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(Work in Progress)

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ABSTRACT

A growing literature has documented the impact of home sharing. We study a new externality in which local people can enjoy more job opportunities because of the entry of home sharing. Using data from Airbnb and employing a quasi-experimental design, we find the following evidences. We find that home sharing provides more employment options to locals especially for less-education and low-income population. As home sharing becomes an incentive for local employment, our study provides important understanding of home sharing and its implications to local welfare, Airbnb hosts, and policy makers.

Keywords: Home-sharing, local employment, Airbnb, education, income.

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INTRODUCTION

Airbnb, a pioneer of the sharing economy, provides a handy platform for individuals to rent their spare space (Xie & Kwok, 2017). Starting from renting out three air mattresses in 2008, Airbnb now supplies 4.5 million properties in over 81,000 cities of more than 191 countries (Airbnb 2018). A key benefit of sharing economy like Airbnb is that it maintains low barriers to entry and enables flexible working arrangements and low transaction cost (Cheng, 2016).

Airbnb is closely associated with local employment. On the one hand, Zervas et al. (2017) found that a 1% increase in Airbnb listings in Texas results in a 0.05% decrease in quarterly hotel revenues, especially for the lower-priced hotels. Therefore, the entry of Airbnb may cause unemployment because of the revenue shrinkage of lower-priced hotels. On the other hand, the entry of Airbnb can benefit the local tourism industry by generating new job opportunities serving travelers (e.g., restaurants, guided tours, stores, and cleaning) as low accommodation cost of Airbnb generates more tourists and longer stays (Fang et al., 2016).

Although studies such as Fang et al. (2016) found a positive correlation between Airbnb supply and local employment in the tourism industry using 220 (44 counties × 5 years) observations from Idaho. The question "whether the entry of Airbnb benefits local employment" remains an open question. Because the research samples of current studies are very limited and their empirical settings are subject to endogeneity issues that may bias the effect of Airbnb on local employment. Moreover, the literature investigating the impact of Airbnb on local employment lags in answering "who benefits (or not) from home sharing." According to the trickle-down effect (Aghion & Bolton 1997), resources and support such as tax cut to the businesses can serve as a means to stimulate business investment in the short term and benefit society at large in the long term. The emergence of home sharing is similar to such support because it allows homeowners (i.e., the hosts) to invest on Airbnb businesses and hire affiliated workers to provide ancillary services for listing operation, which may essentially generate local welfare. An investigation of how Airbnb affects the employment of demographically heterogenous local groups will help us extend the understanding of trickle-down effect and guide policymaking.

To add evidence to the literature, we attempt to examine (1) the impact of the entry of Airbnb on local employment and (2) which demographic groups (in terms of education and income) of the locals benefit from home sharing. To answer these questions, we collect data of 320,243 Airbnb listings from the top ten metro areas in the U.S. over six years and employ a difference in difference (DID) design with time and zip code fixed effects included to eliminate macroeconomic fluctuations over time and economic disparities across areas. Our findings offer direct implications for Airbnb hosts and policymakers to identify opportunities for local employment stimulation.

DATA AND METHODOLOGY

Data and Variable

We collect the home sharing data from Airbnb and the employment and census data from the Bureau of Labor Statistics (BLS). The top ten metro areas in the U.S. are our empirical setting, which covers 535 zip codes and 320,243 Airbnb listings (see Table 1).

We then exclude zip codes without employment statistics and construct a panel dataset of 2,886 observations (481 zip codes × 6 years).

Table 1. Description of Airbnb listings

Rank	Metro Areas	Zip Codes	Listings
1	New York-Newark-Jersey City, NY-NJ-PA Metro Area	204	148,113
2	Los Angeles-Long Beach-Anaheim, CA Metro Area	65	48,358
3	San Francisco-Oakland-Hayward, CA Metro Area	28	30,025
4	San Diego-Carlsbad, CA Metro Area	35	19,466
5	Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area	40	19,844
6	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD Metro Area	48	15,900
7	Seattle-Tacoma-Bellevue, WA Metro Area	37	14,626
8	Portland-Vancouver-Hillsboro, OR-WA Metro Area	34	10,228
9	Boston-Cambridge-Newton, MA-NH Metro Area	16	7,457
10	San Jose-Sunnyvale-Santa Clara, CA Metro Area	28	6,226
Total		535	320,243

We first examine whether the entry of Airbnb affects local employment. The dependent variable is *Employment*, measured by the actual employment rate. The independent variable of interest is the supply of Airbnb listings, which is measured by *Cum.Supply* (the cumulative amount of local Airbnb listings before a given year) and *Inst.Supply* (the net growth of local Airbnb listings in a given year). The first review of the property marks the entry time of an Airbnb to each zip code.

