The Effect of the Shared Economy on Crime: Evidence from Airbnb*

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Abstract

The rapid growth of Airbnb and the shared economy has made it critically important that we develop a better understanding of the impact of the Airbnb market on other segments of the economy and the safety of neighborhoods. We empirically examine the impact of Airbnb on neighborhood crime. The results indicate that a 10% increase in the number of Airbnb hosts decreases neighborhood crime by over 2.5%. The effect is largest in locations with higher incomes and more expensive housing. The results are robust across a variety of controls for selection bias, endogeneity, and different measures of Airbnb activity.

JEL Codes: R3, 033, M21, I31, L85

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1 Introduction

The rapid expansion of peer-to-peer markets has garnered substantial interest in both the popular press and academic literature. What is most clear, at this point in time, is that peer-to-peer markets provide a variety of benefits and costs, some of which are easily anticipated while others are harder to foresee. This research focuses on how the peer-to-peer short term rental of real estate property through the Airbnb platform affects safety in a neighborhood.

Airbnb provides a platform where an owner (and sometimes a long term renter) of real estate can, with minimal entry or exit costs, become an Airbnb host and offer the real estate for short term rent. As the use of Airbnb becomes more prevalent, the types of people and the amount of economic activity can change. These changes can influence the type and amount of crime in locations with Airbnb rentals. It is important to study the effects of Airbnb on crime because crime has been shown to have a negative effect on property values and business (Lens and Meltzer, 2016). Although the effects of different policies on crime have been studied in the literature, we are the first paper to use detailed block group level data to study the effects of Airbnb on crime (Stacy, 2018).

The peer-to-peer short term rental of property can have a variety of costs and benefits to the neighborhood. In fact, there is some evidence that short term renters can create a nuisance and disrupt year round residents (Lee, 2016; Gurran, 2018; Schäfer and Braun, 2016; Wachsmuth and Weisler, 2018; Gant, 2016). In terms of crime, the perceived costs of committing a crime may be reduced when partying on vacation. In addition, the amount of crime is related to the opportunity to commit crime. Tourists can provide an increased opportunity for would-be criminals, because tourists are not familiar with their surroundings, are more likely to be carrying cash, and are spending money on entertainment, food and drink. In short, the introduction of tourists into a location can increase crime by reducing the expected cost and increasing the benefits of committing crime.

However, there are a variety of factors that may reduce crime. For example, tourists increase the presence of people on the street. This can make it more likely that a criminal will be caught and identified, thus deterring crime. There is also evidence that Airbnb raises local house prices and this may lead to gentrification (Wyman and McLeod, 2019; Sheppard et al., 2016). In fact, as part of this gentrification, we find evidence that the introduction of Airbnb to a neighborhood is associated with an increase in sales and employment by establishments that provide amenities (such as restaurants, bars, entertainment, and cultural establishments).

In summary, there are a variety of mechanisms through which Airbnb rentals could affect crime rates. In this paper we conduct an empirical examination at the local or neighborhood level to see if Airbnb increases or decreases crime. We use individual incident level reports provided by the City of Milwaukee in Wisconsin and Airbnb host level information to examine the interplay between Airbnb and crime from before the introduction of Airbnb to the region in 2011 through the end of 2017.

Since Airbnb is not randomly assigned to different parts of the city, we include a wide array of demographic and economic variables to control for the selection process. Neighborhood level (census block group) fixed effects are also included to control for unobserved time invariant local factors. As a result, identification relies on the relationship between neighborhood level monthly changes in Airbnb and crime. Since crime and Airbnb are clearly jointly determined, we use a Bartik style instrumental variable approach. To help control for recent criticism of Bartik style instruments (for example, Goldsmith-Pinkham et al. (2018), Broxterman and Larson (2020)), we construct the instrument using a long-lagged measure of the extent of tourist attractiveness interacted with worldwide internet searches for Airbnb. Our approach is aided by the fact that crime changes over time and has a high variance. As a result of all these factors, our results indicate that the instrument meets all exclusion restrictions.

We find consistent evidence that having more Airbnb rentals in an area meaningfully reduces crime, suggesting that Airbnb can be a mechanism to help spur gentrification and enhance neighborhood safety. While these results are derived from a single city, they do suggest that in urban areas, especially those with modest growth, the presence of Airbnb can meaningfully improve the safety of a neighborhood.

