Resurrecting Dead Capital:
The Sharing Economy, Entrepreneurship, and Job Creation

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* We remain responsible for all errors and omissions.

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Abstract

This paper examines how a pioneer for the sharing economy—Airbnb— affects entrepreneurship. We show that the staggered entry of Airbnb across counties is associated with an increase of 3% in the number of new business creations. Using the interaction of venture capital infusions and local tourism as an instrument for Airbnb listings, we find that that Airbnb penetration leads to more new businesses creations in the local area. Airbnb spurs entrepreneurship by increasing the rental income for landlords, and more importantly, by increasing the local demand. Specifically, we show that Airbnb penetration attracts more tourists and reduces the hotel prices, which lead to higher local business income and more job creations. Furthermore, the new businesses created following Airbnb penetration has higher survival rate and better performance both at the creation and in the long run. Our paper suggests that Airbnb has positive spillover effect to the local economy and serves as a net job creator.

Keywords: Airbnb, sharing economy, entrepreneurship, local demand, rental income, job creation

JEL code: L26, L85, L86, M13

1. Introduction

In the recent decade, the development of digital platforms has spawned a new marketplace, often called peer-to-peer rental marketplace. On this new marketplace, asset owners supply excess capacity of their assets that may otherwise go underutilized directly to the demanders. Therefore, such marketplaces are also referred to as "sharing economy", which is projected to grow from $15 billion in 2014 to $335 billion in 2025.[1] While the sharing economy is growing rapidly, the economic consequence of this new business model is still unclear. On the one hand, the sharing economy could increase asset utilization and thus bolster economic efficiency, by lowering the costs for owners to "share" their assets for personal consumption through short-term rental (Einav, Farronato, and Levin, 2016). On the other hand, the sharing economy disrupts the traditional business models and could cause market failure in its new business model, and thus raises unprecedented regulation challenges. This paper attempts to study the economic consequences of the sharing economy through the lens of its impact on local new business and job creations.

How should the sharing economy affect the creation of local businesses? We argue that there are mainly two channels. First, by improving asset utilization rates, the sharing economy relaxes financial constraints of potential entrepreneurs, which helps promote entrepreneurship. Second, sharing economy increases local demand and could create more business opportunities. We use Airbnb, a precursor of the sharing economy, to test how the sharing economy's penetration into local areas affects entrepreneurship. Airbnb enables people to list and rent their spare rooms for short-term lodging in residential properties. We argue that the launch of Airbnb provides more more rental income, which relaxes the financial constraints of landlords who could be potential entrepreneurs. In addition, Airbnb increases local demand by attracting new tourists and increasing their welfare (through lowered hotel pricing), which increases the investment opportunities for the new businesses.

We begin with the extensive margin, that is, how the staggered arrival of Airbnb across counties spurs new firm creations in the local area. A natural concern is that Airbnb platforms did not launch in specific counties randomly. For example, if Airbnb platforms specifically entered into "entrepreneurial" cities first, then the association we find between Airbnb and entrepreneurship is not causal. This does not appear to be the case. Using a hazard model approach,

[1] See article https://www.forbes.com/sites/forbeslacouncil/2019/03/04/the-sharing-economy-is-still-growing-and-businesses-should-take-note/?sh=60aeca8f4c33

we document that the rollout timing of Airbnb platforms into counties is, as expected, predicted by several local demographic and economic characteristics. However, the arrival of Airbnb appears not to be predicted by the growth of entrepreneurial activity within a county. In addition, examining the dynamics of new firm creations surrounding the Airbnb entry time, we find no prior trend. Taken together, the parallel trend assumption for a difference-in-difference analysis does not appear to be violated. Accordingly, we utilize a difference-in-differences specification with county and year fixed effects, as well as controls for local demographic and economic characteristics that might affect entrepreneurship. We find an increase of around 3% probability in new business creations following the arrival of Airbnb in a county.[2]

We further examine the intensive margin, that is, how Airbnb penetration in a local county affects new business creations. To measure Airbnb penetration, we use the number of Airbnb listings at the county-year level. The results suggest a positive relation between Airbnb listings and new business creations. An important concern is that, While Airbnb arrival might be exogenous, Airbnb supply is likely to be endogenous with unobservable county characteristics that are correlated with new business creations conditions.

To establish the causal link for the intensive margin, that is, how Airbnb penetration affects entrepreneurship, we use the Bartik instrument that exploits two sources of variations. Following the literature (Bartik, 1991, Dube and Vargas, 2013; Nunn and Qian, 2014; Diamond, 2016), we construct the instrument by combining an exogenous time-series shock and a plausibly endogenous cross-sectional variable. First, we exploit plausibly exogenous time variation in Airbnb growth, which is driven by venture capital (VC) investors' capital infusions in Airbnb in each financing round. The VC's capital infusion in Airbnb is based on their own expectation regarding Airbnb's long-term prospects and is unlikely to be based on the economic performance of any specific county. Second, we exploit cross-sectional variation in a county's likelihood to experience more Airbnb expansion, which we assume is primarily driven by the attractiveness of a county to tourists. We measure how attractive a county is to tourists using the number of establishments in the tourism section (NAICS 72) at the beginning of our sample period (2007), such that this measure would not be affected by the Airbnb entry into the local area.

[2] The magnitude we find is comparable to the findings in Barrios, Hochberg, and Yi (2022), who show that the introduction of Uber and Lyft is associated with an increase of 4-5% of the number of new business registration in the local area.

Combining the above two sources of variations together, we construct the interaction of the cumulative rounds of VC funding received by Airbnb in a year and the county-level number of establishments in the tourism section measured at the beginning of our sample period (2007). We use this interaction as an instrument for the entry and expansion of Airbnb at a county in a given year. Using the instrumental variable approach, we find that Airbnb listings continue to have a positive and significant effect on the creations of new businesses. The magnitude is economically and statistically meaningful: Increasing Airbnb listings in a county by 10% is associated with a 0.3% increase in new firm creations. This translates to 38% of new business creations out of Airbnb listings.

The validity of this identification strategy relies on this interaction term being exogenous conditional on the baseline controls. The strategy is essentially analogous to a difference-in-differences analysis. That is, in the reduced-form estimates, the analyses compare the differences in entrepreneurship before and after Airbnb entry in counties that have high tourism relative to counties that have low tourism. The identification assumption for difference-in-differences is parallel trends, which require that the high tourism counties would have experienced the same change in new business creations as low-tourism counties in the absence of Airbnb entry. We examine the dynamics of new firm creations surrounding the Airbnb entry time for high tourism counties and low counties, and find no prior trend. The results suggest that the parallel trend assumption is likely to hold.

We also run a battery of robustness checks to validate the identification. First, we randomize the number of Airbnb listings across the counties for counties with at least one Airbnb listing. If our instrument is valid, we should observe an insignificant correlation between the instrumental variable and randomized Airbnb listings. This is indeed what we find. Second, we estimate whether the instrumental variable predicts new business creations in counties that never had any Airbnb listings. If our instrument is valid, it should affect firm creations only through Airbnb, and thus should have no effect on firm creations in counties without any Airbnb listings. We find consistent results.

Having established a causal link between Airbnb penetration and entrepreneurship, we turn to examine plausible underlying channels to better understand the magnitude fo the effect. We start from the group that is most likely to benefit from the lower entry cost for short-term rental service—the landlords. Indeed, we find that landlord households are more likely to become

entrepreneurs with higher Airbnb penetration. The economic magnitude is also sensible. On average, for 100 Airbnb listings in a county, there would be 13 additional landlord entrepreneurs. Combining this magnitude with the baseline magnitude (100 Airbnb listings translate to 38 new business creations), it suggests that at least two thirds of the new business creations are not started by landlords.

To better understand the magnitude of the landlord regression, we examine why landlords are more likely to start businesses with Airbnb penetration. We hypothesize that it is because Airbnb increases the income of landlords and thus relaxes the financial constraint for them to become entrepreneurs. To understand this, we start from Airbnb's impact on the housing market. We show that Airbnb increases the number of households that receive rental income. In particular, Airbnb increases the supply in the short-term rental market, and lowers the supply in the long-term rental market. We argue that it is because Airbnb lowers the entry cost to the short term rental market, and attracts landlords from the long-term rental market to the short-term rental market. As the housing supply in the long-term rental market drops, and more short-term rental becomes available (where rental rates tend to be higher), the average rental rates increase. In addition to rental rates, Airbnb also increases housing price. While landlords both receive higher rental income and obtain easier access to collateral credit, we only find supporting evidence that Airbnb promotes entrepreneurship through higher rental income. We further show that Airbnb does not lead to higher new business growth in counties that are more likely to get higher collateral value, and individuals who take a second mortgage do not exhibit higher likelihood of becoming entrepreneurs when Airbnb penetration increases. The reason could be that the Airbnb-induced house price increase is too small compared to rental income. Therefore, we term the channel through which Airbnb enables more landlords to start new businesses the *rental income channel*.

We next turn to understand how Airbnb spurs entrepreneurship through channels other than the housing market. We hypothesize that it is through the local demand increase, which is crucial for new business creations (Adelino, Ma, and Robinson, 2017). Airbnb appears to increase local demand mainly in two ways. First, Airbnb increases toursits (as proxied by the incoming air passengers) to the local area. Second, Airbnb reduces hotel pricing, which could lead to an increase in the budget that can be spent on non-lodging service by the tourists. With the increased tourists and more spending on local services, there would be more local investment opportunities for potential entrepreneurs. For example, it could be more profitable to open restaurants given the

increased local demand. To further validate the effect of Airbnb on local demand, we examine local income and employment, which are classic proxies for local demand (e.g., Mian and Sufi, 2014; Adelino, Ma, and Robinson, 2017) We find that business income increases in the local area as a response to Airbnb penetration, and interestingly, this does not translate to higher wages, but translate to more job creations. The job creations by the new businesses do not crowd out the existing businesses, and the small existing businesses also experience an employment increase. The evidence above provides support that Airbnb overall increases local demand and serves as a net job creator. Finally, we show that Airbnb indeed creates more businesses in non-tradable industries, which have been shown in the literature to be more sensitive to local demand (Adelino et al., 2015; Adelino et al., 2017). Taken together, we term the above channel the *local demand channel*.

Both the rental income channel and the local demand channel predict that Airbnb's effect on new business creations would be more pronounced when entrepreneurs are more likely to be financially constrained. This is indeed what we find. We show that the effect of Airbnb on entrepreneurship is more pronounced in counties with worse credit access (as measured by lower local bank shares, higher historical housing price volatility, and higher loan denial rates), for small-sized startups that face more severe financial constraint, and on startups that need less startup capital. The cross-sectional results provide further credentials to the identification and channels.

Finally, we examine the quality of the new firms started under Airbnb penetration. While Airbnb penetration relaxes potential entrepreneurs' financial constraint, it is important to understand whether they start new businesses out of higher risk preference. It is because the literature (e.g., Hurst and Lusardi, 2004) shows, as wealth grows, households are more willing to take risk. We find that new businesses created following Airbnb penetration exhibit a higher survival rate over the first three years and better performance both at the entrance and in the long term. The results suggest that the entrepreneurs are unlikely to start the new businesses out of higher risk tolerance, which typically leads to new businesses with higher risk and thus worse performance and survival rate. The effect further validates that Airbnb has positive spillover effect to the local economy.

Our paper mainly contributes to two strands of literature. First, we build on the literature that documents financial constraint as one of the main hurdles to start and grow a new business (see, e.g., a survey paper by Kerr and Nanda (2009)). There are two main streams of work in this

literature. One stream considers the effect of financial market development on entrepreneurship (e.g., King and Levine, 1993 a, b; Levine, 1997; Black and Strahan, 2002; Guiso et al., 2004; Contorelli and Strahan, 2006; Hombert et al., 2020). The other stream focuses on how personal wealth affects new business creations (e.g., Evans and Jovanovic, 1989; Gentry and Hubbard, 2005; Cagetti and De Nardi, 2006), although some studies have argued that this relation is present only at the very top of wealth distribution (Hurst and Lusardi, 2004). In particular, more closely related to this paper, existing studies have shown that housing value, through a collateral channel, is an important factor in the funding of new firms (Corradin and Popov, 2013; Schmalz et al., 2013; Adelino et al., 2015). Our paper supplements the existing literature by proposing a new channel through which the housing sector could help boost entrepreneurship. That is, the sharing economy, by improving asset utilization rates, could relax potential entrepreneurs' financial constraints. In particular, Airbnb increases rental income of households and leads to more entrepreneurship. This finding also sheds new light on how the housing sector could affect entrepreneurship through a channel other than collateral.

Second, our paper is related to the growing literature on the sharing economy. Einav et al. (2016) gives an overview of the economics of peer-to-peer markets and Proserpio and Tellis (2017) reviews the literature on the sharing economy. For instance, focusing on observations in one state, i.e., Texas, Zervas et al. (2016) find that Airbnb entry negatively affects the hotel industry. Farronato and Fradkin (2022) theoretically show that Airbnb generates consumer surplus and host surplus while reducing hotel profits from accommodations. Other than the hotel industry, there are papers that examine Airbnb's effect on real estate. For example, Sheppard and Udell (2017) focus on Airbnb's effects in New York City, and find that a doubling of Airbnb listings is associated with an increase of 6% to 11% in house values. Barron et al. (2021) find that Airbnb listings lead to increases in rents and house prices across the U.S. Different from the above studies, our paper covers a wider range of states (i.e., all states across the U.S. instead of just one state) and examines Airbnb's effect on entrepreneurship and local employment.[3] Most of the critics focus on the impact of Airbnb on the neighborhood and housing affordability (Filippas and Horton, 2020;

[3] There are 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 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), fatal accidents, arrests for assault, and disorderly conduct, but increases vehicle thefts. Chen et al. (2017) show that Uber allows drivers to earn more than twice the surplus they would in less flexible arrangements.

Barron et al., 2021). We examine the effect of Airbnb from a different angle. We argue that the launch of Airbnb provides more renting options and potentially higher rental income, which relaxes the financial constraints of households and leads to more entrepreneurship and job creations. Our findings uncover a novel role that the housing sector could play in entrepreneurship. There are two contemporary papers that are closely related to our study. While Barrios, Hochberg, and Yi (2022) show that the introduction of Uber spurs entrepreneurship, Burtch, Garnahan and Graham (2018) find that the introduction of Uber hinders entrepreneurship. Our paper's findings are in general consistent with the results in Barrios, Hochberg, and Yi (2022). We, however, differ from these papers in two main ways. First, we focus on a different economic mechanism. While these two papers focus on how the entry of Uber provides additional labor income, we focus on the rental market and local demand effect from Airbnb. In particular, we show that Airbnb expansion increases the rental income, which helps relax the potential entrepreneurs' financial constraints. The effect of Airbnb on new business creations is further magnified by the increase in local demand, which creates a lot more new investment opportunities. Second, in addition to new firm creations, we show that the sharing economy affects local job creations and thus the unemployment rate.

