Economics Bulletin

Volume 42, Issue 3

The impact of Airbnb: New evidence from Taiwanese hotels

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Abstract

We investigate the impact of Airbnb on incumbent hotels in Taiwan. Different from previous studies, we propose a novel set of instrumental variables, which measure unused resources or capcities, to identify the causal impact. Compared to OLS estimates, IV-2SLS estimates indicate larger negative effects from Airbnb, suggesting potential biases resulted from endogeneity issues. Furthermore, smaller and lower quality hotels are heavily affected by Airbnb listings.

We are grateful for valuable comments received from discussants and participants at National Taipei University, Industrial Economics Conference, and TEA 2020 Annual Conference. All remaining errors are our own.
Citation: Fang-chang Kuo and Hsin-hsi Shih, (2022) "The impact of Airbnb: New evidence from Taiwanese hotels", *Economics Bulletin*, Volume 42, Issue 3, pages 1340-1348
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Submitted: September 27, 2021. **Published:** September 30, 2022.

1 Introduction

In the past few decades, advances in information technology and spread of Internet have been facilitating the development in sharing economy. Airbnb and Uber are two most well-known and successful examples in hotel and taxi industry.[1] The success of Airbnb imposes competition pressures on the lodging industry. However, previous studies have shown mixed results about the impact of Airbnb on incumbent hotels' performances. Some find that Airbnb is a formidable competitor to the lodging industry (Zervas et al., 2017; Dogru et al., 2019, 2020), while others find insignificant or no effects from Airbnb (Blal et al., 2018; Chang and Sokol, 2021). The main challenge for identifying a casual link lies in the fact that entry of Airbnb listings is not exogenous. Specifically, Airbnb hosts can flexibly adjust their listings in response to potential future or present demand shocks. The common trend assumption for difference-in-differences (DD) research design is not valid in this setting. Hotels in treatment group will not follow the same trend as the control group when Airbnb's entry is absent since a positive demand shock, which attracts more listings from Airbnb, could increase treated hotels' performances at the same time.

In this paper, we investigate the impact of Airbnb on incumbent hotels' revenue in Taiwan. This study uses a unique dataset containing various hotel performance metrics from the entire population of legitimate hotels in Taiwan, and Airbnb listing data scraped from Airbnb website. Different from previous studies, we propose a novel set of instrumental variables (IV) and use two-stage least square approach to address the endogeneity issue. The instrumental variables measure the total number of vacant houses and housing inventories. The logic behind these two variables follows the mechanism of sharing economy, featuring the utilization of idle capacity, as more unused housing capacities could drive the supply of Airbnb but not correlate with specific demand shocks in a market.

The empirical estimates show noticeable difference between estimates in OLS and IV-2SLS estimation, suggesting biases caused by potential endogeneity. IV-2SLS estimate indicates larger negative effect of Airbnb listings on hotel revenues. The estimated treatment effect is statistically and economically significant. In addition, hotels of lower tiers and smaller capacities are heavily affected by Airbnb.

Our empirical results add to a growing literature on various impacts of sharing economy (Einav et al., 2016). Focusing on Airbnb in Taiwan, our empirical results indicate negative effects on hotels, which are consistent with previous studies (Zervas et al., 2017; Dogru et al., 2019, 2020; Chang and Sokol, 2021; Lee and Lin, 2022).[2] However, our estimated impacts are larger than those in prior literature. In addition, we find that Airbnb brings stronger business stealing effects on low quality and small hotels. The results provide important managerial implications for hotel managers in that the effects from Airbnb may be underestimated

[1] Founded in 2008, Airbnb has grown rapidly in the past decade. As of 2020, Airbnb has hosted more than 750 million guests with around 7 million listings in 100 thousand different cities.

[2] Chang and Sokol (2021) also studies Airbnb's impacts on the lodging industry in Taiwan. However, this paper uses whole population of the legitimate hotels while Chang and Sokol (2021) focuses on only tourist hotels. This could lead to different statistical significance. Since Airbnb takes advantage of unused housing resources, it could also have repercussions on the housing market (Chang, 2020).

and thus more strategic responses to the competition pressure are sorely need to mitigate the adverse effects. This paper distinguishes from previous studies on Airbnb and hotel performance in a way that we are able to find instrumental variables to address endogeneity. The intuitions of our proposed instrumental variables could pave the way for overcoming endogeneity problems in future researches related to sharing economy.

