The Real Effects of Sharing Economy: Evidence from Airbnb

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Abstract

Sharing economy has developed rapidly in recent years, but little is known regarding its real effects. This paper examines how a pioneer of sharing economy—Airbnb—affects local economy. Using venture capital infusions as plausibly exogenous shocks to Airbnb's expansion into a new county, we find that Airbnb expansion leads to poorer hotel performance in the local county. Meanwhile, Airbnb expansion appears to reduce unemployment rate and increase household income. Further analysis suggests that increased employment is concentrated in industries that are complementary to Airbnb's business and in employee groups with lower education levels. Our study sheds new light on the real effects of the sharing economy and provides important policy implications for policymakers.

Keywords: Airbnb, Sharing economy, Hotel performance, Unemployment, Venture capital

JEL code: G22, G29, D31, J21

1. Introduction

Sharing economy, often referred to as "peer to peer" business transactions, has been growing rapidly in recent years. By facilitating individuals to share resources with each other, the emergence of sharing economy has disrupted traditional business models and challenged policy makers with unprecedented problems. On the one hand, sharing economy expands the opportunity set from which individuals or families could generate extra income and lowers the cost of consumers. On the other hand, sharing economy intensifies business competition and increases unexpected criminal cases, and as a result sharing economy casts doubt on this new business model.[1] Therefore, it is important to understand the real effects of the entry of sharing economy on local economy.

Airbnb, a pioneer of the sharing economy, enables people to list or rent short-term lodging in residential properties. Since its foundation in 2008, Airbnb has expanded at a dramatic rate, received both applause and scrutiny from the society, and attracted a fair amount of regulatory attention. It is, however, still unclear to researchers and policymakers how Airbnb affects the local economy, although the understanding of this question is important for policy making. In this paper, we attempt to fill in this gap in the literature and explore the real effects of Airbnb on local economy.

A major challenge of our empirical analysis is that Airbnb's expansion into a county is likely endogenous with unobservable county characteristics, such as the county's economic conditions and local culture. Therefore, a correlation between Airbnb's expansion into a county and local hotel performance, unemployment rate, and household income may tell us little about the causal effect of Airbnb on local economy. We alleviate the endogeneity concern by exploiting plausible exogenous variation in venture capital (VC)'s capital infusions in Airbnb and use it as an instrumental variable for the identification purpose. Airbnb has attracted multiple rounds of VC financing, and each round of financing has largely improved its products and services, which facilitates its entry into new counties and boosts its growth. To the extent that VCs' investment in Airbnb is based on considerations regarding Airbnb's own long-term prospects instead of the economic performance of counties that Airbnb has not entered yet, VC

[1] For example, Dills and Mulholland (2017) find that Uber's entry in a county lowers the arrests for assault and disorderly conduct, but increases vehicle theft. Xu, Kim, and Pennington-Gray (2017) find that Airbnb is positively related with property crime, and negatively related with violent crime.

financing of Airbnb affects a county's local economy only through its effect on Airbnb's expansion in the county and hence reasonably satisfies the exclusion restriction.

Another challenge is that Airbnb's entry in a county is endogenous with the county unobservable characteristics. As a result, different counties could have different levels of Airbnb entry and different marginal reactions to VCs' capital infusions in Airbnb. To mitigate this concern, we use an event-time analysis by treating the month of Airbnb's entrance into a county as the event month (i.e., month 0). Under the event-time framework, VC financing shocks happen at different calendar times in different counties, but at similar Airbnb development stages. Therefore, the event-time analysis has two advantages in our empirical setup. First, it allows us to better capture an average effect of Airbnb expansion triggered by VC financing on local economy. Second, it represents staggered shocks to Airbnb expansion in the cross section and avoids a common identification difficulty faced by studies using a single shock, i.e., potential omitted variables coinciding with the shock could directly affect local economy.

As a first step, to verify the impact of VC financing on Airbnb expansion, we examine the changes in total Airbnb rooms listed on the market after each round of VC capital infusions. Consistent with our conjecture, there is a significant increase in the number of Airbnb rooms following each round of VC financing. The economic magnitude is sizable: A one additional round of VC financing increases the number of Airbnb listings by 11.7% in the following 3 months.

Next, we examine how Airbnb expansion triggered by VC capital infusions affects local economy. We first explore the effect of Airbnb on its direct competitor, i.e., traditional hotels. Airbnb, as a disruptor to the hotel industry, has been viewed as a potential business threat by the hotel industry. This is because Airbnb provides customized travel accommodations at a lower cost and is able to lure customers with its low prices and high flexibility in room types. We hypothesize that Airbnb has a crowding-out effect on hotel business and hence negatively affects hotel performance in counties into which it enters. Consistent with our conjecture, we find that the growth of Airbnb in a county negatively affects the local hotel business in multiple dimensions. In particular, a 10% increase in Airbnb listing in a month leads to local hotels' occupancy rate drop by 2.7%, room demand drop by 4.7%, room supply drop by 0.3%, total room revenue drop by 5.8%, revenue per sold room drop by 1.1%, and revenue per available room drop by 5.4% in three months in the county.

We next examine how Airbnb expansion affects local unemployment rate. We conjecture that Airbnb expansion could reduce unemployment rate because of at least two reasons. First, it is likely that the option of relying on Airbnb to generate income could reduce labor supply, i.e., individuals who actively search for jobs before now switch to manage their own Airbnb listings. Second, Airbnb might increase labor demand, in particularly in industries that provide complementary services to Airbnb. Consistent with our conjecture, we find that, a 10% increase in the number of Airbnb listings leads to a 1.2% decrease in local unemployment rate. The drop in the unemployment rate is driven by an increase in employment and a drop in labor supply. In particular, a 10% increase in Airbnb listings leads to a 0.4% increase in employment and a 0.8% drop in labor force.

The decrease in unemployment is most pronounced in less-educated groups (the ones lower than high school) and least pronounced in the better-educated group of people (the ones with bachelor or more advanced degrees). This observation is consistent with the fact that Airbnb related job positions is relatively low-tech, and does not require room providers to have high levels of education. The decrease in unemployment rate is also more pronounced in groups of young and senior individuals, compared to middle-age group of individuals. This finding is perhaps due to the fact that younger and aged individuals are more likely to be in Airbnb-related service industries that require less hard skills and stamina. Finally, the decrease in unemployment rate is concentrated in administrative, support & waste management, and accommodation & food services industries. These industries are exactly the ones that are complementary to Airbnb business. The cross-sectional employment findings lend further credence to our hypothesis that Airbnb is likely to have a causal, negative effect on local unemployment rate.

Finally, we examine how Airbnb affects household income. We find that household income experiences an increase after Airbnb expansions. In particular, Airbnb expansion reduces the number of households in the low annual income bucket (i.e., annual household income lower than $50,000) and increase the number of households in the higher annual income buckets (i.e., annual household income between $50,000 and $100,000 and annual household income higher than $100,000). It appears that by offering local residents an additional channel that generates income, Airbnb increases local household income.