2. Institutional Background

2.1 Sharing economy

In recent years, there is a rise of a new business model called the "sharing economy", which is also known as "peer-to-peer marketplace", "collaborative economy", or "gig economy". While there is no universally accepted definition of this new business model, it is commonly agreed that the sharing economy is a new type of marketplace, which brings together individuals to share or exchange otherwise underutilized consumer-owned assets (e.g., Koopman, Mitchell, and Thierer, 2014; Filippas, Horton, and Zeckhauser, 2020). Sharing underutilized consumer assets is hardly a recent phenomenon, given that owners of most durable goods use them substantially less than 100% of the time. Therefore, it is interesting that the sharing economy has only begun to flourish in recent years; some prominent examples of it include home-sharing service (Airbnb), ride-sharing service (Uber, Lyft), food delivery service (Instacart, Postmates), household tasks (TaskRabbit, Handy), etc. As argued in the literature, there are two main factors that contribute to the rise of the sharing economy (Filippas, Horton, and Zeckhauser, 2020). First, technological advances, such as

the mass adoption of smartphones with high-definition digital cameras and the falling cost and rising capabilities of the Internet, are important in helping build the digital platforms for the sharing economy. Second, often understated, the electronic commerce predecessors of the sharing economy, such as eBay and Amazon, provide important industrial experience in building online marketplaces and solving their fundamental problems (such as search algorithms, recommendation systems, and bilateral reputation systems), which mitigates information asymmetry and makes matching more efficient.

Sharing economy digital platforms differ in the way they match the supply and demand, and how they rely on the reputation mechanisms. In terms of matching, there could be centralized matching and decentralized matching systems. For example, Uber is operated through a centralized matching system, where the platform performs the action of searching and matching following a customer's request, and the service provider could decide whether to accept it or not. The platform is in charge of setting prices, and could increase or decrease prices depending on the market conditions. On the other hand, Airbnb is operated through a decentralized matching system, where the buyers and sellers do the match and the platform serves merely as escrow (i.e., collecting fees from the customer and delivering compensation to the service provider). The difference in the matching system is due to the nature of the business. The heterogeneity in a ride-sharing service is much lower than that in the home accommodation. Therefore, centralized matching is more appropriate for Uber, and decentralized matching is more appropriate for Airbnb.

Overall, the advantage of the sharing economy is that it could help turn noncommercial capital and individuals' spare time into valuable commercial assets. Specifically, it allows underutilized consumer-owned goods to be put into more productive usage. Different from a traditional rental market in which the rental assets are usually infrequently used goods for longer rental periods (such as vacation homes, pleasure boats), using the sharing economy platform, owners can sometimes use their assets for personal consumption and other times rent them out. In addition, by matching the supply and demand using the online marketplace, the sharing economy lowers the entry cost for a household to the rental market and thus expands the opportunity set for households to earn additional income.

The sharing economy, while still at its infancy, attracts substantial policy interest. The critics on the sharing economy are generally concerned about the disruptive nature of the sharing economy on affected industries and how these platforms duck costly regulations that protect third

parties and remedy market failures (Avital et al. 2015, Filippas and Horton, 2020). At the same time, the counter argument is often made that these sharing-economy platforms solve the market failure problems in an innovative fashion, with better information provision and reputation systems, making the existing regulations not appropriate to be applied to the sharing economy (Koopman et al., 2014).

2.2 Airbnb

We use Airbnb's penetration in counties as a proxy for the launching and growth of the sharing economy. Considered as a precursor of the sharing economy, Airbnb, a platform for short-term rental accommodations, was founded in August 2008 in San Francisco, California. The accommodations can be rooms, apartments, houses, etc. The hosts, who want to monetize their extra space, list their accommodations on Airbnb's online platform and showcase them to the potential guests. Meanwhile, the guests, who want to explore an experiment in these unique spaces, identify and book the accommodations on the platform. As of 2021, Airbnb has grown to 4 million hosts who share 5.6 million homes in more than 100,000 cities worldwide, making them comparable in inventory and transaction volume to the world's largest hotel brands.[4]

As shown in the US Census, America has over 460 million bedrooms in more than 190 million housing units; it translates to 1.5 bedrooms for every man, woman, and child in the country.[5] This represents a great deal of capital that people own but aren't leveraging to earn returns. The introduction of the Airbnb platform helps bring this "dead capital" that people don't formerly think of as productive capital into the stream of commerce. This is mainly because Airbnb platform lowers the entry cost into the short-term rental market for hosts, by providing the digital platform that helps make the matching more effective and mitigates the information asymmetry problem. Since Airbnb gets started, the hosts have earned more than $100 billion from home sharing.[6]

[4] About Us. https://news.airbnb.com/about-us/

[5] The vast majority of American adults have assets that they could make economically productive. For example, more than 90 percent of American households have one or more cars, with half owning two or more; the median household has over $6,800 equity in motor vehicles. For more information, see Daniel M. Rothschild, How Uber and Airbnb Resurrect "Dead Capital", UMLAUT (Apr. 9, 2014), https://theumlaut.com/how-uber-and-airbnb-resurrect-dead-capital-4475a2fa91f1

[6] Rural Stays and Online Experiences Boost Host Income (July 8, 2020) https://news.airbnb.com/rural-stays-and-online-experiences-boost-host-income/

The rise of Airbnb has attracted a lot of regulation attention. While the literature argued that Airbnb penetration in a local area could increase consumer welfare (Farronato and Fradkin, 2022), the critics mainly argue that home-sharing platforms like Airbnb raise the cost of living. This is because by reducing frictions in the peer-to-peer market for short-term rentals, home-sharing platforms cause some landlords to switch from supplying the market for long-term rentals to supplying the short-term market. The reduction in the supply of housing in the long-term rental market may drive up the rental rates (Barron et al., 2021). Concerns over the impact of home-sharing on housing affordability have motivated many cities to impose stricter regulations on home-sharing.

3 Empirical strategy

The main challenges for estimating the causal effect of Airbnb entry on entrepreneurship are the issues of reverse causality and joint determination. In this section, we motivate and describe our empirical strategy for addressing these difficulties. Specifically, we discuss the methodology to capture the extensive margin in Section 3.1: how the Airbnb's staggered entry is associated with new business creations. We discuss the methology to capture the intensive margin in Section 3.2: how the intensity of Airbnb's penetration affects new business creations.

3.1 Airbnb entry and new business creations

To assess how the staggered entry of Airbnb affects the creation of new firms, we estimate a model of the following form:

$$Number\ of\ firms\ created_{i,t+1} = \exp(\alpha + \beta Airbnb\ entry_{i,t} + \gamma Z_{i,t} + County_i + Year_t) + \varepsilon_{i,t+1} \quad (1)$$

where i indexes county and t indexes year. $Number\ of\ Firms\ Created_{i,t+1}$, the dependent variable, is the number of new firms created at county *i* in year *t*. The key variable of interest, $Airbnb\ entry_{i,t}$, is a dummy variable that equals one if there has been Airbnb entry at county *i* in year *t*. To control for time-varying county characteristics, we include a set of local economic and demographic variables ($Z_{i,t}$), including the logarithm of median household income, unemployment rate, labor force rate, the logarithm of house price index, the logarithm of population, white population rate, age 20-64 population rate and age 65+ population rate. Due to the count-based nature of our dependent variables, we employ a fixed effects Poisson estimator (e.g., Hausman et

al., 1984). We also include county fixed effect and year fixed effects to absorb time-invariant county characteristics and time trends. We cluster standard errors at the county level to control for within-county serial correlations.

One natural concern is that Airbnb did not enter the specific counties randomly. To examine the concern, we use the Cox hazard model to examine the determinants of Airbn entry, and examine the dynamic trend of new business creations around the Airbnb entry time. We discuss the tests in detail in Section 5.1.

3.2 Airbnb penetration and new business creations

To examine how the intensity of Airbnb's penetration in a county leads to new business creations, we examine the ordinary least squares (OLS) regressions in the following model:

$$Ln(number\ of\ firms\ created)_{i,t+1} = \alpha + \beta Ln(Airbnb\ listings)_{i,t} + \gamma Z_{i,t} + County_i + Year_t + \varepsilon_{i,t+1} \quad (2)$$

where *i* indexes county and *t* indexes year. $Ln(Number\ of\ Firms\ Created)_{i,t+1}$, the dependent variable, is the natural logarithm of one plus the number of new firms created at county *i* in year *t*. the key variable of interest, $Ln(Airbnb\ listings)_{i,t}$, is the natural logarithm of one plus the number of Airbnb listings at county *i* in year *t*. All the other variables are defined the same way as in Equation (1). We cluster standard errors at the county level to control for within-county serial correlations. Given both new business creations and Airbnb listings are in logarithm forms, the regression coefficient estimate β on $Ln(Airbnb\ listings)$ can be interpreted as the elasticity of new firm creations to Airbnb's expansion. A higher β indicates that Airbnb's penetration in a county is associated with more creations of new firms.

The concern associated with the OLS regression is that the coefficient estimate on $Ln(Airbnb\ listings)_{i,t}$ could be driven by some unobserved factors, such as local economic conditions. For example, local vibrant economic activities could attract both more hosts to list their empty rooms on the Airbnb platform and more entrepreneurs to start new businesses. To identify the causal effect of Airbnb's penetration in a local area on entrepreneurship, we employ an instrumental variable approach that exploits a plausibly exogenous time-series variable with a potentially endogenous cross-sectional exposure variable. This instrumental variable approach was first developed by Bartik (1991) and then widely used in the literature (Dube and Vargas, 2013;

Hanna and Oliva, 2015; Nunn and Qian, 2014; Diamond, 2016; Barron et al, 2021). The identifying assumption for the instrument is that the interaction term is exogenous conditional on the controls.

To construct the instrument, we start with the VC infusions into Airbnb as the plausibly exogenous time-series variation. Capital infusions from VCs significantly increase Airbnb's operational funding, which can be used in advertising, employee hiring, online platform improving, etc., which, as a result, attracts more potential hosts and stimulates Airbnb's expansion. Since Airbnb is an internet online platform, it services all counties across the country. Once a host wants to share an empty room, no matter where she lives, all she needs to do is to create a listing on the Airbnb platform. The infusion of VC funding into Airbnb, thus, is a plausibly exogenous shock to Airbnb expansion across the country.

A natural concern about using the VC instrument, however, is that there could be other changes over time that are spuriously corrected with Airbnb expansion, which could then confound the two-stage least square (2SLS) estimates. This concern can be addressed by the inclusion of time-fixed effects. However, since the VC capital infusions into Airbnb only vary over time, it will be collinear with time fixed effects. Therefore, we introduce counties' pre-existing tourism condition as the endogenous cross-sectional exposure variable in the instrument. This is because Airbnb penetration is likely to be more intense among counties that have more preexisting tourism sources. Exploring this form of heterogeneity allows us to flexibly control for time effects (with time-fixed effects) and to improve the strength of the first stage.

Overall, our instrument is the interaction between VC infusions into Airbnb and a country's ex-ante exposure to tourism. Causal inference using the instrumental variable relies on the assumption that, conditional on the controls, the interaction between VC capital infusions into Airbnb and the county's preexisting tourism condition only affects entrepreneurship through Airbnb penetration. We further explore the validity of this assumption in Section 5.3.

Using the shift-share instrument, we estimate the 2SLS regressions as below. Specifically, Equation (2) shows the first stage regression and Equation (3) shows the second stage regression:

$$Ln(Airbnb\ listings)_{\iota,t} = \alpha + \beta\ VC\ index_{t-1}\widehat{\times Ln(tourism)_{2007}} + \gamma\ Z_{\iota,t} + County_{\iota} + Year_t + \varepsilon_{\iota,t} \quad (3)$$

$$Ln(number\ of\ firms\ created)_{i,t+1} = \alpha + \beta\ \widehat{Ln(Airbnb\ listings)_{\iota,t}} + \gamma\ Z_{i,t} + County_i + Year_t + \varepsilon_{i,t+1} \quad (4)$$

where $VC\ index_{t-1}$ is the number of accumulated VC financing rounds received by Airbnb until year *t*. According to the VentureXpert database, Airbnb receives 9 rounds of VC financing between 2008 and 2015 (i.e., January, 2009; April, 2009; November, 2010; July, 2011; February, 2012; October, 2013; April, 2014; June, 2015; November, 2015). $Ln(tourism)_{2007}$ is the logarithm of establishments in the tourism sector in a county as of 2007. We instrument $Ln(Airbnb\ listings)$ with $VC\ index \times Ln(tourism)$ in Equation (2). $Ln(\widehat{Airbnb\ listings})_{i,t}$ is the predicted value of $Ln(Airbnb\ listings)_{i,t}$ from Equation (2). All the other variables are defined the same way as in Equation (2).

4. Data and sample construction

To assess the effect of Airbnb on firm creations, we gather data on Airbnb listings, firm creations, and control variables.

4.1 Measuring Airbnb penetration

Our Airbnb data are collected from Inside Airbnb (http://insideairbnb.com). Inside Airbnb is an independent, non-commercial set of tools and data. They collect detailed listing information from the Airbnb website (www.airbnb.com), including property type, county-level location, the first date that the host becomes a member of Airbnb, host name, the number of bedrooms, the number of beds, and the price charged per night. The advantage of using this dataset is that they collect Airbnb information in each year, so our Airbnb listing data is not subject to survival bias. [7] We aggregate Airbnb listings to the county-year level, and use it to measure Airbnb expansion at a county in a given year.

Since being founded, Airbnb has expanded at a dramatic rate. It has created more than 10,000 listings in the United States by December 2011. By August 2014, this number reached 100,000. By the end of our sample, 2015, Airbnb has more than 330,000 listings. Figure 1 plots the number of Airbnb listings in the US between 2008 and 2015.

[Insert Figure 1 about here]

In our sample, all states and the District of Columbia in the United States have Airbnb listings. Popular tourism states, such as California, Florida, and New York, have the most available

[7] If a county never has Airbnb, it would not show up in our Airbnb data set, because it would not have Airbnb listing on the Airbnb website.

rooms. California has more than 70,000 listings. States on the east coast and the west coast have more Airbnb rooms than inland states. Figure 2 plots the distribution of county-level Airbnb listings as of 2015.

[Insert Figure 2 about here]

4.2 Measuring firm creations

We obtain establishment-level firm creation information from Your-economy Time Series (YTS), an annual-level time-series database, tracking all US establishments since 1997.[8] Each year is an aggregation using annual snapshot of the Infogroup Business Data by Business Dynamics Research Consortium at the University of Wisconsin System Institute for Business & Entrepreneurship. The data contain detailed information on establishment sales and employment. Compared to the Current Employment Statistics (CES), a commonly used firm creation database, YTS is more representative, especially among births and younger/smaller businesses. Because YTS usually starts tracking a business within one year from its start date, while CES does not start tracking a business until it hires a full-time employee (Kunkle, 2020), this data has been widely used in finance academic research (e.g. Arefeva et al, 2020; Flynn and Ghent, 2020). We measure firm creations as the number of new stand-alone establishments founded in a given year in a county.

