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

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Abstract

We use the staggered entry of Airbnb—a pioneer of sharing economy—to examine the effect of sharing economy on entrepreneurship. Both the Airbnb arrival and penetration lead to new business creations in the local region. To address identification concerns, we use the interaction of venture capital infusions and local tourism as an instrument for Airbnb penetration. Airbnb appears to spur entrepreneurship through both increasing rental income and enhancing local demand, leading to higher local income and more job creations. Newly created businesses have higher survival rate and better performance both at the creation and in the long run.

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", the size of which is projected to grow $335 billion in 2025.[1] While the sharing economy is growing rapidly, the economic consequences of this new business model are still unclear. On the one hand, the proponents claim that the sharing economy platform increases economic efficiency by reducing frictions that cause capacity to go underutilized, and thus could improve welfare of the society (Einav, Farronato, and Levin, 2016). On the other hand, critics argue that the sharing economy disrupts the traditional business models (Farronato and Fradkin, 2022) and could generate negative externalities to the society (Flippas and Horton, 2020). In this paper, we contribute to the discussion by focusing on how sharing economy affects entrepreneurship, which is the ultimate force for long-run economic growth and job creations (Haltiwanger, Jarmin, and Miranda, 2013). However, there has been increasing concerns about the decline in entrepreneurship in the U.S. (Decker, Haltiwanger, Jarmin, and Miranda, 2016).

We empirically explore the effect of sharing economy on entrepreneurship using the staggered entry of a major source of sharing economy: the home sharing platform—Airbnb. Airbnb enables people to list and rent their spare rooms for short-term lodging in residential properties. The platform it provides facilitates the matching between short-rental supply and demand. How could Airbnb affect entrepreneurship? We hypothesize that there are mainly two channels. On the supply side, Airbnb lowers the entry cost of property owners to short-term rental market.[2] As a result, there could be additional rental income for property owners, which could help relax their financial constraints when entering into entrepreneurship. We term this as the *rental income channel*. On the demand side, Airbnb provides more travel lodging options to travelers.[3] With the increase in travel and tourism spending, there would be higher local income

[1]See article "The sharing economy is still growing, and businesses should take note" by Forbes 2019.
[2] Up till today, over 4 million hosts have 6 million listings on Airbnb worldwide, and over 60% of U.S hosts say they rent out their primary home while they are on vacation. See "Airbnb Statistics" by IpropertyManagement on August 3, 2022.
[3] Till now, over 1 billion guests have stayed at Airbnb because of its low cost, convenient location, household amenities, and others. See article "Billionth guest gests year of stays around the world" by Airbnb on September 27, 2021.

and thus more investment opportunities for startups, which spurs more local business creations. We term this as the *local demand channel.*

We start our empirical analysis along 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 do not launch in counties randomly. For example, if Airbnb platforms enter into "entrepreneurial" cities first, then the association we find between Airbnb and entrepreneurship is not causal. This argument, however, does not appear to be the case. Using a hazard model approach, 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 does not appear to be predicted by the growth of entrepreneurial activities within a county. In addition, examining the dynamics of new firm creations surrounding the Airbnb entry time, we find no prior trend. Therefore, we use Airbnb arrivals to predict new firm creations, while controlling for 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.[4]

We further examine the intensive margin, that is, how does Airbnb penetration in a local county affect new business creations? To measure Airbnb penetration, we use the number of Airbnb listings at the county-year level. We find a positive relation between Airbnb listings and new business creations, controlling for time and county fixed effects, and other time-varying economic and demographic characteristics of the counties.

An important concern is that, while Airbnb arrivals could be exogenous, Airbnb supply is likely to be endogenous with unobservable county characteristics that are correlated with new business creation conditions. To establish how Airbnb penetration causally affects entrepreneurship, we construct a Bartik-type instrument, which has been developed by Bartik (1991) and used in many prominent studies (e.g., Dube and Vargas, 2013; Nunn and Qian, 2014; Diamond, 2016) and estimate the two-stage least squares (2SLS hereafter) regressions. This type of instruments exploits a plausibly exogenous time-series variable and a potentially endogenous cross-sectional exposure variable. Following this logic, we first exploit plausibly exogenous time

[4] 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.

variation in Airbnb growth, which is driven by venture capital (VC) investors' capital infusions in Airbnb in each financing round. 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 facilitates Airbnb's penetration. We then exploit cross-sectional variation in a county's likelihood of experiencing higher Airbnb penetration, which we assume is affected 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.

Combining the above two sources of variations together, we construct the instrument for Airbnb penetration as the interaction between 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). Using this instrument, we find that Airbnb listings continue to have a positive and significant effect on the creation of new businesses. The economic magnitude is also sizable. In particular, an average annual Airbnb growth rate accounts for about 4.9% of new firm creation growth.

We then discuss whether the exclusion restriction is satisfied for our instrument. As for all the Bartik-type instrument, the exclusion restriction requires that this interaction term being exogenous conditional on the baseline controls, which translates to either the time trend or the exposure variable being independent of the error term (Goldsmith-Pinkham, Sorkin, and Swift, 2020). In our setting, it requires the ex-ante levels of touristiness not to be systematically correlated with ex post unobserved shocks to entrepreneurship at the county level that are also correlated in time with VC funding rounds for Airbnb. To investigate the identifying assumption, we first note that our strategy is analogous to a difference-in-differences (DD hereafter) estimator. This is because the variation in our instrument comes from the differences in Airbnb listings between high- and low-touristiness counties, in years following more- and fewer- VC funding rounds shocks to Airbnb. Therefore, we examine the identifying assumption for a DD study: parallel trends. We find that there is no differential trend in new firm creations prior to Airbnb entry for high tourism counties and low counties, which suggests the parallel trend assumption is unlikely to be violated.

We also conducted two additional tests for the exclusion restriction. First, we investigate the possibility of spurious time trend by conducting a randomization test. Specifically, we randomize the number of Airbnb listings across the counties with at least one Airbnb listing but preserving the aggregate number of Airbnb listings each year. The randomized Airbnb listings preserve the overall trend in Airbnb penetration but randomize the Airbnb growth in each county. Therefore, if the results are driven by a spurious time trend, the 2SLS results would remain significant. However, we find weak first-stage and insignificant second stage results with a large variation. Second, we conduct a placebo test in counties that never have 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. This is indeed what we find.

After establishing the baseline results, we explore the underlying economic channels. First, we start from the supply side of entrepreneurship and examine the group that is most likely to benefit from the lower entry cost for short-term rental services—landlords. We find that landlord households are more likely to become entrepreneurs with higher Airbnb penetration and examine why. We hypothesize that Airbnb increases the income of landlords and thus relaxes the financial constraint for them to become entrepreneurs. To test this conjecture, 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 (in which rental rates tend to be higher), the average rental rates increase.

Besides increasing rental rates, Airbnb could also increase house prices, which increases the collateral value of houses and hence encourages entrepreneurship, (e.g., Adelino et al., 2015; Schmalz et al., 2017). We, however, do not find evidence that is consistent with this argument. We find 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 appear to exhibit higher likelihood of becoming entrepreneurs when Airbnb penetration increases. The reason could be that the percentage of Airbnb-induced house price increases is too small compared to that in 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 the demand side. We hypothesize that Airbnb spurs entrepreneurship through enhancing the local demand, 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 tourists (as proxied by the incoming air passengers) to the local area. Second, Airbnb reduces hotel prices, which could increase the budget that can be spent on non-lodging services by 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 local demand channel, 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 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).

We next explore how our main results vary with the degree of entrepreneurs' financial constraints. 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. 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 constraints, and on startups that need less startup capital. The cross-sectional results provide further credentials to the identification and channels.

Finally, we attempt to rule out an alternative interpretation of our findings that argues households are more likely to start new businesses because they expect to earn higher income after Airbnb entries. If this argument was true, the new businesses should be associated with high risks and failure rates because the existing literature (e.g., Hurst and Lusardi, 2004) shows, as wealth grows, households are more willing to take risks. To address this concern, we examine the quality of the new firms started with Airbnb penetration. 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 entrepreneurs are unlikely to start the new businesses out of their higher risk preference and tolerance, which typically leads to new businesses with higher risk and thus worse performance and low survival rate. These observations also suggest that Airbnb has a positive spillover effect to the local economy.