Our paper contributes to several strands of the literature. First, it is related to the nascent literature on the sharing economy. A limited number of papers have examined how different forms of sharing economy affect the incumbent industry. For instance, focusing on observations in one state, i.e., Texas, Zervas et al. (2015) find that Airbnb entry negatively affects the hotel industry. Sheppard and Udell (2016) study Airbnb in New York City, and find that a doubling of Airbnb listings is associated with an increase of 6% to 11% in house values. Different from the above studies, our paper examines Airbnb's impact on local employment and household income in addition to hotel performance. Our sample covers all states across the U.S. instead of just one state. There are also a few studies that focus on Uber—another sharing economy giant. For example, using individual-level data and a regression discontinuity design, Cohen et al. (2016) estimate that Uber service generates approximately $6.8 billion consumer surplus in the United States in 2015. Dills and Mulholland (2016) find that Uber entry lowers the rate of driving under the influence (DUIs) and fatal accidents, arrests for assault, and disorderly conduct, but increases vehicle thefts. Chen et al. (2017) use high-frequency data of hourly earnings for Uber drivers and find that Uber allows drivers to earn more than twice the surplus they would in less flexible arrangements. Our paper contributes to this strand of studies on the sharing economy by documenting the real effects of Airbnb, making use of plausibly exogenous variation in Airbnb expansion generated by staggered VC capital infusions, and looking into Airbnb's effect on local employment and household income in addition to its effect on the hotel industry.

Second, our paper is related to the VC literature (see, e.g., Da Rin, Hellmann, and Puri (2013) for an excellent survey of this literature). Many studies have examined how VC financing affects the real economy, such as entrepreneurship, productivity, innovation, and employment. For example, Samila and Sorenson (2011) find a positive impact of VC financing on aggregate employment and aggregate income. Kortum and Lerner (2000), Mollica and Zingales (2008), and Chemmanur et al. (2014) show that increases in VC investments lead to more innovation in terms of new business creation and patents generation. Our paper contributes to this literature by showing that VC investors could spurs business model innovation and affect local economy through their investment in unicorns in a new business model – sharing economy.

The rest of the paper is organized as follows. Section 2 describes our data and sample selection, and discusses variable constructions. Section 3 reports the baseline results regarding the effects of Airbnb expansion on hotel performance. Section 4 discusses our identification strategy. Section 5 examines the effect of Airbnb on employment and household income distribution, as well as the heterogeneous effects of Airbnb expansion on local economy. Section 6 concludes.

2. Data and Main Variables

2.1 Airbnb

Airbnb, based in San Francisco, California and founded in August 2008, is a marketplace for people to list and book accommodations. The accommodations can be rooms, apartments, houses, etc. The hosts, who want monetize their extra space, list their accommodations on Airbnb's online platform and showcase them to the potential guests, while the guests, who want to explore an experiment in these unique space, identify and book the accommodations on the platform. Airbnb charges a 3% of service fee from room providers.

When the hosts post their accommodations on Airbnb platform, they provide detailed information of the property, including property type, county-level location, the first date that the host becomes a member of Airbnb, the name of the host, the number of bedrooms, the number of beds, the number of bathrooms and the price charged per night. Photos of the listing and guest reviews are also available on the Airbnb platform. We collect these pieces of information from the Airbnb website (www.airbnb.com).

In this study, we focus on the county-level analysis. We aggregate Airbnb data up to the county level and define a county as an "Airbnb county" if it has at least one listing by the end of 2015, and a "non-Airbnb county" otherwise. We define our key independent variable, *No. of Airbnb listings*, at the county-month level as follows: for a given county in a month, we count the number of listings that have been cumulatively posted on the Airbnb platform in the county and up to that month. As the entry dates of individual listings are unobservable from the platform, we use the date that their hosts become the members of Airbnb as the proxy. While we note that as the hosts take their listings on and off the platform from time to time, the Airbnb room supply fluctuates. Due to the fact that Airbnb is at the stage of exponential growth, it is reasonable to use the cumulative supply as a proxy for the instantaneous supply. For each Airbnb county, we define *age* as the number of months since the first listing is posted in the county on Airbnb platform.

Table 1 panel A presents the summary statistics for Airbnb variables at the county level. Our sample includes 32,048 distinct listings in 451 counties of 51 states in the United States, spanning a period from 2008 to 2015. By 2015, a typical Airbnb county in our sample has 70.8 listings on the Airbnb platform with the *age* of 47 months.

[Insert Table 1 about Here]

2.2 Hotel Performance

Our hotel performance data come from the STR. STR is an independent research company that collects detailed information about hotel properties and their performance. The performance data are voluntarily provided by hotels. Hotels have strong incentives to provide accurate data to the STR, because as a return, the hotels are able to receive aggregated occupancy and performance of their local hotel market. The STR data cover around 62% properties and 75% of rooms in the U.S. We obtain the county-month level hotel performance data from STR, including occupancy rate, room supply, room demand, total room revenue, revenue per sold room, and revenue per available room. Room supply is labelled as "rooms available", measured by the number of rooms multiplied by the number of days during a given period. Room demand is labelled as "rooms sold", calculated by the number of rooms sold during a given period, excluding complimentary rooms. Occupancy rate is measured by rooms sold divided by rooms available. Total room revenue generated from the sale or rental of rooms is referred to total room revenue. Revenue per sold room is measured by total room revenue divided by rooms sold. Revenue per available room is measured by total room revenue divided by rooms available.

Among all Airbnb counties, we obtain hotel performance data of 221 counties from the STR.[2] These 221 sample counties contain 30,436 Airbnb listings, covering more than 95% of all Airbnb listings by the end of 2015. Table 1 panel B presents the summary statistics of hotel variables at the county-month level. To minimize the effect of outliers, all variables are winsorized at the 1st and 99th percentiles. A typical county in our sample receives total room revenue of $37.3 million, revenue per sold room of $115.0, and revenue per available room of $75.0, as well as has an occupancy rate of 62.9%, a supply of 437,650 rooms, and a demand of 291,874 rooms per month.

[2] We obtain hotel data from STR under strict confidentiality agreement.

2.3 Control Variables

To control for the effect of local economy on both Airbnb supply and hotel performance, we include a few control variables, including population, median household income, unemployment rate, and median housing values, in the analyses. Our population data and income data are from the Census Bureau. The Census provides county-level population estimates as of July 1st of each year, and we use it as a proxy for population for each month in the same year. The Census also provides county-year level poverty and median income estimates. We divide annual median household income by 12 as a proxy for monthly median household income. Our unemployment rate data are obtained from the Bureau of Labor Statistics (BLS). The BLS reports unemployment rate at the county-month level. Our housing value data are retrieved from Zillow (www.zillow.com). Zillow provides county-month level median housing values.[3]

Table 1 panel B presents the summary statistics of control variables, including population, median household income, unemployment rate, and median housing values, at the county-month level. A typical county in our sample has a population of 573,406, median household income of $4,657, unemployment rate of 6.8%, and median housing value of $233,204.

2.4 VC Financing Data

We obtain information on VC investment in Airbnb from the VentureXpert database. VentureXpert provides detailed information on each round of VC financing, including financing round date, financing amount, the name of investing VCs, and the development stage of startups when they receive VC investment. Between 2009 and 2015, Airbnb receives a total of 9 rounds of financing from VCs.

3. The effect of Airbnb on Hotel Performance

We start our analysis by exploring the effect of Airbnb on hotel performance. We estimate the following model by using the ordinary least squares (OLS) regressions:

$$HP_{i,t+l} = \alpha + \beta \times Ln(\,Airbnb\ listings)_{i,t} + \gamma \times M_{i,t} + FE + \varepsilon_{i,t+l} \qquad (1)$$

where *i* indexes county, *t* indexes age, and *l* indexes the number of months ($l \in \{1,2,3\}$) that the dependent variable (*HP*) leads the independent variables. The unit of observation in our tests is

[3] For the county-month with missing median housing value form Zillow, we use state-month level data, which also comes from Zillow, as proxy.

county-age. The key variable of interest is *Ln(Airbnb listings)*, measured by the natural logarithm of the number of Airbnb listings in a county in a month. Given that the Airbnb is at the stage of exponential growth, to make our results more comparable and meaningful, we require each county in our county-month level sample has at least five Airbnb listings.[4] To address the concern that local economy may affect both Airbnb growth and hotel performance, we include a set of local economy condition variables (*M*) as controls, including median household income, population, unemployment rate, and median housing values. We use the natural logarithm of median household income, population, and median housing values in our regressions. To further absorb the potential variation that is unrelated to Airbnb supply but may affect our results, we include a set of fixed effects, *FE*, including county fixed effect, age fixed effect, and first listing year-month fixed effect. For each county, first year-month is measured as the year-month of a county's first listing on the Airbnb platform. We cluster standard errors at the county level to control potential serial correlations.