It is worth noting that Airbnb hosts are not part of our measure for new business creations. 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, and their income is subject to net investment income tax, unless the hosts are the owners of a hotel or motel, who provide services to travelers or work as real estate dealers that 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 recommends 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 unemployed. If other things do not change, leasing out accommodation through Airbnb and receiving rental income do not change the person's employed or unemployed status.

[8] Additional information on YTS data is available at https://wisconsinbdrc.org/data/

4.3 Measuring other control variables

We construct a set of county-year level economic and demographic variables as controls, including median household income, unemployment rate, labor force rate, house price index, population, population by race and age, and college rate. Data on median household income, population, and college rate are obtained from the US Census; data on unemployment rate and labor force rate comes from the Bureau of Labor Statistics; data on house price index is extracted from the Federal Housing Finance Agency.

Additionally, we use individual-level survey data from the Census American Community Survey (ACS). The Census collects detailed information about American population and housing characteristics through the ACS project. Since 2005, the ACS samples represent 1% of the population every year. In the survey, individuals are asked questions about gender, race, education, employment, income, etc. Following the literature, we define entrepreneurs in two ways: individuals who are self-employed and individuals who are self-employed with positive business income.

Our county-level rental measures are also extracted from the Census American Community Survey, including landlords (households receiving rental income), units vacant for seasonal rental, units vacant for long-term rental. The long-term rental price is from the HUD Fair Market Rents Database.

4.4 Sample construction and summary statistics

We use Airbnb listings data in each county-year from 2008 to 2015, and match it to YTS new business creations in each county one year ahead. Our sample includes 2,403 unique counties that span 9 years. In Table 1 Panel A, we present the summary statistics on county-year level measures. An average county in our sample has 27 Airbnb listings, 112,080 individuals, and 369 new startups each year. The mean household income is $46,840. In Panel B, we report the summary statistics on firm-level sales and employment at the entrant year. An average new startup in our sample has about 4 employees. Panel C reports the summary statistics of individual-level dataset from the ACS. There are about 10% of the individuals in the sample who are self-employed.

[Insert Table 1 about here]

5 Empirical results

This section presents our main empirical findings. First, we examine how Airbnb's penetration into the counties affects the local business creations. Specifically, Section 5.1 examines the extensitive margin, that is, how Airbnb's staggered entry into couties is associated with local business creations. Section 5.2 examines the extensive margin, that is, how the intensity of Airbnb entry as measured by Airbnb listings affect local business creations. Section 5.3 discusses the validity of the instrumental variable approach. Section 5.4 examines how local landlords benefit from Airbnb penetration and create new businesses. Section 5.5 explores the rental channel versus the collateral channel. Section 5.6 explores the heterogeneity of results across the financial constraints. Section 5.7 explores the risk tolerance channel.

5.1 Extensive margin: Airbnb entry and new business creations

We examine the extensive margin in Table 2, where we conduct varaitions of the Poisson regressions as specified in equation (1). Column 1 presents the univariate regression and column 2 includes the controls ($Z_{i,t}$). Both columns report a positive and significant correlation between Airbnb entry and new firm creations. The economic magnitude is sizable. For example, column 2 shows that Airbnb entry in a county, on average, leads to 3.1% increase in local business creation (or 11 new firms).[9]

[Insert Table 2 about here]

We conduct two additional tests to show that Airbnb entry to counties was not based on local new business formation, which is the main outcome variable of interest in the study. First, we estimate a Cox proportional hazards model for Airbnb entry into the sample counties with or without different set of economic and demographic control variables. As shown by the Internet Appendix Table IA1, many economic and demographic factors predict the entry of Airbnb as expected, but the growth in the number of new firms cannot predict the entry of Airbnb. Second, we plot the dynamic effects of Airbnb Entry on the number of new businesses created controlling for other observable characteristics as in the baseline regressions. Figure 4 panel (a) shows that before the Airbnb entry, there is no significant trend in new business formation among all counties, while counties with Airbnb services experience significantly greater increase in the number of

[9] The magnitude is comparable to Barrios, Hochberg, and Yi (2022), where the introduction of Uber and Lyft is associate with a 4-5% increase.

business created after the Airbnb entry. The above two tests provide supporting evidence that the parallel trend assumption required for a difference-in-differences setting is not violated in this study.

[Insert Figure 4 about here]

5.2 Intensive margin: Airbnb penetration and new business creations

We further examine the intensive margin, that is, how the intensity of Airbnb entry affects local new business creation. Specifically, we use the natural logarithm of the number of Airbnb rooms as the key independent variable. First, we conduct OLS regressions as sepcificed in equation (2) in Table 3, where the coefficient estimate on Ln(Airbnb listings) represents the elasticity of of new business creations with regard to Airbnb penetration. The coefficient estimates in columns 1 and 2 are positive and statistically significant at 1% and 5% significance level, indicating that increasing Airbnb listings in a county by 10% is associated with a 0.1% increase in new businesses creations.

While and OLS regression shows a strong relation between local Airbnb penetration and new firm creations, Airbnb's expansion might be correlated with some unobservable factors which could affect new firm creations as well. To identify the causal effect of Airbnb penetration on new business creations, we use 2SLS as described in Section 3.2. Columns 3 and 4 in Table 3 present the estimation results. Column 3 reports the first-stage regression results estimating Equation (3). We find a positive and significant coefficient estimate on the instrument, $VC\ index \times Ln(tourism)$. The F statistics of the weak instrument test has a p-value of less than 0.001, suggesting that our instrument is not weak (Bound et al., 1995) and hence we do not appear to suffer from weak instrument problem.

Table 3 column 4 presents the second-stage regression results estimating Equation (4). The coefficient estimate on the instrumented Airbnb variable is positive and significant at the 1% level, suggesting that Airbnb penetration spurs entrepreneurship. The economic magnitude of the coefficient estimate is sizable: Increasing Airbnb listings in a county by 10% is associated with a 0.28% increase in new firm creations. In other words, 100 Airbnb listings lead to about 38 new business creations.[10] Comparing the 2SLS results in column 4 of Table 3 with OLS regression

[10] The calculation process for the 38 businesses is as following: 0.28% × Average business creation (368.5) = 1.03, 1.03/10% of Average Airbnb listings (27.09) = 38%.

results in column 2 of Table 3, we find that the magnitude of the 2SLS coefficient estimate is larger than that of the OLS estimate. This goes against our initial intuitition that some omitted factors (e.g., local vibrant economic activitie) could be positively correlated with both Airbnb listings and new business creations. However, we note the 2SLS estimate magnitude might be larger than the OLS estimate for two reasons. First, simultaneity bias may be negative if some omitted factors lead to more new business creations, and thus reduce the incentives for these entreprneaurs to supply to the short-term rental market. Second, as with all instrumental varaiable estimates, our 2SLS estimates reflect the average effect for observations that comply with the instrument, i.e., a local average treatment effect (Jiang, 2017). The compliers are the Airbnb listings coming at the margin from the dissemination of Airbnb in tourist area given VC capital.

[Insert Table 3 about here]

We conduct several robustness tests on the baseline regression and report the results in Internet Appendix Table IA2. In column 1, we control for regional economic trends by adding state × year fixed effect. Our results are qualitatively similar to our main findings in Table 3, suggesting that the regional economic trends do not explain our results. In column 2, we repeat our analysis using the sample after 2010 to mitigate the concern that the 2008 financial crisis could drive our results, and we find robust results. In column 3, we repeat our analysis using firm creation measures from the Census Statistics of U.S. Businesses and find consistent results. In column 4, we repeat our analysis at the county-industry-year level and add industry × year fixed effects to control for industry trends, addressing the concern that unobservable industry specific shocks that are correlated with the entry of Airbnb could be driving our results. We continue to find a strong, positive effect of Airbnb listings on new firm creations after controlling for the industry-year fixed effects.

5.3 Validity of the instrumental variable

Causal inference using the interacted instrumental variable relies on the assumption that, conditional on the controls, the interaction between VC infusions into Airbnb and county tourism only affects entrepreneurship through its effect on Airbnb penetration in the local area. While the assumption cannot be directly tested, we conduct several analyses to check its validity.

First, this instrumental variable approach is essentially a difference-in-differences. We verify the parallel trends assumption for the difference-in-differences approach. The assumption

requires that the high-tourism counties experience similar change in local entrepreneurship as low-tourism counties in the absence of Airbnb entry. In Figure 4 Panel (b), we plot the dynamics of new firm creations surrounding the Airbnb entry time for high tourism counties and low counties. The figure shows that there is no significant trend before the Airbnb arrival for both types of counties while the number of new businesses increases significantly for counties with high tourism and the number of new businesses in counties with low tourism does not experience such an increase. The results suggest that the parallel trend assumption is likely to hold in our setting.

Second, we examine whether our instrument is correlated with some spurious time trend, which drives the results. To this end, we implement a form of randomization inference by following Christian and Barrett (2017). Specifically, among the counties with at least one Airbnb listing, we randomly swap the number of Airbnb listings across these counties, while we keep constant the aggregate number of Airbnb listings in each year. We also keep constant the outcome variables, instrumental variable, and controls. The randomized Airbnb listings preserve the overall trends in Airbnb's expansion but randomize the Airbnb growth in each county, and thus eliminates the impact of local tourism resources on intensive margin of Airbnb listings. Therefore, if the results are primarily driven by a spurious time trend that interacts with the extensive margin of whether there are any Airbnb listings, then the 2SLS estimate under this randomization would continue to be positive and statically significant. In contrast, if the cross-sectional variation in touristiness drives the intensive margin of Airbnb listings, then this randomization would lead to a weak first-stage, and correspondingly insignificant estimates in the second-stage regression with a large variation.

We conduct the randomization for 5,000 times and estimate the 2SLS specification as in Equation (3) accordingly. Figure 5 plots the distributions of the coefficient estimates and *t*-statistics of randomized Airbnb listings. As predicted, the coefficient estimate has a mean that is statistically insignificantly different from zero, and exhibits a large variation. The finding suggests that our instrument does not affect entrepreneurship through spurious time trends.

[Insert Figure 5 about here]

Third, we provide evidence suggesting the satisfaction of the exclusion restriction for the instrument. In particular, we estimate whether the instrumental variable predicts new business creations in counties that never have any Airbnb listings (we call these counties as "non-Airbnb counties"). If our instrument is valid, it should be correlated with new business creations only

through its effects on Airbnb listings. Therefore, in areas with no Airbnb, we should not observe a strong correlation between our instrument and new business creations. To conduct the test, we restrict the sample to counties with no Airbnb entry throughout our sample period and conduct the regression as described in Equation (3). Table IA3 column 1 reports the results. The coefficient estimate on the instrumental variable is close to zero and statistically insignificant. In contrast, in column 2 where we conduct the regression as described in Equation (3) in counties with Airbnb entry during our sample period and find a strong, positive coefficient estimate on the instrumental variable. Taken together, these results suggest that the instrument affects entrepreneurship only through its impact on Airbnb listings.

Overall, the above analyses provide strong support for the validity of our instrument. We, therefore, use the instrument and present 2SLS estimates for all the following tests in this paper.

5.4 Airbnb, landlords, and business creations

Having established a causal link between Airbnb penetration and entrepreneurship, we turn to examine plausible underlying channels. First, we examine the group that is most likely to benefit from the lower entry cost for short-term rental service—the landlords. We start by examining whether landlords who receive more rental income are more likely to become entrepreneurs as Airbnb grows. We focus on landlords because they enjoy a lower entry cost for short-term rental services than non-landlords. It is worth noting that the landlords do not necessarily need to be Airbnb hosts.

We use individual-level data from the Census American Community Survey to conduct this test. Our sample includes 3.5 million individual-level observations.[11] Following the literature (e.g. Dillon and Stanton, 2017), we use two measures of entrepreneurship, including *I{entrepreneur}* and *I{entrepreneur receiving business income}*. *I{entrepreneur}* is an indicator that equals one if an individual is self-employed, and zero if she works for someone or is unemployed. *I{entrepreneur receiving business income}* is an indicator that equals one if an individual is self-employed and receives positive business income, and zero otherwise.[12] To measure rental income opportunities, we construct an indicator, *I{landlord}*, which equals one if

[11] Since income information is collected at household level, our sample includes only the individuals who are the head of the households of working age (between 18 and 65 years old). In unreported tables, we find consistent results using all individuals of working age.

[12] ACS does not distinguish fame income from business income.

an individual receives rental income, and zero otherwise. We then instrument Airbnb listings and its interaction with *I{landlord}* using our instrumental variable and its interaction with *I{landlord}*. We add a set of individual characteristic measures to control for the effects of individual characteristics, including age, gender, race, education, whether she was employed last year, and whether she owns her housing units. This individual-level sample allows us to include county-year fixed effects in the regressions that further mitigate concerns on local economic conditions driving the results.

Table 4 presents the results. The unit of observation is individual by year. In columns 1 and 2, the dependent variable is *I{entrepreneur}*; in columns 3 and 4, the dependent variable is *I{entrepreneur receiving business income}*.[13] Given that we have individual by year level data, rather than county-by-year level data, we use more restrictive fixed effects than county fixed effects and year fixed effects. That is, we include time-varying county fixed effects (county × year) in all columns to absorb the time trends across counties. The coefficient estimate on the interaction term *Instrumented Ln (Airbnb listings)* × *I{landlord}* is positive and significant across all specifications, suggesting that Airbnb penetration in a local area increases the likelihood of a landlord becoming an entrepreneur.[14] The magnitude of the coefficient estimates suggests that, on average, for 100 Airbnb listings in a county, there would be 13 additional landlord entrepreneurs.[15] Combining this magnitude with the baseline magnitude (100 Airbnb listings translate to 38 new business creations), it tells us that at least 2/3 of the new business creations are not started by landlords.[16] This evidence supports our conjecture that Airbnb spurs entrepreneurship by relaxing local entrepreneurs' financial constraints and expanding local demand and investment opportunities.

[Insert Table 4 about here]

We then examine why landlords are more likely to start businesses with Airbnb penetration by testing its effect on the local rental market. In Table IA5, we report the 2SLS estimates that

[13] All individual measures are at *t*+1, such as *I{entrepreneur}*, *I{entrepreneur receiving business income}*, and *I{landlord}*. County-level Airbnb measures and controls are at *t*.

[14] Our approach is appropriate given Bun and Harrison (2019) find that the coefficients on the interaction terms of an endgeneous variable and an exogenous variable are asymptotically consistent.