Our paper mainly contributes to two strands of literature. First, we contribute to the entrepreneurship literature. This literature has investigated the factors that are crucial for entrepreneurship, including financial constraints (Holtz-Eakin et al., 1994; Hurst and Lusardi, 2004), downside protection (Hombert et al., 2020; Gottlieb et al., 2021), time flexibility (Agarwal et al., 2015; Burthch et al., 2018), financial market development (Black and Strahan, 2002; Guiso et al., 2004;), personal wealth (Evans and Jovanovic, 1989; Gentry and Hubbard, 2005; Cagetti and De Nardi, 2006), collateral value (Corradin and Popov, 2013; Adelino et al., 2015; Schmalz et al., 2017), speculation incentives (Tian and Wang, 2022), and others. Our paper supplements the existing literature by showing that the introduction of a new business model—sharing economy—could spur entrepreneurship. Our findings uncover two new plausible economic channels, the rental income channel and the local demand channel.

Second, our paper contributes to the growing literature on the sharing economy. The economic mechanism of the sharing economy has been modeled in several theoretical studies (Einav et al., 2016; Filippas et al., 2020), and discussed in survey papers (Proserpio and Tellis, 2017). Specifically, several studies examine the impact from a pioneer of the sharing economy—Uber. Burtch, Garnahan and Graham (2018) find that the introduction of Uber reduces Kickstarter campaigns and self-reported self-employment. Barrios, Hochberg, and Yi (2022) show that the introduction of Uber and Lyft spurs entrepreneurship because they provide flexible gig work opportunities and therefore the fallback opportunities for would-be entrepreneurs. Other studies focus on the effects from another pioneer of the sharing economy—Airbnb. They find that Airbnb negatively affects hotel industry (Zervas et al., 2017), generates consumer surplus and host surplus while reducing hotel profits from accommodations (Farronato and Fradkin, 2022), increases rental prices and house prices (Garcia-Lopez et al., 2020; Barron et al., 2021), changes restaurants and other local amenities (Almagro and Dominguez-lino, 2021), and others. We contribute to this literature by focusing on a new angle, that is, how Airbnb affects entrepreneurship.

In a contemporary paper, Denes, Lagaras, and Tsoutsoura (2022) find that gig work opportunities increases local entrepreneurship, particularly among gig workers. Our paper's findings are in general consistent with theirs in the sense that the introduction of sharing economy increases local entrepreneurship. However, the underlying economic mechanisms we document are very different. Rather than focusing on flexible work opportunities provided by sharing economy, we examine how sharing economy facilitates generating passive income from assets (i.e., the rental income) and spurs local demand, which leads to positive spillover effect to local income and employment.

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 2007 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.[5]

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.[6] 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.[7]

The rise of Airbnb has attracted a lot of regulation attention. While the literature argues 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

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

[6] 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

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

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. Section 3.1 discusses the methodology for examining the extensive margin: how does the Airbnb's staggered entry affect new business creations? Section 3.2 discusses the methodology for examining the intensive margin: how does the intensity of Airbnb's penetration affect 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 the following equation

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

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 and zero otherwise. 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 effect Poisson estimation (e.g., Hausman et al., 1984). We also include county fixed effects 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 does not enter the specific counties randomly. To examine this concern, we use the Cox hazard model to examine the determinants of Airbnb 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 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 construct an instrumental variable that is plausibly uncorrelated with local shocks to the new business creations at the county level, but likely to affect the number of Airbnb listings. To this end, we employ a Bartik-type instrument (also called shift-share instrument), which exploits the interaction of a plausibly exogenous time-series variable with a potentially endogenous cross-sectional exposure variable. This instrumental variable approach is developed by Bartik (1991), in which he instruments local labor demand by the national trends in industry-specific productivity interacted with the historical local industry composition. The approach is then popularized in Blanchard and Katz (1992) and used in many influential studies (e.g., Nunn and Qian, 2014; Diamond, 2016). The rationale behind the approach is that some plausibly exogenous aggregate time trend affects different spatial units systematically along some cross-sectional exposure variable.

Following the logic of the Bartik instrument, we construct the instrument by starting with a plausibly exogenous time-series variation— the VC infusions into Airbnb. 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. Therefore, VC infusions into Airbnb would affect the number of Airbnb listings in each county. A natural concern about using the VC infusions, 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 potentially 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, to complete the instrument, we introduce counties' pre-existing tourism condition (measured by the number of establishments in the food services and accommodations industry (NAICS code 72) as the endogenous cross-sectional exposure variable. 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.

In summary, our instrument is the interaction between VC infusions into Airbnb and a county's ex-ante exposure to tourism. Using the instrument, we estimate the 2SLS regressions as below. Specifically, Equation (3) shows the first stage regression and Equation (4) shows the second stage regression:

$$Ln(Airbnb\ listings)_{i,t} = \alpha + \beta\ VC\ index_{t-1} \times Ln(tourism)_{2007} + \gamma\ Z_{i,t} + County_i + Year_t + \epsilon_{i,t}, \tag{3}$$

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

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 the number of establishments in the tourism sector in a county as of 2007. We instrument $Ln(Airbnb\, listings)$ with $VC\, index_{t-1} \times Ln(tourism)_{2007}$ 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).

For the Bartik instrument to be valid, it is important that the interaction of the aggregate time trend with the exposure variable is independent of the error term. This could happen if either the time trend is independent of the error term or the exposure variable is independent of the error term (Goldsmith-pinkham, Sorkin, and Swift, 2020). Under our setting, the identifying assumption translates to: 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. In other words, for the instrument to be valid, $VC\, index_{t-1} \times Ln(tourism)_{2007}$ must be uncorrelated with the county-specific, time-varying shocks to entrepreneurship, $\varepsilon_{i,t+1}$. This would be true if either ex ante touristness in 2007 $Ln(tourism)_{2007}$ is independent of time-varying county-level shocks ($\varepsilon_{i,t+1}$) or $VC\, index_{t-1}$ is independent of the specific timing of those shocks. To understand how plausible the independence requirement is, consider county-level economics as an omitted variable for example. It is not clear whether the changes to economics across all counties are systematically correlated in time with country-level VC funding. Even if they were, they would have to correlate in such a way that the correlation is systematically stronger or weaker in more touristy counties. Moreover, those biases would have to be systematically present within all counties in our sample. With that said, we cannot completely rule out this possibility. We turn to a detailed discussion of the instrument validity and present some exercises that suggest that the exogeneity assumption is likely satisfied in Section 5.3.

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 from various sources.

4.1 Measuring Airbnb penetration

We obtain the Airbnb data from Inside Airbnb (http://insideairbnb.com), a third party that collects Airbnb data. Inside Airbnb collects 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.

Using the Inside Airbnb data, we construct a measure that captures how intensive Airbnb penetrates into the local region. To this end, we use the number of Airbnb listings available at the county-year level. According to Inside Airbnb's data collection algorithm, they monitor the Airbnb website and collects the snapshot of the Airbnb listing information monthly starting from June 2015. Therefore, following the literature (Barron et al., 2022), we back out the number of Airbnb listings available in each county year, taking advantage of the information about when the host becomes a member of Airbnb in the June 2015 snapshot. We assume that the listing exists starting from the year that the host becomes a member of Airbnb until 2015. We then aggregate the listings available each county-year to get the penetration measure.

From above procedures, our Airbnb penetration measure captures the Airbnb listings that are available in the long term. We do not include the listings that are put on the website shortly and taken off before 2015, and we do not take into consideration of whether the listings have guests. Essentially, the variation of our Airbnb penetration measure comes from the number of individuals that becomes hosts till at least 2015 at the county-year level. Our measure has two advantages in measuring Airbnb penetration. First, it captures the long-term Airbnb listings, and thus are less likely to be affected by the endogenous factors that cause Airbnb to be delisted. Second, by ignoring whether the listing has any guest, we are able to focus on disentangling Airbnb supply from the demand. We plot how the aggregate number of Airbnb listings in our sample grow exponentially between 2008 and 2015 in Figure 1. The number of Airbnb listings in our sample is comparable to those reported in the existing literature (see Figure 3 Panel C in Barron et al. (2022)).

