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

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Abstract

We use the staggered entry of Airbnb—a sharing economy pioneer—to examine the sharing economy's effect on entrepreneurship. Airbnb's arrival and penetration have both led to the creation of new, local businesses that have higher survival rates and better performance, both at creation and in the long run. To address identification concerns, we use the interaction between venture capital infusion and local tourism as an instrument for Airbnb penetration. Airbnb appears to spur entrepreneurship by increasing passive income and by enhancing local demand, leading to higher local income and the creation of more jobs.

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

JEL code: L26, L85, L86, M13

1. Introduction

In the past decade, the development of digital platforms has spawned a new marketplace, often called the peer-to-peer rental marketplace. In this new marketplace, asset owners supply the excess capacity of their assets—that may otherwise go underutilized—directly to demanders. Therefore, such marketplaces are also referred to as a "sharing economy," the size of which is projected to grow to $335 billion in 2025.[1] While the sharing economy is growing rapidly, the economic consequences of this new business model are still unclear. On one hand, its proponents claim that the sharing economy platform increases economic efficiency by reducing frictions that cause capacity to be underutilized, and thus may improve the welfare of the society (Einav, Farronato, and Levin, 2016). On the other hand, critics argue that the sharing economy disrupts traditional business models (Farronato and Fradkin, 2022) and may generate negative externalities to the society (Flippas and Horton, 2020). In this paper, we contribute to the discussion by focusing on how the sharing economy affects entrepreneurship. Notably, there have been increasing concerns about the decline in entrepreneurship (Decker, Haltiwanger, Jarmin, and Miranda, 2016), which is the ultimate force for long-run economic growth and job creation in the U.S. (Haltiwanger, Jarmin, and Miranda, 2013).

We empirically explore the effect of the sharing economy on entrepreneurship using the staggered entry of a major source of the sharing economy: the home-sharing platform, Airbnb. Airbnb enables people to list and rent their spare rooms for short-term lodging in residential properties. Its platform facilitates matching short-term rental supply with demand. How could Airbnb affect entrepreneurship? We hypothesize that there are two main channels. First, Airbnb lowers the cost for property owners to enter the short-term rental market.[2] The increased opportunities to rent their homes could mean increased income for property owners, which could help relax their financial constraints and provide more time flexibility when entering into entrepreneurship. We term this the *passive income channel*. Second, Airbnb provides travelers with more lodging options.[3] The increase in spending on travel and tourism could mean higher

[1]See Sarote Tabcum, "The Sharing Economy Is Still Growing, and Businesses Should Take Note," *Forbes* March 4, 2019.

[2] More than four million hosts have six million listings on Airbnb worldwide, and more than 60 percent of US hosts say they rent out their primary home while they are on vacation. See "Airbnb Statistics" by IpropertyManagement on August 3, 2022.

[3] More than one billion guests have stayed at Airbnb sites because of low cost, convenient location, household amenities, and other reasons. See Airbnb, "Billionth Guest Gets Year of Stays around the World," September 27, 2021.

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

We start our empirical analysis along the extensive margin, that is, with how the staggered arrival of Airbnb across counties has spurred the creation of new firms 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, 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. Moreover, we find no prior trend when we examine the dynamics of new firm creation surrounding the time of Airbnb entry. Therefore, we use Airbnb arrivals to predict new firm creation, while controlling for county- and year-fixed effects, as well as for local demographic and economic characteristics that might affect entrepreneurship. We find that Airbnb's arrival leads to 3.1 percent increase in the creation of local businesses.[4]

We further examine the intensive margin, that is, how does Airbnb's 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 the creation of new businesses, controlling for time- and county-fixed effects, and other time-varying economic and demographic county characteristics.

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 was developed by Bartik (1991) and used in many prominent studies (e.g., Nunn and Qian, 2014; Diamond, 2016), and estimate the two-stage least-squares (2SLS hereafter) regressions. This type of instrument exploits a plausibly exogenous time-series variable and a potentially endogenous cross-sectional exposure variable. Following this logic, we first exploit plausibly exogenous time variation in Airbnb growth,

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

which is driven by capital infusions by venture capital (VC) investors 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 improvement, etcetera; this increase, 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 how attractive a county is to tourists. We measure a county's attractiveness to tourists by using the number of establishments in the tourism section (NAICS 72) at the beginning of our sample period (2007) when the measure would not be affected by Airbnb's entry into the local area.

Combining the above two sources of variations, we construct, as the instrument for Airbnb penetration, 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, the average annual Airbnb growth rate accounts for about 4.9 percent in the growth of new firm creation.

We then discuss whether the exclusion restriction is satisfied for our instrument. For all Bartik-type instruments, the exclusion restriction requires the interaction term to be 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). Our setting requires the ex ante levels of tourism 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 in counties with high and low levels of tourism in years following more and fewer rounds of VC funding shocks to Airbnb. Therefore, we examine the identifying assumption for a DD study: parallel trends. We find no differential trend in new firm creation prior to Airbnb entry for high-tourism counties and low-tourism counties, which suggests the parallel trend assumption is unlikely to be violated.

We also conduct two additional tests for the exclusion restriction. First, we investigate the possibility of a 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 preserve 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 have never had any Airbnb listings. If our instrument is valid, it should affect firm creation only through Airbnb, and thus should have no effect on firm creation in counties without any Airbnb listings. This is indeed what we find.

After establishing the baseline results, we explore the underlying economic channels. We first examine the *passive income channel*. As Airbnb lowers the entry cost to the short-term rental market, it attracts landlords from the long-term rental market. As a result, the housing supply in the long-term rental market drops (which leads to higher long-term rental rates), and more short-term rentals become available (in which case the rental rates tend to be higher than that of the long-term rental), leading to higher average rental rates. We hypothesize that higher rental income relaxes landlords' financial constraints and provides more time flexibility for them to become entrepreneurs. Consistently, we find that landlord householders are more likely to become entrepreneurs when Airbnb penetration is higher and that new firms created tend to be of larger size and higher quality following Airbnb penetration.

We next turn to the *local demand channel*. We hypothesize that Airbnb spurs entrepreneurship by enhancing the local demand, which is crucial for creating new business (Adelino, Ma, and Robinson, 2017). Airbnb appears to increase local demand primarily in two ways. First, it increases the number of tourists (as proxied by the incoming air passengers) to the local area. Second, it reduces hotel prices, which could increase tourists' budgets for non-lodging services. With more 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 a restaurant given an increase in local demand. To further explore the 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; interestingly this does not translate to higher wages, but to the creation of more jobs. The jobs created by these new businesses do not crowd out existing businesses and small, existing businesses employ more workers. The evidence above supports the argument that, overall, Airbnb 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, Schoar, and Severino, 2015; Adelino et al., 2017).

We also rule out an alternative interpretation of our findings that argues householders are more likely to start new businesses because they expect to earn higher income after Airbnb enters their local communities. If this argument were true, the new businesses should be associated with higher risks and higher rates of failure. The existing literature (e.g., Hurst and Lusardi, 2004) shows that, 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 perform better both at their entrance and in the long term. The results suggest that entrepreneurs are unlikely to start new businesses as a result of higher risk preference and tolerance, factors that typically lead to new businesses with higher risk and thus worse performance and lower survival rates. These observations also suggest that Airbnb does not affect entrepreneurship through a risk-taking channel. Finally, to provide a robustness test to our instrumental variable approach, we perform a case study by using short-term rental restrictions in New York state as a plausibly exogenous shock to Airbnb penetration. We find that a negative shock to short-term rental indeed reduces Airbnb listings, and leads to lower new firm creations.

Our paper contributes mainly 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 (Evans and Jovanovic, 1989; Holtz-Eakin, Joulfaian, and Rosen, 1994a; Holtz-Eakin, Joulfaian, and Rosen, 1994b; Hurst and Lusardi, 2004; Kerr and Nanda, 2009a), downside protection (Hombert, Scholar, Sraer, and Thesmar, 2020; Gottlieb, Townsend, and Xu, 2022), financial market development (Black and Strahan, 2002; Guiso, Sapeienza, and Zingales, 2004; Bertrand, Schoar, and Thesmar, 2007; Kerr and Nanda, 2009b), personal wealth (Evans and Jovanovic, 1989; Gentry and Hubbard, 2005; Cagetti and De Nardi, 2006), collateral value (Adelino, Schoar, and Severino, 2015; Corradin and Popov, 2015; Schmalz, Sraer, and Thesmar, 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—the sharing economy—could spur entrepreneurship. Our findings uncover two new plausible economic channels, the passive 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, Horton, and Zeckhauser, 2020), and discussed in survey papers (Proserpio and Tellis, 2017). Specifically, several studies examine the impact of a pioneer of the sharing economy—Uber. Burtch, Carnahan and Geenwood (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 these businesses provide flexible gig work opportunities and therefore the fallback opportunities for would-be entrepreneurs. Other studies focus on the effects of another pioneer of the sharing economy—Airbnb—and find that Airbnb negatively affects the hotel industry (Zervas, Proserpio, and Byers, 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, Jofre-Monseny, Martinez-Mazza, and Segu, 2020; Barron, Kung, and Proserpio. 2021), and changes restaurants and other local amenities (Almagro and Dominguez-lino, 2021). We contribute to this literature by focusing on a new angle, that is, how Airbnb affects entrepreneurship, a main driving force of economic growth.

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

2. Institutional background

2.1 Sharing economy

In recent years, a new business model called the “sharing economy,” has emerged. This model is also known as the “peer-to-peer marketplace,” the “collaborative economy,” or the “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, one that 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 those goods substantially less than 100 percent of the time. Therefore, it is interesting that the sharing economy has only begun to flourish in recent years; prominent examples include home-sharing services (Airbnb), ride-sharing services (Uber, Lyft), food delivery services (Instacart, Postmates), household tasks (TaskRabbit, Handy), etc. As argued in the literature, two main factors have contributed to the rise of the sharing economy (Filippas, et al., 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, and often understated, the electronic commerce predecessors of the sharing economy, such as eBay and Amazon, have provided important industrial experience in building online marketplaces and solving such fundamental problems as search algorithms, recommendation systems, and bilateral reputation systems thereby mitigating information asymmetry and improving the efficiency of matching.