The remainder of the paper is organized as follows. Section 2 reviews the current state of the literature on Airbnb. Section 3 describes the conceptual framework regarding the effects of Airbnb on crime. Section 4 discusses data sources and descriptive statistics. Section 5 describes our empirical approach and identification strategy. Section 6 presents the empirical results. Section 7 concludes the paper.

2 Literature on Airbnb

Since Airbnb rentals are mostly short term (typically ranging from a single day to about a week), Airbnb is in direct competition with the hotel industry. Airbnb typically offers a lower cost option to a traditional hotel. It also usually provides a different mix of amenities and services (such as food service or on site gyms) and is less regulated and taxed than hotels. Airbnb listings are very flexible because a host can enter and exit the market with only trivial costs. It should be no surprise that this flexible supply of rentable space with a low marginal cost function is an effective competitor with hotels and has its largest impact on hotel revenues during periods of peak demand. While empirical estimates all agree that Airbnb listings reduce revenue and occupancy for hotels, the order of magnitude varies substantially, ranging from 0.36 to 10 percent reduction in revenue in response to a 10 percent increase in Airbnb listings (Farronato and Fradkin, 2018; Zervas et al., 2017; Mao et al., 2019).

The returns to home ownership generally include both the value of consuming the benefits of property use and any financial gains associated with ownership. Airbnb provides a platform where a homeowner can explicitly earn rent periodically (similar to a dividend yield for corporations or the capitalization rate for commercial property), thus increasing the explicit financial returns of ownership. Through this mechanism and others, Airbnb increases the value of the property itself (Wyman and McLeod, 2019) as well as nearby property (Wyman and McLeod, 2019; Barron et al., 2018; Sheppard et al., 2016; Kim et al., 2017). This is in contrast to multifamily rentals, which tend to depress the value of nearby property. The negative spillovers associated with multifamily housing are typically related to maintenance issues (Iwata and Yamaga, 2008; Gatzlaff et al., 1998; Clauretie and Wolverton, 2006; Stull, 1975; Autor et al., 2014; Turnbull and Zahirovic-Herbert, 2012; Thomas and Neil, 1996; Gatzlaff et al., 1998). Wyman and McLeod (2019) hypothesize that owners of short-term rentals do a better job than long-term rental owners in maintaining their property, because of the quick feedback and the need for reputation-building through the Airbnb listing service. Rapid turnover also gives an owner easier access to the building to resolve maintenance issues.

In addition to having different spillover effects than multifamily property, Airbnb has some direct impacts on the multifamily market itself. For example, due to the conversion of long term rentals into short term rentals, Airbnb is associated with higher long term (or traditional) rental rates (Barron et al., 2018; Horn and Merante, 2017). While an increase in rental income is positive for the owner, it imposes increased costs on existing long-term renters. In worldwide tourist destinations (for example, Berlin, Barcelona, Los Angeles, New Orleans and New York City), formerly residential areas have been converted into rental/tourist-dominated areas. The loss of neighborhood feel and the spatial concentration of tourists has led to complaints of poor tourist behavior and perceptions of increased traffic and decreased safety (Lee, 2016; Gurran, 2018; Schäfer and Braun, 2016; Wachsmuth and Weisler, 2018; Gant, 2016). Concerns about these negative spillovers have led to increased regulations, which typically limit the number of guests and the number of days a property can be available, increase or institute new fees, and in some locations partially ban Airbnb (Nieuwland and van Melik, 2018; Palombo, 2015; Schäfer and Braun, 2016; Leshinsky and Schatz, 2018; Samaan, 2015).

In summary, the literature indicates that there are large economic gains to property owners from becoming Airbnb hosts. On the other hand, the social costs to the neighborhood and residents who rent property in the long-term market may be significant. This paper does not address the relative magnitude of the costs and benefits of peer-to-peer short term renting on a neighborhood, but instead focuses on the relation between Airbnb and local incidence of crime.

3 Motivation and Theory

Becker (1968) posits that a person commits a criminal offense if the expected benefit exceeds the expected cost. That is, a person will only commit a crime in a neighborhood if

$$E[Benefit] > E[cost(P, S, R)] \tag{1}$$

The expected cost of committing a crime is a function of the probability of being caught P, searching cost for potential victims S, and legal punishment if caught R. In a partial equilibrium, as the probability of being caught, search cost for potential victims, and legal punishment increase, it becomes more costly to commit a crime which leads to a lower crime rate. As a result, $\frac{\partial E[cost]}{\partial P} > 0$, $\frac{\partial E[cost]}{\partial S} > 0$, and $\frac{\partial E[cost]}{\partial R} > 0$.