We plot the Airbnb listings across US in 2015 in Figure 2. 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 more Airbnb listings. States on the east coast and the west coast also tend to have more Airbnb listings than inland states.

4.2 Measuring firm creations

We obtain establishment-level firm creation, employment and sales information from Your-economy Time Series (YTS), an annual-level time-series database, tracking all US establishments since 1997.[8] YTS aggregates the data in each year using annual snapshot of the Infogroup Business Data Historical files, which are provided by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin System Institute for Business & Entrepreneurship. Kundle (2020) details Inforgroup's methodology to gather the data underlying YTS, and compares YTS data with several other databases.[9] The YTS data are widely used in academic research (e.g. Arefeva et al, 2020; Flynn and Ghent, 2020).

Using YTS data, we measure firm creations as the number of new stand-alone establishments founded in a given year in a county. YTS tends to track "real" businesses. According to YTS data description, "YTS focuses on establishments that are 'in-business' meaning they are, or intent on, conducting commercial activities. By contrast, businesses that are created for the purpose of housing financial, real estate, and tax reporting entities, or are suspected of never actually starting commercial activities are not included in YTS."

It is worth noting that whether Airbnb hosting is considered as new business creations or not depends on how much service they provide for the guests. 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 the self-employment tax).

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.

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

[9] Kundle (2020) points out that 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.

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 their 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. We also obtain our county-level rental measures from the ACS, 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 Department of Housing and Urban Development (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 8 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.

5 Empirical results

This section presents our main findings. Section 5.1 examines the extensive margin, that is, how Airbnb's staggered entry into counties 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 underlying economic channels. Section 5.5 explores heterogeneity in financial constraints. Section 5.6 investigates the performance of the newly created businesses following Airbnb penetration.

5.1 Extensive margin: Airbnb entry and new business creations

We first utilize the staggered arrival of Airbnb in counties to examine the effect of the sharing economy entry on new business formation. Specifically, in Table 2, we conduct variations 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, is associated with a 3.1% increase in local business creation, which translates to 11 new firms (average number of firms created 368.52×3.1%=11).[10]

A natural concern is that Airbnb platform does not launch in specific counties randomly. This would be particularly concerning for identification, for example, if Airbnb platforms specifically enter into "entrepreneurial" counties first. In other words, to have a causal interpretation of the results reported in Table 2, it is important to show that there is no differential growth of new firms in the treated and untreated counties that are absent the Airbnb entry.

To explore whether the Airbnb entry satisfies the above condition, we conduct two additional tests. First, we estimate a Cox proportional hazards model for Airbnb entry into the counties. As shown in the Internet Appendix Table IA1, the rollout timing of Airbnb platform is predicted by several economic and demographic factors. However, the growth in the number of new firms does not appear to predict the entry of Airbnb. Second, we plot the dynamic effects of Airbnb entry on the number of newly created businesses, while controlling for other observable characteristics as in the baseline regressions. Figure 4 panel (a) shows that before Airbnb entry, there is no differential trend in new business creations in counties with Airbnb entry and counties without Airbnb entry ex post. In contrast, after Airbnb entry, counties with Airbnb entries experience significantly greater increase in the number of business created compared to counties without Airbnb entries. The above two tests provide supporting evidence that there is no differential growth of new firms in counties with and without Airbnb entries.

5.2 Intensive margin: Airbnb penetration and new business creations

[10] The percentage increase in local business creation is comparable to the findings in Barrios, Hochberg, and Yi (2022). They find that the introduction of Uber and Lyft is associate with a 4—5% increase.

In addition to the extensive margin, we next examine the intensive margin, that is, how the intensity of Airbnb entry affects local new business creations. Specifically, we are interested in the elasticity of the new business creation with respect to Airbnb penetration into a county. To this end, we use the natural logarithm of one plus the new business creation as the dependent variable, and the natural logarithm of one plus the number of Airbnb rooms as the key independent variable.

We begin with OLS regressions as specified in Equation (2) and report the results in Table 3, where the coefficient estimate on *Ln(Airbnb listings)* represents the elasticity of new business creations with regard to Airbnb penetration. The coefficient estimates in columns 1 and 2 are positive and significant at the 1% and 5% level. The magnitude of *Ln(Airbnb listings)* coefficient estimate in column 2 suggests that increasing Airbnb listings in a county by 10% is associated with a 0.1% increase in new businesses creations. While an 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 as we discussed before.

To identify the causal effect of Airbnb penetration on new business creations, we use 2SLS as described in Section 3.2. Table 3 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 we do not appear to suffer from the weak instrument problem (Bound et al., 1995). 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. Specifically, the magnitude of the coefficient estimate suggests that increasing Airbnb listings in a county by 10% is associated with a 0.28% increase in new firm creations.

To evaluate the economic magnitude, we calculate the average annual Airbnb growth rate in the sample, which is 46.5%. Therefore, an average annual Airbnb growth rate leads to a 1.3% (=46.5%×0.028) increase in new firm creations. Given that the actual new firm creation growth rate in our sample is 26.7%, an average annual Airbnb growth rate accounts for 4.9% (=1.3%/26.7%) of new firm creation growth. We also evaluate the economic magnitude in terms of standard deviations. One standard deviation of *Instrumented Ln(Airbnb listings)* is 4.52.

Therefore, a one standard deviation increase in *Instrumented Ln(Airbnb listings)* leads to a 12.7% (=4.52×0.28) increase in *Ln(number of firms created)*, which accounts for 9% (=12.7%/1.4) of the standard deviation of *Ln(number of firms created)*.[11]

Comparing the 2SLS results in column 4 of Table 3 with the OLS regression 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. There are two plausible reasons. First, there could exist some omitted variables that lead to more Airbnb listings but lower entrepreneurship, then the coefficient magnitude of OLS could be smaller than 2SLS. For example, in regions with special landscape which attracts a lot of visitors, there could be more Airbnb listings but at the same time less entrepreneurship due to land restrictions. Second, as with all instrumental variable 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. It is likely in these areas Airbnb has a higher marginal effect on entrepreneurship given the faster economic growth (e.g., in San Francisco).

We also 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.

[11] To evaluate the economic magnitude, we use the average annual growth rate of the Airbnb listings rather than examine how the average number of Airbnb listings translates to the number of new business creations. This is because both the level of Airbnb listings and new business creations are highly skewed, and therefore their means are not highly representative of the sample.

5.3 Validity of the instrumental variable

We have discussed our instrumental variable approach in Section 3.2. As mentioned there, for this Bartik-type instrument to be valid, it is crucial that conditional on the controls, the interaction between VC infusions into Airbnb and county tourism is independent of the error term. As pointed out by Christian and Barret (2017), if there are long-run time trends in the error term, and if the long-run trends are systematically different along the exposure variable, then this exclusion assumption may fail. In our setting, our instrument does not satisfy the exclusion restriction if the followings happen: First, there is a long-run economic revival trend in counties which lead to more entrepreneurship over time; Second, the trend of economic revival is higher in more touristy zip codes. In these cases, the two-stage least squares (2SLS) estimates are confounded by the effects of economic revival. While it is not clear why such an economic trend would exit, we proceed to conduct three groups of test to show why our instrument is likely to be valid.

First, we draw on the argument that Bartik instrument is analogous to a difference-in-differences (DD) approach (Nathan and Qian, 2014), and test the identifying assumption for the DD approach—the parallel trend assumption. To see why our instrumentation strategy is similar to a DD estimation strategy, it is important to understand that the variation in our instrument comes from the differences in Airbnb listings between high- and low- touristiness counties, in years following more- and fewer- VC funding rounds which promotes Airbnb entry across the country. Therefore, similar to a DD design, causal inferences of 2SLS rely on the parallel trend assumption that the growth in new firm creations would be the same for high- and low-touristiness counties absent the Airbnb entry shocks. While the parallel trend assumption cannot be directly tested because there is no counterfactual, we examine the new firm creations surrounding the Airbnb entry time for high tourism counties and low tourism counties in Figure 4 Panel (b). The figure shows that there is no differential trend for the counties with high-tourism exposure and low-tourism exposure in 2007 before the Airbnb entry, and in contrast, high-tourism exposure counties start to experience significantly higher growth in new firm creations after Airbnb entry compared to the low-tourism exposure counties. The results suggest that the parallel trend assumption is unlikely to be violated in our setting.