Digital platforms for sharing economies differ in how they match supply and demand and in how they rely on reputation mechanisms. Matching systems may be centralized or decentralized. For example, Uber is operated through a centralized matching system where, following a customer's request, the platform performs the action of searching and matching. The service provider decides whether to accept the request. The platform sets prices and can increase or decrease prices depending on market conditions. On the other hand, Airbnb uses a decentralized matching system where buyers and sellers make the matches and the platform serves merely as escrow (i.e., collecting fees from the customer and delivering compensation to the service provider). The difference in matching systems is due to the nature of the businesses. Because heterogeneity in a ride-sharing service is much lower than that in home accommodation, centralized matching is more appropriate for Uber and decentralized matching is more appropriate for Airbnb.

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

The sharing economy, while still in its infancy, attracts substantial policy interest. Its critics are generally concerned with its disruption of affected industries and with these platforms' ability to duck costly regulations that protect third parties and remedy market failures (Avital, Carrol, Hjalmarsson, Levina, Malhorta, and Sundararajan, 2015, Filippas and Horton, 2020). A counter argument is often made that these sharing economy platforms solve problems of market failure in an innovative fashion through better information provision and reputation systems, making the application of existing regulations to the sharing economy inappropriate (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. Rental accommodations can be rooms, apartments, houses, etcetera. The hosts, who want to monetize their extra space, list their accommodations on Airbnb's online platform and showcase them to potential guests. Meanwhile, the guests, who want to explore these unique spaces, identify and book the accommodations on the platform. As of 2021, Airbnb had grown to 4 million hosts sharing 5.6 million homes in more than 100,000 cities worldwide, making the company comparable in inventory and transaction volume to the world's largest hotel brands.[5]

According to the US Census, America has more than 460 million bedrooms in more than 190 million housing units; this 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 are not leveraging to earn

[5] Airbnb, "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 more than $6,800 equity in motor vehicles. For more information, see Daniel M. Rothschild, "How Uber and

returns. The introduction of the Airbnb platform has helped bring this "dead capital," which people formerly did not think of as productive capital, into the stream of commerce. The Airbnb platform has lowered hosts' cost of entering the short-term rental market by providing a digital platform that makes matching more effective and mitigates the problem of information asymmetry. Since Airbnb began, home-sharing hosts have earned more than $100 billion.[7]

The rise of Airbnb has attracted a great deal of regulatory attention. While the literature argues that Airbnb penetration in a local area could increase consumer welfare (Farronato and Fradkin, 2022), critics argue that home-sharing platforms like Airbnb raise the cost of living by reducing frictions in the peer-to-peer market for short-term rentals. Home-sharing platforms cause some landlords to switch from supplying the market for long-term rentals to supplying the short-term market. The reduction in the housing supply in the long-term rental market may drive up 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 in 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 Airbnb's staggered entry affect the creation of new businesses? Section 3.2 discusses the methodology for examining the intensive margin: how does the intensity of Airbnb's penetration affect the creation of new businesses?

3.1 Airbnb entry and the creation of new businesses

To assess how the staggered entry of Airbnb affects the creation of new firms, we estimate the following equation

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

Airbnb Resurrect 'Dead Capital,'" UMLAUT (Apr. 9, 2014), https://theumlaut.com/how-uber-and-airbnb-resurrect-dead-capital-4475a2fa91f1.

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

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, the rate of white population, the rate of population ages 20–64, and the rate of population ages 65 and above. Due to the count-based nature of our dependent variables, we employ a fixed-effect Poisson estimation.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 specific counties randomly. To examine this concern, in Section 5.1 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.

3.2 Airbnb penetration and the creation of new businesses

To examine how the intensity of Airbnb's penetration in a county leads to the creation of new businesses 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 that 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 the creation of new firms to Airbnb's expansion. A higher β indicates that Airbnb's penetration in a county is associated with the creation of more new firms. The concern associated with the OLS regression is that the coefficient estimate on $Ln(Airbnb\ listings)_{i,t}$ could be driven by unobserved factors such as local economic conditions. For example, vibrant local 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 creation of new business at the county level but is 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. Bartik (1991) developed this instrumental variable approach that instruments local labor demand by the interaction between national trends in industry-specific productivity and the composition of historical local industry composition. This approach has been popularized and used in many influential studies (e.g., Nunn and Qian, 2014; Diamond, 2016). The rationale behind this approach is that some plausibly exogenous aggregate time trends affect different spatial units systematically along some cross-sectional exposure variables.

Following the logic of the Bartik-type instrument, we construct our instrument by starting with a plausibly exogenous time-series variation—the infusions of venture capital (VC) into Airbnb. Capital infusions from VCs significantly increase Airbnb's operational funding, which can be used in advertising, employee hiring, online platform improvement, etcetera thereby attracting more potential hosts and stimulating Airbnb's expansion. In this way, 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, they will be collinear with time-fixed effects. Therefore, to complete the instrument—because Airbnb penetration is likely to be more intense among counties that have more preexisting tourism sources—we introduce the preexisting tourism condition of counties as measured by the number of establishments in the food service and accommodation industry (NAICS code 72) as the endogenous cross-sectional exposure variable. Exploring this form of heterogeneity allows us to flexibly control for the effect of time (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 received nine rounds of VC financing from 2008 through 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-type 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 either if the time trend is independent of the error term, or if the exposure variable is independent of the error term (Goldsmith-Pinkham, et al., 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 tourism 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 the plausibility of the independence requirement, consider the example of county-level economies as an omitted variable. It is not clear whether changes to economies 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 counties that are more tourist-oriented. 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 the creation of firms, 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); this information includes the property type, the county-level location, the first date that the host became a member of Airbnb, the host's 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 intensively Airbnb penetrates into the local region. To this end, we use the number of Airbnb listings available at the county-year level. Using its data collection algorithm, Inside Airbnb has monitored the Airbnb website and collected a monthly snapshot of the Airbnb listing information starting from June 2015. Therefore, following the literature (Barron et al., 2021), we use the June 2015 snapshot and back out the number of Airbnb listings available in each county-year, taking advantage of information about when the host became a member of Airbnb. We assume that listing continued to exist from the year that the host became a member of Airbnb until 2015. We then aggregate the listings available each county-year to get the penetration measure.

From the above procedures, our Airbnb penetration measure captures the Airbnb listings available in the long term. We do not include listings that were put on the website for a brief period and were removed before 2015, and we do not take into consideration whether the listings have guests. Essentially, the variation of our Airbnb penetration measure comes from the number of individuals who became hosts prior to 2015 at the county-year level. Our measure has two advantages in measuring Airbnb penetration. First, it captures long-term Airbnb listings, and thus is less likely to be affected by the endogenous factors that cause the accommodations to be delisted. Second, by ignoring whether the listing had any guests, we are able to focus on disentangling

Airbnb's supply from the demand. In Figure 1 we plot how the aggregate number of Airbnb listings in our sample grew exponentially between 2008 and 2015. The number of Airbnb listings in our sample is comparable to those reported in the existing literature.[8]

We plot the 2015 Airbnb listings across the U.S. in Figure 2. In our sample, all US states and the District of Columbia 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 firm creation, employment, and sales information from Your-economy Time Series (YTS), an annual-level time-series database that tracks all US establishments since 1997.[9] YTS aggregates the data in each year using an annual snapshot of the Infogroup Historical Business Data files, which are provided by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin's Institute for Business and Entrepreneurship. Kundle (2020) details Infogroup's methodology to gather the data underlying YTS, and compares YTS data with several other databases.[10] The YTS data are widely used in academic research (e.g., Arefeva, Davis, Ghent, and Park, 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's 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."[11]

It is worth noting that whether Airbnb hosting is considered the creation of a new business depends on the level of service the host provides the guests. According to the "Guidance on the Taxation of Rental Income" provided by Airbnb, hosts should report their rental income and

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[8] See Barron et al., (2021), p. 32, Figure 3, Panel C.
[9] Additional information on YTS data is available at https://wisconsinbdrc.org/data/
[10] Kunkle (2020) points out that compared to Current Employment Statistics (CES), a commonly used firm-creation database, YTS is more representative, especially for births and younger/smaller businesses. YTS usually starts tracking a business within one year of its start date while CES does not start tracking a business until it has hired a full-time employee.
[11] See YTS data description available at https://wisconsinbdrc.org/wpcontent/uploads/sites/6/2022/01/YTSdatabasedescription.pdf.

expenses on Schedule E of Form 1040; their income is subject to net investment income tax unless the hosts are the owners of a hotel or motel that provide services to travelers, or work as real estate dealers engaged in the business of selling real estate; in these two cases, rental income and expenses should be reported on 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 graduate rate. Data on median household income, population, and the college graduation rate are obtained from the US Census; data on the unemployment rate and the labor force come from the Bureau of Labor Statistics; data on the house-price index is extracted from records maintained by the Federal Housing Finance Agency.

