Airbnb and Private Investment in Chicago Neighborhoods

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Abstract

The Airbnb-based home-sharing platform reduces the market frictions of short-term rentals, which raises the potential economic returns to a property. The conversion of residential units into tourist accommodation and the associated new revenue flows create incentives for capital investment. This study examines how the expansion of the Airbnb market has stimulated capital investment in Chicago neighborhoods. The instrumental variable estimates show that, given a 1% increase in the Airbnb listings, the number building permits issued in a quarter increased by 0.84% while capital investment increased by 3.19% or $81,000 equivalently. Besides direct investment in residential properties, we find spillover capital flows to retail and commercial zones where amenities and businesses arise to meet the demand of the shifting population. We show that the effects were primarily driven by commercial hosts rather than casual hosts. Moreover, Airbnb disproportionately enhanced capital investment in declining and stable communities.

Introduction

Neighborhood redevelopment is a key driver of urban decline and renewal (Rosenthal, 2018). Periodic redevelopment of deteriorated housing stocks been prevalent in American cities, where existing housing stock is upgraded through renovation and remodeling or torn down and replaced by new housing (Dye and McMillen, 2007). The urban spatial growth theory expects that redevelopment will occur when the price of land for new development, minus the replacement capital expenses, exceeds the price of land in its current use (Brueckner, 1980; Wheaton, 1982). Likewise, the rent gap model in the gentrification literature also predicts that real estate investment flows into the neighborhoods with a widening gap between the actual capitalized ground rent given its present use and the potential ground rent that might be gleaned under a higher and better use (Smith, 1979; Smith, 1996). In the recently emerging home-sharing market, advances in matching technologies facilitate homeowners to share underutilized housing resources. The conversion from residential units into short-term tourist accommodation creates a gap between the current and the potential economic returns to a property that may attract capital flows. This study examines how the growth of the home-sharing market has stimulated investment in neighborhoods of Chicago.

The dominant home-sharing service provider, Airbnb, is an online platform that technologically reduces the frictions and improves the match efficiency of the short-term rental markets. It has boasted over six million listings worldwide since its launch in 2008.[2] In the Airbnb-based home-sharing market, homeowners earn new revenue streams by renting out unused bedrooms or the entire homes, raising the potential economic returns to a property as a short-term rental use. We

[2] Data source: https://press.airbnb.com/fast-facts/

expect capital investment to flow into the residential zone of a neighborhood first as the potential hosts renovate their units to become more competitive on the Airbnb market. When the returns on real estate investment are sufficiently high, investors may also initiate larger-scale of projects such as demolition and new construction. In addition to accommodation demand, tourists attracted by this platform to a neighborhood create a larger and new pool of demands for tourism infrastructure such as gastronomy facilities, transport, leisure services, retail chains, information services, and equipment rental services. Hence, besides direct investment on residential properties, we also expect spillovers of capital flows to the retail and the commercial zones in a neighborhood where amenities and businesses arise to meet the demands of the shifting population.

The response of investment to the capital gains brought about by the Airbnb platform may depend on specific market conditions and the current phase of neighborhood redevelopment. We examine the heterogeneous effects of the Airbnb market expansion on investment along the two dimensions. We first expect that an expanding short-term rental market composed mainly of commercial hosts rather than causal hosts is more likely to spur investment. Commercial hosts are identified as those who offer multiple properties, while casual hosts occasionally rent out their underutilized primary residences (Edelman, Luca, and Svirsky, 2017). The former could be more likely to renovate or rebuild their units since they can operate multiple rental units simultaneously to achieve economies of scale. In addition, when commercial hosts rent out several units in the same or adjacent buildings, the concentrated rentals may cause larger impact on flows of short-term renters to the community (Bergeron III, 2015). Retail and commercial investment will thus be more responsive to a growing commercial market than a causal market due to greater tourist demand and higher expected capital returns. Second, we compare the differential effects across neighborhoods in different phases of redevelopment according to the gentrification index provided by the Nathalie P. Voorhees Center. Compared with the stable and declining neighborhoods of Chicago, the gentrified and gentrifying communities are located near the city center, featuring a higher preexisting tourist demand, higher ground rents, and more concentrated Airbnb listings and hotels. While the growing Airbnb market may lead to stronger response of investment in these neighborhoods due to higher tourism demand, their response could also be weaker since the fiercer market competition and the higher costs may lower the profit of short-term rentals. Moreover, the availability of short-term rentals causes lesser impact on tourism volume to these neighborhoods, which may also decrease the incentives of retail and commercial investors.

This study identifies the response of private investment to the growth of the short-term rental market in Chicago, exploiting the number of the Airbnb listings and building permits at the Census tract level over six inconsecutive quarters from 2015 to 2019. We specifically examine how the number and the costs of building permits issued in a quarter changed with the stock of the Airbnb listings observed at the beginning of a wave. The main difficulties in identifying the causal effect result from the endogeneity in the location and the size of the Airbnb listings. While a reverse causality and unobservable amenities may generate an upward bias, the concentration of the Airbnb listings in gentrified neighborhoods may bias the estimates downward. We construct an instrumental variable by a plausibly exogenous time-series variable, the Google search trends in "Airbnb", interacted with a potentially endogenous variable, the 2010 baseline White and Asian population. The former is assumed to be driven by the prevalence and the maturity of the Airbnb platform rather than the time-variant tourism volume (Barron, Kung, and Proserpio, 2018). The latter serves as a cross-sectional exposure variable that predicts the number of the potential Airbnb listings due to the higher homeownership rates of the two races. The instrumental variable estimates show that a one-percent expansion of the Airbnb market increased the number and the costs of the building permits in a quarter by 0.84% and 3.19% at the 1% significance level. The costs of the additional investment were worth $81,000 mainly for new construction and renovation rather than demolition.

This study first adds to the literature on the dynamics of neighborhood change with a focus on the effect of the sharing economy on neighborhood redevelopment. Many studies have explored determinants of renovations and teardowns at the property level, such as structural attributes, neighborhood amenities and locations (Helms, 2003; Dye and McMillen, 2007; Charles, 2013; Munneke and Womack, 2015), household composition and recent home improvements (Baker and Kault, 2002; Plaut and Plaut, 2010), environmental attributes (Culp, 2010), and neighborhood peer effects (Helms, 2012). Another strand of studies examines the best approaches to encourage urban renewal at the neighborhood level, discussing policies such as the enterprise zone program (Kolko and Neumark, 2010), artists and galleries (Schuetz, 2014), and crime (Lacoe, Bostic, Acolin, 2018). Our study shows positive response of investment to increased returns to housing in the growing short-term rental market, which not only occurred in residential investment but also spilled over into the retail, the commercial, and the planned development zone. The results indicate that the capital gains generated in this market could affect the incentives of private investment and thus reshape a neighborhood's trajectory of redevelopment.

Next, we extend the literature on the influence of the sharing economy on the housing markets. Existing studies show that the short-term rental option facilitated by Airbnb reduces the available housing supply for the long-term rentals, which consequently raises residential rents and housing prices (Sheppard and Udell, 2016; Horn and Merante, 2017; Barron, Kung, and Proserpio, 2018). While casual hosts take advantage of underutilized housing resources that would otherwise be idle, commercial hosts are held liable for occupying the long-term rental housing which exacerbates the housing affordability issue for local residents (Horn and Merante, 2017; Li, 2018). Our study finds that the expansion of an Airbnb market dominated by commercial hosts had a particularly greater effect on residential and retail investment. The results indicate that commercial hosts play a major role in spurring residential investment and tourism demand than casual hosts.