Second, we examine whether our instrument is primarily driven by some spurious time trend. To this end, we implement a form of randomization inference 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 penetration but randomize the Airbnb growth in each county, and thus eliminate 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 estimate the 2SLS regression as in Equation (4) for 5,000 draws of randomized allocations of Airbnb listings among counties that had positive Airbnb listings. Figure 5 plots the distributions of the coefficient estimates (in Panel a) and *t*-statistics of randomized Airbnb listings (in Panel b). We find that the measured effect of Airbnb estimates exhibits a large variation, and is statistically insignificant for over 99% of the randomized draws for the new firm creations. If the spurious time trends were driving our results, it is likely we would still have statistically significant estimates even with the randomized regressor (see Figure 6 in Christian and Barrett (2017)). Therefore, the results of this test suggest that our 2SLS findings are not driven by some spurious time trend which correlates with Airbnb's entry.

Third, we conduct a placebo test to examine whether our instrument satisfies the exclusion restriction. 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). We report the results in Internet Appendix Table IA3. The coefficient estimate on the instrumental variable is close to zero and statistically insignificant. In contrast, in column 2 in which we conduct the regression as described in Equation (3) in counties with Airbnb entries during our sample period, we 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 Plausible economic channels

In this section, we explore plausible underlying economic channels through which Airbnb promotes entrepreneurship. We hypothesize that there are mainly two channels. First, from the supply side, by facilitating peer-to-peer short-term rental, Airbnb provides more flexible renting options for the landlords and could increase their rental income, which relaxes the financial constraint for potential entrepreneurs. We call this the "*Rental Income Channel*". Second, from the demand side, by providing more flexible lodging options to the travelers, Airbnb could potentially attract more tourists and thus spur local demand that generates various investment opportunities for entrepreneurs. We call this the "*Local Demand Channel*".

5.4.1 The rental income channel

We examine the rental income channel in this subsection. To start with, we classify the individuals into landlords (who receive rental income) and non-landlords (who do not receive rental income). We then examine whether Airbnb penetration allows landlords to gain more rental income, which could help us disentangle the effect from the rental income channel and the local demand channel. To address this question, we use individual-level data from the Census American Community Survey.[12]

We conduct a regression as below:

$$\begin{aligned} Y_{i,t+1} = \ & \alpha + \beta\ Instrumented\ Ln\ (Airbnb\ listings)_{i,t} \times I\{landlord\}_{i,t+1} \\ & + \gamma I\{landlord\}_{i,t+1} + \theta\ Z_{i,t}\ + County_i \times Year_t \\ & + \epsilon_{i,t}, \qquad (5) \end{aligned}$$

[12] Our sample includes 3.5 million individual-level observations. We only examine head/householder of the family of working age (between 18 and 65 years old), who is most relevant for the study. Householder of the family accounts for about half of the working age population in the sample (the rest are their spouse and children of working age).

where $Y_{i,t}$ is either $I\{entrepreneur\}_{i,t}$ or $I\{entrepreneur\ receiving\ business\ income\}_{i,t}$. Following the literature (e.g. Dillon and Stanton, 2017), $I\{entrepreneur\}_{i,t}$ is an indicator that equals one if an individual is self-employed, and zero if she works for someone or is unemployed. $I\{entrepreneur\ receiving\ business\ income\}_{i,t}$ is an indicator that equals one if an individual is self-employed and receives positive business income, and zero otherwise.[13] $I\{landlord\}_{i,t+1}$ equals one if an individual receives rental income, and zero otherwise. $Instrumented\ Ln(Airbnb\ listings)_{i,t}$ is the the logarithm of Airbnb listings instrumented from equation (4).[14] The controls $Z_{i,t}$ are the same as defined in equation (4). This individual-level sample allows us to include county-year fixed effects ($County_i \times Year_t$) in the regressions that further mitigate concerns on local economic conditions driving the results.

The coefficient estimate β on the interaction term represents the marginal effect of Airbnb penetration on the likelihood of a landlord to become an entrepreneur.[15] Table 4 presents the results. The coefficient estimate on the interaction term is positive and significant across all specifications, suggesting that Airbnb penetration in a local area increases the likelihood of a landlord to become an entrepreneur. The economic significance is sizable, a one standard deviation increase in *Instrumented Ln(Airbnb listings)* (i.e., 4.68) increases the probability for a landlord to become an entrepreneur by 0.05% (=0.001×4.68), which accounts for 1.58% (=0.0468%/0.297) of the standard deviation on the dependent variable *I{entrepreneur}*. Combining this observation with the economic magnitude of the main results discussed in Section 5.2 that one standard deviation increase in *Instrumented Ln(Airbnb listings)* accounts for 9% (=12.7%/1.4) of the standard deviation of *Ln(number of firms created)*, it suggests that the rental income channel could partially explain the increase in entrepreneurship following Airbnb penetration.

To further understand the rental income channel, we investigate how Airbnb affects the real estate market. In Table IA4, we report the 2SLS estimates that regress rental market

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

[14] Our approach of interacting the instrumented Airbnb with the landlord indicator is appropriate given Bun and Harrison (2019) find that the coefficients on the interaction terms of an endogenous variable and an exogenous variable are asymptotically consistent.

[15] It is worth noting given that the ACS survey is conducted each year and does not track the individuals across years, we have to take all the individual measures (*I{entrepreneur}*, *I{entrepreneur receiving business income}*, and *I{landlord}*) in the same year to keep consistency. We do not exclude the possibility that an individual might become a landlord and an entrepreneurship at the same time. Therefore, we interpret the coefficient estimate β as measuring an upperbound of marginal effect of Airbnb on the likelihood for a landlord to become an entrepreneur.

variables on the instrumented Airbnb variable. We first investigate how Airbnb affects the housing supply in the short-term rental market in column 1 and housing supply in the long-term rental market in column 2. 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 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 is 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 3 in which the rental price is the dependent variable, we find a positive effect of Airbnb listings on rental prices.

It is worth noting that we use the Fair Market Rents Database from the Department of Housing and Urban Development as the proxy for rent in a county. Therefore, the rental price increase is the effect of both more rentals in the short-term market and increased long-term rental prices. Therefore, it is possible that households gain higher rental income from either short-term rental market or long-term rental market. This implies that not only Airbnb hosts benefit through the rental income channel, but the owners who have long-term rental may also gain higher rental income through Airbnb penetration.

The magnitude of the rental channel is comparable to the literature. Our average Airbnb growth rate is 46.5%, therefore, an average Airbnb growth rate accounts for 0.4% (=46.5%×0.009) in annual rent growth, which is similar to the findings in Barron et al. (2022).[16] To further understand the economic magnitude, we do a back-of-envelope calculation mapping short-term rental income to startup cost. According to the Kauffman survey, the average cost of starting a new business from scratch is about $31,150 (in 2008 dollars).[17] According to the ACS data, the average rental income across the US for a household is $4,202 in 2008. Therefore, the rental income from Airbnb accounts for about 13.4% (=4,202/31,150) of the startup cost, representing a non-trivial proportion.

[16] Barron et al. (2022) find that the median year-on-year growth rate in Airbnb listings in the top 100 CBSAs leads to 0.5% in annual rent growth.
[17] See https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.607.5828&rep=rep1&type=pdf for Kauffman survey.