Additionally, we use individual-level survey data from the American Community Survey (ACS) conducted by the US Census Bureau. The ACS project collects detailed information about the American population and housing characteristics. Since 2005, the ACS has sampled a representative one percent of the population every year. In the survey, individuals are asked about their gender, race, education, employment, income, etcetera. Following the literature, we define individuals as entrepreneurs if they are identified as self-employed in the survey. From the ACS we also obtain county-level rental measures, including landlords (households receiving rental income), units vacant for seasonal rental, and 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 through 2015, and match these to YTS data on new business creation in each county one year ahead. Our sample includes 2,403 unique counties that span eight 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 four employees. Panel C reports the summary statistics of the individual-level dataset from the ACS. About 10 percent of the individuals in the sample 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 the creation of local businesses. Section 5.2 examines the intensive margin, that is, how the intensity of Airbnb entry—as measured by Airbnb listings—affects local business creations. Section 5.3 discusses the validity of the instrumental variable approach. Section 5.4 examines underlying economic channels. In Section 5.5 we investigate 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 show 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 the creation of new firms. The economic magnitude is sizable. For example, column 2 shows that Airbnb entry in a county, on average, is associated with a 3.1 percent increase in local business creation, which translates to eleven new firms (average number of firms created 368.52 × 3.1% = 11).[12]

A natural concern is that the Airbnb platform does not launch in specific counties randomly. This would be particularly concerning for identification, for example, if Airbnb platforms specifically enter first into "entrepreneurial" counties. 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 entry of Airbnb.

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 Internet Appendix Table IA1, the rollout timing of the Airbnb platform is predicted by several economic and demographic factors. However, the growth in the number of

[12] The percentage increase in local business creation is comparable to the findings of Barrios, Hochberg, and Yi (2022) who find that the introduction of Uber and Lyft is associated with a 4–5 percent increase.

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 businesses 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

In addition to the extensive margin, we next examine the intensive margin, that is, how the intensity of Airbnb entry affects the creation of new local businesses. We are specifically 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 number of new businesses created 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 creation with regard to Airbnb penetration. The coefficient estimates in columns 1 and 2 are positive and significant at the 1 percent and 5 percent levels. The magnitude of *Ln(Airbnb listings)* coefficient estimate in column 2 suggests that increasing Airbnb listings in a county by 10 percent is associated with a 0.1 percent increase in new businesses created. While an OLS regression shows a strong relation between local Airbnb penetration and new firm creation, Airbnb's expansion might be correlated with some unobservable factors that could affect the creation of new firms as discussed previously.

To identify the causal effect of Airbnb penetration on new business creation, 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 there does not appear to be a weak instrument problem (Bound, Jaeger, and Baker, 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 percent level, suggesting that Airbnb penetration spurs entrepreneurship. Specifically, the magnitude of the coefficient estimate suggests that increasing Airbnb listings in a county by 10 percent is associated with a 0.28 percent increase in the number of new firms created.

To evaluate the economic magnitude, we calculate the average annual Airbnb growth rate as 46.5 percent in the sample. Therefore, an average annual Airbnb growth rate leads to a 1.3 percent (=46.5%×0.028) increase in new firm creation. Given that the actual growth rate for the creation of new firms in our sample is 26.7 percent, an average annual Airbnb growth rate accounts for 4.9 percent (=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 percent (=4.52×0.28) increase in *Ln(number of firms created)*, which accounts for 9 percent (=12.7%/1.4) of the standard deviation of *Ln(number of firms created)*.[13]

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 landscapes that attract many visitors, there could be more Airbnb listings; at the same time, there may be 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, that is, a local average treatment effect (Jiang, 2017). The compliers are the Airbnb listings coming at the margin from the dissemination of Airbnb in a tourist area given VC capital. It is likely in these areas that Airbnb has a higher marginal effect on entrepreneurship given the area's 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. We find our main results are robust to controlling for regional

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

economic trends, to the time period after 2010, to firm-creation measures from the Statistics of U.S. Businesses, and to controlling for industry-year-time trends.

5.3 Validity of the instrumental variable

In discussing our instrumental variable approach in Section 3.2, we mentioned that, 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 following events happen: first, if there is a long-run economic revival trend in counties that leads to more entrepreneurship over time; second, if the trend of economic revival is higher in zip codes with more tourism. 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 exist, we proceed to conduct three groups of tests to show why our instrument is likely to be valid.

To begin, we draw on the argument (Nunn and Qian, 2014) that the Bartik-type instrument is analogous to a difference-in-differences (DD) approach, 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 is due to differences in Airbnb listings between counties with high and low levels of tourism in years following more and fewer rounds of VC funding that promote 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 counties with high and low levels of tourism absent the Airbnb entry shocks. Although the parallel trend assumption cannot be directly tested because there is no counterfactual, we examine the number of new firms created surrounding the Airbnb entry time for high-tourism counties and low-tourism counties. Figure 4 Panel (b) shows that there is no differential trend for the counties with high-tourism exposure and those with low-tourism exposure in 2007 (before the Airbnb entry); in contrast, high-tourism-exposure counties start to experience significantly higher growth in the creation of new firms after Airbnb entry compared to low-tourism-exposure counties. The results suggest that the parallel trend assumption is unlikely to be violated in our setting.

Next, we examine whether our instrument is driven primarily 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 keeping constant the aggregate number of Airbnb listings in each year. We also keep constant the outcome variables, the instrumental variable, and the controls. The randomized Airbnb listings preserve the overall trends in Airbnb's penetration but randomize the Airbnb growth in each county, thus eliminating the impact of local tourism resources on the 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 statistically significant. In contrast, if the cross-sectional variation in tourism drives the intensive margin of Airbnb listings, then this randomization would lead to a weak first stage and to 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 more than 99 percent of the randomized draws for the creation of new firms. If the spurious time trends were driving our results, we would likely still have statistically significant estimates, even with the randomized regressor. 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.

Finally, 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 creation in counties that never have any Airbnb listings ("non-Airbnb counties"). If our instrument is valid, it should be correlated only with new businesses created through the entrance of Airbnb listings. Therefore, in areas with no Airbnb, we should not observe a strong correlation between our instrument and new business creations. This is indeed what we find and report in Internet Appendix Table IA3.

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 two main channels. First, by facilitating peer-to-peer short-term rentals, Airbnb provides more flexible renting options for landlords and may increase their rental income. The increased rental income relaxes financial constraints and provides more time flexibility for landlords to enter entrepreneurship; we call this the "*passive income channel.*" Second, by providing more flexible lodging options to travelers, Airbnb may 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 passive income channel

Airbnb, by providing an online short-term rental platform, makes short-term rental more accessible to landlords. As a result, landlords on average could earn higher rental income as a result of Airbnb penetration. Given that rental income—unlike labor income—is earned passively on properties, renting provides landlords with greater time flexibility. Time flexibility, though often understated, is important to entrepreneurship because creating a new business usually requires significantly more time than a paid job (e.g., Agarwal and Lenka, 2015).

To examine whether Airbnb spurs entrepreneurship through the passive income channel, we first examine whether landlords are more likely to start new businesses. To this end, we use individual-level data from the American Community Survey and classify the population of each county into landlords (who receive rental income) and non-landlords (who do not receive rental income). [14] We conduct a regression as below:

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

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 the individual is working for someone or

[14] Our sample includes 3.5 million individual-level observations. We examine only householders/heads of the family who are of working age (between 18 and 65 years of age) and who are most relevant for the study. Heads of families account for about half of the working-age population in the sample; the remainder are spouse and children of working age.

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.[15] $I\{landlord\}_{i,t+1}$ 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).[16] 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 about 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.[17] 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 becoming 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 percent (=0.0468%/0.297) of the standard deviation on the dependent variable *I{entrepreneur}*. We combine 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 percent (=12.7%/1.4) of the standard deviation of *Ln(number of firms created)*. This suggests that the passive income channel could partially explain the increase in entrepreneurship following Airbnb penetration.

To shed light on the source of landlords' additional income we first investigate how Airbnb affects the real estate market. In Internet Appendix Table IA4, we show that Airbnb reduces housing supply in the short-term rental market and increases housing supply in the long-term rental market, and increases average rental prices and average housing prices.[18] The rental price increase

[15] ACS does not distinguish farm income from business income.

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

[17] It is worth noting given that, since the ACS survey is conducted each year and does not track individuals across years, we must take all the individual measures—(*I{entrepreneur}*, *I{entrepreneur receiving business income}*, and *I{landlord}*)—in the same year to maintain 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 upper bound of the marginal effect of Airbnb on the likelihood of a landlord becoming an entrepreneur.

[18] There are several reasons why Airbnb penetration might increase housing prices. First, the price of a house represents the present value of all the future cash flows generated from owning the house. As long-term rental rates increase, house prices increase as well. Second, the option for short-term rentals could reduce householders'

is the effect of both more rentals in the short-term market and increased long-term rental prices (a drop in long-term rental supply leads to increases in long-term rental prices; short-term rental prices are also higher than those of long-term rentals), Therefore, it is possible that households gain higher rental income from either the short-term rental market or the long-term rental market. This implies that not only Airbnb hosts benefit through the rental income channel, but owners who have long-term rentals may also gain higher rental income through Airbnb penetration.Our finding on the magnitude of rental income is comparable to that indicated in the literature. Our average Airbnb growth rate is 46.5 percent; therefore, an average Airbnb growth rate accounts for 0.4 percent (=46.5%×0.009) in annual rent growth, which is similar to the findings of Barron et al. (2021).[19] 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 Firm survey, the average cost of starting a new business from scratch was about $31,150 (in 2008 dollars).[20] According to the ACS data, the average rental income per household across the U.S. was $4,202 in 2008. Therefore, the rental income from Airbnb accounts for about 13.4 percent (=4,202/31,150) of the startup cost, representing a nontrivial proportion.

We also examine whether our results are driven by increases in rental income or by increases in collateral value. To start, we test whether Airbnb spurs new business creation more in counties with higher growth in rental prices. 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 for growth during 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 the creation of new business is stronger in counties with higher rental price growth, confirming that rent increases could be one underlying channel. We then examine whether the results are driven by the increase in collateral value 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

propensity to put their houses on sale in the market; the resulting reduction in housing supply could also increase house prices.

[19] 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 percent growth in annual rent.