Airbnb affects crime rates through two channels.

Gentrification. First, Airbnb has the potential to change a neighborhood through gentrification. Wachsmuth and Weisler (2018) identify the neighborhoods that have been significantly changed by Airbnb and Airbnb-induced gentrification. McDonald (1986) and Autor et al. (2014) show that gentrification reduces crime. In particular, a pseudo-natural experiment found that removing rent controls in Cambridge, Massachusetts led to a 16 percent reduction in crime.

There are several mechanisms by which Airbnb-induced gentrification can increase the probability of criminals being caught P and thus reduce crime rates. Airbnb generates rental income, which create incentives for hosts to upgrade their properties. Farrell et al. (2011) show that wealthier residents are more likely to invest in private security measures, such as alarm systems, which could increase the probability of a criminal being captured and thereby deter crime. Their research implies that with rental income generated from Airbnb, hosts are more likely to improve safety measures to deter crime and attract tourists.

Furthermore, the increase in property value due to Airbnb leads to an increase in the local property tax base, which can increase resources devoted to crime-fighting. In addition, the rental flow generated from Airbnb discourages property abandonment and foreclosure, which promotes neighborhood stability. Wilson (2012) and Sampson et al. (1997) show that neighborhood turnover increases crime by reducing social cohesion. By contrast, neighborhood stability increases resident attachment to the neighborhood and encourages active engagement, such as participation in neighborhood watch programs and other crime prevention activities.

Figure 1 provides suggestive evidence that one channel for Airbnb-related gentrification is an increase in economic and cultural vibrancy in the neighborhood. Using establishment level data, the figure shows an increase in employment and sales by amenity-producing establishments in locations with Airbnb. In fact, both sales and employment increases by over 40 percent after entry of Airbnb in a location. These amenity-producing establishments include restaurants, bars, live music, movie theaters, aquariums, museums and other related establishments.

Therefore, in a partial equilibrium, more Airbnb rentals in an area will increase the probability of getting caught committing a crime, $\frac{\partial P}{\partial Airbnb} > 0$. Since the probability of getting caught increases the expected cost of committing crime $\frac{\partial E[cost]}{\partial P} > 0$, Airbnb also increases the expected cost of criminal activities $\frac{\partial E[cost]}{\partial Airbnb} > 0$. Through this channel, the presence of Airbnb in a neighborhood can reduce crime rates.

Spatial Impacts. In the second channel, Airbnb can affect the spatial location of crime. Airbnb brings tourists into residential neighborhoods, and those tourists can become targets of crime or commit crime themselves (especially if popular tourist activities involve use of alcohol or drugs). Therefore, an increase in Airbnb activity can be viewed as reducing the search cost for potential victims $\frac{\partial S}{\partial Airbnb} > 0$. Because $\frac{\partial E[cost]}{\partial S} > 0$, as Airbnb reduces S, the cost of committing a crime is reduced, $\frac{\partial E[cost]}{\partial S} > 0$, which leads to an increase in the incidence of crime.

Overall, in theory, the effects of Airbnb activities on the local crime rate are ambiguous. If the gentrification effects of Airbnb activities dominate the spatial effects, the net effect of Airbnb will be to decrease crime rates in neighborhoods with more Airbnb.

4 Data

We collect and merge information from various data sources to create a panel data set for the city of Milwaukee. Since crime is typically committed locally and is spatially clustered (Metz and Burdina, 2018), smaller neighborhood geographical units are preferable. Therefore, our unit of observation is the census block group in a given month from June 2011 until June 2017. The variable of interest is the total crime per capita, which we merge with information about the Airbnb properties in the neighborhood. In addition, we collect demographic data, land use information, tourist related establishment counts, Google searches with the word "Airbnb," and funding rounds by Airbnb.

Our crime data comes from the Wisconsin Incident Based Report (WIBR) for the city of Milwaukee.[1] The data represents police services where a report about a crime was made and does not include calls made for other police services. Each crime receives a time, an address or location, and a classification (arson, assault offense, burglary, criminal damage, homicide, locked vehicle, sex offense, theft or vehicle theft). For incidents that did not report latitude and longitude, we georeference each occurrence using google maps API. The incident level data is aggregated to the census block group and month.