One alternative channel that might confound with the rental income channel is the collateral channel. That is, if Airbnb penetration also increases house prices, households could extract higher collateral value from their houses for new business creations. In Table IA4 column 4, we find that Airbnb listings lead to an increase in house prices.[18] 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. Table 5 column 1 shows that the coefficient estimate on the interaction term between *I{high rental price growth}* and *Instrumented Ln(Airbnb listings)* 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 growth and run a similar regression in Table 5 column 2. The coefficient estimate on the interaction term between the instrumented Airbnb listing and *I{high house 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.[19] Because house prices could be endogenous to local firm creations, we also split the sample in two other alternative ways. In Table 5 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 Table 5 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

[18] Airbnb penetration could increase housing price for several reasons. 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.

[19] The magnitude of the house price growth is comparable to the literature. Our average Airbnb growth rate is 46.52%, therefore, an average Airbnb growth rate leads to 0.37% (=46.52%×0.008) in annual price growth, which is similar to the findings in Barron et al. (2022), who find that the median year-on-year growth rate in Airbnb listings in the top 100 CBSAs leads to 0.7% in annual price growth.

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.[20]

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. Instead, our findings only suggest that Airbnb expansion is more likely to spur new business creations through increased rental opportunities (and hence more rental income) rather than increased house prices.[21]

5.4.2 The local demand channel

We next turn to understand how Airbnb spurs entrepreneurship through the local demand channel, which is crucial for new business creations (Adelino, Ma, and Robinson, 2017). We hypothesize that Airbnb increases local demand mainly in two ways. First, the option of Airbnb lodging could attract more tourists (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 test our hypotheses above, we first examine how Airbnb penetration affects the tourist flow in Table 6. We proxy the number of visitors by incoming air passengers and collect data from the Bureau of Transportation Statistics U.S Domestic Airline Traffic. The data set keeps record of the total number of passengers arriving each airport in the U.S. as well as the distance of the flight. We construct our dependent variable, *Ln (incoming air passengers),* as the natural

[20] We also directly examine the plausibility of the collateral channel using individual-level mortgage data from ACS and report the results in Internet Appendix Table IA5. 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.

[21] There are three reasons that could explain this observation. First, the house price increase induced by Airbnb listing is small. 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.

logarithm of one plus the number of incoming air passengers to airports that are located within 25 miles to a county. As expected, Table 6 column 1 shows that Airbnb penetration leads to a positive and significant increase in the total number of air passengers to town. We further break down the sample by the flight distance traveled by the incoming air passengers, and find that the increase is mainly in the sample in which travelers travel for more than 1000 miles but not in the sample in which the travelers travel less than 1000 miles. Given that the longer the flight distance, the more likely the stay is longer, this result suggests that Airbnb is more likely to attract visitors that stay for more nights. The finding is consistent with the survey that shows that Airbnb guests tend to stay longer than hotel guests.[22] One underlying reason is 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.[23] Therefore, if it is only one-day stay, staying at Airbnb is not necessarily advantageous than staying at hotel.

Second, we examine how Airbnb affects hotel performance. We obtain information on hotel performance from Smith Travel Research. Following the specification in Farronato and Fradkin (2022), we conduct regressions and report the results in Table 7. We find that Aribnb penetration significantly lowers hotel revenues, reduced occupancy rates, lowers room prices and hurts revenues per available room of hotels. The results suggest that, for tourists with the same budget, they can spend less on lodging with Airbnb entry, and thus more budget is available for spending on local services (such as restaurants, entertainment, etc.), which would boost local demand.

If the local demand is enhanced by Airbnb entries, we should observe an increase in local income, which is often used as a proxy for local demand (Adelino, Ma, and Robinson, 2017). We obtain the information on local residents' income from the IRS Individual Tax Statistics and report the results in Table 8. Table 8 column 1 shows that Airbnb penetration has a positive effect on local residents' adjusted gross income, which includes both wage income and non-wage income. Table 8 further shows that Airbnb increases non-wage income (column 2), especially business income (column 3), but does not increase wage income significantly (column 4).[24] The

[22] Haywood, J., P. Mayock, J. Freitag, K. Owoo, and B. Fiorilla, 2017. Airbnb and Hotel Performance, *STR publication*.

[23] Pohle, A. 2022. Why Airbnb cleaning fees cost so much now, *Wall Street Journal*, April 12.

[24] A person files Schedule C to report business income only when she operates a business as a sole proprietor. Therefore, personal business income is also a measure reflecting entrepreneurial income.

results suggest that, as Airbnb increases local demand, local businesses are able to obtain more income.

An implication of Table 8 is that the higher business income following Airbnb penetration is not accompanied with higher wages for employees. To see whether higher business income could be accompanied with higher employment, we examine how Airbnb penetration affects employment in Table 9. Specifically, we aggregate establishment employment information in the YTS data to the county level using the YTS data, and obtain the unemployment rate from the Bureau of Labor Statistics data. In Table 9 column 1, we investigate how Airbnb affects the total number of jobs in a county. The coefficient estimate is positive and significant at the 1% level, suggesting that Airbnb penetration increases total job creations. Consistently, in column 2, we find that unemployment rate decreases significantly following Airbnb penetration.

We further examine job creation by the new firms and existing firms. As expected, we find that a significant number of jobs is created by the new firms in column 3. We next examine whether the job creation by the new firms crowds out the job creations by the existing firms. As shown in column 4, Airbnb penetration does not seem to have a significant effect on job creations by the existing firms, which suggests that there is no crowding-out effect going on. We then break down the employment of existing firms by their employment size and categorize them into "large," which employ at least 10 people, versus "small," which employ less than 10 people. We find that Airbnb penetration does not lead to significant changes in the employment of those "large" existing firms (as shown in column 5). Interestingly, Airbnb penetration increases the employment of "small" existing firms. This observation is consistent with the local demand channel, which suggests that Airbnb brings more tourism and demand for new businesses. The above tests suggest that Airbnb entries have a positive net effect on local job creations.

Finally, if the local demand channel is the one through which Airbnb penetration promotes entrepreneurship, we should observe Airbnb penetration increases business creations in that industries that are sensitive to local demand. To this end, we follow the definition in Mian and Sufi (2014), and classify the businesses to tradable sector and the non-tradable and construction sector. As pointed out in the literature, the non-tradable sector is more sensitive to local demand than tradable industries (Adelino et al., 2015; Adelino et al., 2017). In Table 10, we show that Airbnb penetration significantly and positively affects business creations in both the tradable sector and non-tradable sector. The elasticity of new business creations with regard to Airbnb penetration seems is larger in tradable industries. However, if we take into account of the average business creations across tradable and non-tradable sectors, the magnitude of the effect is larger in non-tradable sector than tradable sector. [25]

In addition to investigating the aggregate business creations in tradable sectors and non-tradable sectors, we examine business creations in each industry. In Figure 6, we plot the number of firms created caused by a 10% increase in local Airbnb listings across industries. We observe that the industries that are more sensitive to local demand tend to have larger increase in new firm creations. These industries include "Construction," "Retail Trade," "Other Services," "Professional, Scientific, and Technical Services," "Real Estate and Rental and Leasing," "Transportation and Warehousing," "Accommodation and Food Services", etc. In contrast, there is very little changes in industries such as "Utilities", which do not seem to be affected by local demand. The results suggest that the penetration of Airbnb results in entrepreneurship in local service and construction-related industries through expanding local demand.

Overall, the findings in this subsection suggest that local demand is a plausible underlying channel through which Airbnb penetration increase new business creations. Specifically, Airbnb entry attracts more tourists to the local region and reduces their cost of lodging. As a result, local income and employment increases, and there are also more business creations, especially in industries that are sensitive to local demand.

5.5 Heterogeneity of results

Both the rental income channel and the local demand channel are consistent with the relaxation of financial constraints for entrepreneurs. In this section, we examine the heterogeneity of our results across samples with different levels of financial constraints.

To begin with, 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

[25] The calculation is as follows. In tradable industries: 0.099 × average new business creations in tradable industries (9.79) = 0.97. In non-tradable and construction industries: 0.066 × average new business creations in non-tradable industries (127.9) = 8.44.

entrepreneurship (Petersen and Rajan, 1994, 2002; Guiso et al, 2004). Compared to large, established firms, startups are more opaque 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 benefit from an increase in income. 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 year *t-1*, and zero otherwise. In Table 11 column 1, we interact *I{low local bank share}* with *Instrumented Ln(Airbnb listings),* and find that the coefficient estimate on the interaction term is positive and significant at the 1% level. The results suggest that Airbnb's impact on new business creations is more pronounced in areas with lower local bank shares.