[20] See https://www.kauffman.org/entrepreneurship/reports/kauffman-firm-survey-series/an-overview-of-the-kauffman-firm-survey-20042008/ for Kauffman survey.

instrumented Airbnb listing and *I{high house price growth}* is insignificant, suggesting that the effect of Airbnb on new business creation is similar across counties that experience high and low growth in house prices.[21] Because house prices could be endogenous to the creation of local firms, we also split the sample in two other ways. Table 5 column 3 shows counties in the sample split into those with high and low land-use regulation using the Wharton Residential Land Use Regulation Index (Gyourko, Saiz, and Summers, 2008). Table 5 column 4 shows the sample split into counties with high and low elasticity in housing supply 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 the creation of new business is similar in counties with high and low land-use regulation as well as in counties with high and low housing-supply elasticity. In Internet Appendix Table IA5, we also show that Airbnb penetration does not increase the likelihood for entrepreneurs to get second mortgages. Taking the above evidence together, we conclude that our results are more likely to be driven by an increase in rental income than by increases in collateral value.[22]

As passive income earned from the property ownership, rental income is different from the labor income earned through other sharing economy platforms such as Uber and Lyft. Passive income is particularly useful for entrepreneurs because entrepreneurship is typically more time-consuming than paid work. If entrepreneurs have more time flexibility, the new businesses they started could be larger and of higher quality. To test this conjecture, we examine the effect of Airbnb penetration on sales and on sales per employee of newly started firms at their entrance year; the results are shown in Table 6. It appears that Airbnb penetration leads to higher sales and to higher sales per employee; this is consistent with the conjecture that entrepreneurs have more time flexibility with passive income earned under Airbnb penetration.

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

[22] It is worth noting that our evidence does not imply that house-price appreciation has no impact on the creation of new business. Instead, our findings suggest only that Airbnb expansion is more likely to spur new business creation through increased rental opportunities (and hence more rental income) than through increased house prices. There are three reasons that could explain this observation. First, the increase in house prices 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 their new businesses fail. Third, for primary homes, the mortgage rate for second liens is usually high; for rental properties, taking a second lien loan is usually difficult. In contrast, obtaining rental income is relatively easier and less costly.

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 the creation of new business (Adelino, Ma, and Robinson, 2017). We hypothesize two ways that Airbnb increases local demand. 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 tourists can spend on non-lodging services. With more 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 a restaurant given increased local demand.

To test our hypotheses, we first examine how Airbnb penetration affects the tourist flow; these results are shown in Table 7. We proxy the number of visitors by incoming air passengers and collect data on US domestic airline traffic published by the Bureau of Transportation Statistics." The data set records the total number of passengers arriving at 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 logarithm of one plus the number of incoming air passengers to airports that are located within twenty-five miles of a county. As expected, Table 7 column 1 shows that Airbnb penetration leads to a positive and significant increase in the total number of air passengers to a town. We further break down the sample by the flight distance traveled by incoming air passengers. We find that the increase is mainly in the sample in which travelers travel for more than 1,000 miles but not in the sample in which the travelers travel fewer than 1,000 miles. Given that a longer flight distance is likely to correlate with a longer stay, this result suggests that Airbnb is more likely to attract visitors who stay for more nights. The finding is consistent with a survey that shows that Airbnb guests tend to stay longer than hotel guests.[23] One underlying reason may be that Airbnb rentals charge a one-time cleaning fee—a nontrivial cost—regardless of the length of the stay.[24] Therefore, a short stay of only one day at Airbnb is not necessarily more advantageous than staying at hotel.

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[23]According to the survey, "Airbnb guests typically stayed longer than the average hotel guest, with roughly half of Airbnb roomnights coming from trips of seven days or longer" (Haywood, Mayock, Owoo, and Fiorilla, 2017).
[24] According to Pohle (2022), "in the U.S., about 85 percent of short-term rental listings have a cleaning fee."

We then 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 8. We find that Airbnb penetration significantly lowers hotel revenues, reduces occupancy rates, lowers room prices, and hurts revenues per the number of available hotel rooms. The results suggest that, for tourists with the same budget, lodging costs are less with Airbnb entry, and thus tourists have more available to spend 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 information on local residents' income from the IRS's Individual Tax Statistics and report the results in Table 9. Table 9 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).[25] The results suggest that, as Airbnb increases local demand, local businesses are able to obtain more income.

An implication of Table 9 is that the higher business income following Airbnb penetration is not accompanied by higher wages for employees. To see whether higher business income could be accompanied by higher rates of employment, we show how Airbnb penetration affects employment in Table 10. Specifically, we aggregate establishment employment information in the YTS data to the county level, and obtain the unemployment rate from the Bureau of Labor Statistics data. In Table 10 column 1, we report how Airbnb affects the total number of jobs in a county. The coefficient estimate is positive and significant at the 1 percent level, suggesting that Airbnb penetration increases total job creation. Consistently, in column 2, we find that the unemployment rate decreases significantly following Airbnb penetration.

We further examine job creation by new firms and existing firms. As expected, we find that a significant number of jobs are created by the new firms (column 3). We next examine whether the jobs created by new firms crowd out the jobs created by existing firms. As shown in Table 9 column 4, Airbnb penetration does not seem to have a significant effect on job creation by existing firms, which suggests that there is no crowding-out effect. We then break down the

[25]Individuals only file Schedule C to report business income when they operate a business as a sole proprietor. Therefore, personal business income is also a measure reflecting entrepreneurial income.

employment of existing firms by their number of employees and categorize the firms into “large,” which employ at least 10 people, versus “small,” which employ fewer than 10 people. We find that Airbnb penetration does not lead to significant changes in the employment by those “large” existing firms (as shown in column 5). Interestingly, Airbnb penetration increases the number of employees 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 creation.

Finally, if the local demand channel is the one through which Airbnb penetration promotes entrepreneurship, we should observe that Airbnb penetration increases the creation of businesses in industries that are sensitive to local demand. To this end, we follow the definition in Mian and Sufi (2014) and classify businesses as in the 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 those industries in the tradable sector (Adelino et al., 2015; Adelino et al., 2017). In Table 11, we show that Airbnb penetration significantly and positively affects business creation in both the tradable and non-tradable sectors. The elasticity of new business creation with regard to Airbnb penetration is larger in tradable industries. However, if we take into account the average number of businesses created across both tradable and non-tradable sectors, the magnitude of the effect is larger in the non-tradable sector than in the tradable sector.[26]

In addition to investigating the aggregate of businesses created in tradable and non-tradable sectors, we examine business creation in each industry. In Figure 6, we plot the number of firms created caused by a 10 percent increase in local Airbnb listings across industries. Industries that are observed to be more sensitive to local demand tend to have larger increases in the number of new firms created; these industries include: Construction; Retail Trade; Other Services; Professional, Scientific, and Technical Services; Real Estate and Rental and Leasing; Transportation and Warehousing; and Accommodation and Food Services. In contrast, there are few changes in industries, such as Utilities, that seem unaffected by local demand.[27] The results

[26] 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.
[27] The pattern is consistent with the findings of Kerr, Kerr, and Nanda (2022) that construction tends to respond strongly to increase in local demand.

suggest that the penetration of Airbnb leads to 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 increases the creation of new businesses. Specifically, Airbnb entry attracts more tourists to the local region and reduces their lodging cost. As a result, local income and employment increases, and more businesses are created, especially in industries that are sensitive to local demand.

5.5 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, householders 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 the creation of new business is mainly driven by higher levels of risk tolerance rather than by 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 report a higher rate of failure (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 12 Panel A, 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 fewer than three years. The coefficient estimate on the instrumented Airbnb variable in column 2, however, is positive and significant at the 1 percent level, suggesting a positive effect of Airbnb's growth on the creation of new businesses that survive for a long period (more than three years). In fact, 83 percent 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 business survival rate in the U.S. According to National

Business Capital, as of 2019, the average two-year survival rate for new startups is 30 percent.[28] Overall, the results suggest that the new businesses created as a result of Airbnb penetration 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 and report the results in Table 12 Panel B. First, we examine short-term performance by testing revenue (measured by sales) and productivity (measured by sales per employee) at the entrance year. To control for time-varying industry trends, we add industry-by-year fixed effects in addition to county-fixed effects. The coefficient estimates on the instrumented Airbnb variable in columns 1 and 2 are positive and significant at the 1 percent 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 percent level, suggesting that Airbnb's expansion also positively affects long-term revenues and productivity. The findings reported in Table 14 suggest that Airbnb does not spur startups with poor quality, which is consistent with the findings in Table 12 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 the expansion of Airbnb.

6. Case study

In addition to the instrumental variable approach, we use exogenous shocks directly to Airbnb listings as a robustness check to our identification. A natural candidate is short-term rental restrictions, which limit Airbnb penetration in an area. However, it is difficult to get systematic short-term restriction data for the entire U.S., and many of these restrictions start after 2015, the end of our sample. Therefore, we resort to a case study for a single state, New York.

In New York, the Multiple Dwelling Law (hereafter MDL), which was enacted in 1929, sets minimum standards for multiple dwellings. In 2010 (two years after Airbnb's founding), the

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

law was amended in an effort to fight illegal hotels. The amendment requires that multiple dwellings be occupied by the same person or family for at least thirty days.[29]

The passage of the MDL amendment provides a DD setting for analysis for two reasons: passage of this amendment restricts short-term rental and thus restricts Airbnb's development, and the MDL applies only to municipalities with populations of 325,000 or more. Only New York City and Buffalo meet the law's population requirement (Shortt, 2011). Therefore, there are both treatment and control groups.

Using the MDL amendment as a shock to Airbnb penetration, we conduct analysis at the county-year level within the State of New York. Specifically, we run the following regression.

$$Y_{i,t+1} = \alpha + \beta Restricted_i \times RPost_t + \gamma Z_{i,t} + County_i \ + Year_t + \varepsilon_{i,t+1} \quad (6)$$

where $Y_{i,}$ is either $Ln(Airbnb)_{i,t+1}$, or $Ln(number\ of\ firms\ created)_{i,t+1}$. $Restricted_i$ is a dummy variable that equals one for counties containing cities affected by the MDL amendment.[30] $RPost_t$ is a dummy variable that equals one after the MDL amendment. The results of estimating Equation (6) are reported in Internet Appendix Table IA6 and show that the MDL law amendment has reduced Airbnb listings in the affected cities by about 70.6 percent, and reduced the creation of new firms in the affected areas by about 19.2 percent.[31] This case study confirms our findings that Airbnb entry and expansion boosted local entrepreneurship.