Airbnb data comes from AirDNA,[2] a company that collects information from each property available in the Airbnb website. The property and host information includes the number of bedrooms, number of baths, capacity measured as maximum number of guests allowed in the house, type of listing (i.e. Entire home/apt, Private room, shared room, etc.), location, rating measured in stars, and cancellation policy. The data also contains monthly performance information for each property. This includes reservation data measured by the number of times and the number of days the property was booked, the number of days the property was available for rent, the Average Daily Rate (ADR), and the total revenue.

Figure 2 shows the time series of the total number of crimes committed in the city of Milwaukee and the number of properties in Airbnb over our time period. The total number of crimes between June 2011 and June 2017 is 386,256. While there is a strong seasonal pattern to crime, there is no obvious long term trend, especially since 2014.

AirDNA tracks more than 11,400 listed properties in Milwaukee and, as the figure indicates, the number of properties available for rent though Airbnb has been increasing steadily

[1]https://data.milwaukee.gov/dataset/wibr
[2]https://www.airdna.co

since the middle of 2014. Figures 3 and 4 show the spatial distribution of Airbnb hosts and the log of crime per capita. The growth of Airbnb has focused on locations near downtown, along Lake Michigan, and close to the waterfront park system and Summerfest grounds (the location of a large summer musical festival). Crime is spread around the city but tends to be higher in the northwest quadrant of the city.

Table 1 describes each variable, as well as its source, and Table 2 provides summary statistics. For ease of interpretation, we include all variables in their level forms. Some variables are transformed by taking natural logs for estimation. There are just over 39,000 observations in the block group monthly panel data set. There is substantial variation in all variables. For example, the average count of Airbnb hosts within a census block group is 0.31 with a minimum of 0 and a maximum of approximately 33. There are on average 6.21 crime incidents of crime per 1,000 people per month and per block group, but the numbers vary from 0 to over 233. Following the literature on crime, we include a variety of controls for economic conditions and demographic information. In general, indicators of social and economic stress (disorder in the crime literature), as well as lower income and social inequality, are expected to be associated with higher rates of crime (Grogger, 1998; OBrien and Sampson, 2015; Alba et al., 1994; Boggess and Hipp, 2010; Cornwell and Trumbull, 1994; Cook, 2008; Kelly, 2000, See for example,). To control for these factors, we use the American Community Survey and collect a variety of measures at the census block group level. These control variables include measures of income, poverty, unemployment, race, educational attainment, age, renter versus homeowners, and the mode of transportation to work. Property vacancy rates are included to proxy for stress and the opportunity to commit a property-related crime. Inequality is measured using the income Gini coefficient at the Tract level and the ratio of median to mean income within the block group. The ACS data is reported annually and interpolated (straight line) across all months within the year.

The last three variables, which we will discuss in more detail later in the paper, relate to the construction of our preferred instrumental variable (to identify the impact of Airbnb on crime). The variable Establishments 1990 is the number of establishments in 1990 that indicate the attractiveness of a location for tourists. For example, we include establishments identified as lodging, restaurants, bars, entertainment (such as music and theater venues), sports and athletics, gambling, zoos, aquariums, museums, and so on. These establishments include not only places where tourists stay overnight, but also the key activities that tourists would be attracted to and engage in. The source for this data is the Dun and Bradstreet establishment data compiled into a panel in the National Establishments Time Series (NETS) data set. To identify time varying interest in, or demand for, Airbnb, we include a measure of worldwide searches for "Airbnb" found in Google Trends. Google sets this measure to 100 in the time period when searches for Airbnb are at the highest level ever. A value of 60 in a particular time period indicates that searches were 60 percent of the all-time high. For Airbnb searches, the all-time high occurred after our data set ends in 2017. As a result, our maximum observed Google Trend measure is slightly less than 90. These two variables (Google Trend and Establishments 1990) are multiplied together in the style of a shift-share or Bartik instrumental variable: the share is measured by the count of establishments and the shift is measured by Google searches.