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, and are more likely to benefit more from increased rental opportunities or local demand. To test this conjecture, we classify 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 year *t-1*, and zero otherwise, and interact *I{high house price volatility}* with *Instrumented Ln(Airbnb listings).* Table 11 column 2 shows that 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.[26] 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. Table 11 column 3 presents the

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

results. The coefficient estimate on the interaction term 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 more opaque, 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 in column 2 and the difference between the coefficients in these two subsamples is statistically significant. The results suggest that Airbnb spurs the creation of small but not large startups.

Next, we repeat our regressions disaggregated into industries based on the degree of needs for startup capital. We use survey data from Survey of Business Owners Public Use Microdata Sample (SBO PUMS) to compute the average startup capital needs for each industry. The relaxed financial constraint 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.

5.6 Ruling out alternative interpretations

Existing literature (e.g., Hurst and Lusardi, 2004) argues that, as wealth grows, households are more risk-tolerant. Therefore, an alternative interpretation of our main findings is that, with the expectation that they can earn higher income, households could be more likely to start new businesses, which are typically associated with high risks. To explore this alternative risk preference 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 through higher rental income and enhanced local demand, 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%.[27] Overall, the results suggest that the new businesses created do not exhibit a higher failure rate.

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

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

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 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 affects long-term revenues 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.

6. Conclusion

In this paper, we find that both staggered entry and gradual penetration of sharing economy increase the new business creations in the local region. We document two novel channels underlying the results. First, Airbnb increases rental income, which relaxes the financial constraints of potential landlord entrepreneurs. Second, Airbnb attracts more tourists and increases their spending power outside lodging, which leads to an increase in local demand, as reflected in increase in local income and employment. The increase in local demand presents more investment opportunities for startups. The finding is particularly interesting to policy makers in the sense that sharing economy could generate demand that did not previously exist, and thus impose positive spillover effect into local economy, which has important policy implications.

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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.