[15] The calculation process is as following: Number of additional landlord entrepreneurs = average landlord (24,381) × increased probability of becoming an entrepreneur (0.001 × average Instrumented Ln(Airbnb listings)(3.123)) = 76.14. 76.14/average Airbnb listings (580) = 13%.

[16] It is worth noting that this test does not distinguish short-term rental from long-term rental due to data limitations. Hence, it is likely that Airbnb expansion spurs entrepreneurship either through its effect on more opportunities for short-term rental or increased long-term rental prices.

regress rental market variables on the instrumented Airbnb variable. In column 1, the coefficient estimate on the instrumented Airbnb variable is positive and significant at the 1% level, suggesting that Airbnb listings increase the number of landlord households who receive rental income.[17] The results suggest that as the Airbnb platform provides more short-term rental opportunities, more households become landlords. We then investigate how Airbnb affects the housing supply in the short-term rental market and housing supply in the long-term rental market. We use vacant units available for seasonal use as the proxy for the short-term rental market supply and vacant units available for long-term rental as the measure of the long-term rental market supply. We report the results in columns 2 and 3 in Table IA5. We find a positive effect of Airbnb listings on units vacant for short-term rental, and a negative effect on units vacant for long-term rental. The results suggest that Airbnb increases the housing supply in the short-term rental market, and at the same time, decreases the housing supply in the long-term rental market. The reduced long-term rental market supply suggests that with the local penetration of Airbnb, more households transfer their vacant units, which used to target long-term tenants to short-term rental. As supply decreases, the market price of the rental market may be affected. Consistently, in column 4 in which the rental price is the dependent variable, we find a positive effect of Airbnb listings on rental prices.[18] In column 5, we examine the impact of Airbnb penetration on local house prices and find a positive and significant coefficient estimate. However, the economic magnitude of the house price increase is small: A 10% increase in Airbnb listings is only associated with a 0.08% increase in the house price.

The above results suggest that Airbnb expands the opportunities for landlords to collect rental income through two channels. First, as Airbnb expands, more households receive rental income by listing their empty units. Second, as more vacant units are listed on the Airbnb platform, the supply of the long-term rental market decreases, driving up the rental price.

To examine the economic magnitude of the rental channel, we do a back-of-envelope calculation mapping short-term rental income to startup cost. According to Earnest, for a low-interest lender in San Francisco, the average income of Airbnb hosts is $924 per month, translating to $11,088 (=924×12) income per year. According to the Kauffman survey, the average cost to

[17] We obtain the data from Census American Community Survey (ACS), which does not distinguish interest and dividend income from rental income.

[18] We use Fair Market Rents from HUD as the proxy for rent in a county. In unreported tables, we find robust results using rental price from Zillow. The results are available upon request.

start a new business from scratch is about $31,150 (in 2008 dollars), translating to $37,444 (in 2020 dollars). Therefore, the short-term rental income from Airbnb accounts for about 30% (=11,088/37,444) of the startup cost, representing a non-trivial proportion.[19]

One alternative interpretation of our main findings is that Airbnb increases the collateral value of homes, which promotes entrepreneurship. So far, we have established that Airbnb causes a reallocation of housing supply from the long-term to the short-term rental market, and as a result, leads to an increase in the rental rates. At the same time, Airbnb could also affect housing prices, which increases their collateral value. First, house prices represent the present value of all the future cash flows generated from owning the house. As the long-term rental rates increase, house prices increase as well. Second, the option to do short-term rental could reduce households' propensity to put their houses on sale in the market, and thus the reduction in housing supply could also increase house prices. Consistent with the above arguments and the literature (Barron et al., 2021), we find that Airbnb's growth leads to an increase in housing prices.[20] Hence, an increase in housing prices suggests that households are able to extract additional collateral credit from the housing price appreciation and use the capital to start new businesses (Adelino et al., 2015; Schmalz et al., 2017). If this argument is true, then our results reflect a collateral channel rather than a rental channel.

To examine whether our main results are driven by increases in rental rates or collateral value, we start by testing whether Airbnb spurs new business creations more in counties with higher rental price growth. To this end, we split our sample into counties that experience high and low rental price growth from t to t+1. We construct an indicator *I{high rental price growth}* that equals one if rental price growth in a county is above the median growth of the same period, and zero otherwise. We instrument Airbnb listings and its interaction with *I{high rental price growth}* using our instrumental variable and its interaction with *I{high rental price growth}*. Table 8 column 1 shows that the coefficient estimate on the interaction term is statistically significant, suggesting that the effect of Airbnb on new business creations is stronger in counties with higher rental price growth, confirming that rent increases could be one underlying channel. We then examine the collateral channel by splitting the sample into counties with high and low house price

[19] See https://www.earnest.com/blog/sharing-economy-income-data/ for income from Airbnb. See https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.607.5828&rep=rep1&type=pdf for Kauffman survey.
[20] The results are not report but available upon request.

growth and run a similar regression. The coefficient estimate on the interaction term between the instrumented Airbnb listing and *I{high rental price growth}* is insignificant, suggesting that the effect of Airbnb on new business creations is very similar across counties that experience high and low house price growth. Because house prices could be endogenous to local startup births, we also split the sample in two other alternative ways. In column 3, we split the sample into high and low land use regulation counties, using the Wharton Residential Land Use Regulation Index (Gyourko et al., 2008). In column 4, we split the sample into counties with high and low housing supply elasticity using the elasticity measures defined by Saiz (2010). The coefficient estimates on the interaction term are statistically insignificant in both columns, suggesting that the effect of Airbnb penetration on new business creations is similar in counties with high and low land use regulation as well as in counties with high and low housing supply elasticity.

[Insert Table 5 about here]

Finally, we directly examine the collateral channel using individual-level mortgage data from ACS and report the results in Table IA4. We use the information on the second mortgage to measure the effect of collateral. Specifically, we construct two indicators, *I{second mortgage}* and *I{home equity loan}*. *I{second mortgage}* equals one if an individual has a second mortgage (including home equity loans), and zero otherwise. *I{home equity loan}* equals one if an individual has home equity loans, and zero otherwise. Results reported in Table IA4 show that the relation between Airbnb's expansion and an individual's probability of becoming an entrepreneur is unchanged no matter whether the individual obtains second mortgages. This finding suggests that Airbnb does not affect entrepreneurship through increases in collateral value.

If Airbnb indeed spurs entrepreneurship through the rental channel, we expect to see that the results are more pronounced when entrepreneurs are subject to a higher degree of financial constraints. In this subsection, we explore the above conjecture and use heterogeneity in financial constraints in the cross sections to strengthen the rental channel.

5.5 Airbnb, local demand, and entrepreneurship

We next turn to understand how Airbnb spurs entrepreneurship through channels other than the housing market. We hypothesize that it is through the local demand increase, which is crucial for new business creations (Adelino, Ma, and Robinson, 2017). Airbnb appears to increase local demand mainly in two ways. First, Airbnb increases toursits (as proxied by the incoming air

passengers) to the local area. Second, Airbnb reduces hotel pricing, which could lead to an increase in the budget that can be spent on non-lodging service by the tourists. With the increased tourists and more spending on local services, there would be more local investment opportunities for potential entrepreneurs. For example, it could be more profitable to open restaurants given the increased local demand.

First, we examine how Airbnb penetration is associated with the increase in visitors in Table 6. We proxy the number of visitors by incoming air passengers and collect data from Bureau of Transportation Statistics U.S Domestic Airline Traffic. The dataset provides the total number of passengers arriving each airport in the U.S. as well as the distance of the flight. We then aggregate the number of incoming air passengers to ariports within 25 miles to a county in a year (*Ln(IncomingAirPassengers)*. Table 6 column 1 shows that Airbnb penetration leads to a positive increase in the total number of air passengers to town. When breaking down by the flight distance, we observe that the increase is mainly in those flights that are more than 1000 miles but not those short flights with a distance less than 1000 miles.[21]

[Insert Table 6 about here]

Second, we exaimine whether Airbnb lowers the prices charged by hotel and increases consumer welfare (Farronato and Fradkin, 2022), and thus increases the budget that can be spent locally for non-lodging consumption. We collect information on hotel performance from Smith Travel Research and present the results in Table 7. We find that Aribnb penetration significantly lowers hotel revenue, decreased the occupancy rate, and lowers room price and the revenue per available room of hotels.

[Insert Table 7 about here]

We also show supporting evidence for the local demand channel by examining the impact of Airbnb growth on the income and wage of local residents. We obtain the information on local residents' income from the IRS Individual Tax Statistics. Table 8 column 1 shows that Airbnb entry has a positive impact on local residents' adjusted gross income, which includes both wage

[21] The finding is very intuitive, given that there is a fixed cost for Airbnb stay. For example, there is usually a one-time cleaning fee charged for Airbnb stay, which is a nontrivial cost for staying at Airbnb (Pohle, A. 2022. Why Airbnb cleaning fees cost so much now, *Wall Streee Journal*, April 12.) Therefore, if it is only one-day stay, staying at Airbnb is not necessarily advantageous than staying at hotel. Given that the longer the flight distance, the more likely the stay will be longer, Airbnb's is more likely to be attractive to to longer-distance travelers.
thereforeWhen there are results when travel distance is over 1000 mile. (1. Fixed cost for Airbnb stay; 2. Overnight stay probabibily for 1000 mile passengers will be lower)

income and non-wage income. We further show in Table 8 columns 2, 3, and 4 that Airbnb increases the non-wage income, especially business income, but do not increase wage income significantly.[22] The results support that Airbnb expands the demand for local residents.

[Insert Table 8 about here].

We also examine how Airbnb affects employment in Table 9. We aggregate establishment employment information to the county level using the YTS data. We also examine the unemployment rate using the Bureau of Labor Statistics data. We start by examining whether Airbnb affects the total number of jobs in a county or not in Column 1. The coefficient estimate on the instrumented Airbnb variable in column 1 is positive and significant at the 1% level, suggesting that Airbnb penetration significantly increases local employment created by new businesses. When looking at the unemployment rate in Column 2, we find that unemployment rate decreases significantly after Airbnb expansion. In Column 3, we examine the impact of Airbnb on new jobs by creating new firms. We are also interested in whether jobs created by new firms would substitute existing firms' employment. In Column 4, we examine the total number of jobs supported by existing firms and fail to find any significant effect of Airbnb penetration on it and show that new firms do not crowd out jobs in the existing firms. We further break down the employment of existing firms by their employment size and categorize them into "large," which employ at least ten people, versus "small," which employ less than ten people. We find that Airbnb penetration does not lead to significant changes in the employment of those "large" existing firms. On the other hand, Airbnb penetration increases the employment of "small" existing firms, which provides supporting evidence for the local demand channel that Airbnb brings more tourism and demand for new businesses. The above tests suggest that Airbnb entry has a positive net effect on local job creation.

[Insert Table 9 about here]

We next examine how Airbnb affects employment in different industries. We first examine job creation in different sectors. Table IA6 columns 1 and 2 report the impact of Airbnb penetration on local employment for tradable as well as non-tradable and construction sectors. The coefficient estimates are all positive and statistically significant at 1% level, suggesting that the net effect for job creation cross sectors are positive. Further, as pointed out by Zervas et al (2017), Airbnb

[22] Only when a person operates a businessesas a sole proprietor files Schedule C to report business income. Therefore, personal business income is also a measure reflecting entrepreneurial income.

negatively affects revenues in the hospitality industry. Under the concern that the penetration of Airbnb could also reduce job opportunities in the local hospitality industry, we examine employment from the hospitality industry (NAICS 7211). Column 3 shows a negative but insignificant effect of Airbnb on the hospitality industry employment, suggesting that the development of Airbnb does not crowd out the hospitality industry employment. Column 4 shows that non-hotel employment increases significantly. Considering the employment results in Table IA6 columns 3 that the employment in the hotel industry does not change significantly after Airbnb entry, Airbnb entry's potential negative impact on the hotel industry is limited.

Finally, we show that Airbnb indeed creates more businesses in non-tradable industries, which have been shown in the literature to be more sensitive to local demand (Adelino et al., 2015; Adelino et al., 2017). Table 10 shows the impact of Airbnb expansion on local business creation in different sectors and industries. In Columns 1 and 2, we follow the sector definition in Mian and Sufi (2014) and examine the tradable sector versus the non-tradable and construction sectors. Of 38 new businesses started after Airbnb's entry, about four are in tradable industries, and about 31 are in non-tradable or construction industries.[23] In Columns 3 to 6, we report the results of the 2SLS in four relevant industries to Airbnb's growth in the non-tradable and construction sectors. The significant coefficient estimates in "Art, Entertainment, and Recreation" (NAICS 71), Accommodation and Food Services (NAICS 72), Real Estate and Rental Leasing (NAICS 53), and Construction (NAICS 23) confirm our hypothesis that Airbnb listings attract more tourists, and therefore increases the demand for local service industries (e.g., restaurants, retail stores, and house cleaning service) or construction services (e.g., more remodeling or new housing construction).

[Insert Table 10 about here]

In Figure 6, we plot the number of firms created due to a 10% increase in local Airbnb listings across industries. The industries with most number of firms created are "Construction," "Retail Trade," "Other Services," "Professional, Scientific, and Technical Services," "Real Estate and Rental and Leasing," "Transportation and Warehousing," "Accommodation and Food Services," confirming that the penetration of Airbnb results in entrepreneurship in local service and construction-related industries through expanding local demand.

[23] We obtain the statistics through the following calculations. In tradable industries: 0.099 × average new business creations in tradable industries (9.79) = 1, 1/average Airbnb listings (27.1) = 3.6%. In non-tradable and construction industries: 0.066 × Average new business creations in tradable industries (127.9)=8.4, 8.4/average Airbnb listings (27.1)=31.2%.

[Insert Figure 6 about here]

Overall, the results suggest that Airbnb penetration positively affects local economy by creating new jobs through new business creation. At the same time, Airbnb's entry brings tourists to town and expands local demand but does not lead to job destruction in the existing firms and hotel industry, generating a positive spillover effect on the local economy.

5.6 Financial constraint

Then, we explore counties' *ex ante* access to credit for entrepreneurs. First, we use the proportion of local banks (measured by deposits) as a measure of entrepreneurs' access to credit. Following Cortes (2014), a bank is considered local if 50% or more of its deposits is concentrated in a single county. This method builds on the importance of local bank credit to entrepreneurship (Petersen and Rajan, 1994, 2002; Guiso et al, 2004). Compared to large, established firms, startups are opaquer and require more screening and monitoring, increasing difficulty in raising funds at a distance. Therefore, entrepreneurs in counties with lower shares of local banks are likely to have worse access to credit (Adelino et al., 2017) and are more likely to start new businesses when there are better opportunities to earn rental income through Airbnb. In Table 11 column 1, we split the sample into two groups by the share of deposits in local banks in a county at *t*-1. We construct an indicator *I{low local bank share}* that equals one if the proportion of deposits in local banks in a county is below the median of the same period, and zero otherwise. We instrument Airbnb listings and its interaction with *I{low local bank share}* using our instrumental variable and its interaction with *I{low local bank share}*. The coefficient estimate on the interaction term is positive and significant at the 1% level, suggesting that Airbnb's impact on new business creations is more pronounced in areas with lower local bank shares.