3.1 The Effect of Airbnb on Hotel Occupancy Rate

First, we use hotel occupancy rate, room demand, and room supply as the dependent variable (*HP*), and present the results from estimating regression (1) with the OLS model in panels A-C of Table 2, respectively. We use the natural logarithm of room demand and room supply in these regressions.

[Insert Table 2 about Here]

In panel A, the dependent variable is *occupancy rate*. The coefficient estimate of *Ln(Airbnb listings)* is negative in all columns, and significant at the 1% level in columns (2) and (3). These results suggest that hotel occupancy rate declines significantly starting from the second month after an increase in Airbnb room supply in the county. The economic effect of Airbnb supply on hotel occupancy rate is sizable: increasing Airbnb supply by one standard deviation (99.3) from its mean value (70.7) is associated with a 7.4% (0.016*ln(99.3)) and a 9.7% (0.021*ln(99.3)) decrease in hotel occupancy rate in the second and third month, respectively.

Regarding economy condition controls, we find that counties with higher median household income are more likely to have higher hotel occupancy, suggested by the fact that the coefficient estimates on median household income are positive and significant at the 10% level

[4] We find similar results when we release this requirement.

in column (1) and at the 5% level in other columns. The coefficient estimates on population are positive and significant at the 1%, suggesting that larger population is associated with a higher hotel occupancy rate. The coefficient estimates on median housing values are negative and significant at the 1% and 5% level in the first and second column, respectively, suggesting that hotel occupancy rate is negatively related to local housing values.

We then turn to the demand and supply for hotel rooms to explore the causes of the negative relation between hotel occupancy rate and Airbnb supply. In panel B, we replace the dependent variable with hotel room demand and estimate equation (1). We suppress the coefficient estimates of control variables to save space. The coefficient estimates on *Ln(Airbnb listings)* are negative and significant at the 1% level in the second and third columns, suggesting that the demand for hotel rooms decreases significantly starting from the second month after an increase in Airbnb supply. Specifically, doubling *Ln(Airbnb listings)* is associated with a 3.4% and 4.3% decrease in hotel room demand in the second and third month, respectively. In panel C, we replace the dependent variable with hotel room supply. The results show that the coefficient estimates on *Ln(Airbnb listings)* are not statistically significant, suggesting that hotels do not make significant adjustments to their room supply in face of an increase in Airbnb supply.

The results reported in Table 2 suggest that, on one hand, the demand on hotel rooms declines starting from the second month following an increase in Airbnb supply; on the other hand, hotels cannot make significant adjustments to increase their room supply at the same time. Combining both effects, the increase in Airbnb supply has a significantly negative effect on hotel performance.

3.2 The Effect of Airbnb on Hotel Revenue

We next explore how Airbnb affects hotel revenue. To shed some lights on this question, we use total room revenue, revenue per sold room, and revenue per available room as the dependent variable and report the results of estimating regression (1) in panels D-E of Table 2, respectively. Results in panel D show that the coefficient estimates on *Ln(Airbnb listings)* are negative in all columns, and statistically significant at the 5% and 1% level in columns (2) and (3), respectively. The effect is economically sizable: hotel total room revenue decreases by 4.0% and 5.3% in the second month and third month if Airbnb supply doubles, respectively. In panel E, the coefficient estimates on *Ln(Airbnb listings)* are not statistically significant, suggesting that revenue per sold room does not significantly change after an increase in Airbnb supply. In panel F, the coefficient estimates on *Ln(Airbnb listings)* are negative in all columns, and significant at 5% and 1% level in columns (2) and (3), respectively. Specifically, doubling Airbnb supply is associated with a 3% and 4.2% decline in revenue per available room in the second and third month, respectively.

Results in Table 2 suggest that Airbnb has a negative effect on hotel revenue. In particular, after an increase in Airbnb supply, revenue per hotel sold room does not have significant change, but as the number of rooms sold (room demand) significantly declines, there is a significant decrease in a hotel's total room revenue. Moreover, as hotels typically cannot make significant adjustments to room supply, revenue per available room declines significantly due to the decrease in total room revenue.

4. Identification

A major challenge of our study is to identify the causal relation between Airbnb expansion and hotel performance. Given that an increase in Airbnb room supply is caused by the new listings posted on Airbnb platform by the hosts, and whether to post a new listing is mostly determined by the vacancy condition of the property rather than the performance of hotels, changes in Airbnb room supply are likely exogenous to hotel performance. Hence, the negative relation between Airbnb room supply and hotel performance in our baseline results are likely causal.

However, it is still possible that our baseline results are driven by reverse causality, whereby the differences in hotel performance across counties trigger the growth of Airbnb expansion. In this section, we attempt to address this endogenous concern and to establish a causal link between Airbnb expansion and hotel performance.

Our identification strategy relies on plausibly exogenous variation in Airbnb supply generated by VC capital infusions in Airbnb. VC financing significantly increases the operation funding of Airbnb, which can be used in advertising, employee hiring, office building, online platform improving, etc., and as a result, attracts more potential hosts and stimulates the growth of Airbnb room supply. One advantage of using VC financing as an instrument for Airbnb room supply is that when VCs invest in Airbnb, they do not intend to promote or demote Airbnb' expansions into specific counties. Thus, VC capital infusions in Airbnb can be considered as staggered shocks that affect Airbnb growth in all counties of the U.S.

One potential concern of using VC financing as an instrument variable for Airbnb room supply is that previous hotel performance might be one of the major considerations of VC investors when they decide whether to invest in Airbnb or not. However, our county-age data structure is able to mitigate this concern. In our framework, we define *age* as the number of months since the county has its first Airbnb listing. As each county has its first listing posted on Airbnb platform at different times, VC financing happens at different times (ages) for each county. Another advantage of using the variation generated by VC financing is that Airbnb receives 9 rounds of VC financing between its founding date and the end of our sample period (i.e., 2015). Thus, VC financing represents multiple shocks affecting different counties at exogenously different times (ages). This fact helps avoid a common identification difficulty faced the studies using a single and general shock, and addresses the concern that there may exist omitted variables that coincide with the VC financing and directly affect hotel performance.

4.1 First-stage Regressions

To construct the instrumental variable for Airbnb room supply, we define *VC financing index*, which equals 0 if the observation is before any round of VC financing, 1 if the observation is since the first VC round, 2 if the observation is since the second VC round, until 9 if the observation is since the ninth VC financing round. Considering the fact that after VC announces an investment in Airbnb, it takes time before Airbnb receives all the funding and launch the funding to daily operation, we use *VC financing index* in period *t-3* as the instrument variable for *Ln(Airbnb listings)* in period *t*. We estimate the effect of *Ln(Airbnb listings)* on hotel performance from period *t+1* to *t+3* by running two-stage least square (2SLS) regressions and estimating equation (1).