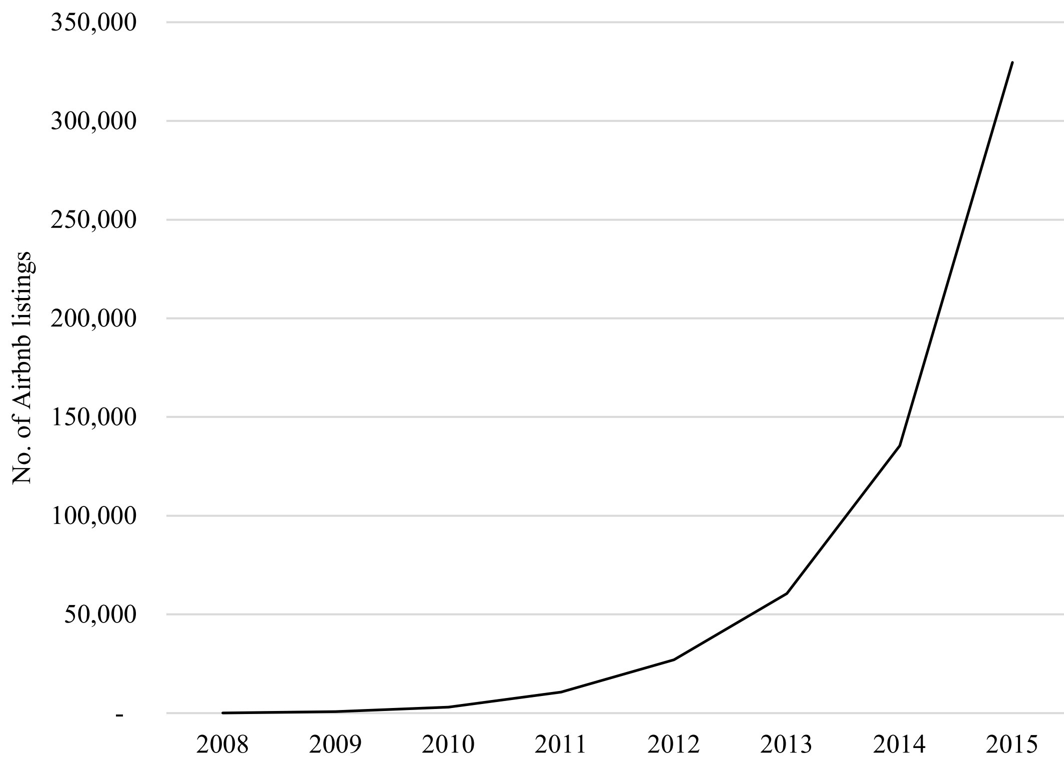


Figure 2: Distribution of Airbnb Listings

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

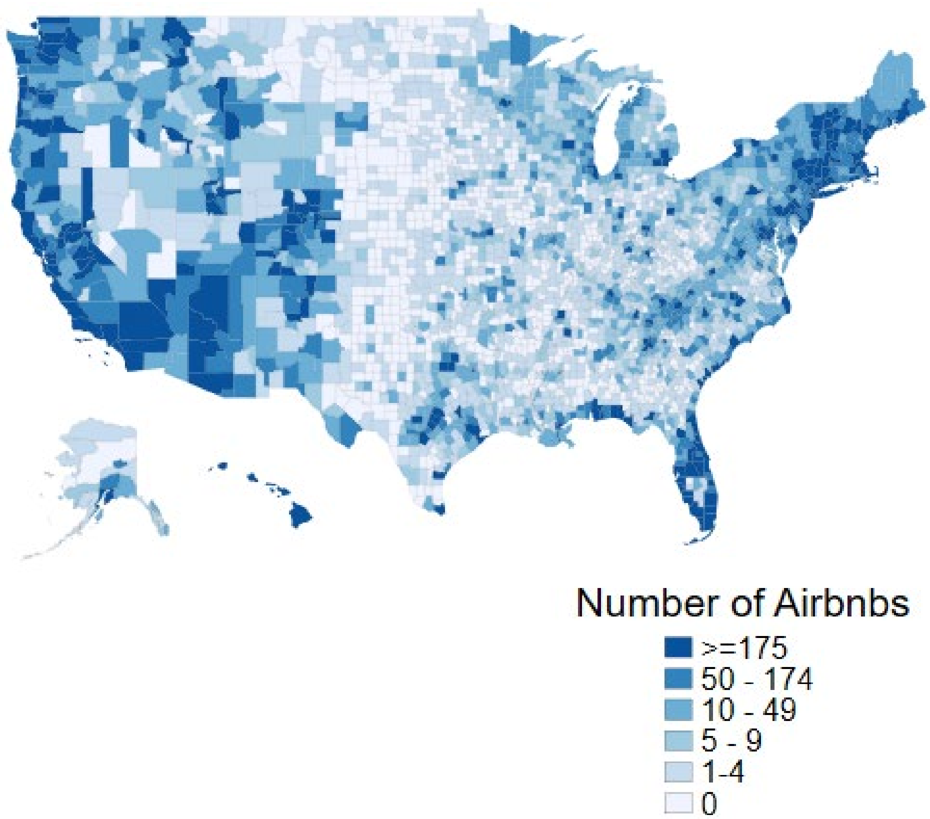


Figure 3: Distribution of New startups

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

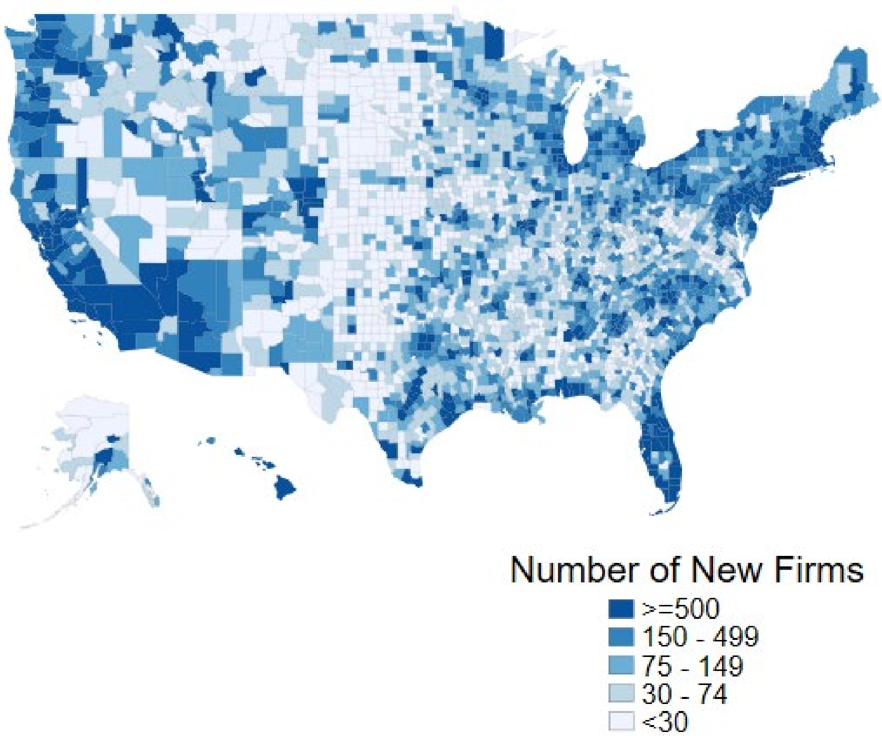
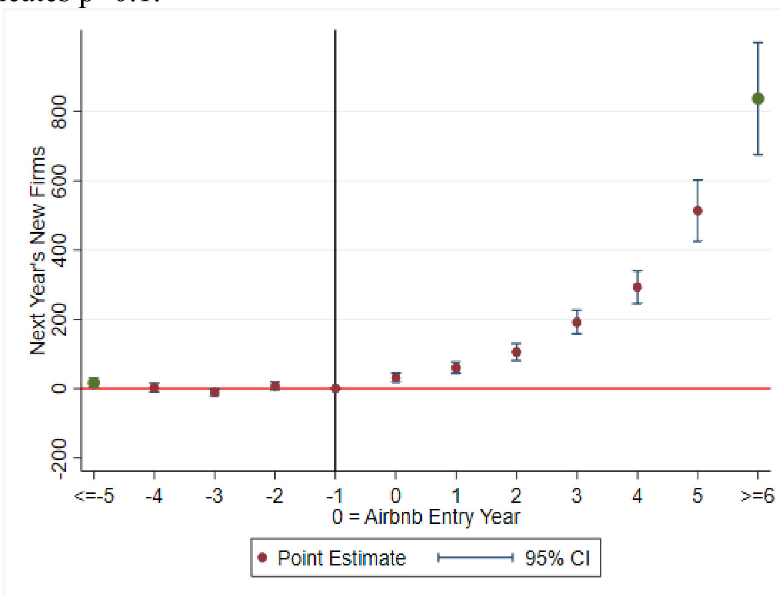
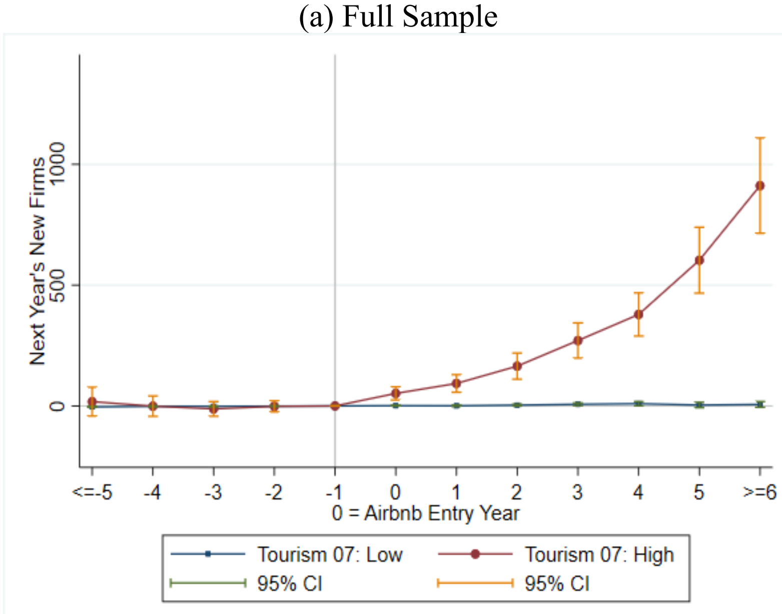


Figure 4: Dynamic Effects of Airbnb Entry on Local Business Creation

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.



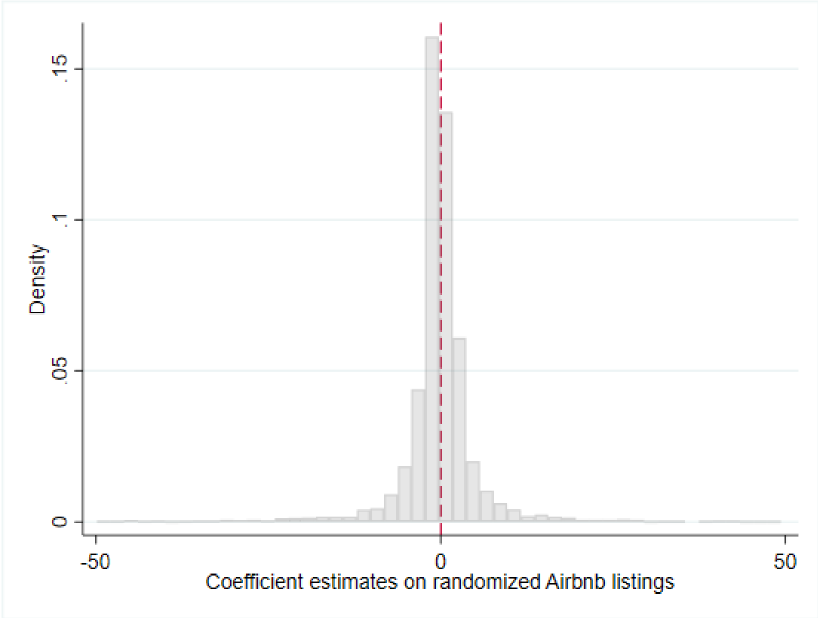
(a) Full Sample



(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.



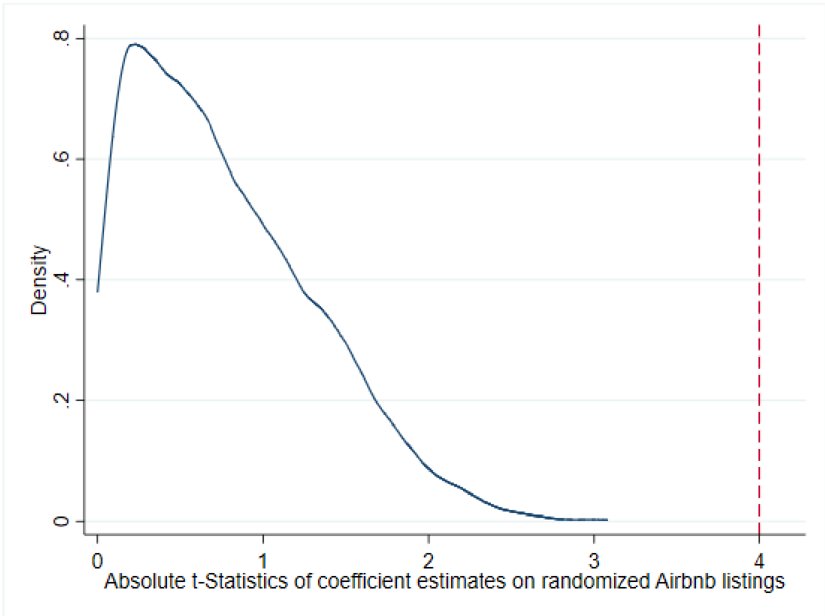


Figure 6: Airbnb and Firm Creation: By Industry

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), and Utilities (NAICS 22).