5 Empirical Methodology

We start with the following regression equation to estimate the effect of Airbnb on crime per capita:

$$lnY_{it} = \alpha + \beta lnAirbnb_{it} + \eta X_{it} + \delta_i + \theta_t + \varepsilon_{it} \tag{2}$$

where lnY_{it} is the natural log of one plus the number of crimes per thousand residents in block group i in year-month t, $lnAirbnb_{it}$ is the natural log of one plus the number of Airbnb properties, X_{it} is a vector of observed time-varying block group characteristics, δ_i is used to control unobserved block group level factors, θ_t controls for unobserved time-varying factors that affect all block groups equally, and ε_{it} represents an identically and independently distributed random error term.

The empirical challenges include both the non-random selection of locations by Airbnb hosts and the possibility that crime could attract or deter Airbnb. Our approach to these selection issues is twofold. First, we include a large number of control variables. The observable controls include measures that describe each neighborhood along various dimensions related to crime – social and economic distress and the ease of the opportunity to commit a crime, X_{it}. In addition, to control for unobservables, the specification includes census block group fixed effects, δ_i reflecting time invariant neighborhood characteristics along with a vector of year*month fixed effects, θ_t, to control for seasonal variation in crime and overall or city-wide trends in crime over time. Therefore, the identification relies on the difference between the monthly time variation of the block relative to the city, after controlling for all observables. All of these controls limit concerns that missing variables could bias the results.

However, if crime itself directly causes Airbnb to locate in a census block, these controls will not be sufficient to rule out reverse causation. To address this endogeneity issue, we construct an instrumental variable which is plausibly uncorrelated with ε_{it} but likely to affect the Airbnb activities. Specifically, we construct a shift-share or Bartik-style instrument where the shift is measured through worldwide Google searches for "Airbnb"(the variable Google Trend), $google_t$, and the share is represented by a long-lagged measure of tourist-related establishments (the variable Establishments 1990), $amenity_{i,1990}$. Thus our instrument is $z_{it} = google_t \cdot amenity_{i,1990}$.

Following Barron et al. (2018), we use the worldwide Google Trends search index for the term "Airbnb" in constructing our instrument. The index measures the quantity of Google searches for "Airbnb" in each year-month t, and as shown in Figure 5, reflects the extent of interest in Airbnb across the world. It is implausible for worldwide searches for Airbnb to be even tangentially related to changes in crime incidences at the census block group in Milwaukee. In contrast, worldwide interest in Airbnb is likely correlated with interest in Airbnb in Milwaukee. See Figure 5 for a plot of the Google Trends index of worldwide and Milwaukee Airbnb searches from year 2011 to 2018.

The variable Google Trend will only extract the time varying portion of Airbnb, but not the variation that is related to geography and intensity of interest. For that, we turn to a count of amenities that would make a neighborhood attractive to tourists, 1990 Establishments. Airbnb listings tend to be higher in more touristy areas with abundant amenities. However, such a measure will still create significant endogeneity problems if the count is contemporaneous with our data set. Our solution is to disentangle this measure from crime by using a long lag, more than 20 years. Crime tends to be volatile and unstable over time and space; it is common for crime rates to change dramatically and quickly in local neighborhoods. By contrast, the types of establishments that support tourism are likely to be more stable and long-term. In fact, the correlation of the log of establishments in 1990 with the log of establishments in 2015 is 0.5, indicating that the "touristy" nature of a location does have some persistence. Both of these factors – the volatility of crime rates and the long-term stability of establishments – help us create a valid instrument.

We also will test three other potential instruments. In the first, we interact the funding or capital raising history of Airbnb with 1990 Establishments to create the variable Venture Capital IV. Table 3 provides the history of the Airbnb funding rounds. In our specification, the variable, which we refer to as Venture Capital, indicates a new funding round by being increased by one unit. So, Venture Capital increases from 1 to 12 as the funding rounds occur over time. Venture capital infusions provide exogenous (to Milwaukee neighborhoods) shocks to Airbnb's ability to expand (Mao et al. (2019)). Hence, this variable will function as a proxy for supply changes in Airbnb over time that are not related to crime. In the second potential instrument, we focus on the number of establishments in the food and accommodation industry in 1990, as a more limited measure of location amenities. This is interacted with Google Trend to create the Food IV variable. The last instrument we test includes a measure of property use derived from the 2005 City of Milwaukee master property file to approximate the zoning regulation at each location. It is the fraction of land in the block group that is zoned for residential (multifamily or single family) use. Again, it is interacted with 1990 Establishments to create the variable Zoning IV.