In Table 3, we present the results of the first-stage regressions. The coefficient estimate on *VC financing index* is positive and significant at the 1% level, suggesting a positive relation between VC financing and Airbnb room supply. The economic effect is sizable: after a new round of VC financing in Airbnb, i.e. VC financing index increase by one, *No. of Airbnb listings* increases by 2.5% (0.117/ln(99.309)). To address the concern on whether *VC financing index* is a proper instrumental variable for *Ln(Airbnb listings)*, we run both the Sanderson-Windmeijer (SW) under-identification test and the SW weak identification test (Sanderson and Windmeijer, 2015), and report the *Chi-squared* Wald statistics from under-identification test and *F*-statistics from weak identification test in the last two rows of Table 3, respectively. The results reject the null hypothesis that the endogenous regressor, *Ln(Airbnb listings)*, is unidentified and the null hypothesis that *Ln(Airbnb listings)* is weakly identified.

In summary, we find that VC financing is significantly related to Airbnb supply, and it passes the under-identification and weak instrument tests. Hence, our proposed instrument reasonably satisfies the relevance condition.

4.2 Second-stage Regressions

In table 4, we present the results of the second-stage of the 2SLS regressions in which instrumented *Ln(Airbnb listings)* is the main variable of interest. In each panel, we use occupancy rate, room demand, room supply, total room revenue, revenue per sold room, and revenue per available room as the dependent variable, respectively. Results in panel A show that the coefficient estimates on instrumented *Ln(Airbnb listings)* are negative and significant at the 1% level in all columns, suggesting that an increase in Airbnb room supply leads to a decrease in hotel occupancy in the following three months. These findings are consistent with the results in Table 2 in which an OLS analysis is undertaken. While the results in Table 2 suggest that Airbnb supply does not significantly affect hotel occupancy in the first month, results in Table 4 show that, after addressing endogeneity concerns with the proposed instrument, hotel occupancy rate declines significantly immediately after an increase in Airbnb room supply.

Results in panel B are also consistent with those reported in panel B of Table 2 but are even stronger, suggesting that increasing Airbnb room supply leads to a drop in hotel room demand in all of the following three months. The coefficient estimates on *Ln(Airbnb listings)* in panel C are negative in all columns and significant at the 10% level in the first column and at the 1% in the third column. These findings suggest that, in response to an increase in Airbnb room supply, hotels reduce their room supply, which is not revealed in the results in Table 2 panel B. Comparing the results in panel B and panel C, all coefficient estimates on *Ln(Airbnb listings)* are larger in panel B, suggesting that while both demand and supply of hotel rooms decline after an increase in Airbnb room supply, demand declines more significantly. These results help explain the decrease in hotels’ occupancy rate.

In panels D and F, we find a negative effect of Airbnb supply on hotel total room revenue and revenue per available room. These results are consistent with those reported in Table 2 panels D and F. The coefficient estimates on *Ln(Airbnb listings)* in panel E are negative in all columns and significant at the 1% level in the second and third columns, suggesting a negative relation between Airbnb room supply and revenue per sold room, which is not revealed by the results reported in Table 2 panel E.

In summary, using *VC financing index* as an instrumental variable for *Ln(Airbnb listings)*, and the 2SLS approach, we observe a negative, causal effect of Airbnb supply on hotel performance. In particular, we find that after an increase in Airbnb room supply, hotel room demand decreases, and hotels reduce their room supply. Because demand declines faster than supply does, hotel occupancy rate decreases. The decrease in revenue per sold room, combined with the decrease in room demand, results in a decrease in hotels' total room revenue. Putting these facts all together, although hotel room supply decreases, there is a decrease in revenue per available.

5. The Effect of Airbnb on Employment and Household Income Distribution

In this section, we explore the "bottom-line" question regarding the real effects of Airbnb: Does Airbnb affect local employment and income distribution? On one hand, Airbnb provides the hosts a marketplace to monetize their extra space, and as a result, it changes the income structure of these individuals. For example, income collected from leasing accommodations through Airbnb might release the financial constraints of these hosts to a large extent. Thus, some of them might exit from the labor market and live on the rental income, and some of them might use the rental income to start their own businesses. On the other hand, the emergence of available accommodations and the arrivals of guests might bring changes and opportunities to local business. For example, after the guests check out, the hosts might hire cleaning and housekeeping companies to clean and maintain the rooms, which would increase job positions in, for example, waste management and remediation service industry. The arrivals of new travelers may require developments of local infrastructure, such as new restaurants, cafes, and bars, and thus create new job positions.

In this session, we try to uncover whether and how Airbnb affects local employment and household income distribution. We present the results on Airbnb's effect on employment in

Session 5.1. We then explore the heterogeneity and report the results in Session 5.2. In Session 5.3, we explore Airbnb's effect on household income distribution.

5.1 The Effect of Airbnb on Employment

The first hurdle of studying the effect of Airbnb on employment is the ambiguous relation between Airbnb hosts and labor force statistics from the Bureau of Labor Statistics (BLS): If a host receives rental income from leasing accommodation on Airbnb and has no other income resource, it is not clear whether the BLS count the individual as employed. To address this question, we start with the tax type of rental income collected by the host. According to The Guidance on The Taxation of Rental Income provided by Airbnb, the hosts should report their rental income and expenses on Schedule E of Form 1040. Their income may be subject to net investment income tax, unless the hosts are owners of a hotel or motel who provide services to guests or work as real estate dealers who are engaged in real estate selling business (in these two cases, rental income and expenses should be reported in Schedule C, and may be subject to self-employment tax). Airbnb suggests that most individual taxpayers report their rental income and expenses on Schedule E. Thus, if a host does not have any work for pay or profit besides leasing out accommodation, she would be considered as employed in the labor force statistics of the BLS. If other things do not change, leasing out accommodation through Airbnb and receiving rental income do not change the employed or unemployed status recorded by the BLS. Given this fact, we then use the labor force statistics provided by the BLS to examine the effect of Airbnb on local labor market.

The BLS provides county-year level labor force statistics. The BKS provides information on unemployment rate, the number of employed individuals, the number of unemployed individuals, and labor force. Labor force is measured by the total number of employed and unemployed individuals. Unemployment rate is measured as the number employed individuals divided by labor force. Summary statistics are presented in Table 1 panel C. Both Airbnb counties and non-Airbnb counties are included in this sample. A typical county in our sample has an unemployment rate of 7.7%, the number of employed individuals of 45,591, the number of unemployed individuals of 3,861, and labor force of 49,452.

We start our analysis by estimating the following model using the 2SLS regressions with the same instrumental variable we proposed before:

$$LF_{i,t+1} = \alpha + \beta \times Ln(Airbnb\ listings)_{i,t} + \gamma \times M_{i,t} + FE + \varepsilon_{i,t+1} \quad (2)$$

where i indexes county and t indexes year. The unit of observation is county-year. We use unemployment rate, the number of employed individuals, the number of unemployed individuals, and labor force as the dependent variable. We take natural logarithm for the last three variables. The key variable of interest is *Ln(Airbnb listings)*. We use *VC financing index* as the instrument variable. The set of control variables (*M*) includes median household income, population, and median housing values. As *VC financing index* is the same for each county at any given year, we do not control for year fixed effects but only county fixed effects. We cluster standard errors at the county level to control for potential serial correlations.

We report the first-stage results in column (1) of Table 5. The results suggest a positive relation between *VC financing index* and *Ln(Airbnb listings)*. We also show that *VC financing index*, as the instrumental variable of *Ln(Airbnb listings)*, passes the under identification test and weak identification test. We report the second-stage results in columns (2)-(4). In column (2), we use unemployment rate as the dependent variable. The coefficient estimate on *Ln(Airbnb listings)* is negative and significant at the 1% level, suggesting that an increase in Airbnb supply is followed by a decrease in unemployment rate in the next year.[5] Hence, Airbnb appears to have a positive effect on local unemployment rate.