[Insert Table 11 about here]

Second, we use house price volatility as a proxy for entrepreneurs' access to credit. As house price volatility affects banks' willingness to lend against real estate (Mao, 2021), counties with higher house price volatility are likely to have worse access to credit. If Airbnb relaxes entrepreneurs' financial constraints through the rental channel, we expect to observe that entrepreneurs in counties with worse access to credit should benefit more from increased rental opportunities and would be more likely to start new businesses. To test this conjecture, we split the sample into two groups by house price volatility, which is measured as the standard deviation

of house price index in the previous 20 years in a county. We construct an indicator *I{high house price volatility}* that equals one if house price volatility in a county is above the median of the same period, and zero otherwise. We instrument Airbnb listings and its interaction with *I{high house price volatility}* using our instrumental variable and its interaction with *I{high house price volatility}*. Table 11 column 2 presents the results. The coefficient estimate on the interaction term is positive and significant at the 5% level, suggesting that the effect of Airbnb on new business creations is more pronounced in regions with higher house price volatility.

Third, we use refinance denial rate as a measure of entrepreneurs' access to credit. Counties with a higher rate of denial on refinance applications can be considered as ones where homeowners are less likely to extract equity from a home, and thus have worse access to credit. Therefore, counties with higher denial rate on refinance applications should have more new business creations following local Airbnb growth. To test this conjecture, we extract all refinance mortgage data in the US from Home Mortgage Disclosure Act.[24] We construct an indicator *I{high refinance denial rate}* that equals one if the ratio of denied applications in a county at *t*-1 is above the median of the same period, and zero otherwise. We instrument Airbnb listings and its interaction with *I{high refinance denial rate}* using our instrumental variable and its interaction with *I{high refinance denial rate}*. Table 11 column 3 presents the results. The coefficient estimate on the interaction is positive and significant at the 1% level, which is consistent with our conjecture.

To further investigate the financial constraint heterogeneity, we repeat our analysis disaggregated by startup capital needs. We first disaggregate startups by size. Firm size could alter the effect of Airbnb on new firm creations through two channels: (1) small firms require relatively less capital. The amount of rental income collected by Airbnb listings is more likely to be enough to start a small firm than a large firm. (2) small firms are opaquer, and thus have less access to credit. Hence, the rental income from Airbnb listings, as a substitute for bank credit, is more important to small, opaquer firms than large firms. If the conjecture is supported, we should observe more creations of small startups following Airbnb penetration in local counties. To test this conjecture, we repeat our regressions disaggregated into small startups (with 1-9 employees) and large startups (with 10 or more employees). The coefficient estimate on the instrumented Airbnb variable is positive and significant at the 1% level in Table 12 column 1 but insignificant

[24] Home Mortgage Disclosure Act does not distinguish regular refinance mortgage from cash-out refinance mortgages.

in column 2 and the difference between the coefficients in these two subsamples is statistically significant, suggesting that Airbnb spurs the creation of small but not large startups.

[Insert Table 12 about here]

Next, we repeat our regressions disaggregated into industries based on the degree of needs for startup capital. We use survey data from SBO PUMS to compute the average startup capital needs for each industry. The increased rental income is more likely to benefit new business creations in industries that require less startup capital. If Airbnb spurs new business creations by relaxing financial constraints, we should observe a stronger effect in industries that require less startup capital. The results are consistent with our conjecture. Table 12 column 3 shows positive and significant effect of Airbnb listings on the creation of new startups among industries with below-median needs for startup capital; Table 12 column 4 shows no significant effect of Airbnb on the creation of new firms among industries with above-median needs for startup capital. The difference between the coefficients in the two subsamples is statistically significant.

In summary, we find that the effect of Airbnb penetration on firm creations is more pronounced in counties with worse access to credit, as measured by lower local bank share, higher house price volatility, and lower refinance denial rate. We also find stronger effect of Airbnb on startups with smaller startup size or lower capital needs. These findings support the argument that Airbnb spurs the creation of new startups by relaxing entrepreneurs' financial constraints.

Taken the above evidence together, our results are more likely to be driven by a rental channel rather than increases in collateral value. It is worth noting that our evidence does not imply that house price appreciation does not lead to new business creations. Our findings only suggest that Airbnb expansion is more likely to spur new business creations through increased short-term rental opportunities (and hence more rental income) rather than increased house prices. There are three reasons that could explain this observation. First, the house price increase induced by Airbnb listing is small as shown in Table IA5 column 5. Second, house prices tend to be more volatile than rental income, and thus entrepreneurs are more likely to view rental income as a safe fallback if the new businesses they start fail. Third, for primary homes, the mortgage rate to place a second lien is usually high; for rental properties, it is usually difficult to extract a second lien. In contrast, getting rental income is relatively easier and less costly.

5.7 Risk tolerance

Existing literature (e.g., Hurst and Lusardi, 2004) argues that, as wealth grows, households are more risk-tolerant. Therefore, with the expectation that they can collect more rental income, households could be more likely to start new businesses, which are typically associated with high risk. To explore this alternative interpretation, we study the survival rate and performance of new businesses created following the expansion of Airbnb. If Airbnb's impact on new business creations is mainly driven by higher levels of risk tolerance rather than the relaxation of financial constraints, then the newly created businesses should be associated with higher risk, and thus higher failure rate (Schmalz, Sraer, and Thesmar, 2017).

The YTS data allow us to track startups over a long period, enabling us to test whether Airbnb expansion is more likely to spur the creation of startups with worse quality. In Table 13, we disaggregate the new business creations into two groups: the ones that fail within three years and the ones that survive for more than three years. The coefficient estimate on the instrumented Airbnb variable in column 1 is statistically insignificant, suggesting that Airbnb growth does not lead to the creation of new startups that stand for less than three years. The coefficient estimate on the instrumented Airbnb variable in column 2, however, is positive and significant at the 1% level, suggesting a positive effect of Airbnb's growth on the creation of new businesses that survive for a long period (over three years). In fact, 83% of startups created as a consequence of the expansion of Airbnb survive for at least three years. This number is much higher than the average survival rate in US: according to the National Business Capital and Services, as of 2019, the average new startup survival rate for two years is 30%.[25] Overall, the results suggest that the new businesses created do not exhibit a higher failure rate.

[Insert Table 13 about here]

To further understand the risk of new businesses started following Airbnb penetration, we directly investigate the performance of new businesses at the establishment level in Table 14. First, we examine short-term performance by testing the revenue (measured by sales) and productivity (measured by sales per employee) at the entrance year. To control for time-varying industry trends, we add industry-by-year fixed effects in addition to county fixed effects. The coefficient estimates on the instrumented Airbnb variable in columns 1 and 2 are positive and significant at the 1% level, suggesting that Airbnb expansion significantly affects new startups' revenue and productivity at

[25] https://www.national.biz/2019-small-business-failure-rate-startup-statistics-industry/

the entrance year. Second, we investigate the long-term performance three years after entrance. The coefficient estimates on the instrumented Airbnb variable in columns 3 and 4 are positive and significant at the 1% level, suggesting that Airbnb's expansion also positively affect long-term revenue and productivity in the long term. The findings reported in Table 14 suggest that Airbnb does not spur startups with poor quality, which is consistent with the findings in Table 13 that new businesses created following Airbnb penetration survive a longer period. Overall, the findings suggest that our results are unlikely to be driven by increased risk tolerance of households who collect more rental income after Airbnb grows.

[Insert Table 14 about here]

6. Conclusion

In this paper, we have examined the effect of the sharing economy on entrepreneurship. Using Airbnb's penetration across counties as a proxy for the growth of the sharing economy and venture capital infusions interacted with local tourism as an instrument, we find that Airbnb spurs firm creation. Two plausible underlying channels are that Airbnb facilitates short-term rental, which relaxes the financial constraint of potential entrepreneurs, and Airbnb expands local demand, which boosts the business creation in local service and construction-related industries. Increases in entrepreneurs' risk tolerance and increased collateral value caused by Airbnb penetration do not appear to explain our main findings. Airbnb creates new jobs and promotes local employment rate. Our paper sheds new light on the real effects of the sharing economy.

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Figure 1: Trend in Airbnb Listings

This figure plots the total number of Airbnb listings in U.S. from 2008 to 2015.

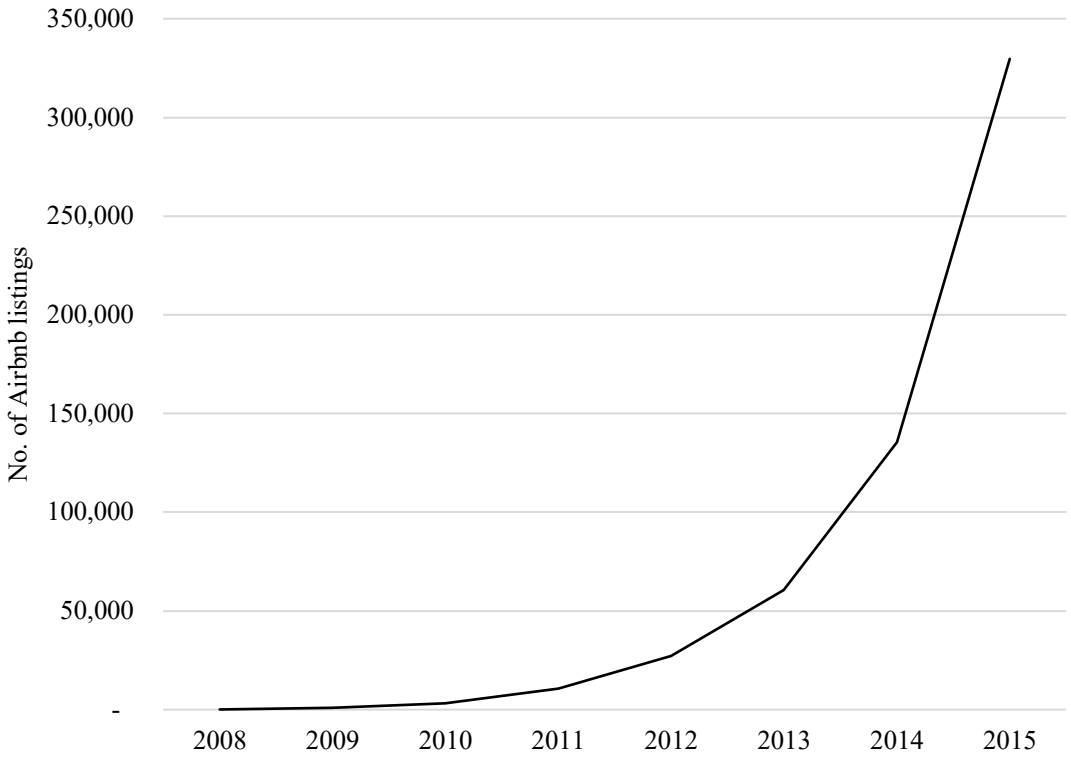


Figure 2: Distribution of Airbnb Listings

This figure plots the number of Airbnb listings as of 2015 by county.

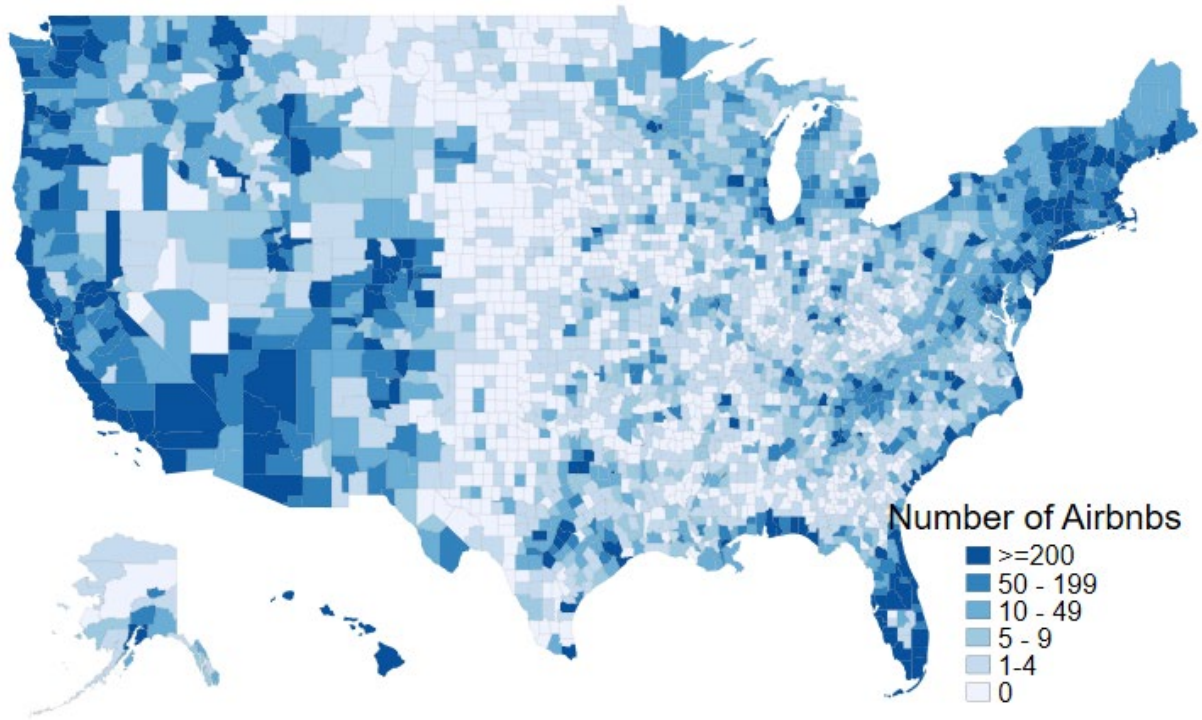


Figure 3: Distribution of New startups

This figure plots average number of new startups during 2009-2016 by county.