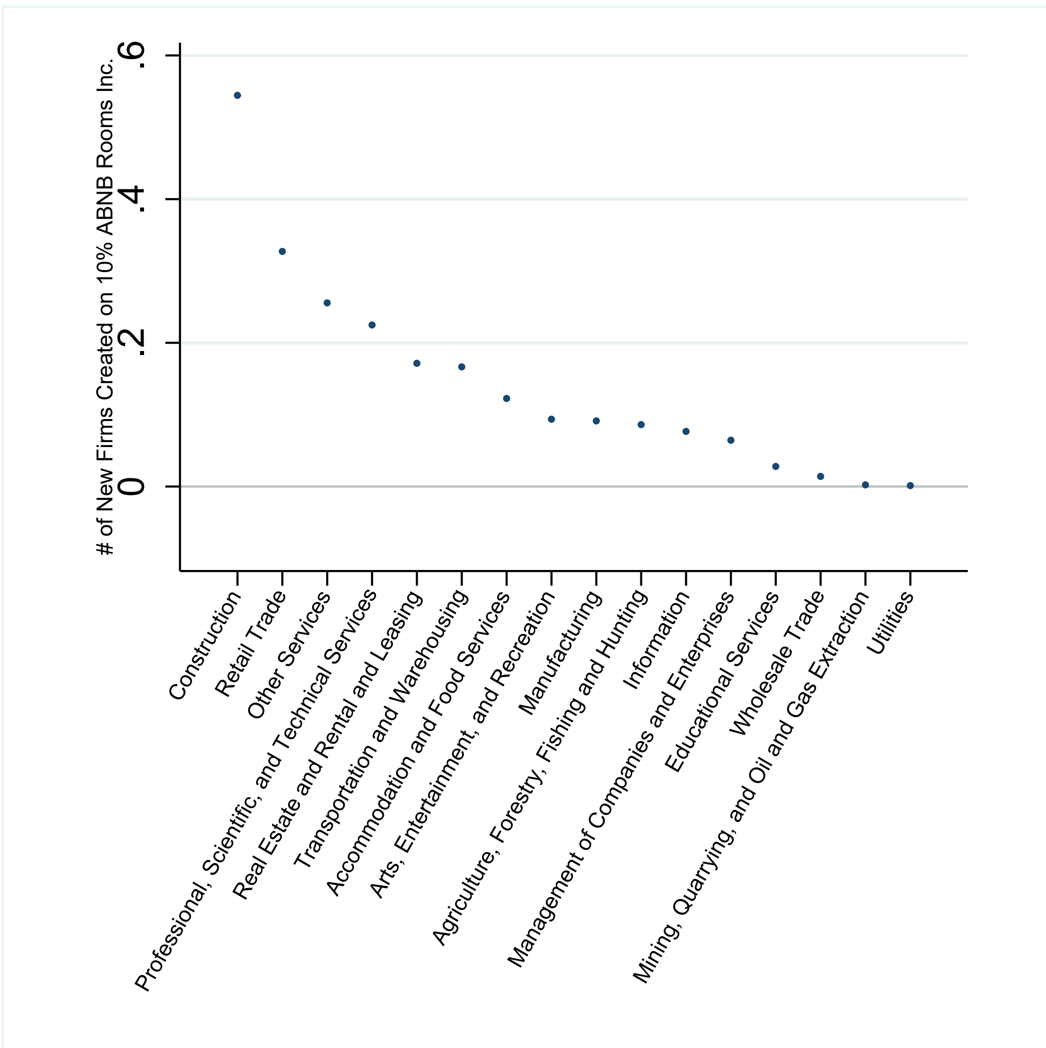


Table 1: Summary statistics

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
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	0.10	0.00	0.00	0.00	0.30
I{landlord}	3,471,353	0.16	0.00	0.00	0.00	0.37
Ln(age)	3,458,531	3.78	3.58	3.83	4.01	0.28
I{home owner}	3,458,531	0.64	0.00	1.00	1.00	0.48
I{employed last year}	3,471,353	0.98	1.00	1.00	1.00	0.16
I{male}	3,471,353	0.55	0.00	1.00	1.00	0.50
I{white}	3,471,353	0.74	0.00	1.00	1.00	0.44
I{black}	3,471,353	0.12	0.00	0.00	0.00	0.32
I{low-skilled}	3,471,353	0.32	0.00	0.00	1.00	0.47
I{mid-skilled}	3,471,353	0.09	0.00	0.00	0.00	0.29

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)
Ln(Airbnb listings)	0.015***	0.010**		
	(0.004)	(0.004)		
VC index × Ln(tourism)			0.136***	
			(0.003)	
Instrumented Ln(Airbnb listings)				0.028***
				(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 times and 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(incoming air passengers)			
	Total	Dist.<1000Miles	Dist.1000-2000Miles	Dist.>2000Miles
	(1)	(2)	(3)	(4)
Instrumented	0.038**	0.017	0.056**	0.093***
Ln(Airbnb listings)	(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
Adjusted 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 inelasticity dummy (equals one if the elasticity measure estimated in Saiz (2010) is below median value in the sample), 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 times and 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)	-0.061***	-0.012*	-0.036***	-0.060***
× land inelasticity	(0.019)	(0.007)	(0.011)	(0.022)
Instrumented Ln(Airbnb listings)	0.051***	0.004	0.012**	0.017
	(0.010)	(0.003)	(0.006)	(0.010)
Ln(hotel supply)× land inelasticity	-0.437***	0.002	-0.082**	-0.084
	(0.049)	(0.020)	(0.034)	(0.057)
Ln(hotel supply)	1.354***	-0.084***	0.140***	0.009
	(0.014)	(0.012)	(0.020)	(0.033)
Ln(incoming air passengers)	0.014***	0.005***	0.006***	0.014***
	(0.004)	(0.001)	(0.002)	(0.004)
County fixed effect	Yes	Yes	Yes	Yes
Year-Month fixed effect	Yes	Yes	Yes	Yes
Observations	8,828	8,566	8,566	8,566
Adjusted R^2	0.994	0.600	0.731	0.647

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	0.007***	0.025***	0.032***	0.001
Ln(Airbnb listings)	(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
Adjusted 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)	Unemploy ment rate	Ln(number of jobs created by new firms)	Ln(employment of existing firms)		
				All	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented	0.002***	-0.142***	0.020**	-0.003	-0.004	0.009***
Ln(Airbnb listings)	(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

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 columns 1 and 3, the logarithm of the number of new firms created in the non-tradable and construction sectors in columns 2 and 4. The sectors are defined as Mian and Sufi (2014). 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	Tradable	Non-tradable& Construction
	(1)	(2)	(3)	(4)
Instrumented Ln(Airbnb listings)	0.121***	0.082***	0.099***	0.066***
	(0.007)	(0.007)	(0.008)	(0.008)
County controls	No	No	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	0.828	0.921	0.830	0.924

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	19,191	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: Department of Housing and Urban Development (HUD) Fair Market Rents Database.
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., the appearance of the first Airbnb listing) into a county, and the county is excluded from the sample post the entry. The dependent variable is the number of years from 2007 when a county had its Airbnb 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 variables 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 Housing Market

This table presents two-stage least square estimation of how Airbnb affects the rental market. The outcome variable is the logarithm of vacant units available for seasonal rental in column 1, the logarithm of vacant units available for long-term rental in column 2, and the logarithm of rental price in column 3. The outcome variable in column 4 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(vacant for seasonal rental) (1)	Ln(vacant for long-term rental) (2)	Ln(rental price) (3)	Ln(house price) (4)
Instrumented Ln(Airbnb listings)	0.033*	-0.041***	0.009**	0.008***
	(0.018)	(0.015)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	4,843	4,843	19,191	19,191
Adjusted R^2	0.894	0.882	0.823	0.570

Table IA5: 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 times and 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)	-0.106		-0.055	
× I{second mortgage}	(0.199)		(0.134)	
I{second mortgage}	0.022***		0.009***	
	(0.001)		(0.001)	
Instrumented Ln(Airbnb listings)		-0.073		-0.129
× I{home equity loan}		(0.228)		(0.159)
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