This research is also linked to the gentrification literature where researchers identify the economic and demographic catalyst of the process (Bostic and Martin, 2003; McKinnish, Walsh, and White, 2010). While the rent gap model predicts that redevelopment and gentrification tend to occur when potential ground rent exceeds actual ground rent, Wachsmuth and Weisler (2018) expect that the Airbnb-induced gentrification will occur without redevelopment, since the conversion from a long-term rental to a short-term one can be accomplished by simply evicting existing tenants or waiting till the current lease ends. However, our study identifies increased residential capital flows where the Airbnb market grows. Moreover, the spillover effects beyond the residential zone suggest that retail and commercial investors expect higher tourist flows that may potentially displace existing residents. Moreover, while the Chicago Airbnb rentals were also concentrated in the gentrified and gentrifying areas near the city center, which is similar to the case of New York (Coles et al., 2017; Wachsmuth and Weisler, 2018), we find that those stable and declining communities were more responsive to the growth of Airbnb in residential and retail investment due to lower costs and a greater impact on the tourism volume. The findings highlight the differential reactions to the new opportunities of capital gains across neighborhoods at various redevelopment phases.

Empirical Strategy

1. Instrumental Variable

The main challenges for estimating the causal effect of the Airbnb-based sharing economy platform on neighborhood investment are the issues of reverse causality and joint determination. In this section, we motivate and describe our empirical strategy for addressing these difficulties. OLS estimates of the effect of Airbnb on neighborhood investment would be biased upward if, for example, home renovations and remodeling enhance the success of home-sharing business and thus attract more hosts to join the Airbnb platform. An upward bias may also result from third factors, such as natural amenities, historical amenities, restaurants, and shops, that tend to increase both the Airbnb listings and neighborhood investment. At the same time, OLS estimates would be biased downwards if the Airbnb listings were concentrated in post-gentrified neighborhoods that could be less responsive to the new investment opportunities of the short-term rental market. For instance, Wachsmuth and Weisler (2018) find that Airbnb in New York has had its biggest impact in neighborhoods that have already been restructured by capital over the last several decades.

To address the endogeneity of the Airbnb listings, we exploit the Google search trends in "Airbnb" interacted with the baseline White and Asian population as an instrumental variable, which results from two sources of variation. First, we exploit plausibly exogenous time variation in the worldwide Google search interest in "Airbnb" (Figure 1), which is unlikely to reflect the trends of local neighborhood development but is largely driven by information diffusion and technological improvements to the Airbnb platform as the company matures over time (Barron, Kung, and Proserpio, 2018). Second, we exploit cross-sectional variation in the potential size of Airbnb hosts of a Census tract, which we measure as the White and the Asian population in the baseline year of 2010 before the emergence of the Airbnb home-sharing platform. Wachsmuth and Weisler (2018) find that in New York neighborhoods suffering high current impact of Airbnb are only 34% non-white, while across the New York City 61% of households are non-white. The results suggest a higher prospect of becoming Airbnb hosts for the White population. Part of the reason lies in the higher homeownership rate of the Whites compared to other races. In 2010, the homeownership rate of Whites in Chicago was 52.7% followed by a rate of 44.4% for the Asians, which exceeded the rates for all the other races with an average of 36.3%.[3] Even though tenants of a home are also allowed by Airbnb to list their units for short-term rental, the likelihood is getting lower for two reasons. First, tenants are subject to warning or notice of eviction whenever subletting is prohibited or restricted by landlords, which is common in most rental agreements (Said, 2014). Second, Horn and Merante (2017) find that in Boston of October 2015 the Airbnb price premium remained over 100% above the long-term rental market. Such an Airbnb price premium may attract landlords to convert an existing long-term rental to a short-term one by themselves rather than leaving the tenants to profit off the units as hosts. For the above reasons, we expect the baseline Whites and Asians, which have a larger share of homeowners across the population, to well predict the number of the potential Airbnb listings of a neighborhood when the home-sharing platform expands. Using

[3] Homeownership rate is calculated by the authors as the ratio between the owner-occupied units and the total of the owner- and the renter-occupied units by race using the 2010 Census data.

the two sources of variation together, we construct the interaction of the baseline White and Asian population and the Google search trends in "Airbnb" and use this as an instrument for the number of the Airbnb listings in a given period.

2. Empirical Model

We estimate the following equation:

(1) $\log(Airbnb_{ict} + 1) = \alpha P_i * S_t + \mathbf{X_i} + \mathbf{N_{it}} + wave_{ct} + v_{ict}$

(2) $\log(y_{ict} + 1) = \beta \log(Airbnb_{ict} + 1) + \mathbf{X_i} + \mathbf{N_{it}} + wave_{ct} + \varepsilon_{ict}$

Equation (1) is the first stage of our two-stage-least-square system and equation (2) is the second stage. The sample of analysis is a panel of 800 Census tracts over six waves. The index i denotes Census tract, the index c denotes community area, and the index t denotes wave with a length of a quarter.

The dependent variable, $\log(y_{ict} + 1)$, is the log transformation of the number of building permits, y_{ict}, issued during an observed wave. $Airbnb_{ict}$, is the endogenous variable of interest, the snapshot number of Airbnb units listed at the beginning of a quarter. $\mathbf{X_i}$ is a vector of the Census-tract level amenities including the share of land in retail zone, commercial zone, manufacturing zone, and residential zone, the average distance to the nearest three bus stops, railway stations, or parks, the share of historic districts, and the land zoning diversity. We further include the time-varying Census-tract level characteristics including the population density, the log form of median family income, the log form of median rent, the share of bachelor's degree or higher, the share of buildings built before 1940, the share of blacks, and the share of Hispanics. $wave_{ct}$ denotes the community-area-specific time trends, controlling for any confounders that have a common effect on neighborhood investment across all Census tracts within a community area in the same wave.

The coefficient of interest, β, is the estimated effect of an additional Airbnb unit on the percentage change in building permits issued over the following three months. The interaction between P_i, the White and Asian population in 2010 for Census tract i, and S_t, the Google search interest in Airbnb at the beginning of wave t, serves as the instrument.

Data

We acquire information about the Airbnb listings in Chicago from the Inside Airbnb, which utilizes public information compiled from the Airbnb website. We obtain snapshots of listings at six points of time, including October 3, 2015, May 10, 2017, April 15, 2018, July 18, 2018, November 15, 2018, and March 12, 2019. We then exploit the geographic information of each listing to calculate the aggregated number of the Airbnb listings in each wave at the Census tract level. We distinguish listings of casual hosts from those of commercial hosts, exploiting the number of the simultaneous listings of a host in a wave (Edelman, Luca, and Svirsky, 2017; Li, 2018). In specific, casual hosts are defined as those with only one listing in a wave, who are more likely to exploit their primary residences that are not fully occupied as housing resources to earn extra income. By comparison, commercial hosts are defined as those with multiple listings per wave, who are more likely to be landlords switching from the long-term to the short-term rental markets or investors purchasing or renting housing units for the short-term rental use (Li, 2018).

Next, we obtain the building permits data from the City of Chicago Data Portal. A building permit is required by the City of Chicago before beginning most construction, demolition, and repair work except for a limited range of minor repairs to existing buildings.[4] We exploit the coordinates of a permit to identify the Census tract and the specific zoning district where the permitted project took place. In specific, we identify twelve types of zoning districts by retail, commercial, manufacturing, residential, planned developments, planned manufacturing, downtown mixed-use, downtown core, downtown residential, downtown service, transport, parks and open space as divided by the City of Chicago. We then aggregate the number and the costs of the building permits to the Census tract level by zoning district. Our analysis specifically focuses on building permits for new construction, renovation or alteration, and wrecking or demolition that were issued during the six sampled quarters. For example, we examine changes in the total number of building permits issued from October 3, 2015 to January 3, 2016 in response to a one-unit increase in the number of the Airbnb listings observed at October 3, 2015.

In addition, the City of Chicago Data Portal provides the baseline amenities information. We first calculate the distance from the centroid of each Census tract to the nearest three Chicago Transit Authority (CTA) bus stops and then take the average. We use the same method to measure the proximity of a Census tract to CTA rail stations and park facilities. Next, we calculate the share of a Census tract that are listed as the National Register of Historic Places (NRHP) or designated as National Historic Landmarks (NHL). We further calculate the share of zoning districts for retail,

[4] See more at https://www.chicago.gov/city/en/depts/bldgs/provdrs/permits/svcs/no-permit-reqd.html

commercial, manufacturing, residential, and planned developments use respectively in a Census tract. In addition, we also construct a Herfindahl index to measure the land zoning diversity of a neighborhood by $\sum_i share_i^2$, where i indicates the type of zoning district. Besides, the American Community Survey provides time-varying socioeconomic characteristics for the first two waves in 2015 and 2017. We add the additional control variables available for the subsample in robustness check, which control for the time-varying changes in population density, median family income, median rent, the percentage of bachelor's degree or higher, the percentage of old buildings built before 1940, the share of blacks, and the share of Hispanics.