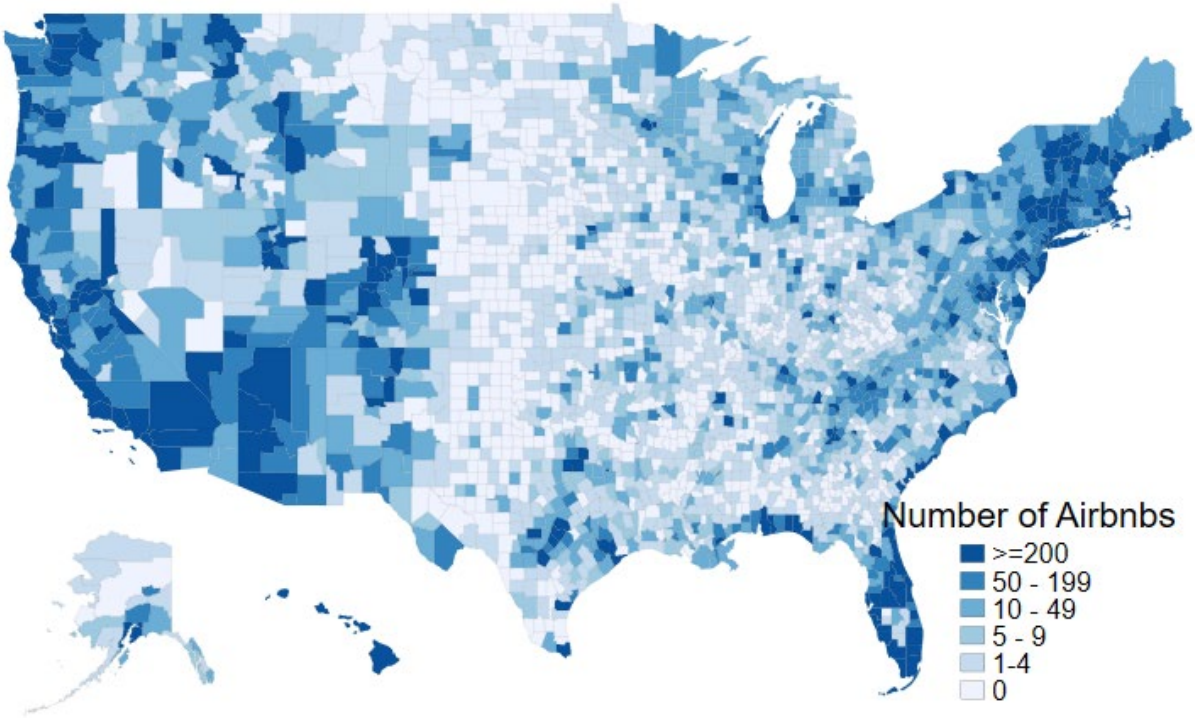
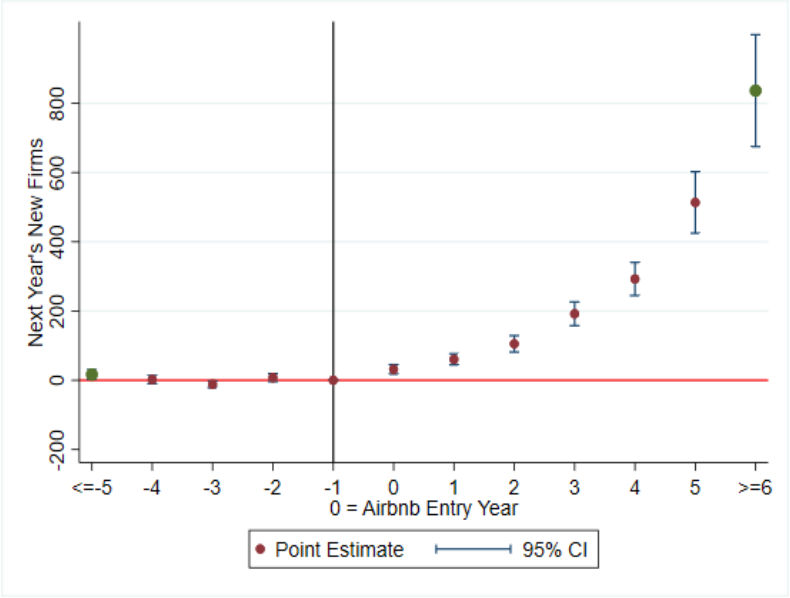
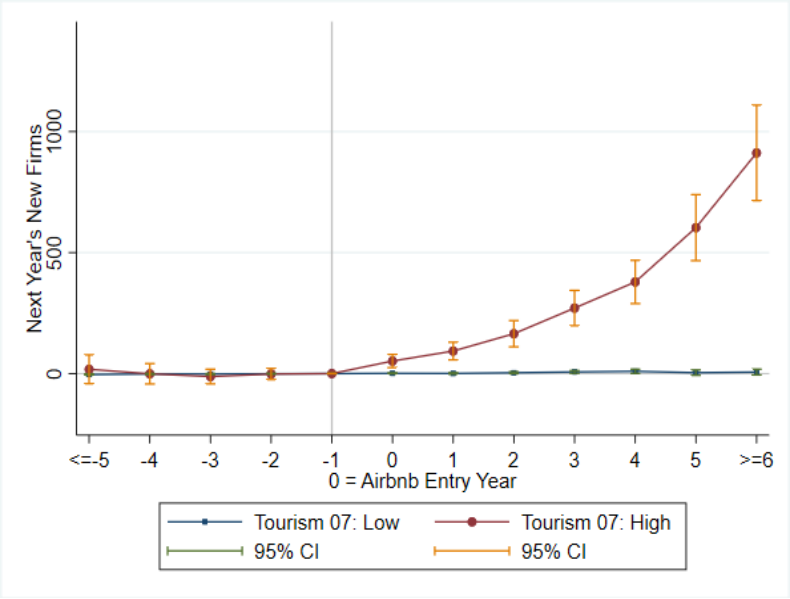


Figure 4: Dynamic Effects of Airbnb Entry on Local Business Creation

This figure shows the results of ordinary least square estimation of the dynamic effects of Airbnb entry on local entrepreneurship. We estimate the following equation:
$Number\ of\ Firms\ Created_{i,t+1} = \alpha + \beta_{-5}1(t \leq -5)_{i,t} + \sum \beta_t 1(t = \tau, -4 \leq \tau \leq 5, t \neq -1)_{i,t} + \beta_6 1(t \geq 6)_{i,t} + \gamma Z_{i,t} + County_i + Year_t + \varepsilon_{i,t+1}$
The dependent variable is the number of new firms created in a county in a year. The event year is the year that Airbnb enters a county (t=0). The benchmark group comprises of observations from one year prior to the Airbnb counties (t=-1). Panel (a) shows the full sample results. Panel (b) shows the estimation in two sub-sample based on the tourism in 2007. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.



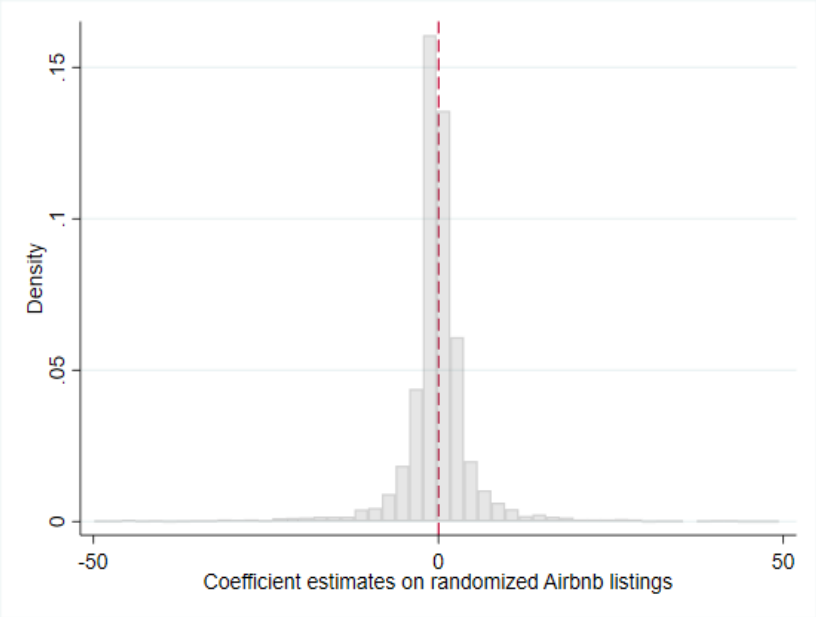
(a) Full Sample



(b) By Tourism in 2007

Figure 5: Placebo Test: Randomize Airbnb Listings

This figure plots the density distribution of the estimates and t-statistics for the coefficient of randomized Airbnb listings using Equation (4), where the dependent variable is the logarithm of new startups. The red dashed lines plot the estimate and t-statistics for the coefficient of non-randomized Airbnb listings.



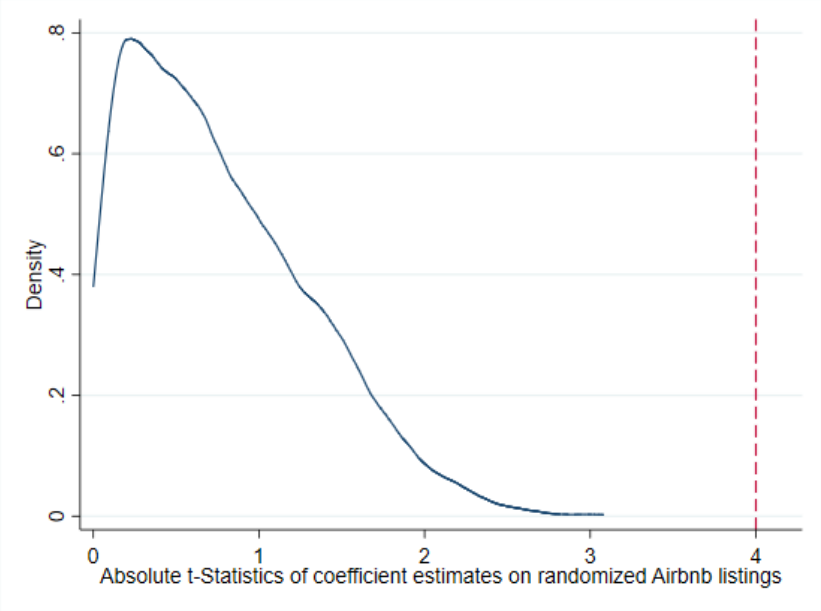


Figure 6: Airbnb and Firm Creation: By Industry

This figure plots the number of firms created due to a 10% increase in local Airbnb rooms in different industries. The numbers in the figure are obtained by multiplying the coefficient estimate from two-stage-least-squared regressions by the mean number of new firms created in each industry and 10%. The 2-digit NAICS code defines industries as Construction (NAICS 23), Retail Trade (NAICS 44 - 45), Other Services (NAICS 81), Professional, Scientific, and Technical Services (NAICS 54), Real Estate and Rental and Leasing (NAICS 53), Transportation and Warehousing (NAICS 48 - 49), Accommodation and Food Services (NAICS 72), Arts, Entertainment, and Recreation (NAICS 71), Manufacturing (NAICS 31 - 33), Agriculture, Forestry, Fishing and Hunting (NAICS 11), Information (NAICS 51), Management of Companies and Enterprises (NAICS 55), Educational Services (NAICS 61), Wholesale Trade (NAICS 42), Mining, Quarrying, and Oil and Gas Extraction (NAICS 21), Utilities (NAICS 22), and Health Care and Social Assistance (NAICS 62).

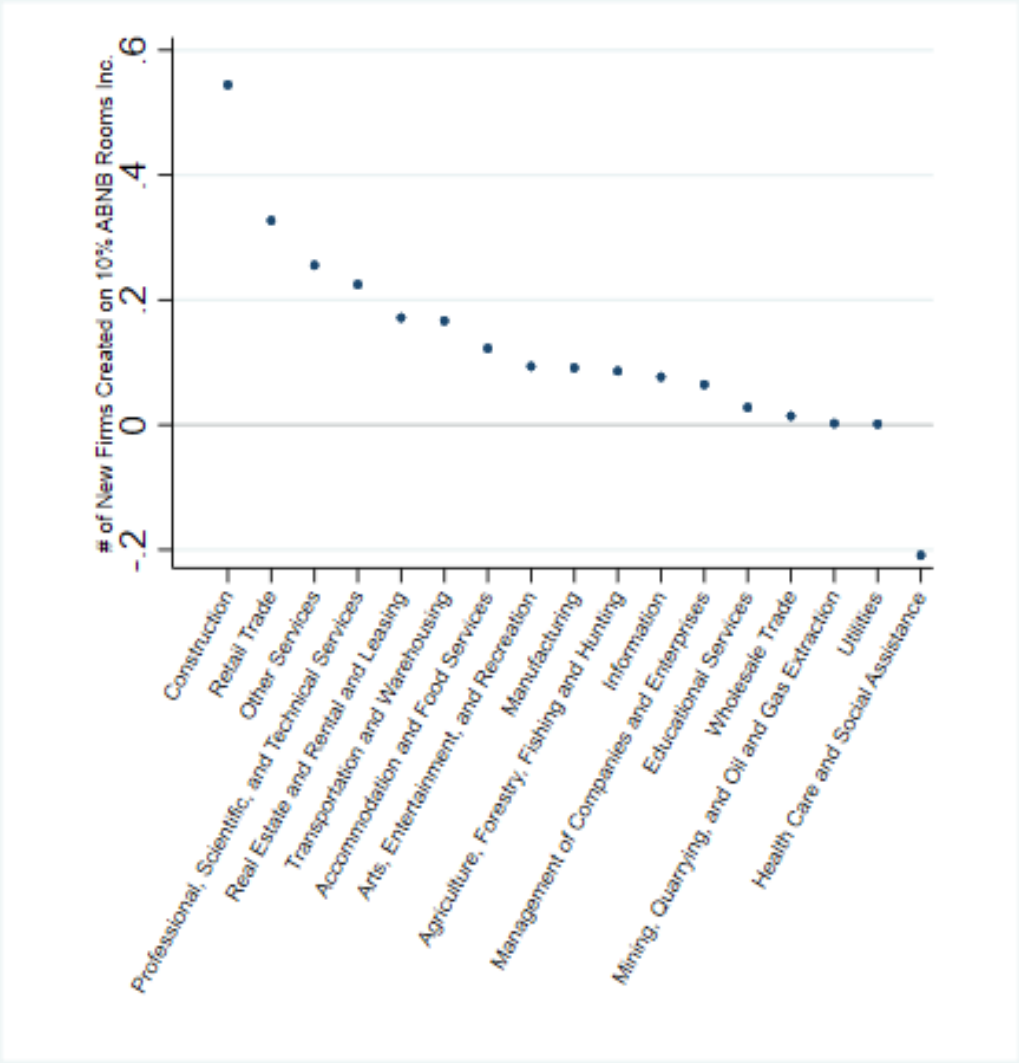


Table 1: Summary statistics

This table reports descriptive statistics. Panel A reports the summary statistics of county-year level measures, including Airbnb listings and local economic and demographic characteristics. Panel B reports the summary statistics on establishment-level measures, including sales and employment. All variables are winsorized at the 1st and 99th percentiles.