7. Conclusion

We find that both staggered entry and gradual penetration of the sharing economy increase the creation of new businesses in local regions. We document two novel channels underlying the results. In the first, Airbnb increases rental income, which relaxes the financial constraints on potential landlord entrepreneurs and provides them with greater time flexibility. In the second, Airbnb attracts more tourists and enables them to save money on lodging, thereby increasing their

[29] As in Shortt (2011), a multiple dwelling is defined as "a dwelling which is either rented, leased, let or hired out, to be occupied, or is occupied as the (temporary or permanent) residence or home of three or more families living independently of each other."

[30] Specifically, *Restricted* takes a value one for the following counties: Erie County for Buffalo (FIPS 36029), New York County for Manhattan (FIPS 36061), Queens County for Queens (FIPS 36081), and Kings County for Brooklyn (FIPS 36047). We did not include the other two New York City boroughs, Bronx and Staten Island, because the rule change affects only multifamily buildings, not single or two-family buildings, There are relatively few multifamily buildings in these two boroughs.

[31] The coefficient estimate in column (1) is -1.224. Therefore, the amended MDL reduces Airbnb listings by -70.6% ($e^{-1.224} - 1$), and the amended MDL reduces the creation of new firms by -19.2% (= $e^{-0.213} - 1$).

spending power for other purchases; this leads to an increase in local demand, as reflected in an increase in local income and employment. The increase in local demand presents more investment opportunities for startups. The finding has important policy implications and is of particular interest to policy makers because the sharing economy could generate demand that did not previously exist, and thus could impose a positive spillover effect into the local economy.

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Figure 1: Trend in Airbnb Listings

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

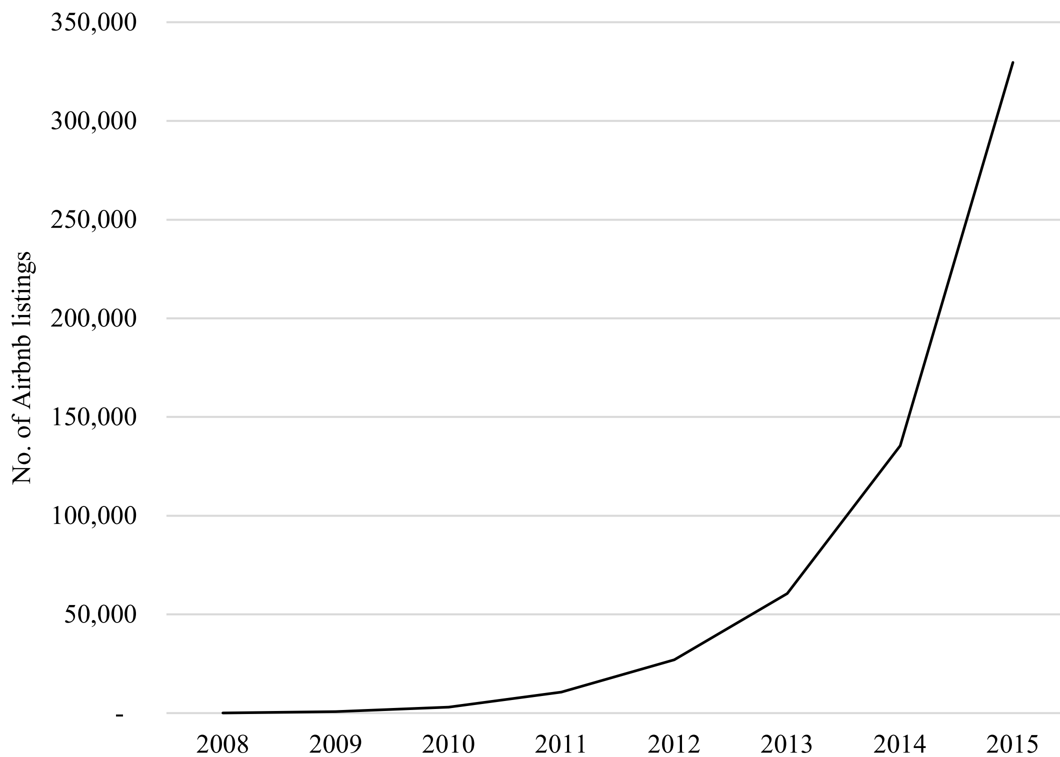


Figure 2: Distribution of Airbnb Listings

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

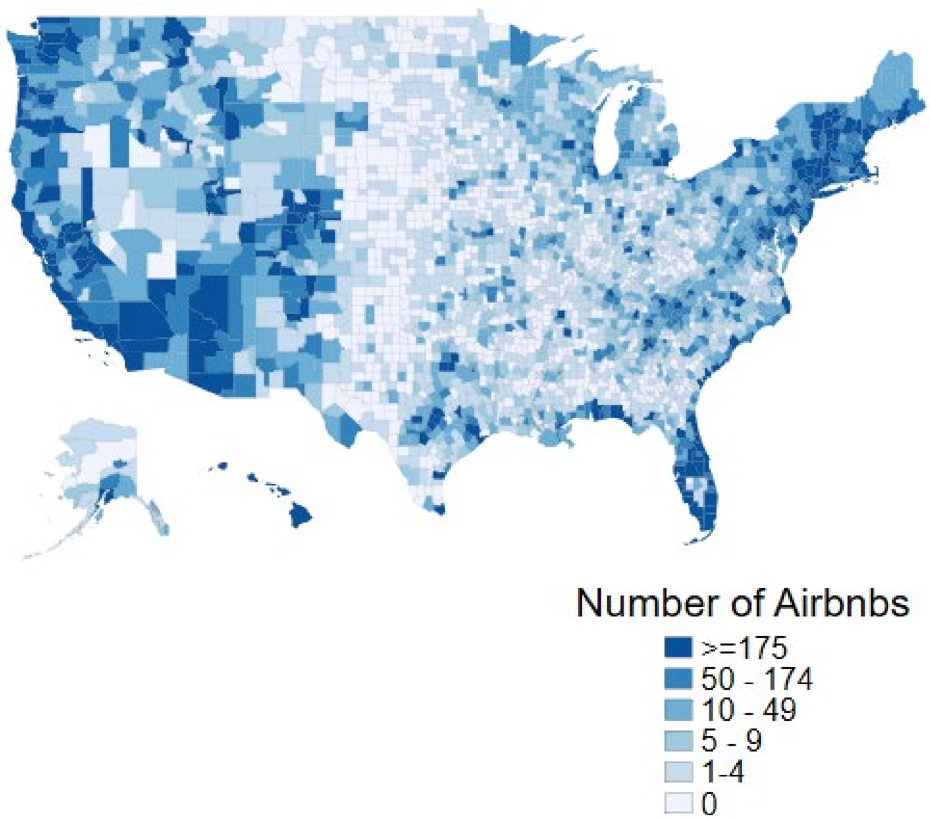


Figure 3: Distribution of New Startups

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

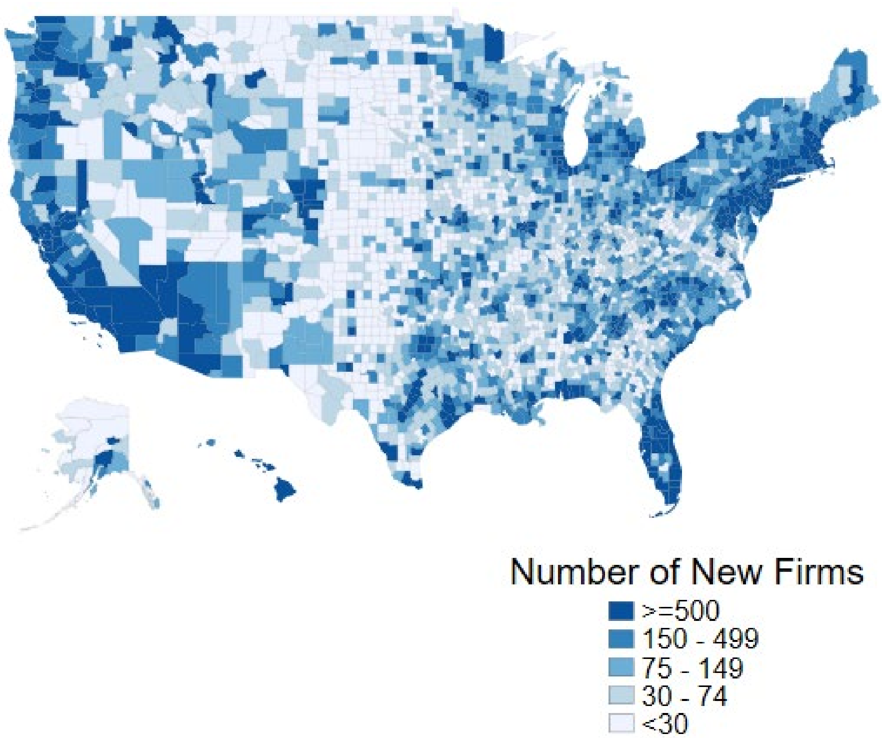
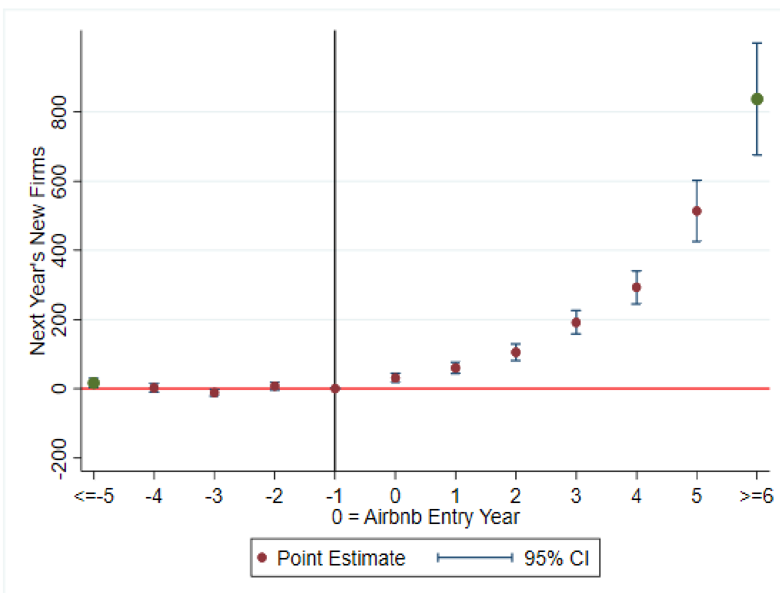