2 Data

We construct a unique dataset containing monthly panel of hotel performances, Airbnb listing, and vacant houses and housing inventories. Three main data-sets collected from various sources, and are merged according to county and month.

In 2008, the Bureau of Tourism requested all legitimate hotels to submit monthly reports of operating performances including room revenues, sales, employees, and number of rooms. The data spans the period between January 2009 and June 2016.[3] Revenue per available room (RevPAR) is the dependent variable measuring hotel performance.[4] We supplement hotel data with a panel of consumer ratings from major online review platforms, including TripAdvisor, Agoda, Expedia, and Bookings.com. Following Lewis and Zervas (2016), online ratings are aggregated across different rating websites and serve as a proxy for time-varying hotel-specific quality measure.[5]

Listing information is scraped from Airbnb website during November 2019 and December 2019. In each listing, we extract the registration date of Airbnb host to proxy the entry date of the listing. Using the time information over all available listings in all counties, we construct the cumulative number of listings in the past. This strategy is also adopted by Zervas et al. (2017) to measure Airbnb supply in each county.[6]

Two instrumental variables are used in the IV-2SLS estimation to identify the causal impact of Airbnb listings on hotel revenues. Vacant house is defined as residential property with power usage lower than 60 kilowatt hours per month. Housing inventory is the number of newly-built houses, within five years, to be sold in a city or county. Both variables are collected from Platform of Real Estate Information from Ministry of the Interior in Taiwan as the numbers are reported in every quarter. The intuition for choosing vacant house and housing inventory as IVs will be explained in the next section.

[3] Note that our sample periods are before the outbreak of COVID-19. While this choice of sample periods yields cleaner effects of Airbnb on hotel performances, our study cannot speak to the changes of COVID-19 on the lodging industry as the pandemic fundamentally change the landscape of the whole tourism industry. For the impact of COVID-19 on hotels in Taiwan, please see Kuo (2022).

[4] RevPAR is the most commonly-used performance measure in the lodging industry. With room revenues and sales in each month, we can calculate average daily rate (ADR) for each room-night sold. Occupancy rate is obtained by dividing sales with total number of room available in each month. Revenue per available is the product of average daily rate and occupancy rate.

[5] Some platform use five point scale while others use ten point scale. We use ten point scale and convert five point scale into ten by multiplying rating scores by two.

[6] In Online Appendix A, we provide a table of cumulative counts of Airbnb listings in each year for all counties.

3 Empirical Model

The panel structure of our dataset allows for the possibility of controlling various levels of fixed-effects. Following Zervas et al. (2017), we use the following regression equation:

$$\log(\text{RevPAR}_{jkt}) = \beta \cdot \log(\text{Airbnb listing}_{kt}) + \boldsymbol{X}'_{jkt}\boldsymbol{\gamma} + \nu_j + \tau_t + \text{County}_k \times \text{Month}_t + \epsilon_{jkt} \quad (1)$$

where j indexes hotels, k indexes county, and t indexes year-month. Our main dependent variable, RevPAR, is a common measure of hotel performance in the lodging industry. $\boldsymbol{X}_{jt}$ are controls for hotel characteristics, including age, number of rooms, number of employees, and online rating scores. We also includes total number of hotel rooms supplied in a county to control for changes in total hotel room supplied. Airbnb listing$_{kt}$ is cumulative number of listings in a county. Parameter of interest is β, which measures the impact of Airbnb's listing on hotel revenues. τ_j is hotel fixed effect, which absorbs any time-invariant firm-specific unobserved factor and ν_t is time fixed effect, which captures overall macroeconomic conditions or demand shocks common to all firms in every market. Seasonality in a specific market is included by adding county-month fixed effects. Finally, ϵ_{jkt} is an error term.

This econometric model is widely-used by previous studies as it is essentially a generalized difference-in-differences regression model with a continuous treatment. However, the identifying assumption in a DD framework may not be satisfied in this case since Airbnb hosts can flexibly adjust their room supply in response to future demand shocks, which are unobserved by researchers. Parallel trend assumption is violated as hotels compete with more Airbnb listings would benefit from positive demand shocks such as music festival, or major sports events. The revenue trends would not have been the same in the absence of increase in Airbnb listings.