Our baseline sample is a six-wave panel containing 800 Census tracts across 77 community areas in Chicago. Table 1 reports the summary statistics. During a sampled quarter, each Census tract issued an average of 4 building permits, including 0.58 permits for new construction, 3 permits for renovation or alteration, and 0.35 permits for wrecking or demolition. These permits cost a total of \$2.53 million, among which the costs of new construction (\$1.4 million) and renovation (\$1.13 million) account for a dominant share. Meanwhile, a Census tract had an average of 8.4 Airbnb listings with an almost equivalent share of listings run by casual hosts (4.1) and listings by commercial hosts (4.3). Next, residential use accounts for over 60% of an average Census tract, which dominates the share of districts zoned for retail (9.2%), commercial (3.9%), and manufacturing (6.6%) activities. The average distance from a Census tract to the nearest three CTA rail stations, bus stops, and park facilities are 2.14, 0.28 and 0.47 kilometers, respectively. Besides, the share within a Census tract designated as the national register of historical places or districts is 8.7%. The land zoning diversity ranges between 0 and 1 with an average of 0.53. In the subsample of 2015 and 2017, the average population density is 7,086 per square kilometer. The median family income and median rent is $51,764 and $1,028 respectively. Moreover, about 33.9% of the population aged above 25 acquired bachelor's degree or higher. Almost half of the buildings were constructed before 1940.

Results

1. The Validity of the Instrumental Variable

Parallel Trends Across Exposure Variable

Causal inference requires the assumption that the interaction between the Google search interest in Airbnb and a Census tracts' potential for Airbnb hosts only influences neighborhood investment through the Airbnb listings. One concern about the exclusion restriction is that unobservable changes over time could be spuriously correlated with the cross-sectional exposure variable, which may then confound the instrumental variable estimates (Christian and Barrett, 2017). In specific, the global time trends in Airbnb Google search interest increased steadily after 2010 (Figure 1), suggesting that anything that was increasing in the 2010's could be correlated with the prevalence of the Airbnb platform. If a coincident trend in neighborhood investment existed over this period, and, importantly, this trend was more pronounced in neighborhoods with a higher potential size of Airbnb hosts, then the instrumental variable, $P_i * S_t$, would be correlated with the error term, ε_{ict}, in equation (1), which violates the exclusion restriction.

Figure 3 plots the average number of building permits across the quartile groups of Census tracts by the baseline White and Asian population. Panel A demonstrates a higher level of investment in neighborhoods with a larger Airbnb hosts potential. In particular, the average number of building permits for renovation (Panel B) and new construction (Panel C) is higher in neighborhoods with more Whites and Asians, while the number of permits for demolition (Panel D) is uncorrelated with the rank of the quartile group. In Panel C, new construction exhibits stronger seasonal pattern and slightly upward linear trends over time. However, the trends tend to be homogeneous across the quartile groups, which can be absorbed by the wave fixed effects and thus cannot be correlated with the instrumental variable.

No Correlation with Changes in Tourist Volume

A neighborhood that becomes more touristy over time may attract more capital flows because of higher expected economic returns. Thus, another potential threat to our estimation strategy is that the instrument variable might be correlated with changes in tourist volume in the error term, ε_{ict}. We use the business license data from the City of Chicago Data Portal to calculate changes in the number of active hotel license during each observed quarter as a proxy for changes in the volume of tourists potentially seeking accommodation in a neighborhood. In specific, we add up the month-to-month changes in active hotel license over a quarter, which is weighted by the average hotel occupancy rate of each month in Chicago.[5] In addition to the tourists lodging in local hotels, visitors walking past or into or driving by a commercial establishment, i.e. foot traffic, also suggest the economic prosperity of a neighborhood and thus affect investors' expectation and decisions.

[5] We calculate changes in hotel license during a quarter by $\sum_{i=1}^{3} \text{Hotel license changes}_i * \text{Occupancy rate}_i$, where i indexes month in a quarter. The hotel occupancy rate are sourced from the statistics of the central business district of Chicago at https://www.choosechicago.com/media/research-and-statistics/monthly-occupancy-and-adr-statistics/

Thus, we further examine changes in active business license across sectors of liquor, food, vending, and entertainment, since both startups and shutdowns of these businesses can affect the volume of foot traffic. In each sector, we focus on those businesses that particularly attract onsite visitors and take the difference between the number of active licenses counted at the end and the beginning of each quarter.[6] We then regress changes in business license of respective sector on the instrumental variable controlling for the same baseline neighborhood amenities and the fixed effects.

In Table 2, we do not identify any significant correlation between the instrumental variable and changes in license of any sector. The results suggest that the instrumental variable is exogenous to changes in hospitality business of a neighborhood. It is thus unlikely for the instrumental variable to affect neighborhood capital investment through changes in tourist volume.

2. Baseline Results

Table 3 reports the instrumental variable estimates of the home-sharing elasticities of total and itemized investment for new construction, renovation, and demolition (Columns 1-4). For each investment category, we examine the elasticities of the building permits count, the total capital

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[6] We classify business license into specific sector according to the City of Chicago business license guide at https://www.chicago.gov/city/en/depts/bacp/sbc/business_licensing.html#Outdoor. We exclude license of businesses that are unlikely to affect the quantity of pedestrian visitors. For example, we exclude caterer's liquor license and airport pushcart license from the liquor sector. We also exclude wholesale food license and shared kitchen license from the food sector. See Table A1 in Appendix for detailed description of business license of each sector.

investment, and the average capital investment per permit respectively in Panels A-C. The first-stage F-statistic derived from equation (1) is 79.96, indicating a strong correlation between the instrumental variable and the log number of the Airbnb listings. Panel A shows that the home-sharing elasticity of the total building permits was 0.84% ($p<0.01$) (Column 1), indicating that a 1% increase in the Airbnb listings was associated with a 0.84% higher number of building permits in a quarter. In specific, the elasticities of permits for new construction, renovation, and demolition were 0.38% (Column 2), 0.81% (Column 3), and 0.11% (Column 4) respectively. All the estimates are statistically significant ($p<0.01$). Next, Panel B shows that the home-sharing elasticity of the total capital investment in a quarter was 3.19% ($p<0.01$) (Column 1), or $0.081 million given the sample mean ($= 2.526 * 3.19\%$). Most costs resulted from new construction and renovation, the elasticities of which were 3.07% and 3.58% respectively ($p<0.01$). By contrast, the home-sharing elasticity of capital investment for demolition was 0.12% ($p<0.01$). Moreover, Panel C shows that the average capital investment per permit also went up due to the home-sharing market expansion. Specifically, the home-sharing elasticities of the average per-permit capital investment of new construction, renovation, and demolition were 2.74%, 2.69%, and 0.08% ($p<0.01$), respectively. The results show that home sharing led to additional total capital investment due to both a higher number of building permits and a higher per-permit investment.