To obtain more insights of the effect of Airbnb on labor market, we replace the dependent variable with *Ln(No, of employed)* and *Ln(labor force)* in columns (3) and (4), respectively. The significantly positive coefficient estimate of *Ln(Airbnb listings)* in column (3) suggests that there is an increase in employment, driven by increasing job opportunities in Airbnb-affiliated service industries. The significant coefficient estimate of *Ln(Airbnb listings)* in column (4) suggests that the size of labor market shrinks after an increase in Airbnb supply. It is possible that, because leasing out extra space through Airbnb increases monetary income for the hosts, some of them exit from the labor market and live on the rental income.

In summary, we find that an increase in Airbnb is followed by a decrease in unemployment rate. Specifically, Airbnb growth brings new job positions so that some unemployed people become employed. At the same time, Airbnb decreases labor supply as some individuals exit from the labor market.

[5] Results from estimating equation (1) with OLS models are similar.

5.2 Heterogeneous Effects of Airbnb on Local Employment

We next explore the heterogeneous effects of Airbnb on local employment. Specifically, we examine the types of individuals who have more opportunities to get these new jobs and who are more likely to exit from the labor market. To answer these questions, we explore the heterogeneity of Airbnb's effect on local employment in a few dimensions based on employee characteristics, including education levels and age. To complement the labor force data of the BLS, we retrieve labor market statistics from the Quarterly Workforce Indicators (QWI) provided by the Census. The QWI provides a unique job-level data set that links employees to their employers. The labor market data provided by the QWI include employee gender, age, education, and race/ethnicity, as well as employer industry and location. The QWI data come from the Longitudinal Employer-Household Dynamics (LEHD), which covers over 95% of private sector jobs in the U.S.[6]

The first dimension we explore is employees' education level. We retrieve employee data at the education-county-year level from the QWI, including the number of employees and total payroll. We use group employment, payroll per employee, and group payroll proportion as the dependent variable in each panel of Table 6, respectively. Group employment is measured by the logarithm of the number of employees in an education level group. Payroll per employee is measured by the logarithm of total payroll received by all employees in an education level group divided by the number of employees in the group. Group payroll proportion is measured by total payroll received by employees in a group divided by total payroll received by employees in all groups. There are four education groups, i.e., less-educated group (lower than high school), high school group (high school or equivalent), associate degree group (some college or associate degrees), and bachelor's group (bachelor's or advanced degrees). We report the results for each education-level group in Table 8.

In panel A of Table 6, we show that the coefficient estimates of *Ln(Airbnb listings)* are positive and significant at the 1% level in all columns, suggesting that Airbnb growth is associated with new job positions to employees among all education groups. The economic significance, however, varies across different groups of education levels. The magnitude of *Ln(Airbnb listings)* for less-educated group is more than 20 times larger than that for the

[6] QWI data do not cover self-employment, agricultural jobs, railroad employment, and other exceptions that vary from state to state. Federal employment is available for selected states.

bachelor's group, more than 3 times larger than that for the high school group and associate degree group. This observation suggests that Airbnb growth benefits less-educated individuals most, and leads to the largest increase in less-educated job positions.

In panel B, we report the results of using payroll per employee as the dependent variable. The coefficient estimates on *Ln(Airbnb listings)* are positive and significant at that 1% level in all columns, suggesting that Airbnb growth is associated with a growth in payroll per employee. We find that the magnitude of the *Ln(Airbnb listings)* coefficient decreases as the education level increases: Payroll per employee increases most for less-educated employees, and less for more well-educated employees. The growth of payroll per employee for less-educated employees is more than twice larger for employees who have bachelor or advanced degrees.

In panel C, we present the results with group payroll proportion as the dependent variable. Coefficient estimates of *Ln(Airbnb listings)* are significantly positive in the first two columns and significantly negative in the last two columns. These findings suggest that total payroll received by employees with high school or lower education increases, while payroll received by employees with higher education decreases. The magnitudes of coefficient estimate suggest that payroll received by less-educated employees increases to the largest degree, and payroll received by employees with bachelor and advanced degree decreases most. These observations suggest that total payroll flows from well-educated individuals to ones with relatively lower level of education.

In summary, an increase in Airbnb supply is associated with growth in employment and payroll per employee for all employees, but the effect of Airbnb on each education group varies. Both the number of employees and payroll per employee increase the most for less-educated individuals. The results suggest that total payroll flows from better-educated individuals to less-educated individuals.

The second dimension of heterogeneity we explore is employee age. Each employee is assigned to one of three groups, including the young group (age 14-34), mid-aged group (age 35-54), and senior group (age above 55). We report the results for each group in Table 7. In panel A, we find that the coefficient estimate on *Ln(Airbnb listings)* is significantly negative in column (2), and are significantly positive in the other two columns. These findings suggest that employment is reduced for mid-aged employees, but increase for young and senior individuals. The drop of employment in mid-aged group might be due to the fact that rental income from Airbnb listings improves their financial conditions, and thus some of them exit from the labor market and live on the rental income. The drop might also be due to the drop in employment in some industries that are less related to Airbnb. Together with the coefficient estimates with the other two groups of individuals, it exhibits a “U-shaped” relation between individual age and employment, with an increase in employment for young and senior individuals.

Job growth for mid-aged individuals is the largest, more than three times larger than that of young individuals. This finding suggests that Airbnb could provide more low-end jobs that do not require a sophisticated skill set, which fits the characteristics of individuals who are currently around and above the retirement age. As a result, aged individuals benefit more in terms of employment compared to other groups of individuals.

Panel B presents the results with payroll per employee as the dependent variable. The coefficient estimate on *Ln(Airbnb listings)* is significantly positive in all columns, suggesting that after an increase in Airbnb supply, payroll per employee increases for employees in all age groups. The magnitudes of the coefficient estimates in all groups are at the similar level.

Results in panel C show that the coefficient estimates on *Ln(Airbnb listings)* are significantly positive in young group and senior group, and are significantly negative in mid-aged group. These results are consistent with our earlier findings that employment increases in young and senior group individuals but decrease in mid-aged group individuals, suggesting that total payroll flows from employees with mid-aged employees to young and senior employees.

In summary, we find that an increase in Airbnb supply is associated with the growth in payroll per employee for employees in all age groups. The number of employees decreases for mid-aged employees and increases for younger and more senior employees. Consistently, total payroll flows from mid-aged employees to younger and more senior employees.

5.3 The Effects of Airbnb on Household Income Distribution

The growth of Airbnb affects both the hosts and local residents. On one hand, the hosts collect rental income by leasing out their properties. On the other hand, findings above indicate that local employment and average payroll increase after an increase in Airbnb room supply. In this session, we explore another bottom-line question: the effect of Airbnb expansion on local household income distribution.

We obtain household income data from the Statistics of Income (SOI) division of Census.

The SOI collects data from the individual income tax return records (Forms 1040) from the Internal Revenue Service (IRS) Individual Master File (IMF) system.[7] Based on the adjusted gross income, each household that has non-zero income is assigned to one of the three following income categories: $1-$50,000, $50,000-$100,000, and above $100,000. The SOI provides data on the number of households and adjusted gross income for each category and the data are available at the county-year level. For each category, we measure income per household using the adjusted gross income divided by the number of households; we measure category income proportion as the adjusted gross income in the category divided by the sum of adjusted gross income in all categories. We use the number of households, income per household, and category income proportion as the dependent variable in Table 8, respectively.