5.1 Validity of the Instrument Variable

For our instrument to be valid, the exclusion restriction requires that the instrument z_{it} be uncorrelated with the error term ε_{it}, that is, $cov(z_{it}, \varepsilon_{it}) = 0$. The year month fixed effect and block group fixed effect have absorbed the unobserved variation at the block group level and year month level. Our exclusion restriction requires Google trend $google_t$ and tourist-related establishments in 1990, $amenity_{i,1990}$ to be uncorrelated with unobserved block group, time-varying shocks; and it is unlikely that the changes to crime rates across all block groups are systematically correlated with Google trend $google_t$ and tourist-related establishments in 1990.

Given that Google Trend is plausibly exogenous, our cross-sectional exposure variable (1990 Establishments) must be uncorrelated with the unobserved block-group-specific, time-varying shocks to the crime rate. Therefore, it is important to discuss the validity of the instrument variable.

One intuitive approach to support the validity of the instrument is to test whether the instrument variable directly affects crime in block groups that never had any Airbnb listings. If the instrument is valid, it should correlate to crime only through its effect on Airbnb listings and thus should not directly affect crime in areas that never had any Airbnb listings. To test this, we regress the log of total crime rate per capita on different instrumental variables, using data from block groups that were never observed to have Airbnb listings, while controlling for economic and demographic variables.

Table 4 reports the regression results. Column (1) shows that, conditioned on time fixed effects, block group fixed effects, and economic and demographic factors, there is no statistically significant relationship between our preferred instrument and crime. Column (2) shows that Venture Capital IV does not correlate with crime, and column (3) shows that Food IV also does not directly affect crime. However, column (4) does not provide support for the validity of Zoning IV, because there is a significant relationship between the instrument and crime.

In the second approach, we randomize the number of Airbnb listings. The randomization eliminates the source of variation needed for our instrument to work. If the instrument is valid, it affects crime only through the variation in Airbnb listings. As a result, we should observe zero correlation between Airbnb listing and crime – the instrument should fail to identify the causal effect of Airbnb. This approach follows Christian and Barrett (2017) and Barron et al. (2018). We randomly generate numbers from a uniform distribution and then randomly assign a number as the number of Airbnb listings to each block group. Column (1) in table 5 shows the same regressions as column (3) of table 7, except that the data for Airbnb listings in table 5 is randomly generated. As expected, there is no statistically significant relationship between the randomly generated Airbnb listings and crime, which supports the validity of our instrument.

6 Empirical Results

6.1 Main Results

Table 6 reports the base Ordinary Least Squares (OLS) results using a variety of control variables. All regressions cluster the standard errors at the block group level of geography. The first column shows that Airbnb is negatively correlated with the crime rate. However, columns 2, 3 and 4 show that once block group fixed effects and year-month fixed effects are include, OLS finds no correlation between Airbnb and crime. These results help to control for the non-random way in which Airbnb selects locations but do not control for reverse causation (crime directly impacting Airbnb).

Table 7 presents the base instrumental variable results. As with the OLS results, all regressions include block group fixed effects and year-month fixed effects. The standard errors are clustered by block group. Airbnb is instrumented using the interaction of Google Trends searches and the count of 1990 tourist related establishments, $IVcount_{it}$. The results are very stable. In fact, in column 3, our preferred specification, a 10% increase in Airbnb decreases crime per capita by 2.68%. These results indicate that the gentrification effect of Airbnb dominates the spatial effect. The Kleibergen-Paap F statistics indicate that the instrumental variable provides sufficient explanatory power to identify, at the one percent level, the impact of Airbnb in the first stage results (Airbnb as a function of all exogenous variables and the $IVcount_{it}$).

The results also indicate that economic distress is associated with higher crime rates. While the control variables tend to have the anticipated sign, not all are statistically significant. However, lower income *is* statistically significant and drives up neighborhood crime. Higher rates of vacant property are also very consistently associated with higher crime rates, with statistically significant results. This is consistent with the crime literature, which suggests that social stability (economic distress) and opportunities to commit crime (search costs, which are reduced by vacant property) are important determinants of neighborhood level crime intensity.

Demographics also play a role in crime. In particular, locations with older populations experience more crime; and neighborhoods in which people rely more heavily on public transit are more susceptible to crime. However, we do not find any evidence that educational attainment, racial composition, home ownership, or income disparity have an impact on crime rates. These factors may be correlated with the block group fixed effects and the overall time fixed effects.