Figure 4: Dynamic Effects of Airbnb Entry on Local Business Creation

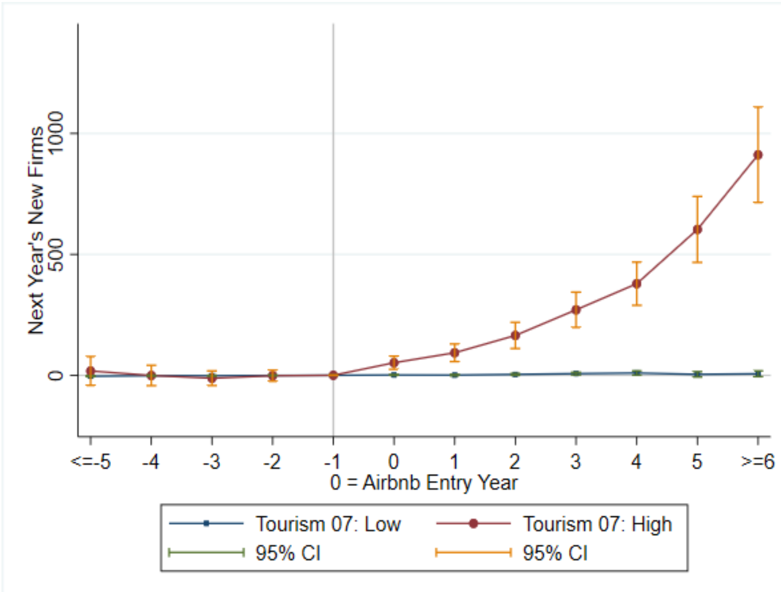
This figure shows the results of ordinary-least-square estimation of the dynamic effects of Airbnb entry on local entrepreneurship. We estimate the following equation:

$$Number\ of\ Firms\ Created_{i,t+1}$$
$$= \alpha + \beta_{-5}1(t \leq -5)_{i,t} + \sum \beta_t 1(t = \tau, -4 \leq \tau \leq 5, t \neq -1)_{i,t} + \beta_6 1(t \geq 6)_{i,t}$$
$$+ \gamma Z_{i,t} + County_i + Year_t + \varepsilon_{i,t+1}$$

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 observations from one year prior to Airbnb's entry into a county (t=–1). Panel (a) shows the full sample results. Panel (b) shows the estimation in two subsamples based on 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.



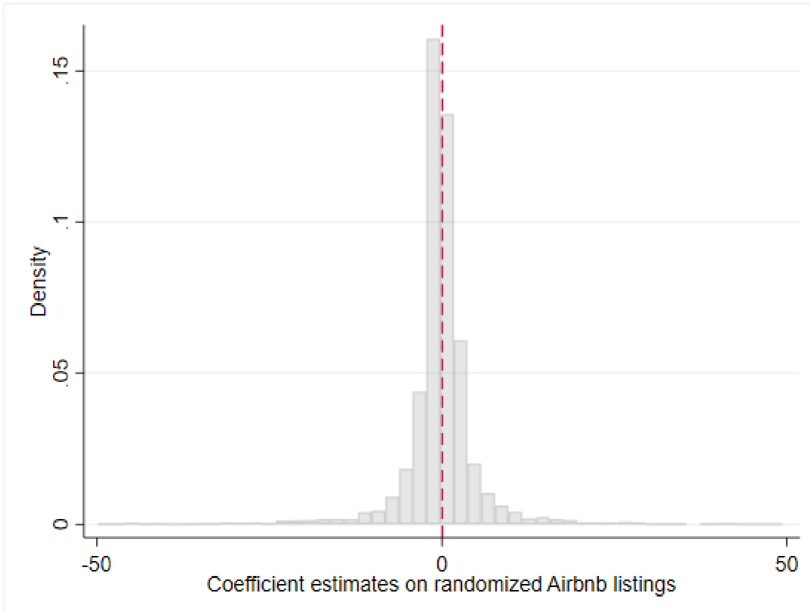
(a) Full sample



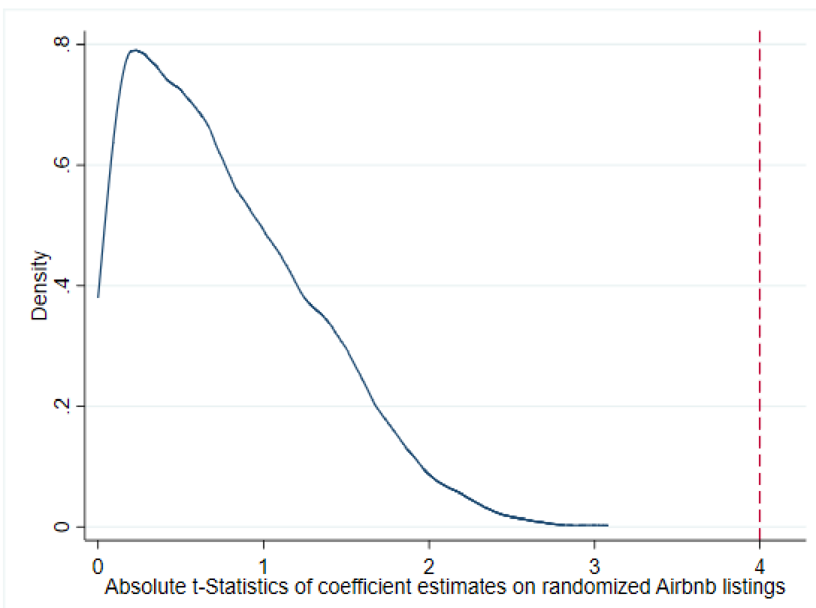
(b) By tourism in 2007

Figure 5: Placebo Test: Randomized 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.



(a) Coefficient estimates



(b) t-statistics

Figure 6: Airbnb and Firm Creation: By Industry

This figure plots the number of firms created in different industries as the result of a 10 percent increase in local Airbnb rooms. The numbers in the figure are obtained by multiplying the coefficient estimate from two-stage least-squares regressions by the mean number of new firms created in each industry and by 10 percent. The 2-digit NAICS codes classify 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).