3. Robustness checks

Additional Controls and Alternative Model Specifications

In this subsection, we first add time-varying Census-tract level characteristics, which are available for the first two sampled waves in 2015 and 2017, as additional controls for potential changes in neighborhood socioeconomic conditions. Column 1 of Table 4 shows that the first-stage F-statistic estimated using the two-wave subsample is 75.93. We obtain robust estimation results with the additional controls of population density, log median family income, log median rent, the share of bachelor's degree or higher, the share of buildings before 1940, the share of Blacks, and the share of Hispanics. The estimation results indicate that the increased capital investment in the Airbnb-expanding Census tracts were not confounded by changes in these socioeconomic characteristics. Next, we estimate a level-log model by replacing the key explanatory variable with the number of the Airbnb listings using the baseline sample. As is reported in Column 2 of Table 5, the first-stage F-statistic decreases to 29.86, which far exceeds the rule of thumb to reject the null hypothesis of the irrelevance between the instrumental variable and the endogenous regressor. The estimation results indicate that one more Airbnb listing increased the total building permits in a quarter by 4.4% ($p<0.01$), which are consistent with the baseline findings. Furthermore, we apply a control function approach to a negative binomial model and a Poisson model in a two-step estimation procedure while reporting the panel bootstrapped standard errors (Wooldridge, 2015). Columns 3-4 of Table 5 show that the control-function estimators of the non-linear models are similar in magnitudes to the instrumental variable estimates of the level-log model.

Non-Airbnb Neighborhoods

Our identification hinges on the assumption that the instrumental variable influences neighborhood capital investment only through the prevalence of the Airbnb home-sharing platform. Thus, in neighborhoods without Airbnb listings, the instrumental variable is expected to be uncorrelated with the issuance of building permits. In this subsection, we perform a falsification test to examine their correlation conditional on the baseline controls using a subsample of 130 Census tracts that never had any Airbnb listing during the sampled period. Table 5 reports statistically insignificant correlations between the instrumental variable and the number and the costs of building permits in these non-Airbnb neighborhoods, indicating that the instrumental variable cannot influence the dependent variables of interest without the presence of Airbnb rental units. The results lend further support to the validity of our identification strategy.

4. Building Permits by Zoning District

Our baseline results show that the expansion of the Airbnb-based home-sharing market has brought in additional investment flows to the local neighborhoods. Next, we exploit the zoning district information to identify the specific zone where a permitted project took place. We expect that investment takes place in the residential district of a neighborhood first, where investors renovate existing properties or construct new residential buildings incentivized by the increased economic returns of the home-sharing industry. Moreover, we expect positive spillover effects to other zones, including the retail and service zone, the commercial and business zone, the planned development zone, and the parks and open space zone,[7] where new amenities and businesses may emerge to meet the greater tourist demand attracted by the short-term rentals. Furthermore, we examine

[7] Retail and service zone accommodates small-scale retail and service uses and large shopping centers. Business and commercial zone allows nearly any type of business, service and commercial uses. Planned development zone includes projects such as air rights, buildings exceeding the height thresholds or certain districts, expansion of existing planned development, large residential, commercial and industrial developments, etc. Parks and open space zone include public open space, public parks and public beaches (Chicago Zoning Ordinance and Land Use Ordinance, 2019).

building permits in the manufacturing zone and the planned manufacturing zone as a falsification test, expecting no changes in capital investment in these two zones in response to the growth of the Airbnb market.

Table 6 reports the estimation results by zoning district. Panel A shows that the size of the Airbnb market was positively associated with the number of residential projects approved in a quarter. In specific, the home-sharing elasticity of residential building permits was 0.48% ($p<0.01$). In the residential zone, the elasticity of new construction and renovation permits were 0.11% and 0.48% respectively ($p<0.01$) while that of demolition permits was 0.05% ($p<0.1$). In addition, we further find that the growth of the Airbnb market increased capital investment in areas beyond the residential zone of a neighborhood. Specifically, the home-sharing elasticities of building permits was 0.27% for the retail and service zone (Column 1 of Panel B) and 0.14% for the commercial and business zone (Column 1 of Panel C) ($p<0.01$). In both types of zones, new construction, renovation, and demolition projects increased. Besides, in the planned development zone, the elasticities of new construction permit and renovation permit were 0.16% ($p<0.1$) and 0.24% ($p<0.01$), respectively (Columns 2-3 of Panel D). The home-sharing elasticity of new construction in the parks and open space zone was 0.08% ($p<0.1$) (Column2 of Panel E). The falsification test on the building permits in the manufacturing zone (Panel F) and the planned manufacturing zone (Panel G) shows that the prevalence of the home-sharing platform did not have any statistically significant effects on investment in either zone, suggesting that the identified effects were not confounded by an overall citywide redevelopment plan.

5. Casual versus Commercial Markets

Next, we test how the response of private investment to the prevalence of the home-sharing market varied with the dominant host type in the local Airbnb market. We first distinguish casual hosts from commercial hosts by whether a host ran more than one Airbnb listing per wave. Casual hosts are usually homeowners who rent out their own underutilized property for supplemental income,[8] whereas commercial hosts are professional entrepreneurs who convert long-term rentals to short-term rentals to make a profit (Edelman, Luca, and Svirsky, 2017; Li, 2018). These commercial hosts usually manage multiple rental units to achieve the economies of scale. They are more likely to make capital investment in their properties because of advantages in capital and cost efficiency. Thus, we expect the home-sharing growth elasticity to be larger in neighborhoods dominated by commercial hosts. In addition, the economies of scale attained in a commercial market may result in a larger impact on tourist volume, which will cause greater spillover capital flows to retail and commercial activities.

We re-estimate the baseline model by adding an interaction term between the log number of the Airbnb listings and the share of commercial hosts in the community area where a Census tract was located, which is instrumented by the baseline instrumental variable interacted with the commercial hosts' share at the community area level. Since the share of commercial hosts ranged between zero and one, the coefficient of the interaction term is interpreted as the difference in the

[8] Since June 22, 2016, the city of Chicago enacted the Shared Housing Ordinance requiring that a shared housing host can only rent out the primary residence. In our sample, casual hosts before 2016 may include renters who rent out underutilized bedrooms or the entire housing unit when they travel away from home.

home-sharing elasticity of capital investment between the community areas composed of casual hosts exclusively (“casual market”) and those composed of commercial hosts only (“commercial market”). In Table 7, the Sanderson-Windmeijer multivariate F-test show that the first-stage F-statistic for the log number of the Airbnb listings and the interaction term is 15.72 and 18.26 respectively, rejecting the irrelevance hypothesis for each variable. Panel A shows that, in casual markets, increased rental listings in a Census tract did not have any statistically significant effect on the number of building permits issued for the residential use or the retail and service use. However, the effect on investment in the two types of zones increased significantly with the share of commercial hosts in the community-area-level market. In particular, a commercial market had a higher home-sharing elasticity of building permits than a casual market by 0.81% ($p<0.05$) for residential investment (Column 1) and by 0.53% ($p<0.1$) for retail and service investment (Column 2). Consistently, the home-sharing elasticity of total capital investment was higher in a commercial market than that in a casual market by 4.77% ($p<0.1$) for residential investment (Column 1) and by 7.76% for retail and service investment ($p<0.1$) (Column 2). However, the growth of the two types of markets did not generate statistically differential effect on either the number or the costs of the building permits in the commercial and business zone, the planned development zone, or the parks and open space zone.

6. Heterogeneous Effects by Redevelopment Phases

Neighborhoods within Chicago differ in their current redevelopment phases. A gentrification index developed by the Nathalie P. Voorhees Center shows that twelve community areas located near the city center have underwent substantial upgrading in the overall socioeconomic characteristics from 1970 to 2010, in which nine (159 Census tracts) have been gentrified and three (42 Census tracts) are currently gentrifying (The Nathalie P. Voorhees Center for Neighborhood and Community Improvement, 2014).[9] In these upgrading neighborhoods, on the one hand, hosts could be more willing to invest, since they benefit from a stronger accommodation demand due to closer proximity to local tourism attractions (Figure 3). On the other hand, hosts may prefer withholding money to renovate a property, since intense competition with preexisting hotels and higher ground rents near the city center reduces the expected returns of investment. Meanwhile, retail and commercial investors may also be less responsive to the home-sharing market expansion, since they expect lower growth of customer flows in these areas that have already featured high baseline tourist flows.