We then explore who benefits from the entry of Airbnb. Three demographic characteristics of locals serve as moderators, including (1) *Education*, which is calculated by the percentage of individuals with a bachelor degree or above; and (2) *Income*, which is the median household income. Lastly, we control the zip code and year fixed effects to account for annual variation in employment rate across zip codes. Table 2 presents the definition and summary statistics of variables in our study.

Table 2. Data Description

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable						
Employment	Employment rate (in %) for a zip code in a given year	2,886	58.814	10.466	0.1	89.1
Independent Variable						
Cum.Supply (in 100)	Scaled cumulative entries of home-sharing of a zip code by a given year	2,886	2.086	5.003	0	79.47
Inst.Supply (in 100)	Scaled instantaneous entries of home-sharing of a zip code in a given year	2,886	0.919	1.967	0	24.61
Moderators						
Education	Percentage of bachelor's degree or higher of a zip code in a given year	2,886	0.275	0.222	0	1
Income	Logged household median income of a zip code in a given year	2,886	10.792	1.384	0	12.411
Control Variable						
Population	Logged population of a zip code in a given year	2,886	10.017	0.988	3.401	11.364

Model specification

The staggered entry (across different zip codes and time) of home sharing on Airbnb provides a quasi-experimental difference-in-differences (DID) setting for estimating the causality between the entry of Airbnb and local employment (Zervas et al., 2017; Angrist & Pischke, 2008). Our DID strategy identifies the Airbnb treatment effect by comparing differences in the employment rate for zip codes affected by Airbnb before and after its entry with a benchmark of differences in the employment rate for zip codes unaffected by Airbnb during the same period. Table 3 illustrates the DID empirical strategy. That is, zip codes without Airbnb entry are the control group, and those with at least one Airbnb entry are the treatment group. Hence the entry of home sharing in a given month can be a treatment stimulus. Through the lens of a quasi-experiment, the DID design is effective in mitigating endogeneity issues when estimating the causal influence of home sharing on local employment.

Table 3. The Difference-in-differences (DID) Design

	Before entry	After entry
Zip codes with Airbnb entry	O	X
Zip codes without Airbnb entry	O	O

For each zip code *i* in year *t*, the impact of Airbnb entry on local employment is specified as

$$Employment_{it} = \beta \cdot Cum.Supply_{it} + \gamma \cdot Cum.Supply_{it} \times Z_{it} + \delta \cdot Z_{it} + \mu_i + v_t + \varepsilon_{it} \tag{1}$$

where $Employment_{it}$ is the employment rate of zip code *i* in year *t*. $Cum.Supply_{it}$ is the cumulative entries of home sharing on Airbnb of zip code *i* in year *t*. Z_{it} is a vector of moderators, including $Education_{it}$, and $Income_{it}$. μ_i is zip code fixed effect, and v_t is year fixed effect. ε_{it} is the idiosyncratic error. β identifies the impact of the entry of Airbnb on local employment, and γ captures the moderating effect of the moderators.

RESULTS

The DID regression results are reported in Table 4. Column (1) presents the main effect of the entry of Airbnb on local employment. The coefficient of *Cum.Supply* is positive and significant at the 0.01 level, indicating that the entry of Airbnb benefits local employment: a 100 increase in home sharing leads to a 0.07% increase in the local employment rate. Considering the average entries (yearly: 2011~2016) of home sharing on Airbnb in each zip code is over 90 in our research samples, the magnitude of 0.07% is economically significant. Columns (2~3) report the moderating effect of three sets of moderators: (1) The coefficient of *Cum.Supply* × *Education* is negative and significant (-0.222***), suggesting that the entry of Airbnb benefits the less-educated population more. This finding is consistent with the "low barriers to entry" feature of Airbnb. (2) The negative and significant (-0.107***) coefficient of *Cum.Supply* × *Income* indicates that the low-income population benefits more from the entry and expansion of Airbnb because they have low transaction cost when switching into Airbnb.