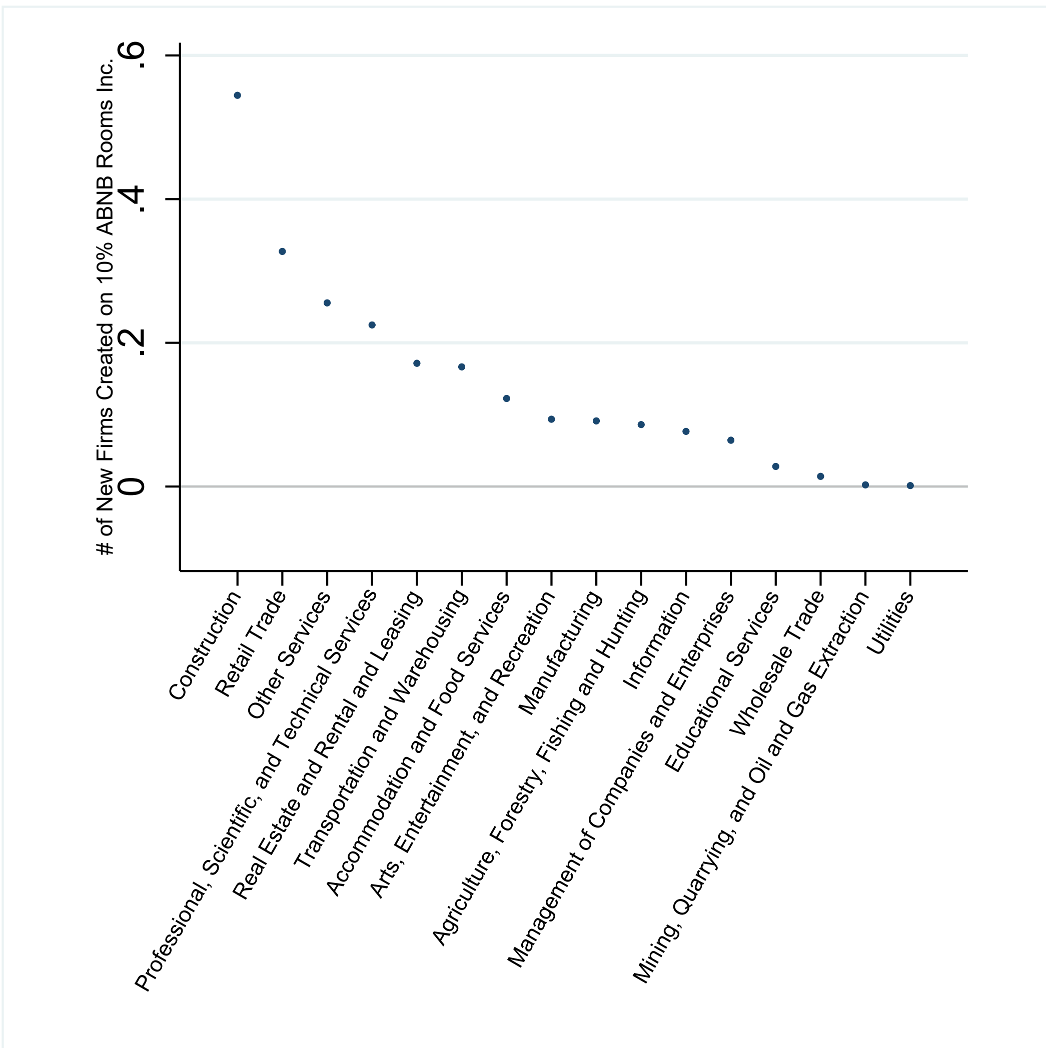


Table 1: Summary Statistics

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-year 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 Airbnb's effect on 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-squares estimation of how Airbnb affects entrepreneurship. Columns (1) and (2) show the results of the OLS regressions with the logarithm of the number of new firms created being the dependent variable. Columns (3) and (4) show the two-stage least-squares estimation. Column (3) presents first-stage results with the 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-squares estimation of how Airbnb affects an individual's likelihood of becoming an entrepreneur by exploring heterogeneity in whether an individual receives rental income. The outcome variables in columns (1) and (2) are indicators of whether an individual is an entrepreneur; those in columns (3) and (4) are indicators of whether an individual is an entrepreneur who receives positive business income. 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 1,000 times and are 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 Income versus Collateral Value

This table presents two-stage least-squares estimation of whether Airbnb affects entrepreneurship through rental income or through collateral value. The outcome variable is the logarithm of the number of new firms created in a county-year. We use rental price growth as the local rental market measure (column 1). We use local house-price growth (column 2), the local land-use regulation index (column 3) from Gyourko et al. (2008), and housing elasticity (column 4) from Saiz (2010) as measures of the local housing market. 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 New Firm Performance

This table presents two-stage least-squares estimation of how Airbnb affects initial performance of new firms. The outcome variable in column (1) is the logarithm of sales and the variable in column (2) is the logarithm of sales per employee. Industry is measured by four-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	
	Ln(sales)	Ln(sales/ employees)
	(1)	(2)
Instrumented Ln(Airbnb listings)	0.085***	0.073***
	(0.014)	(0.013)
Controls	Yes	Yes
County-fixed effect	Yes	Yes
Industry-year-fixed effect	Yes	Yes
Observations	8,466,955	8,466,955
Adjusted R^2	0.653	0.865

Table 7: Airbnb and Local Incoming Air Passengers

This table presents two-stage least-squares estimation of whether Airbnb affects the number of incoming air passengers in the focal county and nearby airports. The outcome variable in column (1) is the logarithm of the total number of air passengers into a county in a year. The outcome variables in columns (2), (3), and (4) are the logarithm numbers of incoming air passengers traveling from an airport from a distance—that is less than 1,000 miles, between 1,000 miles and 2,000 miles, and more than 2,000 miles, respectively—to the airport within 25 miles of a county. Information on incoming passengers was collected from the Bureau of Transportation Statistics, US 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.<1,000 Miles	Dist.1,000-2,000 Miles	Dist.>2,000 Miles
	(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 8: Hotel Performance

This table presents two-stage least-squares estimation of whether Airbnb affects the revenue and price of local hotels. The outcome variable in column (1) is the logarithm of hotel revenue, the occupancy rate is in column (2), the logarithm of room price is in column (3), and the logarithm of revenue per available room is in column (4). We follow the empirical specification of Farronato and Fradkin (2022) and include a land inelasticity dummy (equals one if the elasticity measure estimated in Saiz [2010] is below median value in the sample), the supply of hotels 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 9: Airbnb and Local Income and Wage

This table presents two-stage least-squares 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 in column (2) is the logarithm of the mean value of non-wage income, in column (3) is the logarithm of the mean value of business income (sub-category of non-wage income), and in column (4) is the logarithm of the mean value of wage income. The data is collected from the IRS Individual Tax Statistics. County controls include all additional variables as in Table 3. All variables are defined in the Appendix and winsorized at the 1st and 99th percentiles. Standard errors are clustered at the county level and presented in parentheses. *** indicates p<0.01, ** indicates p<0.05, and * indicates p<0.1.

	Ln(Adj. Gross Income) (1)	Ln(Non-wage) (2)	Ln(Business Income) (3)	Ln(Wage) (4)
Instrumented Ln(Airbnb listings)	0.007*** (0.003)	0.025*** (0.004)	0.032*** (0.002)	0.001 (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 10: 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 by old firms, and the unemployment rate. The outcome variable in column (1) is the logarithm of employment in a county and the unemployment rate is in column (2). Column (3) is the logarithm of jobs created by new firms. The logarithm of employment in all existing firms is in column (4), the logarithm of employment in existing large firms with employment size greater than 9 is in column (5), and the logarithm of employment in existing firms with employment size equal to or smaller than 9 is in column (6). 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(employme-nt)	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 Ln(Airbnb listings)	0.002***	-0.142***	0.020**	-0.003	-0.004	0.009***
	(0.001)	(0.017)	(0.008)	(0.002)	(0.002)	(0.001)
County controls	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,191	19,191	19,191	19,191	19,191	19,191
Adjusted R^2	0.999	0.931	0.923	0.998	0.997	0.999

Table 11: Airbnb and Firm Creation: By Sectors

This table presents the two-stage least-squares estimation of Airbnb's effect on entrepreneurship in different sectors and industries. The outcome variables in columns (1) and (3) are the logarithms of the number of new firms created in the tradable sector; columns (2) and (4) present the logarithm of the number of new firms created in the non-tradable and construction sectors. Sector definitions are from 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 12: Airbnb and New Firm Survival

This table presents two-stage least-squares estimation of Airbnb's effect on the long-run performance of newly created firms. Panel A examines 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 closed within three years after entering. The outcome variable in column (2) is the logarithm of the number of new firms created in a county-year that survived more than three years after entering. Panel B examines how Airbnb affects performance of new firms. The outcome variables in columns (1) are the logarithm of sales and those in columns (2) are the logarithm of sales per employee. Industry is measured by four-digit NAICS. Controls include all additional variables included in Table 3. 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.

Panel A: New firm survival

	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	

Panel B: New firm long-run performance

	Three years after entrance	
	Ln(sale)	Ln(sales/ employees)
	(3)	(4)
Instrumented Ln(Airbnb listings)	0.079***	0.063***
	(0.006)	(0.005)
Controls	Yes	Yes
County-fixed effect	Yes	Yes
Industry-year-fixed effect	Yes	Yes
Observations	3,510,949	3,510,949
Adjusted R^2	0.505	0.745

Appendix: Variable Definitions

Variable	Definition
County-level measures	
Airbnb listings	The number of Airbnb listings in a county. Source: Airbnb.
Income	Median household income in a county. Source: Census.
Unemployment rate	The unemployed population divided by the sum of unemployed and employed population in a county. Source: Bureau of Labor Statistics.
Labor force rate	The sum of employed and unemployed populations divided by the total population in a county. Source: Bureau of Labor Statistics and Census.
House price	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	Total population in a county. Source: Census.
White rate	White population in a county divided by the total population of that county. Source: Census.
Age 20–64 rate	Population between ages 20 and 64 in a county divided by the total population in that county. Source: Census.
Age 65+ rate	Population at or above 65 years of age in a county divided by the total population in that county. Source: Census.
College rate	The number of employees in a county who have obtained some college or Associate, Bachelor's, or advanced degrees divided by the total employees in a county. Source: Census.
Number of firms created	The number of single-stand establishments in a county that exist in the current year but not in the previous year. Source: Your-economy Time Series.
New branches of existing firms	The number of branch establishments in a county that exist in the current year but not in the previous year. Source: Your-economy Time Series.
Number of jobs created by new firms	Employment of single-stand establishments in a county that exist in the current year but not in the previous year. Source: Your-economy Time Series.
Employment of existing firms	Employment of establishments in a county that exist in both the current year and the previous year. Source: Your-economy Time Series.
Employment in hotel industry	Employment in hotel industry (NAICS 7211) in a county. Source: Your-economy Time Series.
Landlords	The number of households in a county that receive interest, dividend, or rental income. Source: Census.
Vacant for seasonal rental	The number of units in a county that are vacant for seasonal rental. Source: Census.
Vacant for long-term rental	The number of units in a county that are vacant for long-term rental. Source: Census.
Long-term rental price	The rents of rental units in a county. Source: Department of Housing and Urban Development (HUD) Fair Market Rents Database.
Survival rate	The percentage of establishments that exist in the sample three years

	after the entrant year. Source: Your-economy Time Series.
I{low local bank share}	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 a local bank if 50 percent or more of its deposits are concentrated in a single county. Source: Federal Deposit Insurance Corporation.
I{high house price volatility}	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}	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}	An indicator that takes a value of one if the house-price growth in a county is above the median of the same period, and zero otherwise. Source: Federal Housing Finance Agency.
I{high land use regulation}	An indicator that takes a value of one if the restrictiveness of the land-use regulation in a county is greater than the sample median, and zero otherwise. Source: Gyourko et al (2008).
I{low house elasticity}	An indicator that takes a value of one if the housing supply elasticity in a county is below than the sample median, and zero otherwise. Source: Saiz (2010).