In this subsection, we examine the heterogeneous home-sharing elasticities of investment across neighborhoods at different redevelopment phases. We identify whether a community area was stable, declining, or upgrading in the overall socioeconomic status from 1970 to 2010 by whether their 2010 gentrification index score is similar, lower, or higher compared with their 1970 score (The Nathalie P. Voorhees Center for Neighborhood and Community Improvement, 2014). We re-estimate the baseline model by adding two terms of the log number of the Airbnb listings interacted

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[9] The index is constructed based on thirteen indicators related to gentrification decennially from 1970 to 2010, including %White, %Black, %Latino, %elderly aged 65 plus, %children aged 5-19, %college education, median family income, %owner occupied, median house value, %family below poverty, %manager occupations, %female households with children, %private school attendance. A higher composite index value reflects a higher socioeconomic status of a community area relative to the average for the City of Chicago.

with dummies indicating the stable and the declining community areas respectively, while the upgrading community areas serve as the reference group. Panel A of Table 8 shows that, compared with the upgrading neighborhoods, the stable neighborhoods had a larger home-sharing elasticity of residential building permits by 0.568% ($p<0.01$) (Column 1). Moreover, such group difference also existed for retail and service building permits by 0.215% ($p<0.05$) (Column 2). We identify consistent group difference in total capital investment across the two types of zones in Panel B. Meanwhile, the stable communities had lower home-sharing elasticities of building permits in the planned development zone (Column 4) and the parks and open space zone (Column 5) ($p<0.1$). However, the evidence is statistically insignificant regarding the total capital investment. Furthermore, we obtain similar findings when comparing the declining neighborhoods with the upgrading ones. The results indicate that the availability of the short-term rental market has served as a new incentive for residential and retail investment particularly for stable and declining neighborhoods that lack investment opportunities historically.

Conclusions

This study explores how the changing number of the Airbnb-based short-term rentals affect private investment across a diverse set of neighborhoods in Chicago. We exploit an instrumental variable approach to address the endogeneity in the location and the size of the Airbnb listings. We show that an increased number of Airbnb listings in a Census tract raised the quantity and the costs of the building permits for new construction, renovation, or demolition. These additional investments emerged not only from residential projects but also from retail, commercial, and the planned development zones. Moreover, the expansion of a market dominated by commercial hosts, which achieved greater cost efficiencies and higher expected returns by operating multiple units, had a significantly larger impact on residential and retail investment relative to a more casual market. We also find that, compared with gentrified and gentrifying neighborhoods near the urban center, the peripheral communities that had been stable or declining since the 1970s were more responsive to the growth of the Airbnb markets, which might be explained by the lower investment costs and the larger impact on the existing tourism volume in these neighborhoods.

This study contributes to the contentious policy debate on the social welfare implications of the rising home sharing market. We show that the potential capital gains arising from the short-term rental markets, especially those dominated by commercial operators, could play an active role in spurring neighborhood redevelopment and urban renewal. On the other hand, besides the positive response of remodeling and rebuilding decisions of residential properties, the spillover effects on the retail and commercial investment suggest increased tourist traffic associated with the short-term rentals. The findings add to the discussion on whether neighborhoods and cities bear the costs of the home-sharing business model, such as noise, disruption, safety concerns, and conflicts with existing housing resources, land-use regulations and zoning codes (Schneiderman, 2014; Samaan, 2015; Lee, 2016; Wachsmuth and Weisler, 2018). Taken together, our findings provide additional information that policymakers could take into account in seeking the balance between the social costs and the economic benefits associated with the home-sharing market.

Our analysis informs how the variation in the short-term rental units could influence the way that property owners and retail and commercial investors allocate their investment spatially across neighborhoods. Compared with the hotel industry that is more centralized due to the zoning rules, Airbnb activity could be distributed across a wider area beyond the city’s traditional tourism areas.

Like the case of Chicago, the Airbnb listings in New York also show a geographic dispersion trend over time while the hotel district is highly centralized around Times Square in Manhattan (Coles et al, 2017; Wachsmuth and Weisler, 2018). Our study shows that the proliferation of the home-sharing markets gained greater investment response from those stable and declining communities where capital flows were insufficient or absent in the past few decades. The findings suggest that the widespread revenue flows of the short-term rentals create redevelopment opportunities for the neighborhoods with desirable cultural features and low ground rents. The results are particularly informative to policymakers and practitioners with respect to the question of how best to improve neighborhoods that lag behind and promote equitable economic development.

Our study also adds to the discussion about the potential effects of home sharing on gentrification, which is characterized as the displacement of lower-income residents in blighted neighborhoods by affluent households moving into with capital flows (Bostic and Martin, 2003). Although a shift from the long-term renters to temporary travelers differs from the traditional form of gentrification, Airbnb may still provide another vehicle for displacement by pushing the lower-income residents and community members into cheaper neighboring communities (Logan, Reyes, and Poston, 2015; Cox, 2017). Our study shows that retail and commercial investors have directed capital flows into the Airbnb-growing neighborhoods in which they expected higher tourist demand. The greater investment response in the stable and declining peripheral neighborhoods further suggests that the tourism volume shock could be proportionally larger in areas that did not historically host tourists in large numbers. However, as higher-income residents may eventually outbid Airbnb tourists as short-term rentals remains potentially in circulation, the magnitudes of the shock and the extent to which short-term rentals could displace current residents calls for future research on the duration of the ground rent gap.

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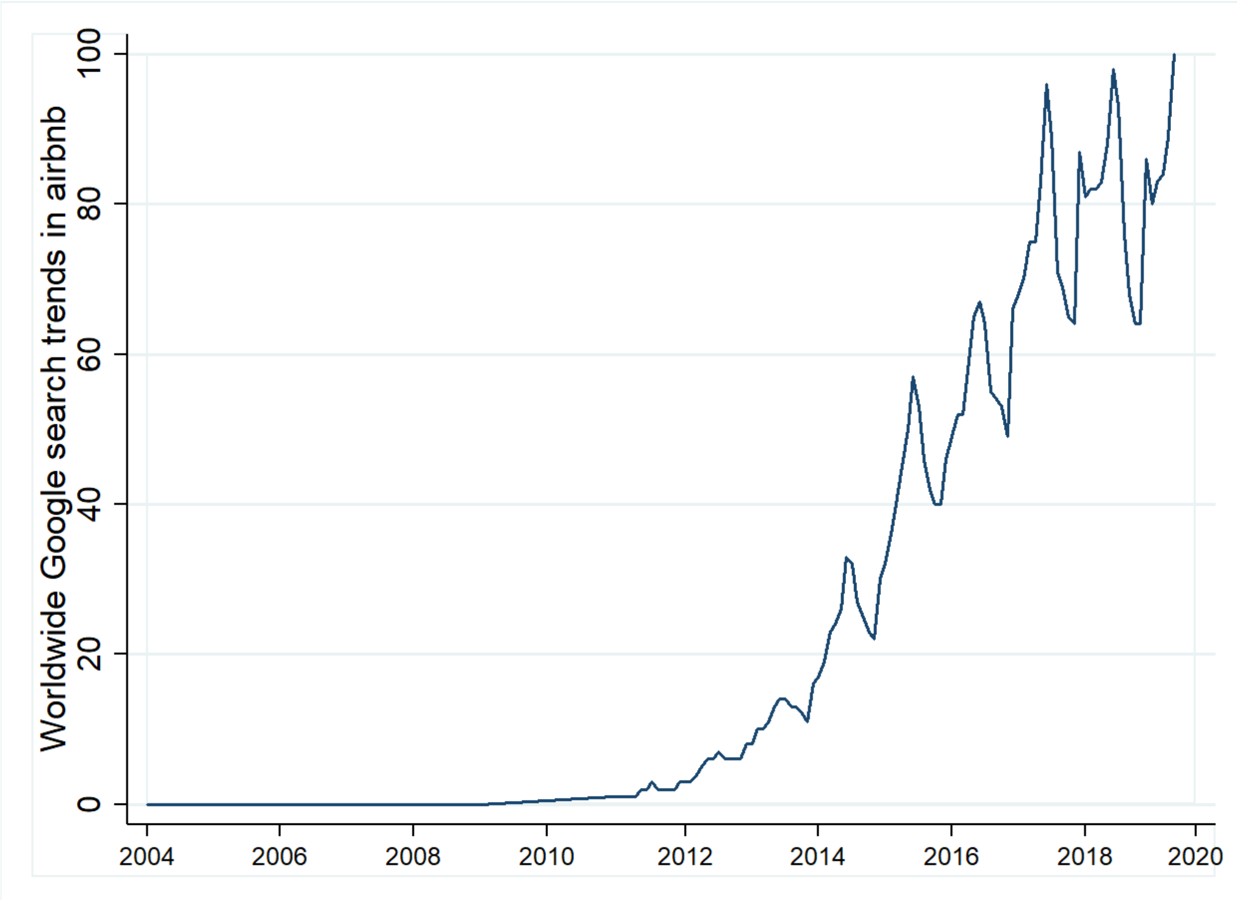
Figure 1. Google Search Interest in Airbnb



Notes: Generated by authors.