Results in panel A of Table 8 show that the coefficient estimates on *Ln(Airbnb listings)* are significantly negative in the $1-$50,000 category, significantly positive in the $50,000-$100,000 category and the above $100,000 category, suggesting that the number of households with annual income lower than $50,000 decreases and the number of households that have income above $50,000 increases. These findings are consistent with our earlier observations that unemployment rate for less-educated individuals decreases. With the rental income collected from leasing out rooms through Airbnb and income from new jobs created by Airbnb-related industries, the number of lower-income households shrinks and that of higher-income households expands.

In panel B, we use income per household as the dependent variable. The coefficient estimates on *Ln(Airbnb listings)* are significantly positive in all categories. These findings suggest that after an increase in Airbnb room supply, average income increases for households in all income categories. The magnitude of *Ln(Airbnb listings)* coefficient estimate is largest for the lower-income category, suggesting that the low-income households benefit more from the increase in Airbnb expansion.

We present the results with category income proportion as the dependent variable in panel C. The coefficient estimates on *Ln(Airbnb listings)* are significantly negative in the first two columns and significantly positive in the last column, suggesting that following Airbnb expansion, the proportion of total gross income for households with income above $10,000 increases.

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[7] Data do not cover the individuals who are not required to file an individual income tax return.

In summary, we find that after an increase in Airbnb supply, the number of lower-income households decreases while the number of higher-income households increases. Average income increases for all households but increases the most for lower-income households. Overall, our findings suggest that Airbnb helps increase social welfare by enhancing households' income, especially for low-income households.

5.4 Heterogeneous Effects across Industry

In this section, we further explore heterogeneity in our baseline findings cross different industries to shed some light on the underlying mechanisms through which Airbnb affects employment and income.

We conjecture that industries that are related to Airbnb guests and hosts might have more growth opportunities and thus provide more new job positions. First, the arrivals of guests might request improvements in infrastructure, such as new restaurants, cafés, and bars, and as a result, new jobs could be created in accommodation and food services industry (i.e., 2-digit NAICS industry code 72). Second, after the guests check out, the hosts may hire cleaning and housekeeping companies to clean up and maintain the rooms. Then more employees in administrative and support and waste management and remediation services industry (2-digit NAICS industry code 56) would be needed. Third, to enhance the attractiveness of their rooms, hosts may hire construction companies to renovate the property before listing it on the Airbnb platform. It is also possible that the rental income attracts people to build new houses or apartments for leasing on the Airbnb platform. Hence, construction industry (2-digit NAICS industry code 23) might need to hire more employees. Fourth, the growth in the construction industry might lead to the growth in the transportation and warehousing industry (2-digit NAICS industry code 48-49).

We retrieve industry-county-year level labor market data from the QWI and report the results for each of the five industries we mentioned above, including administrative & support & waste management & remediation services, accommodation & food services, construction, transportation & warehousing, and professional, scientific and technical services in Table 9.

Results in panel A of Table 9 show that the coefficient estimates of *Ln(Airbnb listings)* are positive and significant at the 1% level in all columns, suggesting that the growth in Airbnb is followed by an increase in employment in these 4 industries. These findings are consistent with our conjecture. The magnitudes of the coefficient estimates in columns (1) and (2) are the largest, suggesting that among these 4 industries, the administrative & support & waste management & remediation services industry and the accommodation & food services industry create most new jobs after the increase in Airbnb room supply. This finding is intuitive and reasonable because these two industries are the most related to the needs of Airbnb hosts and guests.

In panel B, the coefficient estimate of *Ln(Airbnb listings)* is positive and significant at the 1% level in all columns, suggesting that an increase in Airbnb expansion is associated with an increase in payroll per employee in these 4 industries. Average payroll increases the most in the transportation & warehousing industry and construction industry. In panel C, the coefficient estimates of *Ln(Airbnb listings)* are positive and significant at the 1% level in all columns, suggesting that an increase in total payroll in these 4 industries increase faster than other industries.

In summary, the growth of Airbnb brings the growth of five Airbnb business related industries. Specifically, the number of employees, payroll per employee, and group payroll proportion increase after an Airbnb expansion. Among these industries, the administrative& support &waste management & remediation services industry and the accommodation & food services industry create the most new jobs, and the payroll per employee increases the most in the professional, scientific and technical services industry.

6. Conclusion

In this paper, we have explored the real effects of sharing economy that has risen rapidly in recent years. Specifically, we examine how Airbnb, a pioneering sharing company, affects local economy. Using venture capital infusions as plausibly exogenous shocks to Airbnb's expansion into a new county, we find that Airbnb expansion leads to poorer hotel performance in the local county. Meanwhile, Airbnb expansion appears to reduce unemployment rate and increase household income. Further analysis suggests that increased employment is concentrated in industries that are complementary to Airbnb's business and in employee groups with lower education levels. Our study sheds new light on the real effects of the sharing economy and provides important policy implications for policymakers.

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Table 1: Summary statistics

This table reports descriptive summary statistics of main variables used in our study. Panel A reports the summary statistics of Airbnb variables at county level, including age and *No. of Airbnb listing*. Panel B reports county-month level variables, including six hotel variables, occupancy rate, room demand, room supply, total room revenue, revenue per sold room and revenue per available room, and four control variables, median household income, population, median housing values and unemployment rate. Panel C reports county-year level economy variables, including unemployment rate, No. of employed, No. of unemployed and labor force. All variables are winsorized at 1st and 99th percentiles.

Panel A: Airbnb Variables

	N	Mean	Median	Std. Dev
Airbnb Variables				
Age (month)	451	47.000	48.000	24.969
No. of Airbnb listings	451	70.749	9.000	135.253

Panel B: Monthly-Level Variables

	N	Mean	Median	Std. Dev
Hotel Variables				
Occupancy rate	9,164	0.646	0.654	0.128
Room demand (thousand)	9,164	320.496	161.674	470.686
Room supply (thousand)	9,164	468.943	261.512	652.601
Revenue (million dollar)	9,164	41.745	18.617	75.893
Revenue per sold room	9,164	118.897	104.425	48.302
Revenue per available room	9,164	79.459	67.465	43.251
Control Variables				
Median household income (thousand)	9,164	4.762	4.508	1.104
Population (thousand)	9,164	855.824	510.637	1177.176
Median housing values (thousand)	9,164	264.163	210.400	168.795
Unemployment rate	9,164	0.067	0.063	0.022

Panel C: Annual-Level Variables

	N	Mean	Median	Std. Dev
Economy Variables				
Unemployment rate	21,980	0.077	0.074	0.031
No. of employed (Thousand)	21,980	45.591	10.814	146.488
No. of unemployed (Thousand)	21,980	3.861	0.939	14.297
Labor force (Thousand)	21,980	49.452	11.727	160.101

Table 2: The Effect of Airbnb on Hotel Performance: OLS Regressions

This table presents the results of OLS regressions estimating equation (1). In each panel, we use occupancy rate, room demand, room supply, total room revenue, revenue per sold room, and revenue per available room as the dependent variable, respectively. In column (1)-(3), dependent variable one-month, two-month, and three-month leads independent variables, respectively. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a month. Control variables include median household income, population, unemployment rate and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effect, age fixed effect, and first year-month fixed effect. For each county, age is measured by the number of months since the first listing posted on Airbnb platform; first year-month is measured by the year-month of the county's first listing posted on Airbnb platform. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level, and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Occupancy Rate

	t+1 (1)	t+2 (2)	t+3 (3)
Ln(Airbnb listings)	-0.005	-0.016***	-0.021***
	(0.006)	(0.006)	(0.006)
Ln(Median household income)	0.040*	0.048**	0.049**
	(0.022)	(0.022)	(0.019)
Ln(Population)	1.619***	1.611***	1.164***
	(0.199)	(0.228)	(0.236)
Ln(Median housing values)	-0.104***	-0.059**	0.005
	(0.029)	(0.028)	(0.026)
Unemployment rate	-1.266***	-0.104	0.744***
	(0.344)	(0.257)	(0.240)
Constant	-21.787***	-21.644***	-16.643***
	(2.789)	(3.171)	(3.376)
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.375	0.372	0.368
Observations	9,164	8,971	8,778