To address the endogeneity issue, we use two instrumental variables, vacant houses Z^1_{kq} and housing inventories Z^2_{kq}. Both variables measure unused housing resources in county k at year-quarter q. The number of cumulative Airbnb listings could be positively correlated with spare housing capacities, satisfying the relevance condition for IVs.[7] The two IVs are likely to be uncorrelated with unobserved demand shocks and meet the exclusion restriction for two reasons. First, consumers considering hotels and Airbnb are unlikely to purchase residences for their short-term stays. The price and usage are vastly different. Second, surpluses in residential housing markets were determined several years ago and cannot be adjusted in few months as regional demand shocks to Airbnb and hotels tend to be transitory. Therefore, equilibrium in residential housing market would be independent to that in accommodation market, making both instruments valid.

4 Empirical Results

Table 1 reports estimation results for Equation (1) with OLS and IV-2SLS estimation respectively. In the first column in Table 1, in which OLS estimates are presents, we find a negative but insignificant relationship between Airbnb listings and hotel revenues. However,

[7] Our first-stage regression results in Table 1 actually confirm this requirement.

the estimate is close to zero and not economically significant as 1% increase in Airbnb listings is associated with only 0.006% decrease in RevPar. The OLS estimate is potentially affected by omitted variable bias.[8] As unobserved demand shocks could be positively correlated with Airbnb listings and RevPar, the direction of bias is likely to be upward, resulting in a less negative estimate of Airbnb listings.

After addressing the endogeneity issue, IV estimates of column 3 is much more negative and precisely estimated. On average, 1% increase in cumulative Airbnb listings is causing around 0.19% decrease in RevPar.[9] Our estimated impact of Airbnb listings is larger when compared to results in Zervas et al. (2017), in which the author find around 0.04% decrease in revenue when Airbnb listings increase by 1 %. However, despite the fact we implement IV approach in estimation, majority of hotels in Taiwan are in general small hotels in lower tiers.[10] Airbnb could be close substitute for low quality hotels since these hotel only provides basic services without various amenities. Therefore, we compare our results with recent studies focusing on Airbnb in Taiwan. Our estimated adverse effects are notably larger than results in Chang and Sokol (2021), in which the authors did not estimate direct impact on RevPAR. Instead, they separately estimate impact on and price and occupancy rate to investigate strategic responses and find that an increase of 1,000 Airbnb lists lowers the occupancy rate by 4.6 %. In Table A3, our results on occupancy rate is 8.8% decrease when Airbnb listings increase by 1%. Given the average number of Airbnb listings is around 200 in both studies, 1% increase is around 2 listings. Our estimates in revenue is 0.19% decrease per 2 listings, which indicates significantly larger effects. Lee and Lin (2022), on the other hand, do not quantify the impact of Airbnb on hotels in Taipei. However, the authors do conclude that Airbnb is an innovative competitor to conventional hotels.

We further separate our sample based on quality levels and capacities to investigate heterogeneous effects of Airbnb listings. Estimation results are presented in Table 2. Column 1 uses hotel with lower than 3 stars and Column 2 focus on hotel with 3 or more stars. The difference between estimates in Column 1 and 2 is stark. Estimate of -0.237 is larger in magnitude comparing to -0.191 in Table 1. Hotels with lower qualities are heavily affected by Airbnb while hotels of higher quality are less affected with insignificant estimate. The finding is also consistent with those in Chang and Sokol (2021), in which the authors find low quality hotels tend to be more affected in term of occupancy rates and average daily prices. But our estimates show stronger magnitudes. For Column 3 and 4, we run separate IV-2SLS for hotels below and above median capacity, 33 rooms. The estimates of Airbnb listings show that smaller hotels are heavily affected by increase in Airbnb listings. The results can be driven by two facts. First, smaller hotels tend to be of lower quality. As consumers view Airbnb as substitutes of low quality accommodations, these hotels are heavily affected by Airbnb. Second, hotels with smaller capacities often have limited financial resources to moderate the adverse effects from Airbnb.

[8] The number of inbound visitors and number of hotels are growing after 2008. See Online Appendix for more details.

[9] The decrease in RevPar is mainly driven by lower occupancy rates. See Online Appendix Table A3.

[10] According to Hollenbeck (2018) and Zervas et al. (2017), mean capacity of Texas hotels is 86. In contrast, mean capacity of Taiwanese hotels is 33. We present a distribution of hotel capacities in Online Appendix.