Data source: https://trends.google.com/trends/explore?date=all&geo=US&q=airbnb

Figure 2. Parallel Trends in Building Permits across Baseline White and Asian Population

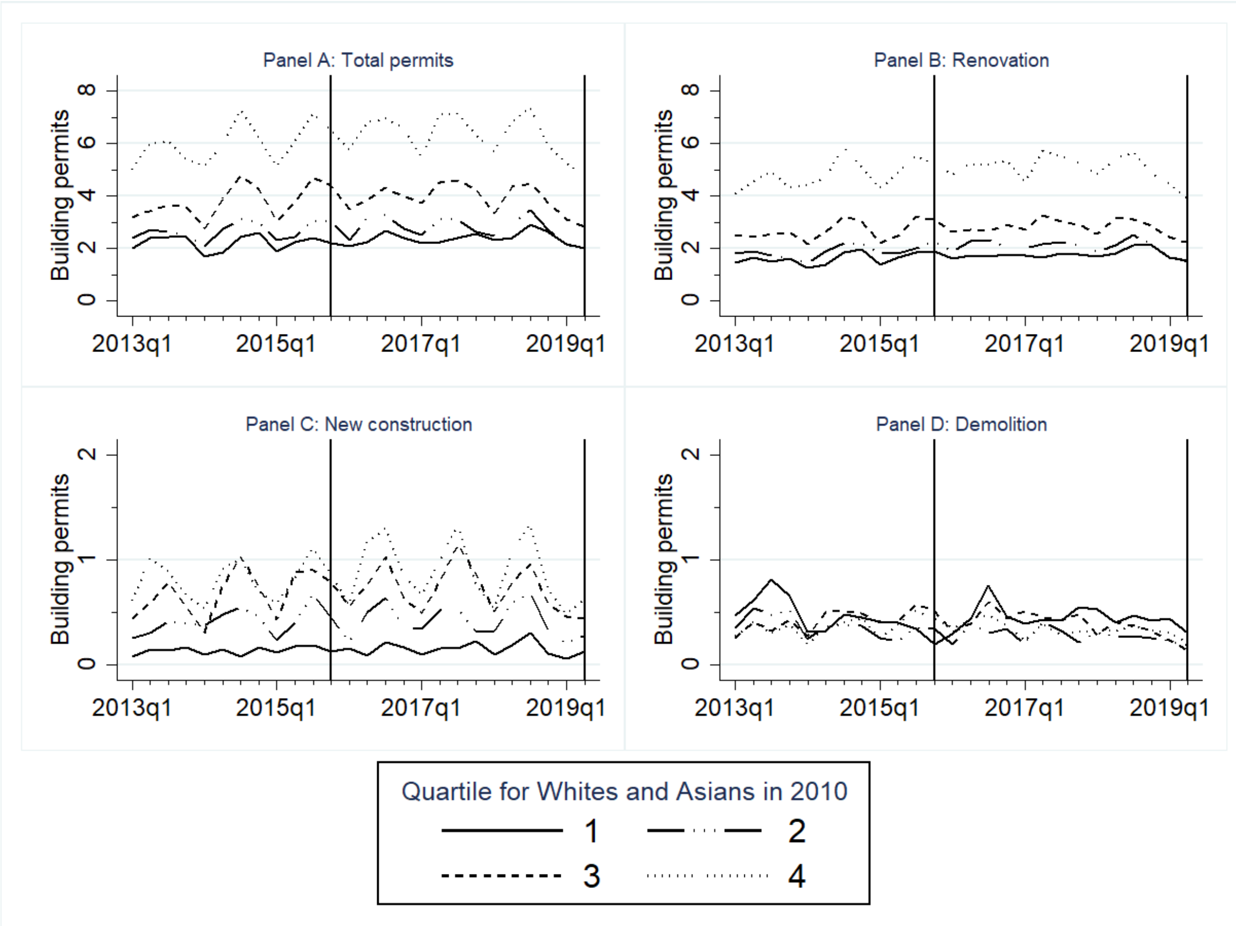


Figure 3. Neighborhood Change from 1970 to 2010

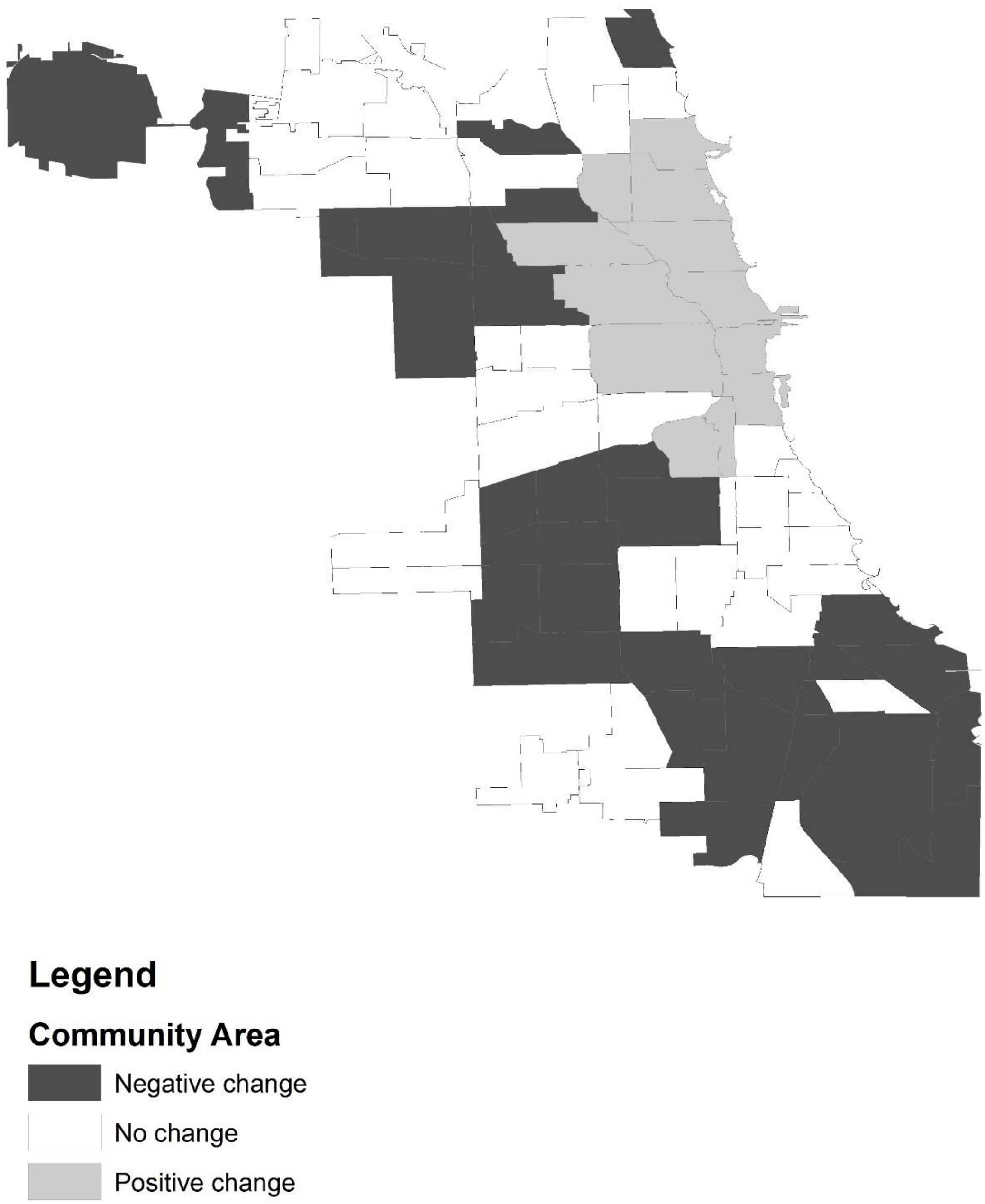


Table 1. Summary Statistics

	Mean	SD	Min	Max
	Dependent variables			
Total permits	3.987	7.795	0	193
New construction permits	0.584	1.636	0	41
Renovation/alteration permits	3.052	6.890	0	184
Wrecking/demolition permits	0.351	0.820	0	9
Total costs ($million)	2.526	15.684	0.000	452.998
New construction costs ($million)	1.401	12.823	0.000	409.891
Renovation/alteration costs ($million)	1.125	7.106	0.000	202.190
Wrecking/demolition costs ($million)	0.00003	0.001	0.000	0.045
	Independent variables			
Airbnb listings	8.356	13.872	0	218
Casual listings	4.102	8.762	0	154
Commercial listings	4.254	6.555	0	74
Baseline Census tract characteristics				
Share in retail zone	0.092	0.075	0.000	0.495
Share in commercial zone	0.039	0.056	0.000	0.534
Share in manufacturing zone	0.066	0.123	0.000	0.799
Share in residential zone	0.606	0.259	0.000	1.000
Distance to rail stations (km)	2.139	1.772	0.253	10.881
Distance to bus stops (km)	0.277	0.304	0.017	6.094
Distance to park facilities (km)	0.471	0.426	0.020	7.050
Historic share	0.087	0.213	0.000	1.000
Land zoning diversity	0.531	0.196	0.000	1.000
Observations				4,800
Time-varying Census tract characteristics				
Population density (1000 per km^2)	7.086	6.859	0.163	175.700
Median family income in $1000	51.764	28.247	5.000	160.833
Median rent in $1000	1.028	0.309	0.279	2.895
%Bachelor's degree or higher	0.339	0.258	0.005	0.952
%Buildings before 1940	0.470	0.227	0.000	0.938
%Black	0.376	0.403	0.000	1.000
%Hispanic	0.260	0.292	0.000	0.996
Observations				1,584

Notes: The table reports the summary statistics of the baseline sample that covers 800 Census tracts for six waves. The bottom panel reports the time-varying Census tract characteristics that are available for 795 Census tracts in the first two waves. *Casual listings* are run by hosts who only had one Airbnb listing in a wave, whereas *Commercial listings* are run by hosts who had more than one Airbnb listing in a wave. *Distances* are calculated as the average distance from the centroid of a Census tract to the nearest three park facilities, subways, or bus stops. *Historic share* is the share of National Register of historic places of districts. *Land zoning diversity* is constructed as a Herfindahl index, based on the land zoning shares in twelve categories: retail, commercial, manufacturing, residential, planned developments, planned manufacturing, downtown mixed-use, downtown core, downtown residential, downtown service, transport, parks and open space.

Table 2. No Correlation with Changes in Tourist Volume

VARIABLES	(1) ΔHotel	(2) ΔLiquor	(3) ΔMobile food	(4) ΔRetail food	(5) ΔVending	(6) ΔEntertainment
Instrumental Variable	-0.0001	-0.0009	0.0007	-0.0007	-0.0004	0.0005
	(0.0003)	(0.0019)	(0.0057)	(0.0024)	(0.0013)	(0.0008)
Observations	4,800	4,800	4,800	4,800	4,800	4,800
R-squared	0.126	0.123	0.116	0.143	0.108	0.179

Notes: The dependent variables are changes in active business license in sectors listed as the column titles, which are calculated as the difference between the number of active licenses observed at the end and the beginning of a wave. The key explanatory variable is the instrumental variable, i.e. the baseline White and Asian Population interacted with the Google search interest. The model controls for the baseline amenities including the residential zone share, the retail zone share, the commercial zone share, the manufacturing zone share, the average distances to the nearest three bus stops, railway stations, and parks respectively, the historic share, and the landing zoning diversity. We also control for the community area by wave fixed effects. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Baseline Results

