbnb and Ctrip. On the basis of raw data, we could establish a dataset including 187 region level records through location matching.

We find prices in Airbnb are negatively related to prices of traditional hotels. This finding is consistent and in high confidence when taking market level and national level factors into consideration. Thus, Airbnb might weakly negatively relate to Ctrip. The main finding in initial analysis is promising. This study contributes to existing literature on sharing economy by providing potential empirical evidence about the impact of sharing economy on traditional economy in accommodation rental sector in tourism and hospitality industry.

The reason for the weak negative relationship between Airbnb and hotels in Ctrip might be that Airbnb and Ctrip would compete for consumers in some levels, but not all of them. Airbnb and Ctrip generally target to different groups of consumers. Sharing economy like Airbnb mainly targets at family travel and leisure trips. Airbnb generally provides a suitable exchange, warm living environment, at a relatively reasonable price. On the other hand, the traditional hotel industry are serving a broader range of customers. The price range of hotels is much larger than that of Airbnb due to the existence of both luxury hotels and budget hostels to meet the needs of different customers.

This work is not without limitations. First, we only collect the top 300 high-quality listings in Airbnb because only the top 300 listings in a city are shown on its websites. Second, the accurate location cannot be crawled because of the strict privacy policies in Airbnb. To address this issue, we match the hotel's geographic location with Airbnb's fuzzy geographic location, leading to a smaller sample size. Finally, other macroeconomic factors, e.g., market issues and policies, might be considered. But we leave these issues for future research.

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