Panel A: County-year level measures

	N	Mean	P25	Median	P75	Std. Dev
Airbnb listings	19,191	27.09	0.00	0.00	2.00	272.52
Income ($ thousand)	19,191	46.84	39.11	44.77	51.99	11.26
Unemployment rate (%)	19,191	7.58	5.50	7.20	9.30	2.78
Labor force rate (%)	19,191	48.34	44.46	48.56	52.30	5.69
House price	19,191	131.85	118.46	129.12	142.73	20.43
Population (thousand)	19,191	112.08	19.72	38.46	96.46	207.33
White rate (%)	19,191	85.80	80.93	91.73	96.01	14.60
Age 20-64 rate (%)	19,191	58.15	56.42	58.07	59.84	2.84
Age 65+ rate (%)	19,191	15.89	13.32	15.69	18.11	3.87
College rate (%)	19,191	55.39	51.91	54.96	58.30	4.85
Number of firms created	19,191	368.52	43.00	95.00	270.00	801.56
- Sector: Tradable	19,191	9.79	1.00	2.00	7.00	39.01
- Sector: Non-tradable & construction	19,191	127.93	14.00	32.00	88.00	360.66
New branches of existing firms	19,191	31.016	3.00	8.00	23.00	86.83
Employment created by new firms (thousand)	19,191	1.886	0.161	0.374	1.112	6.764
- Sector: Tradable	19,191	0.077	0.003	0.011	0.040	0.602
- Sector: Non-tradable & construction	19,191	0.619	0.051	0.125	0.377	2.231
County employment total (thousand)	19,191	58.295	8.382	16.934	43.590	164.812
- Industry: Hotel	19,191	0.904	0.046	0.154	0.562	3.375
- Industry: Non-hotel	19,191	57.391	8.231	16.698	42.878	162.376
Landlords (thousand)	6,490	24.38	7.09	12.14	26.81	31.71
Vacant for seasonal rental (thousand)	4,884	4.56	0.68	1.47	3.73	9.24
Vacant for long-term rental (thousand)	4,884	3.88	0.94	1.83	4.27	5.60
Long-term rental price ($)	6,461	850.34	697.00	806.00	951.00	212.99

Panel B: Establishment-year level measures

	N	Mean	P25	Median	P75	Std. Dev
Sales ($ thousand)	8,653,101	851.67	252.00	489.00	745.00	1441.99
Employment	8,653,101	3.69	2.00	3.00	4.00	3.12

Panel C: Individual-level measures from ACS

	N	Mean	P25	Median	P75	Std. Dev
I{entrepreneur}	3,471,353	0.098	0.000	0.000	0.000	0.297
I{landlord}	3,471,353	0.164	0.000	0.000	0.000	0.370
Ln(age)	3,458,531	3.781	3.584	3.829	4.007	0.278
I{home owner}	3,458,531	0.639	0.000	1.000	1.000	0.480
I{employed last year}	3,471,353	0.975	1.000	1.000	1.000	0.155
I{male}	3,471,353	0.548	0.000	1.000	1.000	0.498
I{white}	3,471,353	0.740	0.000	1.000	1.000	0.439
I{black}	3,471,353	0.118	0.000	0.000	0.000	0.322
I{low-skilled}	3,471,353	0.324	0.000	0.000	1.000	0.468
I{mid-skilled}	3,471,353	0.091	0.000	0.000	0.000	0.288

Table 2: Airbnb and Firm Creation: Poisson Regressions

This table presents Poisson estimation of how Airbnb affects entrepreneurship. The outcome variable is the number of firms created in a county-year. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Poisson: number of firms created	
	(1)	(2)
Post	0.030**	0.031**
	(0.013)	(0.013)
Ln(income)		-0.052
		(0.136)
Unemployment rate		-0.002
		(0.006)
Labor force rate		0.004
		(0.003)
Ln(house price)		0.178**
		(0.090)
Ln(population)		3.594***
		(0.348)
White rate		0.019
		(0.019)
Age 20-64 rate		0.008
		(0.020)
Age 65+rate		0.019
		(0.021)
College rate		0.002
		(0.011)
County fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	19,219	19,191

Table 3: Airbnb and Firm Creation: OLS and 2SLS Regressions

This table presents the ordinary least square estimation and the two-stage least square estimation of how Airbnb affects entrepreneurship. The first two columns show the results of the OLS regressions with the logarithm of number of new firms created being the dependent variable. The second two columns show the two-stage least square estimation. Column 3 presents first-stage results with outcome variable as the logarithm of Airbnb listings. Column 4 presents second-stage results with the outcome variable being the logarithm of the number of new firms created in a county-year. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	OLS: Ln(number of firms created)		IV: Ln(Airbnb listings)	IV: Ln(number of firms created)
	(1)	(2)	(3)	(4)
VC index × Ln(tourism)			0.136***	
			(0.003)	
Instrumented Ln(Airbnb listings)	0.015***	0.010**		0.028***
	(0.004)	(0.004)		(0.007)
Ln(income)		0.101	0.170	0.122*
		(0.070)	(0.128)	(0.071)
Unemployment rate		-0.000	0.030***	-0.001
		(0.003)	(0.006)	(0.003)
Labor force rate		0.002	0.011***	0.001
		(0.002)	(0.004)	(0.002)
Ln(house price)		0.691***	-0.767***	0.712***
		(0.051)	(0.134)	(0.051)
Ln(population)		1.772***	4.981***	1.550***
		(0.164)	(0.432)	(0.178)
White rate		0.014*	0.021	0.018**
		(0.008)	(0.022)	(0.008)
Age 20-64 rate		0.020**	-0.083***	0.019**
		(0.009)	(0.024)	(0.009)
Age 65+rate		0.009	0.321***	0.001
		(0.008)	(0.025)	(0.009)
College rate		-0.008*	-0.022**	-0.005
		(0.004)	(0.010)	(0.004)
P value of F statistics			<0.001	
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,219	19,191	19,191	19,191
Adjusted R^2	0.946	0.948	0.873	0.948

Table 4: Airbnb and Entrepreneurship: Heterogeneity in Landlord

This table presents two-stage least square estimation of how Airbnb affects individual's likelihood to become an entrepreneur, exploring heterogeneity in whether an individual receives rental income. The outcome variables are indicators on whether an individual is entrepreneur in columns 1 and 2, and indicators on whether an individual is entrepreneur and receives positive business income in columns 3 and 4. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are bootstrapped 1000 timesand presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	I{entrepreneur}		I{entrepreneur receiving business income}	
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.001***	0.001***	0.001***	0.001***
× I{landlord}	(0.000)	(0.000)	(0.000)	(0.000)
I{landlord}	0.046***	0.023***	0.024***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(age)		0.097***		0.064***
		(0.002)		(0.002)
I{home owner}		0.014***		-0.001
		(0.001)		(0.001)
I{employed last year}		0.092***		0.062***
		(0.003)		(0.003)
I{male}		0.035***		0.013***
		(0.001)		(0.001)
I{white}		0.011***		0.007***
		(0.002)		(0.001)
I{black}		-0.029***		-0.018***
		(0.002)		(0.001)
I{low-skilled}		0.008***		0.013***
		(0.001)		(0.001)
I{mid-skilled}		-0.016***		-0.007***
		(0.001)		(0.001)
County-year fixed effect	Yes	Yes	Yes	Yes
Observations	3,471,353	3,471,353	3,471,353	3,471,353
Adjusted R^2	0.010	0.029	0.007	0.016

Table 5: Rental channel versus the collateral channel

This table presents two-stage least square estimation of whether Airbnb affects entrepreneurship through the rental channel or the collateral channel.. The outcome variable is the logarithm of the number of new firms created in a county-year. We use rental price growth as the measure for local rental market measure (column 1). We use local house price growth (column 2), local land use regelation index from Gyourko et al (2008) (column 3), and house elasticity from Saiz (2010) (column 4) as local housing market measures. County controls include all additional variables as in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are bootstrapped 1000 timesand presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(number of firms created)			
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings) × I{rental price growth}	0.009**			
	(0.005)			
I{rental price growth}	-0.014**			
	(0.007)			
Instrumented Ln(Airbnb listings) × I{high house price growth}		0.008		
		(0.007)		
I{high house price growth}		0.006		
		(0.008)		
Instrumented Ln(Airbnb listings) × I{high land use regulation}			-0.013	
			(0.008)	
Instrumented Ln(Airbnb listings) × I{low house elasticity}				-0.014
				(0.010)
Instrumented Ln(Airbnb listings)	0.027***	0.022***	0.025**	0.032**
	(0.007)	(0.009)	(0.012)	(0.016)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	8,882	4,568
Adjusted R^2	0.950	0.948	0.956	0.955

Table 6: Airbnb and Local Incoming Air Passengers

This table presents two-stage least square estimation of whether Airbnb affects the number of incoming air passengers to the focal county and nearby airports. The outcome variable is the logarithm of the total number of air passengers to a county in a year in column 1. The outcome variable is the logarithm number of incoming air passengers travelling from an airport from a distance that is within 1000 miles, 1000 miles to 2000 miles, and more than 2000 miles to the airport within 25 miles near a county in column 2, 3 and 4, respectively. Information on incoming passengers are collected from the Bureau of Transportation Statistics U.S. Domestic Airline Traffic dataset. County controls include all additional variables as in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(IncomingAirPassengers)			
	Total	Dist.<1000Miles	Dist.1000-2000Miles	Dist.>2000Miles
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.038**	0.017	0.056**	0.093***
	(0.018)	(0.019)	(0.025)	(0.023)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191
Ajusted R^2	0.986	0.986	0.959	0.946

Table 7: Hotel Performance

This table presents two-stage least square estimation of whether Airbnb affects local hotels' revenue and price. The outcome variable is the logarithm of hotel revenue in columns 1, the occupancy rate in column 2, the logarithm of room price in column 3, and the logarithm of revenue per available room in column 4. We follow empirical specification of Farronato and Fradkin (2022) and include land elasticity, supply of hotel as well as their interaction terms and the number of incoming air passengers. Hotel performance data comes from Smith Travel Research. The unit of observation is county by month. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are bootstrapped 1000 timesand presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(revenue)	Occupancy rate	Ln(price)	Ln(revpar)
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)× land elasticity	-0.012***	-0.003***	-0.003**	-0.008***
	(0.002)	(0.001)	(0.001)	(0.002)
Instrumented Ln(Airbnb listings)	0.030**	-0.003	0.004	-0.009
	(0.012)	(0.004)	(0.007)	(0.013)
Ln(Hotel supply)× land elasticity	0.421***	0.025	0.111***	0.150***
	(0.047)	(0.020)	(0.031)	(0.057)
Ln(Hotel supply)	0.932***	-0.080***	0.040	-0.086*
	(0.045)	(0.016)	(0.025)	(0.045)
Ln(IncomingAirPassengers)	-0.009**	-0.003*	-0.004*	-0.009*
	(0.005)	(0.002)	(0.002)	(0.005)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191
Ajusted R^2	0.919	0.882	0.932	0.988

Table 8: Airbnb and Local Income and Wage

This table presents two-stage least square estimation of whether Airbnb affects local income and wages. In column 1, the outcome variable is the logarithm of the mean value of adjusted gross income, which includes both wage and non-wage income in a county in a year. The outcome variable is the logarithm of the mean value of non-wage income in column 2, the logarithm of the mean value of business income (sub-category of non-wage income) in column 3, and the logarithm of the mean value of wage income in column 4. The data is collected from the IRS Individual Tax Statistics.County controls include all additional variables as in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(Adj. Gross Income) (1)	Ln(Non-wage) (2)	Ln(Business Income) (3)	Ln(Wage) (4)
Instrumented Ln(Airbnb listings)	0.007***	0.025***	0.032***	0.001
	(0.003)	(0.004)	(0.002)	(0.001)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191
Ajusted R^2	0.919	0.882	0.932	0.988

Table 9: Airbnb, Job Creation by New Firms, and Local Employment

This table presents two-stage least square estimation of how Airbnb affects employment, including new jobs created by new firms, employment of old firms, and unemployment rate. The outcome variable is the logarithm of employment in a county in column 1, the unemployment rate in column 2, the logarithm of jobs created by new firms in column 3, the logarithm of employment in existing firms in column 4, the logarithm of employment in existing small firms with employment size greater than 9 in column 4, and the logarithm of employment in existing small firms with employment size equal or smaller than 9 in column 5. County controls include all additional variables included in the baseline regressions. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(employment)	Unemployment rate	Ln(number of jobs created by new firms)	Ln(employment of existing firms)		
				All	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Ln(Airbnb listings)	0.002***	-0.142***	0.020**	-0.003	-0.004	0.009***
	(0.001)	(0.017)	(0.008)	(0.002)	(0.002)	(0.001)
County controls	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191	19,191	19,191
Adjusted R^2	0.999	0.931	0.923	0.998	0.997	0.999

Table 10: Airbnb and Firm Creation: By Sectors and Industries

This table presents the two-stage least square estimation of how Airbnb affects entrepreneurship in different sectors and industries. The outcome variable is the logarithm of the number of new firms created in the tradable sector in column 1, the logarithm of the number of new firms created in the non-tradable and construction sectors in column 2. The sectors are defined as Mian and Sufi (2014). We explore the effect of Airbnb on firm creation in related industries. The outcome variable in columns 3 to 6 is the logarithm of the number of new firms created in Arts, Entertainment, and Recreation (NAICS 71), Accommodation and Food Services (NAICS 72), Real Estate and Rental and Leasing (NAICS 53), and Construction (NAICS 23), respectively. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(number of firms created)					
	Tradable	Non-tradable& Construction	Arts, Entertainment, and Recreation	Accommodation and Food Services	Real Estate and Rental and Leasing	Construction
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Ln(Airbnb listings)	0.099***	0.066***	0.123***	0.066***	0.072***	0.124***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.010)	(0.010)
Ln(income)	-0.043	0.103	-0.078	0.071	0.140	-0.019
	(0.106)	(0.087)	(0.105)	(0.100)	(0.120)	(0.109)
Unemployment rate	-0.000	-0.005	-0.005	0.001	-0.009*	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Labor force rate	0.003	0.003*	-0.002	0.000	-0.000	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Ln(house price)	0.564***	0.893***	0.502***	0.477***	0.756***	0.939***
	(0.074)	(0.065)	(0.083)	(0.075)	(0.081)	(0.082)
Ln(population)	1.057***	1.638***	1.179***	0.894***	1.751***	1.227***
	(0.244)	(0.216)	(0.278)	(0.228)	(0.278)	(0.251)
White rate	0.008	0.027***	0.019	0.009	0.037***	0.032**
	(0.011)	(0.010)	(0.013)	(0.011)	(0.013)	(0.013)
Age 20-64 rate	0.031**	0.022*	0.050***	0.010	0.022	0.041***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Age 65+rate	-0.024**	-0.021*	-0.021	-0.022*	-0.003	-0.043***
	(0.012)	(0.011)	(0.013)	(0.012)	(0.014)	(0.013)
College rate	-0.026***	-0.007	-0.011*	-0.019***	0.008	-0.006
	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191	19,191	19,191
Adjusted R^2	0.830	0.924	0.774	0.401	0.842	0.875