VARIABLES	(1) Total	(2) New construction	(3) Renovation	(4) Demolition
Panel A: The Number of Building Permits				
Airbnb Listings	0.836***	0.378***	0.808***	0.114***
	(0.086)	(0.079)	(0.086)	(0.033)
Observations	4,800	4,800	4,800	4,800
R-squared	0.135	0.246	0.080	0.195
Panel B: Total Capital Investment				
Airbnb Listings	3.190***	3.068***	3.584***	0.120***
	(0.404)	(0.475)	(0.431)	(0.037)
Observations	4,800	4,800	4,800	4,800
R-squared	0.191	0.287	0.120	0.166
Panel C: Capital Investment per Permit				
Airbnb Listings	2.241***	2.741***	2.689***	0.081***
	(0.342)	(0.425)	(0.369)	(0.026)
Observations	4,800	4,800	4,800	4,800
R-squared	0.183	0.287	0.123	0.143
First-stage F-statistic	79.96	79.96	79.96	79.96

Notes: The dependent variables in Panels A-C are the log form of the total number of building permits, the log form of the total capital investment, and the log form of the average capital investment per permit during a wave, respectively, for the purpose listed as the column titles. The key explanatory variable in all the panels are the log form of the number of Airbnb listings observed at the beginning of a wave. The coefficients are interpreted as elasticities, i.e. percentage changes in the outcome variables given a 1% increase in the Airbnb listings. The model controls for the baseline amenities including the residential zone share, the retail zone share, the commercial zone share, the manufacturing zone share, the average distances to the nearest three bus stops, railway stations, and parks respectively, the historic share, and the landing zoning diversity. We also control for the community area by wave fixed effects. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Additional Controls and Alternative Model Specifications

VARIABLES	(1) Two-wave sample	(2) Level-log	(3) Negative Binomial	(4) Poisson
Airbnb Listings	0.801***	0.044***	0.049***	0.028**
	(0.121)	(0.004)	(0.005)	(0.013)
First-stage F-statistic	75.93	29.86	29.86	29.86
Observations	1,584	4,800	4,800	4,800
Baseline amenities	YES	YES	YES	YES
Time-varying characteristics	YES	NO	NO	NO
Community area by wave FE	YES	YES	YES	YES

Notes: The dependent variables are the total number of building permits. Column 1 reports the instrumental variable estimates of the baseline log-log model using the first-two-wave sample with time-varying characteristics, including population density, log median family income, log median rent, %Bachelor's degree or higher, %buildings before 1940, %Blacks, and %Hispanics. The coefficients are interpreted as elasticities, i.e. percentage changes in the building permits given a 1% increase in the Airbnb listings. Column 2 reports the instrumental variable estimates of the level-log model using the baseline sample, where the dependent variable is the log form of the number of building permits and the key explanatory variable is the number of Airbnb listings. The coefficients are interpreted as unit changes in the building permits given a 1% increase in the Airbnb listings. Columns 3-4 report the two-stage control-function estimates of the negative binomial model and the Poisson model, respectively, using the baseline sample. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients are interpreted as percentage changes in the building permits by $\exp(coefficients)$ -1 given an additional Airbnb listing. The coefficients with standard errors clustered at the community area level in parentheses (Columns 1-2) and panel bootstrapped standard errors in parentheses (Columns 3-4) are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Non-Airbnb Neighborhoods