Table 4. Effect of entry of Airbnb on local employment

D.V.: Employment (in 100)	(1)	(2)	(3)
Cum.Supply (in 100)	0.070***	0.200***	1.255***
	(0.014)	(0.035)	(0.362)
Cum.Supply (in 100) × *Education*		-0.222***	
		(0.053)	
Education		0.355	
		(0.846)	
Cum.Supply (in 100) × *Income*			-0.107***
			(0.032)
Income			0.213
			(0.214)
Zip code FE	YES	YES	YES
Year FE	YES	YES	YES
Control Variable	YES	YES	YES
F (*p*)	31.27***	29.98***	29.19***
R^2	0.103	0.111	0.112
Obs.	2,886	2,886	2,886
Groups (Zip codes)	481	481	481

Notes. Robust standard errors clustered at the zip code level are reported in parentheses. The *, **, and *** represent significance at the levels of 10%, 5%, and 1%, respectively.

To further check the robustness of the above results, we first replicate the results in Table 3 using the alternative measure of the instantaneous entries (*Inst.Supply*). As Table 5 shows, the estimated effects are robust and consistent with those reported in Table 4.

Table 5. Effect of entry of Airbnb on local employment (Robustness check: *Inst.Supply*)

D.V.: Employment (in 100)	(1)	(2)	(3)
Inst.Supply (in 100)	0.209***	0.460***	2.558***
	(0.036)	(0.074)	(0.932)
Inst.Supply (in 100) × *Education*		-0.448***	
		(0.123)	

Education		0.329	
		(0.850)	
Inst.Supply (in 100) × *Income*			-0.213**
			(0.084)
Income			0.210
			(0.222)
Zip code FE	YES	YES	YES
Year FE	YES	YES	YES
Control Variable	YES	YES	YES
F (*p*)	39.09***	34.83***	32.51***
R^2	0.106	0.112	0.113
Obs.	2,886	2,886	2,886
Groups (Zip codes)	481	481	481

Notes. Robust standard errors clustered at the zip code level are reported in parentheses. The *, **, and *** represent significance at the levels of 10%, 5%, and 1%, respectively

CONCLUSIONS AND IMPLICATIONS

We investigate the impact of the entry of Airbnb on local employment. Two main findings are drawn from our DID analyses. First, the entry of Airbnb improves local employment. Second, the employment effect of Airbnb is non-uniform: its entry benefits the less-educated, and low-income population more. As sharing economy like Airbnb is overwhelming, our work contributes to the literature and practice in many aspects.

Theoretically, this study fills two major research gaps. First, we add evidence to the debate about the impact of home sharing on local employment. We disclose an increased employment rate after the entry of Airbnb. Using large-scale field evidence and a causal inference approach, we add rigor to the investigation of Airbnb and local employment. Second, this study is among the first to explore which demographic groups of the population can benefit from the entry of Airbnb. Our work contributes to the literature by advocating the welfare effect of home sharing to locals, especially those are less educated or lower-income.

Practically, our findings yield important implications for Airbnb hosts and policymakers. First, Airbnb hosts can outsource the ancillary guest services to local labor markets for amplified welfare to the locals. Particularly, hosts can target the less-educated and low-income population in the local labor markets because these local groups are mostly affected by home sharing. Second, targeted advertising for hiring can be delivered on social media platforms like Facebook and Twitter with considerations of the education, income, and gender of the local audience, which can improve the efficiency and precision of Airbnb online advertising. Lastly, Airbnb is found to be an effective instrument to drive local employment. Policymakers should support the growth of Airbnb in neighborhoods that have less-educated and low-income population.

LIMITATIONS AND FUTURE DIRECTIONS

There are several limitations to this research that need to be acknowledged. First, the dataset represents the entry of Airbnb in USA from 2011 to 2016. The research results may differ with geographic, economic, and cultural conditions. Hence, the findings of this study may not be generalizable to other countries. Future studies may expand to other countries and consider moderation effects of economic development and cultural conditions. Second, we don't have actual industry employment date in zip code level due to data unavailability. Although we introduce moderators to explain the mechanism of the positive effect of entry of Airbnb on local employment and conduct robustness check using instantaneous supply of home-sharing instead of cumulative supply, the specific influencing mechanism is still insufficiently comprehensive. Future studies using more detailed employment data and host data of Airbnb are strongly encouraged and expected. Finally, some variables that may affect local employment have not been included in this study due to the unavailability of data such as the number of tourists which may have an impact on local employment. Future studies may expand this research with more variables. Overall, we encourage future scholars to explore the external impact of sharing economy in a broader dataset with different perspectives.

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