Table 11: Heterogeneity in Access to Credit

This table presents two-stage least square estimation of how Airbnb affects entrepreneurship, exploring heterogeneity in access to credit. The outcome variables are the logarithm of the number of new firms created in a county-year. We use local bank share (column 1), house price volatility (column 2), and refinance denial rate (column 3) as local access to credit measures. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are bootstrapped 1000 timesand presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(number of firms created)		
	(1)	(2)	(3)
Instrumented Ln(Airbnb listings) × I{low local bank share}	0.021***		
	(0.007)		
I{low local bank share}	-0.005		
	(0.012)		
Instrumented Ln(Airbnb listings) × I{high house price volatility}		0.026**	
		(0.013)	
I{high house price volatility}		-0.005	
		(0.016)	
Instrumented Ln(Airbnb listings) × I{high refinance denial rate}			0.038***
			(0.006)
I{high refinance denial rate}			-0.029***
			(0.009)
Instrumented Ln(Airbnb listings)	0.013	0.003	0.015**
	(0.010)	(0.017)	(0.007)
County controls	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	19,169	19,190	19,191
Adjusted R^2	0.948	0.948	0.948

Table 12: Disaggregated by Startup Capital Needs

This table presents two-stage least square estimation of how Airbnb affects entrepreneurship, disaggregated by startup capital needs. The outcome variables are the logarithm of new firms created in a county-year with less than 10 employees in column 1, the logarithm of new firms created in a county-year with 10 or more employees in column 2, the logarithm of new firms created in a county-year in industries with below median needs for startup capital in column 3, and the logarithm of new firms created in a county-year in industries with above median needs for startup capital in column 4. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln (number of firms created)			
	1-9 employees	10+ employees	Low capital needs	High capital needs
Instrumented Ln(Airbnb listings)	0.031***	0.008	0.034***	0.002
	(0.007)	(0.009)	(0.012)	(0.013)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191
Adjusted R^2	0.946	0.877	0.293	0.240
Coefficient difference	0.023**		0.032*	
z statistics	2.017		1.809	

Table 13: Airbnb and New Firm Survival

This table presents two-stage least square estimation of how Airbnb affects survival of newly created firms. The outcome variable in column 1 is the logarithm of the number of new firms created in a county-year that close within 3 years after entrant. The outcome variable in column 2 is the logarithm of the number of new firms created in a county-year that survival more than 3 years after entrant. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln (number of firms created)	
	Close within 3 years	Survive more than 3 years
	(1)	(2)
Instrumented Ln(Airbnb listings)	0.007	0.046***
	(0.010)	(0.008)
County controls	Yes	Yes
County fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	14,390	14,390
Adjusted R^2	0.914	0.945
Churning – long-term startups	-0.039***	
z statistics	3.045	

Table 14: Airbnb and New Firm Performance

This table presents two-stage least square estimation of how Airbnb affects and performance of new firms. The outcome variables are the logarithm of sales in columns 1 and 3, and the logarithm of sales per employee in columns 2 and 4. Industry is measured by 4-digit NAICS. Controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	At entrance year		Three years after entrance	
	Ln(sales)	Ln(sales / employees)	Ln(sales)	Ln(sales / employees)
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.085***	0.073***	0.079***	0.063***
	(0.014)	(0.013)	(0.006)	(0.005)
Controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Industry-year fixed effect	Yes	Yes	Yes	Yes
Observations	8,466,955	8,466,955	3,510,949	3,510,949
Adjusted R^2	0.653	0.865	0.505	0.745

Appendix: Variable Definition

Variable	Definition
County-level measures	
Airbnb listings	It is measured by the number of Airbnb listings in a county. Source: Airbnb.
Income	It is measured by median household income in a county. Source: Census.
Unemployment rate	It is measured by unemployed population divided by the sum of unemployed and employed population in a county. Source: Bureau of Labor Statistics.
Labor force rate	It is measured by sum of employed and unemployed populations divided by total population in a county. Source: Bureau of Labor Statistics and Census.
House price	It is a weighted index, measured by average price of repeat sales or refinancing on single-family house properties whose mortgages are purchased or securitized by Fannie Mae or Freddie Mac. Source: Federal Housing Finance Agency.
Population	It is measured by the total population in a county. Source: Census.
White rate	It is measured by white population divided by total population in a county. Source: Census.
Age 20-64 rate	It is measured by the population between ages 20 and 64 divided by the total population in a county. Source: Census.
Age 65+ rate	It is measured by the population at or above 65 years old divided by the total population in a given county. Source: Census.
College rate	It is measured by employees with college education divided by total employees in a county. Source: Census.
Number of firms created	It is measured by the number of single-stand establishments that exist in the current year but not in the last year in a county. Source: Your-economy Time Series.
New branches of existing firms	It is measured by the number of branch establishments that exist in the current year but not in the last year in a county. Source: Your-economy Time Series.
Number of jobs created by new firms	It is measured by employment of single-stand establishments that exist in the current year but not in the last year in a county. Source: Your-economy Time Series.
Employment of existing firms	It is measured by employment of establishments that exist in both the current year and the last year in a county. Source: Your-economy Time Series.
Employment in hotel industry	It is measured by employment in hotel industry (NAICS 7211) in a county. Source: Your-economy Time Series.
Landlords	It is measured by the number of households that receive interest, dividend, rental income in a county. Source: Census.
Vacant for seasonal rental	It is measured by the number of units that are vacant for seasonal rental in a county. Source: Census.
Vacant for long-term	It is measured by the number of units that are vacant for long-term

rental	rental in a county. Source: Census.
Long-term rental price	It is measured by the rents of rental units in a county. Source: Census.
Survival rate	It is measured percentage of establishments that exist in the sample three years after entrant year. Source: Your-economy Time Series.
I{low local bank share}	It is an indicator that takes a value of one if the proportion of deposits from local banks in a county is below the median of the sample period, and zero otherwise. A bank is defined as local bank if 50% or more of its deposits are concentrated in a single county. Source: Feral Deposit Insurance Corporation.
I{high house price volatility}	It is an indicator that takes a value of one if the standard deviation of house price in the previous 20 years in a county is above the median of the sample period, and zero otherwise. Source: Federal Housing Finance Agency.
I{high refinance denial rate}	It is an indicator that takes a value of one if the denial rate of refinance loans in a county is above the median of the sample period, and zero otherwise. Source: Home Mortgage Disclosure Act.
I{high house price growth}	It is an indicator that takes a value of one if the house price growth in a county is above than the median of the same period, and zero otherwise. Source: Federal Housing Finance Agency.
I{high land use regulation}	It is an indicator that takes a value of one if the land use regulation in a county is above than the sample median, and zero otherwise. Source: Gyourko et al (2008).
I{low house elasticity}	It is an indicator that takes a value of one if the house elasticity in a county is below than the sample median, and zero otherwise. Source: Saiz (2010).

Individual-level measures

I{entrepreneur}	It is an indicator that takes a value of one if an individual is self-employed, and zero is an individual works for someone else or unemployed. Source: Census American Community Survey.
I{entrepreneur with business income}	It is an indicator that takes a value of one if an individual is self-employed and receives positive business and farm income, and zero otherwise. Source: Census American Community Survey.
I{landlord}	It is an indicator that takes a value of one if an individual receives positive interest, dividend, and rental income, and zero otherwise. Source: Census American Community Survey.
Age	It is measured by age of an individual. Source: Census American Community Survey.
I{home owner}	It is an indicator that takes a value of one if an individual owns their housing unit, and zero if an individual rents their housing unit. Source: Census American Community Survey.
I{employed last year}	It is an indicator that takes a value of one if an individual is employed in the last year, and zero if unemployed. Source: Census American Community Survey.
I{male}	It is an indicator that takes a value of one if an individual is a male, and zero if female. Source: Census American Community Survey.

I{white}	It is an indicator that takes a value of one if an individual is white, and zero if otherwise. Source: Census American Community Survey.
I{black}	It is an indicator that takes a value of one if an individual is black, and zero if otherwise. Source: Census American Community Survey.
I{low-skilled}	It is an indicator that takes a value of one if an individual never receives college education, and zero if otherwise. Source: Census American Community Survey.
I{mid-skilled}	It is an indicator that takes a value of one if an individual receives 1-3 years of college education, and zero if otherwise. Source: Census American Community Survey.

INTERNET APPENDIX (Not to be published)

Resurrecting Dead Capital: The Sharing Economy, Entrepreneurship, and Job Creation

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Table IA1: Cox Proportional Hazard Model

This table shows results from proportional cox hazard model estimations. The reported coefficient estimates are hazard ratios. The "failure event" is the entry of Airbnb (i.e., appearance of the first Airbnb listing) into a county, and the county is excluded from the sample post the entry. In column 1, we only include the annual change in new business formation. In columns 2 to 6, we gradually include the lagged control variables as well. We standardize all the independent variable to have a mean of zero and a standard deviation of one to facilitate the comparison between the estimated hazard ratios. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
New Firm Growth	-0.039	-0.034	-0.023	-0.024	-0.024	-0.025
	(0.024)	(0.025)	(0.026)	(0.026)	(0.026)	(0.025)
Ln(income) (lag)		0.386***	0.121***	0.109***	0.176***	0.109***
		(0.027)	(0.028)	(0.028)	(0.029)	(0.030)
Unemployment rate (lag)		0.252***	0.289***	0.300***	0.234***	0.256***
		(0.029)	(0.031)	(0.031)	(0.033)	(0.033)
Labor force rate (lag)		-0.009	0.156***	0.135***	0.116***	0.082***
		(0.028)	(0.031)	(0.032)	(0.031)	(0.031)
Ln(house price) (lag)			0.251***	0.264***	0.245***	0.259***
			(0.022)	(0.022)	(0.022)	(0.021)
Ln(population) (lag)			0.704***	0.729***	0.800***	0.751***
			(0.025)	(0.027)	(0.029)	(0.030)
White rate (lag)				0.083***	0.017	0.026
				(0.022)	(0.023)	(0.023)
Age 20-64 rate (lag)					0.226***	0.172***
					(0.034)	(0.034)
Age 65+rate (lag)					0.403***	0.339***
					(0.032)	(0.033)
College rate (lag)						0.198***
						(0.027)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,261	9,261	9,260	9,260	9,260	9,254

Table IA2: Airbnb and New Firm Creation: Robustness

This table presents two-stage least square estimation of how Airbnb affects entrepreneurship. The outcome variable is the logarithm of the number of firms created in a county-year. Industries are defined by four-digit NAICS. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(number of firms created)			
	State-year fixed effect	>2010	Census data	Industry-year level
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.025***	0.066***	0.009**	0.028***
	(0.007)	(0.013)	(0.003)	(0.002)
County controls	Yes	Yes	Yes	
County fixed effect	Yes	Yes	Yes	
Year fixed effect		Yes	Yes	
State-year fixed effect	Yes			
County-industry fixed effect				Yes
Industry-year fixed effect				Yes
Observations	19,183	12,010	19,191	5,795,682
Adjusted R^2	0.962	0.952	0.984	0.782

Table IA3: Identification Validity

This table presents the results of how Airbnb affects entrepreneurship in various samples. The outcome variable is the logarithm of the number of new firms created in a county-year. Column 1 considers counties never have any Airbnb listings between 2008 and 2015. Column 2 considers counties have some Airbnb listings in any year between 2008 and 2015. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln (number of firms created)	
	Counites without Airbnb ever	Counites with some Airbnb
	(1)	(2)
VC index × Ln(tourism)	0.001	0.004***
	(0.005)	(0.001)
County controls	Yes	Yes
County fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Observations	2,807	16,384
Adjusted R^2	0.787	0.949

Table IA4: Airbnb and Entrepreneurship: Heterogeneity in Refinance

This table presents two-stage least square estimation of how Airbnb affects individual's likelihood to become an entrepreneur, exploring heterogeneity in whether the individual refinance through second mortgage. The outcome variable is an indicator on whether the individual is an entrepreneur in columns 1 and 2, and an indicator on whether the individual is an entrepreneur with positive business income in columns 1 and 2. Individual controls include all additional variables included in Table 6. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are bootstrapped 1000 timesand presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	I{entrepreneur}		I{entrepreneur with business income}	
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	-0.000		-0.000	
× I{second mortgage}	(0.000)		(0.000)	
I{second mortgage}	0.022***		0.009***	
	(0.001)		(0.001)	
Instrumented Ln(Airbnb listings)		-0.000		-0.000
× I{home equity loan}		(0.000)		(0.000)
I{home equity loan}		0.025***		0.010***
		(0.001)		(0.001)
Individual controls	Yes	Yes	Yes	Yes
County-year fixed effect	Yes	Yes	Yes	Yes
Observations	1,811,774	1,811,774	1,811,774	1,811,774
Adjusted R^2	0.025	0.025	0.014	0.014

Table IA5: Airbnb and Housing Market

This table presents two-stage least square estimation of how Airbnb affects the rental market. The outcome variable is the logarithm of households receiving rental income in column 1, the logarithm of vacant units available for seasonal rental in column 2, the logarithm of vacant units available for long-term rental in column 3, and the logarithm of rental price in column 4. The outcome variable in column 5 is the housing price index collected from Federal Housing Finance Agency. County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln (landlords) (1)	Ln(vacant for seasonal rental) (2)	Ln(vacant for long-term rental) (3)	Ln(rental price) (4)	Ln(house price) (5)
Instrumented Ln(Airbnb listings)	0.008***	0.033*	-0.041***	0.009**	0.008***
	(0.003)	(0.018)	(0.015)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	6,490	4,843	4,843	19,191	19,191
Adjusted R^2	0.991	0.894	0.882	0.823	0.570

Table IA6: Airbnb and Job Creation across Industries

This table presents two-stage least square estimation of how Airbnb affects job creation across industries. The outcome variables are the logarithm of the number of new firms created in a county-year. Column 1 examines the employment in tradable industries. Column 2 considers non-tradable and construction industries. Column 3 examines the jobs created in the hospitality industry. Column 4 considers the employment outside of the hospitality industry. Tradable, non-tradable, and construction industries are defined as Mian and Sufi (2014). County controls include all additional variables included in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(number of jobs created)			
	Tradable	Non-Tradable & Construction	Hotel	Non-Hotel
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.079***	0.046***	-0.005	0.003***
	(0.016)	(0.010)	(0.008)	(0.001)
County controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191
Adjusted R^2	0.686	0.898	0.980	0.999