VARIABLES	(1) Total	(2) New construction	(3) Renovation	(4) Demolition
Panel A: The number of building permits				
Instrumental Variable	-0.010	-0.003	-0.003	-0.006
	(0.012)	(0.006)	(0.010)	(0.007)
Observations	726	726	726	726
R-squared	0.372	0.358	0.349	0.286
Panel B: Total capital investment				
Instrumental Variable	-0.059	-0.020	-0.042	-0.007
	(0.091)	(0.069)	(0.090)	(0.007)
Observations	726	726	726	726
R-squared	0.331	0.360	0.314	0.513

Notes: This table reports the estimation results using a subsample of neighborhoods that never had any Airbnb listing over the sampled waves. The dependent variables in Panels A-B are the log form of the total number of the building permits and the log form of the total capital investment during a wave, respectively, for the purpose listed as the column titles. The key explanatory variable is the instrumental variable, i.e. the baseline White and Asian Population interacted with the Google search interest. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 5B. Always-Airbnb Neighborhoods

	(1)	(2)	(3)	(4)
VARIABLES	Total	New construction	Renovation	Demolition
	Panel A: The number of building permits			
Airbnb Listings	0.917***	0.422***	0.897***	0.158***
	(0.120)	(0.095)	(0.124)	(0.043)
Observations	2,340	2,340	2,340	2,340
R-squared	0.304	0.280	0.257	0.232
	Panel B: Total capital investment			
Airbnb Listings	3.152***	3.379***	3.658***	0.165***
	(0.495)	(0.562)	(0.559)	(0.047)
Observations	2,340	2,340	2,340	2,340
R-squared	0.238	0.257	0.192	0.178

Notes: This table reports the estimation results using a subsample of neighborhoods that always had any Airbnb listing over the sampled waves. The dependent variables in Panels A-B are the log form of the total number of the building permits and the log form of the total capital investment during a wave, respectively, for the purpose listed as the column titles. The key explanatory variable in each panel is the log form of the number of the Airbnb listings observed at the beginning of a wave. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Investment by Zoning District

VARIABLES	(1) Total	(2) New construction	(3) Renovation	(4) Demolition
Panel A: Residential Zone				
Airbnb Listings	0.475***	0.105***	0.476***	0.047*
	(0.087)	(0.038)	(0.082)	(0.028)
Observations	4,800	4,800	4,800	4,800
R-squared	0.260	0.250	0.190	0.220
Panel B: Retail and Service Zone				
Airbnb Listings	0.267***	0.046**	0.227***	0.032***
	(0.044)	(0.019)	(0.036)	(0.012)
Observations	4,800	4,800	4,800	4,800
R-squared	0.210	0.136	0.173	0.100
Panel C: Business and Commercial Zone				
Airbnb Listings	0.142***	0.044***	0.113***	0.012*
	(0.029)	(0.013)	(0.024)	(0.006)
Observations	4,800	4,800	4,800	4,800
R-squared	0.239	0.143	0.211	0.089
Panel D: Planned Development Zone				
Airbnb Listings	0.283***	0.163*	0.244***	0.011
	(0.105)	(0.093)	(0.088)	(0.007)
Observations	4,800	4,800	4,800	4,800
R-squared	0.396	0.155	0.383	0.110
Panel E: Parks and Open Space				
Airbnb Listings	0.075*	0.075*	0.000	-0.001
	(0.041)	(0.041)	(0.004)	(0.001)
Observations	4,800	4,800	4,800	4,800
R-squared	0.148	0.141	0.102	0.068
Panel F: Manufacturing Zone				
Airbnb Listings	0.021	0.017	0.005	0.006
	(0.023)	(0.010)	(0.019)	(0.006)
Observations	4,800	4,800	4,800	4,800
R-squared	0.272	0.153	0.234	0.135
Panel G: Planned Manufacturing Zone				
Airbnb Listings	0.017	0.005	0.015	-0.004
	(0.027)	(0.006)	(0.023)	(0.006)
Observations	4,800	4,800	4,800	4,800
R-squared	0.194	0.103	0.185	0.094
Fist-stage F-statistic	79.96	79.96	79.96	79.96

Notes: The table reports the instrumental variable estimates of the home-sharing elasticity of the building permits in the zoning districts listed as the panel titles using the baseline sample. The dependent variables are the log form of the total number of building permits in the respective zones approved during a wave for the purpose listed as the column titles. The key explanatory variable in each panel is the log form of the number of the Airbnb listings observed at the beginning of a wave. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Casual Markets versus Commercial Markets

VARIABLES	(1) Residential	(2) Retail and Service	(3) Business and Commercial	(4) Planned Development	(5) Parks and Open Space
	Panel A: The Number of Building Permits				
Listings	0.061	-0.007	0.231***	0.428**	0.054
	(0.167)	(0.150)	(0.075)	(0.209)	(0.052)
Listings*%Commercial hosts	0.814**	0.529*	-0.176	-0.289	0.041
	(0.319)	(0.271)	(0.124)	(0.354)	(0.090)
Observations	4,707	4,707	4,707	4,707	4,707
R-squared	0.268	0.221	0.226	0.380	0.151
	Panel B: Total Capital Investment				
Listings	0.255	-1.560	2.278***	2.091	0.364
	(1.310)	(1.460)	(0.682)	(1.394)	(0.542)
Listings*%Commercial hosts	4.773*	7.762***	-1.410	-0.817	0.471
	(2.690)	(2.779)	(1.191)	(2.454)	(0.938)
Observations	4,707	4,707	4,707	4,707	4,707
R-squared	0.267	0.212	0.212	0.339	0.158
Sanderson-Windmeijer multivariate F test of excluded instruments:					
Listings	15.72	15.72	15.72	15.72	15.72
Listings*%Commercial hosts	18.26	18.26	18.26	18.26	18.26

Notes: The dependent variables are the log form of the total number of building permits in the respective zones listed as the column titles. *Listings* is the log number of the Airbnb listings observed at the beginning of a wave. *%Commercial hosts* is the share of units run by commercial hosts among all the units in a community area. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Neighborhoods at Different Redevelopment Phases

VARIABLES	(1) Residential	(2) Retail and Service	(3) Business and Commercial	(4) Planned Development	(5) Parks and Open Space
			Panel A: The Number of Building Permits		
Listings	0.282***	0.192***	0.105**	0.374**	0.102*
	(0.099)	(0.059)	(0.049)	(0.148)	(0.054)
Listings*Stable	0.568***	0.215**	0.025	-0.294*	-0.096*
	(0.194)	(0.108)	(0.074)	(0.174)	(0.056)
Listings*Decline	0.425*	0.114	0.050	-0.324*	-0.114**
	(0.243)	(0.118)	(0.076)	(0.168)	(0.056)
Observations	4,800	4,800	4,800	4,800	4,800
R-squared	0.083	0.143	0.274	0.504	0.250
			Panel B: Capital Investment		
Listings	1.363***	1.359***	1.186**	1.842**	0.734*
	(0.484)	(0.455)	(0.580)	(0.721)	(0.398)
Listings* Stable	3.300***	2.975***	0.370	-1.169	-0.520
	(1.232)	(1.019)	(0.843)	(1.141)	(0.455)
Listings* Decline	4.239**	2.209*	0.879	-1.121	-0.854*
	(1.924)	(1.308)	(1.002)	(1.288)	(0.458)
Observations	4,800	4,800	4,800	4,800	4,800
R-squared	0.155	0.133	0.227	0.390	0.224
Sanderson-Windmeijer multivariate F test of excluded instruments:					
Listings	45.14	45.14	45.14	45.14	45.14
Listings*Stable	48.34	48.34	48.34	48.34	48.34
Listings*Decline	64.99	64.99	64.99	64.99	64.99

Notes: The dependent variables are the log form of the total number of building permits in the respective zones listed as the column titles. *Listings* is the log number of the Airbnb listings observed at the beginning of a wave. *Upgrade* and *Decline* are dummies indicating whether a community area has experienced positive or negative socioeconomic changes from 1970 to 2010, respectively. We control for the same baseline amenities and the community area by wave fixed effects as in Table 3. The coefficients with standard errors clustered at the community area level in parentheses are reported. *** p<0.01, ** p<0.05, * p<0.1