Panel B: Room Demand

	t+1 (1)	t+2 (2)	t+3 (3)
Ln(Airbnb listings)	-0.012	-0.034***	-0.043***
	(0.011)	(0.010)	(0.009)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.974	0.974	0.974
Observations	9,164	8,971	8,778

Panel C: Room Supply

	t+1 (1)	t+2 (2)	t+3 (3)
Ln(Airbnb listings)	0.001	-0.005	-0.007
	(0.006)	(0.006)	(0.006)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.998	0.998	0.998
Observations	9,164	8,971	8,778

Panel D: Total room revenue

	t+1 (1)	t+2 (2)	t+3 (3)
Ln(Airbnb listings)	-0.008	-0.040**	-0.053***
	(0.017)	(0.016)	(0.016)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.944	0.943	0.944
Observations	9,164	8,971	8,778

Panel E: Revenue per Sold Room

	t+1	t+2	t+3
	(1)	(2)	(3)
Ln(Airbnb listings)	0.009	-0.000	-0.005
	(0.010)	(0.009)	(0.009)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.842	0.836	0.836
Observations	9,164	8,971	8,778

Panel F: Revenue per Available Room

	t+1	t+2	t+3
	(1)	(2)	(3)
Ln(Airbnb listings)	-0.003	-0.030**	-0.042***
	(0.016)	(0.015)	(0.015)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Adjusted R squared	0.635	0.628	0.628
Observations	9,164	8,971	8,778

Table 3: First Stage of 2SLS Regressions: The Effect of VC Financing on Airbnb

This table presents first-stage results of 2SLS regressions estimating equation (1). We use *VC financing* index at period *t-3* as instrument variable for *Ln(Airbnb listings)* at period *t*. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a month. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population, unemployment rate and median housing values. Median household income, population and median housing values are in the form of natural logarithm. We also include county fixed effect, age fixed effect, and first year-month fixed effect. For each county, age is measured by the number of months since the first listing posted on Airbnb platform; first year-month is measured by the year-month of the county's first listing posted on Airbnb platform. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level, and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Ln(Airbnb listings) (1)
VC financing index	0.117***
	(0.014)
Ln(Median household income)	-0.062
	(0.135)
Ln(Population)	2.723**
	(1.113)
Ln(Median housing values)	-0.106
	(0.209)
Unemployment rate	0.350
	(1.048)
Constant	-28.773**
	(13.159)
County fixed effect	Yes
Age fixed effect	Yes
First year-month fixed effect	Yes
Adjusted R squared	0.960
Observations	9,164
Under-identification test Chi-Squared Wald statistics	68.01***
Weak identification test *F*-statistics	65.57***

Table 4: Second Stage of 2SLS Regressions: The Effect of Airbnb on Hotel Performance
This table presents second-stage results of 2SLS regressions estimating equation (1). We use *VC financing* index at period *t-3* as instrument variable for *Ln(Airbnb listings)* at period *t*. In each panel, we use occupancy rate, room demand, room supply, total room revenue, revenue per sold room, and revenue per available room as the dependent variable, respectively. In column (1)-(3), dependent variable one-month, two-month, and three-month leads independent variables, respectively. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listing in a county in a month. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population, unemployment rate and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effect, age fixed effect, and first year-month fixed effect. For each county, age is measured by the number of months since the first listing posted on Airbnb platform; first year-month is measured by the year-month of the county's first listing posted on Airbnb platform. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level, and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Occupancy Rate

	t+1 (1)	t+2 (2)	t+3 (3)
Instrumented Ln(Airbnb listings)	-0.057***	-0.237***	-0.270***
	(0.016)	(0.032)	(0.036)
Ln(Median household income)	0.033*	0.023	0.019
	(0.018)	(0.024)	(0.028)
Ln(Population)	1.749***	2.219***	1.832***
	(0.222)	(0.366)	(0.395)
Ln(Median housing values)	-0.116***	-0.116**	-0.061
	(0.031)	(0.056)	(0.062)
Unemployment rate	-1.265***	-0.042	0.798*
	(0.390)	(0.397)	(0.413)
Constant	-18.783***	-24.118***	-20.191***
	(2.571)	(4.354)	(4.678)
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.099	0.111	0.114
Observations	9,164	8,971	8,778

Panel B: Room Demand

	t+1	t+2	t+3
	(1)	(2)	(3)
Instrumented Ln(Airbnb listings)	-0.118***	-0.387***	-0.471***
	(0.030)	(0.055)	(0.064)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.184	0.199	0.206
Observations	9,164	8,971	8,778

Panel C: Room Supply

	t+1	t+2	t+3
	(1)	(2)	(3)
Instrumented Ln(Airbnb listings)	-0.024*	-0.004	-0.033***
	(0.014)	(0.013)	(0.013)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.047	0.046	0.046
Observations	9,164	8,971	8,778

Panel D: Total room revenue

	t+1	t+2	t+3
	(1)	(2)	(3)
Instrumented Ln(Airbnb listings)	-0.135***	-0.500***	-0.580***
	(0.044)	(0.074)	(0.083)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.290	0.309	0.314
Observations	9,164	8,971	8,778

Panel E: Revenue per Sold Room

	t+1 (1)	t+2 (2)	t+3 (3)
Instrumented Ln(Airbnb listings)	-0.010 (0.022)	-0.107*** (0.027)	-0.108*** (0.028)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.123	0.127	0.127
Observations	9,164	8,971	8,778

Panel F: Revenue per Available Room

	t+1 (1)	t+2 (2)	t+3 (3)
Instrumented Ln(Airbnb listings)	-0.100*** (0.039)	-0.484*** (0.071)	-0.538*** (0.077)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Age fixed effect	Yes	Yes	Yes
First year-month fixed effect	Yes	Yes	Yes
Root MSE	0.267	0.288	0.292
Observations	9,164	8,971	8,778

Table 5: The Effect of Airbnb on Employment

This table presents the results of 2SLS regressions estimating equation (2). We use *VC financing index* as instrument variable for *No. of Airbnb listings*. In column (1), we report the first-stage results and under identification test and weak identification test results. In columns (2), (3), and (4), we use unemployment rate, the number of employed, and labor force as dependent variable in each column, respectively. Dependent variables one-year lead independent and instrument variables. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a year. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effect. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First Stage

	First Stage	Second Stage		
	Ln(Airbnb listings)	Unemployment rate	Ln(No. of employed)	Ln(Labor force)
	(1)	(2)	(3)	(4)
VC financing index	0.047***			
	(0.003)			
Ln(Airbnb listings)		-0.117***	0.044***	-0.083***
		(0.007)	(0.005)	(0.008)
Population	0.260*	0.035*	0.064***	0.104**
	(0.145)	(0.019)	(0.023)	(0.042)
Median housing values	0.242***	0.020***	0.037***	0.063***
	(0.050)	(0.006)	(0.006)	(0.007)
Median household income	-0.623***	-0.056***	0.074***	0.014
	(0.080)	(0.008)	(0.014)	(0.016)
County fixed effect	Yes	Yes	Yes	Yes
Adjusted R squared	0.092			
Root MSE		0.040	0.035	0.045
Observations	18,685	18,685	18,685	18,685
Under-identification test Chi-Squared Wald statistics	314.63***			
Weak identification test *F*-statistics	314.49***			