Individual-level measures

I{entrepreneur}	An indicator that takes a value of one if an individual is self-employed, and zero is an individual works for someone else or is unemployed. Source: Census American Community Survey.
I{entrepreneur with business income}	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}	An indicator that takes a value of one if an individual receives positive interest, dividend, or rental income, and zero otherwise. Source: Census American Community Survey.
Age	The age of an individual. Source: Census American Community Survey.
I{home owner}	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}	An indicator that takes a value of one if an individual was employed in the last year, and zero if unemployed. Source: Census American Community Survey.
I{male}	An indicator that takes a value of one if an individual is male, and zero if female. Source: Census American Community Survey.
I{white}	An indicator that takes a value of one if an individual is white, and zero if otherwise. Source: Census American Community Survey.
I{black}	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}	An indicator that takes a value of one if an individual has no college education, and zero if otherwise. Source: Census American Community Survey.
I{mid-skilled}	An indicator that takes a value of one if an individual received 1–3 years of college education, and zero if otherwise. Source: Census American Community Survey.

Internet Appendix to
"Resurrecting Dead Capital:
The Sharing Economy, Entrepreneurship, and Job Creation"

This Internet Appendix provides robustness tests and supplemental analyses to the main results presented in "Resurrecting Dead Capital: The Sharing Economy, Entrepreneurship, and Job Creation."

Section 1 Supplemental tests for main results

In this section, we conduct supplemental tests for the main results.

In Internet Appendix Table IA1, we report the estimation of a Cox proportional hazards model for Airbnb entry into the counties. 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 until a county had its first Airbnb entry. As shown in the table, the rollout timing of the 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.

In Internet Appendix Table IA2, we report the results of several robustness tests on the baseline regression and report the results. In column 1, we demonstrate the 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 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 our results could be driven by unobservable industry-specific shocks that are correlated with the entry of Airbnb. We continue to find a strong, positive effect of Airbnb listings on the creation of new firms after controlling for the industry-year-fixed effects.

In Internet Appendix Table IA3, we examine how the instrument affects the number of new firm creations in counties with no Airbnb entry ever and in counties with some Airbnb entry. In column 1, the coefficient estimate on the instrumental variable is close to zero and statistically insignificant. In contrast, in column 2—where we report the regression as described in Equation (3) for counties with Airbnb entries during our sample period—we find a strong, positive coefficient estimate on the instrumental variable.

Section 2 Supplemental tests for passive income channel

In this section, we conduct supplemental tests for the passive income channel.

In Internet Appendix Table IA4, we report the 2SLS estimates that regress rental market variables on the instrumented Airbnb variable. We first investigate how Airbnb affects the housing supply in the short-term rental market (column 1) and housing supply in the long-term rental market (column 2). We use the number of vacant units available for seasonal use as a proxy for the short-term rental market supply and the number of 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 simultaneously decreases the housing supply in the long-term rental market. The reduction in the long-term rental market supply suggests that, with the local penetration of Airbnb, more households transfer their vacant units—previously used to target long-term tenants—to short-term rentals. As supply decreases, the market price in the rental market may be affected. We use the Fair Market Rents Database from the Department of Housing and Urban Development as the proxy for rent in a county; column 3 shows that Airbnb penetration increases the rental price. In Internet Appendix Table IA4 column 4, we further show that Airbnb penetration lead to an increase in house prices.

In Internet Appendix Table IA5, we directly examine the plausibility of the collateral channel using individual-level mortgage data from ACS and report the results. We use the information on second mortgages 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 a 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 Internet Appendix 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 a second mortgage. This finding suggests that Airbnb does not affect entrepreneurship through increases in collateral value.

Section 3 Financial constraints

In this section, we examine the heterogeneity of our results across samples with different levels of financial constraints.

To begin, we explore entrepreneurs' ex ante access to credit by county. 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 percent or more of its deposits are concentrated in a single county. This method builds on the importance of local bank credit to entrepreneurship (Petersen and Rajan, 1994, 2002; Guiso et al, 2004). Compared to large, established firms, startups are more opaque and require more screening and monitoring, making fundraising at a distance more difficult. Therefore, entrepreneurs in counties with fewer local banks are likely to have less 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 Internet Table IA6 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 percent level. The results suggest that Airbnb's impact on the creation of new business is more pronounced in areas with lower proportion of deposits in local banks.

Second, we use the volatility of housing prices as a proxy for entrepreneurs' access to credit. The volatility of housing prices affects banks' willingness to lend against real estate (Mao, 2021). In counties with higher house-price volatility, access to credit is likely to be worse; such areas are more likely to benefit from increased rental opportunities or from an increase in local demand. To test this conjecture, we classify the sample into two groups by house-price volatility, which is measured as the standard deviation in a county's house-price index in the previous twenty years. 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).* Internet Appendix Table IA6 column 2 shows that the coefficient estimate on the interaction term is positive and significant at the 5 percent level, suggesting that the effect of Airbnb on the creation of new business is more pronounced in regions with higher house-price volatility.

Third, we use the refinance denial rate as a measure of entrepreneurs' access to credit. In counties where the rate of denial on refinance applications is higher, homeowners are less likely to extract equity from a home, and thus to have worse access to credit. Therefore, counties where denial rates on refinance applications are higher should have more new businesses created following local Airbnb growth. To test this conjecture, we extract all US refinance mortgage data from the database of the Home Mortgage Disclosure Act.[32] 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. Internet Appendix Table IA6 column 3 presents the results. The coefficient estimate on the interaction term is positive and significant at the 1 percent 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 the creation of new firms through two channels. In the first channel, 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. In the second channel, 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 smaller, more opaque firms than it is to large firms. If the conjecture is supported, we should observe more creations of small startups in local counties following Airbnb penetration. 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 percent level as reported in Internet Appendix Table IA7 column 1, but it is insignificant in column 2; 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 need 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 creation in industries that require less startup capital. If Airbnb spurs new business creation by relaxing financial constraints, we should observe a stronger effect in industries that require less startup capital. The results are consistent

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

with our conjecture. Internet Appendix Table IA7 column 3 shows a positive and significant effect of Airbnb listings on the creation of new startups among industries with below-median needs for startup capital; Internet Appendix Table IA7 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 the creation of firms is more pronounced in counties with worse access to credit, as measured by lower proportion of deposits in local banks, higher house-price volatility, and lower refinance denial rates. We also find a 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.

Section 4 Case study

In this section, we use the MDL amendment as a shock to Airbnb penetration, and conduct analysis at the county-year level within the State of New York. In Internet Appendix Table IA6, we show that the MDL law amendment has reduced Airbnb listings in the affected cities by about 70.6 percent, and reduced the creation of new firms in the affected areas by about 19.2 percent.[33] This case study confirms our findings that Airbnb entry and expansion boosted local entrepreneurship.

[33] The coefficient estimate in column (1) is -1.224. Therefore, the amended MDL reduces Airbnb listings by -70.6% ($e^{-1.224} - 1$), and the amended MDL reduces the creation of new firms by -19.2% ($= e^{-0.213} - 1$).

Table IA1: Cox Proportional Hazard Model

This table presents results from Cox proportional 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 until a county had its first Airbnb entry. In column (1), we include only the annual change in new business formation. In columns (2) through (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-squares 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 Airbnb's effects on 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 that never had any Airbnb listings from 2008 through 2015. Column (2) considers counties with some Airbnb listings in any year from 2008 through 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)	
	Counties without Airbnb ever (1)	Counties with some Airbnb (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-squares estimation of how Airbnb affects the rental market. The outcome variable in column (1) is the logarithm of vacant units available for seasonal rental, in column (2) is the logarithm of vacant units available for long-term rental, and in column (3) is the logarithm of rental price. The outcome variable in column (4) is the housing price index collected from the 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-squares estimation of how Airbnb affects an individual's likelihood of becoming an entrepreneur and explores heterogeneity in whether the individual refinances through a second mortgage. The outcome variables in columns (1) and (2) are indicators of whether the individual is an entrepreneur and those in columns (3) and (4) are indicators of whether the individual is an entrepreneur with positive business income. 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) × I{second mortgage}	-0.106		-0.055	
	(0.199)		(0.134)	
I{second mortgage}	0.022***		0.009***	
	(0.001)		(0.001)	
Instrumented Ln(Airbnb listings) × I{home equity loan}		-0.073		-0.129
		(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

Table IA6: Heterogeneity in Access to Credit

This table presents two-stage least-squares 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 measures of local access to credit. 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(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 IA7: Disaggregation by Startup Capital Needs

This table presents two-stage least-squares estimation of how Airbnb affects entrepreneurship, disaggregated by startup capital needs. The outcome variables in column 1 are the logarithm of new firms created in a county-year with fewer than 10 employees; in column 2 are the logarithm of new firms created in a county-year with 10 or more employees in column 3 are the logarithm of new firms created in a county-year in industries with below-median needs for startup capital; and in column 4 are the logarithm of new firms created in a county-year in industries with above-median needs for startup capital. 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
	(1)	(2)	(3)	(4)
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 IA8: Short-term Rental Restriction, Airbnb, and Entrepreneurship

This table presents OLS estimation of how restrictions on short-term rentals affects Airbnb listings and new firm creation. Restricted is a dummy variable that equals one for counties containing cities affected by the MDL amendment. RPost is a dummy variable that equals one after the MDL amendment. 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 (Airbnb listings) (1)	Ln (number of firms created) (2)
Restricted × RPost	-1.224***	-0.213**
	(0.389)	(0.098)
Ln(income)	1.081	0.191
	(1.665)	(0.506)
Unemployment rate	0.268	-0.196***
	(0.198)	(0.050)
Labor force rate	-0.127	-0.020
	(0.122)	(0.024)
Ln(house price)	-2.046	0.426
	(3.215)	(0.961)
Ln(population)	-10.902	5.823
	(10.260)	(3.542)
White rate	0.142	-0.148
	(0.372)	(0.121)
Age 20–64 rate	-0.606	0.084
	(0.416)	(0.124)
Age 65+rate	-0.634	0.175*
	(0.389)	(0.095)
College rate	0.233	-0.037
	(0.244)	(0.058)
Constant	156.392	-58.286
	(126.652)	(45.392)
County-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
Observations	249	249
Adjusted R^2	0.936	0.983