Table 1: **Effect of Cumulative Airbnb Listings on Hotel Revenue**

	(1) OLS	(2) IV-2SLS 1st	(3) IV-2SLS 2nd
log Cum. Airbnb listings	-0.006		-0.191***
	(0.005)		(0.069)
Hotel Age	-0.119***	-0.018	-0.123***
	(0.029)	(0.028)	(0.029)
log No. of Rooms	-0.678***	-0.014	-0.680***
	(0.044)	(0.043)	(0.045)
log No. of Employees	0.285***	0.014	0.288***
	(0.024)	(0.016)	(0.024)
Is Reviewed	-0.101	-0.045	-0.110
	(0.125)	(0.153)	(0.127)
Average Rating	0.044**	0.013	0.046***
	(0.017)	(0.021)	(0.017)
log Hotel Room Supply	0.047	-0.381***	-0.043
	(0.032)	(0.076)	(0.047)
log Vacant Houses		0.748**	
		(0.309)	
log Housing Inventories		0.163***	
		(0.027)	
Hotel FEs	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes
County-Month FEs	Yes	Yes	Yes
N	201,052	201,052	201,052

Note: Dependent variable in column 1 and 3 is logarithm of revenue per available room. Column 2 is the first-stage regression results of IV-2SLS. Endogenous variable is log cumulative Airbnb listings. Associated F-statistic for excluded instruments is 19.64. The Hansen overidentification test statistic is 0.081, which has a p-value 0.776. Standard errors in parentheses are robust and clustered at firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

In this paper, we use measures of unused resources or capacities as instrumental variables for endogeneous entry of sharing economy. Our empirical findings show significant negative effects of Airbnb listings on hotel revenues. Moreover, small lower quality hotels face stronger competition from Airbnb listings. We argue that the variations in unused resources are

Table 2: **Heterogeneous Effects for Different Qualities and Capacities**

	(1) Low Quality	(2) High Quality	(3) Small Capacity	(4) Large Capacity
log Cum. Airbnb listings	-0.237**	-0.054	-0.288***	-0.131
	(0.093)	(0.065)	(0.109)	(0.102)
Hotel Age	-0.119***	-0.137	-0.083*	-0.137***
	(0.030)	(0.105)	(0.042)	(0.044)
log No. of Rooms	-0.690***	-0.522***	-0.811***	-0.521***
	(0.048)	(0.138)	(0.054)	(0.085)
log No. of Employees	0.298***	0.199***	0.278***	0.277***
	(0.025)	(0.072)	(0.034)	(0.034)
Is Reviewed	-0.252	0.094	-0.511*	-0.052
	(0.154)	(0.193)	(0.302)	(0.140)
Average Rating	0.069***	0.009	0.110**	0.033*
	(0.022)	(0.024)	(0.043)	(0.019)
log Hotel Room Supply	-0.059	0.042	-0.042	-0.059
	(0.057)	(0.077)	(0.074)	(0.066)
Hotel FEs	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes
County-Month FEs	Yes	Yes	Yes	Yes
N	174636	26410	88816	112184
F-statistic	13.38	14.54	9.78	8.93
Overidentification test-stat.	0.004	0.984	0.384	1.934

Note: Column 1 limits to 1-star or 2-star hotels or hotels without any star rating, and Column 2 focuses on hotels of 3-star or more. Dependent variable for all columns is logarithm of revenue per available room. Column 3 and 4 use median capacity, 33 rooms, to define hotel with small capacity and larger hotels. Endogenous variable is log cumulative Airbnb listings. First-stage results are presented in Online Appendix Table A4. Standard errors in parentheses are robust and clustered at firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

orthogonal to unobserved demand shocks. The intuitions of using this type of instrumental variables can be applied to studies on sharing economy.

As our empirics point out, the estimated impact of Airbnb is not only negative but also larger in magnitudes than prior studies. Hotels may underestimate the business stealing effects from Airbnb, and fail to react timely. Small and low quality hotels are the most affected as their market segmentation is close to Airbnb. Moreover, limited financial resources to implement strategic responses make them even more vulnerable. One possible solution is to create a new market segmentation away from Airbnb with product differentiation both horizontally and vertically.

Our study is not free from limitations, some of which are related to the chosen data. These limitations can potentially be the directions of future research. First, the data predates COVID-19, failing to capture important changes in the whole lodging industry in the post-COVID-19 era. Second, we do not have consumer information at regional levels. These information would be important as they drive differential impacts in different areas. Finally, our Airbnb listing data is cumulative. Detailed entries or exits overt time are not observed.

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