Table 6: The Effect of Airbnb on Employment by Different Education

This table presents second-stage results of 2SLS regressions estimating equation (2). We use *VC financing index* as instrument variable for *Ln(Airbnb listings)*. In each panel, we use group employment, payroll per employee, and group payroll proportion as dependent variable, respectively. Group employment is measured by the log logarithm of the number of employees in an education group. Payroll per employee is measured by the log logarithm of total payroll received by all employees in an education group divided by the number of employees in that group. Group payroll proportion is measured by total payroll received by employees in a group divided by total payroll received by all employees in all groups. We report the results of each of the four education groups, including less-educated group (less than high school), high school group (high school or equivalent), associate degree group (some college or associate degree), and bachelor's degree group (bachelor's or advanced degree) in each column, respectively. Dependent variables one-year lead independent and instrument variables. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a year. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effects. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Group Employment

	Less-educated (1)	High school (2)	Associate degree (3)	bachelor's degree (4)
Ln(Airbnb listings)	0.442***	0.122***	0.101***	0.018***
	(0.025)	(0.009)	(0.008)	(0.007)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.158	0.067	0.064	0.061
Observations	18,580	18,580	18,580	18,580

Panel B: Payroll per Employee

	Less-educated	High school	Associate degree	bachelor's degree
	(1)	(2)	(3)	(4)
Ln(Airbnb listings)	0.468***	0.389***	0.318***	0.203***
	(0.028)	(0.023)	(0.019)	(0.013)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.169	0.141	0.119	0.090
Observations	18,580	18,580	18,580	18,580

Panel C: Group Payroll Proportion

	Less-educated	High school	Associate degree	bachelor's degree
	(1)	(2)	(3)	(4)
Ln(Airbnb listings)	0.044***	0.019***	-0.003***	-0.059***
	(0.002)	(0.001)	(0.000)	(0.003)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.015	0.008	0.004	0.021
Observations	18,580	18,580	18,580	18,580

Table 7: The Effect of Airbnb on Employment by Different Age

This table presents second-stage results of 2SLS regressions estimating equation (2). We use *VC financing index* as instrument variable for *Ln(Airbnb listings)*. In each panel, we use group employment, payroll per employee, and group payroll proportion as dependent variable, respectively. Group employment is measured by the log logarithm of the number of employees in an age group. Payroll per employee is measured by the log logarithm of total payroll received by all employees in an age group divided by the number of employees in that group. Group payroll proportion is measured by total payroll received by employees in a group divided by total payroll received by all employees in all groups. We report the results of each of the three age groups, including young group (age 14-34), mid-age group (age 35-54), and senior group (age above 55) in each column, respectively. Dependent variables one-year lead independent and instrument variables. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a year. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effects. All variables are winsorized at 1^{st} and 99^{th} percentiles. Standard errors are clustered at county level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Group Employment

	Young	Mid-aged	Senior
	(1)	(2)	(3)
Ln(Airbnb listings)	0.186***	-0.058***	0.449***
	(0.013)	(0.008)	(0.025)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.093	0.065	0.156
Observations	18,584	18,583	18,583

Panel B: Payroll per Employee

	Young (1)	Mid-aged (2)	Senior (3)
Ln(Airbnb listings)	0.272***	0.308***	0.342***
	(0.018)	(0.019)	(0.021)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.114	0.118	0.129
Observations	18,584	18,583	18,583

Panel C: Group Payroll Proportion

	Young (1)	Mid-aged (2)	Senior (3)
Ln(Airbnb listings)	0.005***	-0.093***	0.090***
	(0.001)	(0.005)	(0.005)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.010	0.033	0.031
Observations	18,584	18,583	18,583

Table 8: The Effect of Airbnb on Household Income by Different Income Class

This table presents second-stage results of 2SLS regressions estimating equation (2). We use *VC financing index* as instrument variable for *Ln(Airbnb listings)*. In each panel, we use the number of households, income per household, and group income proportion as dependent variable, respectively. Income per household is measured by the log logarithm of total income received by all households in an income class divided by the number of household in that class. Class income proportion is measured by total income received by households in an income class divided by total income received by all households in all classes. We report the results of each of the three household income classes, including class $1-$50,000, class $50,000-$100,000, and class above $100,000 in each column, respectively. Dependent variables one-year lead independent and instrument variables. *Ln(Airbnb listings)* is measured by the natural logarithm of the number of Airbnb listings in a county in a year. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effects. All variables are winsorized at 1st and 99th percentiles. Standard errors are clustered at county level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The Number of Households

	$1-$50,000 (1)	$50,000-$100,000 (2)	Above $100,000 (3)
Ln(Airbnb listings)	-0.165***	0.171***	1.030***
	(0.011)	(0.011)	(0.059)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.075	0.076	0.358
Observations	18,682	18,678	18,651

Panel B: Income per Household

	$1-$50,000 (1)	$50,000-$100,000 (2)	Above $100,000 (3)
Ln(Airbnb listings)	0.068***	0.030***	0.047***
	(0.004)	(0.003)	(0.010)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.031	0.031	0.111
Observations	18,682	18,678	18,651

Panel C: Class Income Proportion

	$1-$50,000 (1)	$50,000-$100,000 (2)	Above $100,000 (3)
Ln(Airbnb listings)	-0.158***	-0.075***	0.214***
	(0.009)	(0.005)	(0.012)
Control variables	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Root MSE	0.058	0.034	0.078
Observations	18,682	18,678	18,651

Table 9: The Effect of Airbnb on Employment by Different Industry

This table presents second-stage results of 2SLS regressions estimating equation (2). We use *VC financing index* as instrument variable for *No. of Airbnb listings*. Industry definition is based on two-digit NAICS codes. In each panel, we use group employment, payroll per employee, and group payroll proportion as dependent variable, respectively. Group employment is measured by the log logarithm of the number of employees in an industry group. Payroll per employee is measured by the log logarithm of total payroll received by all employees in an industry group divided by the number of employees in that group. Group payroll proportion is measured by total payroll received by employees in a group divided by total payroll received by all employees in all groups. We report the results of each of the five industries, including administrative and support and waste management and remediation services (NAICS industry code: 56) in column (1), accommodation and food services (72) in column (2), construction (23) in column (3), and transportation and warehousing (48-49) in column (4) respectively. Dependent variables one-year lead independent and instrument variables. *No. of Airbnb listings* is measured by the natural logarithm of the number of Airbnb listings in a county in a year. *VC financing index* is 0 before any round of financing, 1 since the first round, 2 since the second round, until 9 since the ninth round. Control variables include median household income, population and median housing values. Median household income, population and median housing values are in the form of natural logarithm. All specifications include county fixed effect. All variables are winsorized at 1^{st} and 99^{th} percentiles. Standard errors are clustered at county level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Group Employment

	(1)	(2)	(3)	(4)
No. of Airbnb listings	0.409***	0.325***	0.247***	0.285***
	(0.042)	(0.022)	(0.026)	(0.033)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.382	0.172	0.235	0.301
Observations	16,352	18,085	17,885	16,807

Panel B: Payroll per Employee

	(1)	(2)	(3)	(4)
No. of Airbnb listings	0.266***	0.239***	0.309***	0.306***
	(0.026)	(0.017)	(0.025)	(0.026)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.255	0.133	0.219	0.238
Observations	16,352	18,085	17,885	16,807

Panel C: Group Payroll Proportion

	(1)	(2)	(3)	(4)
No. of Airbnb listings	0.008***	0.006***	0.011***	0.006***
	(0.001)	(0.001)	(0.002)	(0.001)
Control variables	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Root MSE	0.010	0.007	0.018	0.010
Observations	16,352	18,085	17,885	16,807