Goldsmith-Pinkham et al. (2018) indicate that one way to test for whether our instrumental variable meets the exclusion restrictions (that our instrument does not predict crime through different channels than Airbnb), is to run empirical tests examining the stability of the estimated coefficient using alternative instruments. Table 8 conducts this test using three plausible, but not preferred, instruments. Column (1) uses Venture Capital IV as a proxy for supply changes in Airbnb over time that are not related to crime. The Kleibergen-Paap F Statistic indicates that it is a strong instrument. The impact of Airbnb on crime is very similar to the results using our preferred instrument. Column (2) uses Food IV. Again, the coefficient is very similar to the original point estimate and is a strong instrument (the Kleibergen-Paap F Statistic is significant at the 1 percent level). Likewise, Column (3), Zoning IV, shows results that are very similar to our original results. The variable is again an adequate instrument in terms of identification (the Kleibergen-Paap F Statistic is significant at the 1 percent level). However, this last result should be interpreted with caution because land use patterns are typically slow to change over time. This table provides additional evidence that our results are robust and meet the exclusion requirements.

6.2 Neighborhood and Spillover Effects

It is also likely that different types of neighborhoods will react in unique ways to the introduction of Airbnb. To investigate this possibility we create subsamples of neighborhoods based on income and rent. We start by identifying the median income of each block group in our sample. We define high income neighborhoods as the block groups in the top third of the median income distribution; low income neighborhoods are those in the bottom third. The first two columns in Table 9 show that Airbnb has no statistically significant impact on low income neighborhoods but reduces crime in high income neighborhoods. We examine the role rent in the same way. As with income, Airbnb has no effect on the low rent (bottom third) neighborhoods but reduces crime in the high rent (top third) neighborhoods. It should be noted that the signs are negative in all specifications, but there is a lack of precision in some of the results.Airbnb tends to reduce crime more in more affluent neighborhoods. In other words, positive spillovers from Airbnb are differentiated across wealth when it comes to crime: the most well-off neighborhoods obtain more benefit from the presence of Airbnb rentals. Thus, Airbnb can contribute to even more disparity between urban neighborhoods in terms of safety and stability.

The results so far indicate that the presence of Airbnb tends to reduce crime. However, the impact of Airbnb on crime may spillover into nearby neighborhoods. There is evidence of spatial spillovers when enforcement and deterrence are increased (Bronars and Lott (1998), Galletta (2017) and Rincke and Traxler (2011)). Although most of the spill over evidence suggests that increases in enforcement decreases crime in nearby locations, there is evidence of the opposite too (Bronars and Lott (1998)). In our case, Airbnb impacts crime through a decrease in search cost of potential targets of crime (i.e. more tourists to be a victim of a crime) or though an increase in the opportunity cost through a more vibrant local economy (i.e. more employment). Therefore, spillovers in our case could be positive or negative. For example, if reductions in local crime improve conditions in neighboring blocks, then the spatial spillover would be a positive. This could reinforce the idea that Airbnb is a gentrifying force that drives down overall crime. However, crime can also move to locations where the expected returns to crime are higher. This would reduce the overall positive impact of Airbnb as crime shifts to new neighborhoods. Table 10 tests for these spatial spillovers. Three specifications are included, but they all show the same results. While Airbnb does decrease crime in the local neighborhood, Airbnb in nearby blocks (next to the local neighborhood) increases crime. Our spillover variable $Airbnbtract_{it}$ is defined as the log of 1 + the count of Airbnb hosts in all the census block groups within the census tract, after excluding the count within the local block. So, it provides a measure of the density of Airbnb surrounding the local neighborhood. Both of these variables are treated as endogenous and instrumented. The instrumental variable use for $Airbnbtract_{it}$ is the preferred IV while using the same geography described above. The coefficient estimates indicate that a 10 percent increase in Airbnb in the local neighborhood with no nearby Airbnb would lead to a reduction in crime of 3.36 percent. If the nearby neighborhoods also see a 10 percent increase in Airbnb, crime is still reduced, but by 2.04 percent (-0.336 + 0.132). In fact, if growth in Airbnb in the nearby neighborhood is a little over 2.5 times more than local neighborhood, local crime can increase.

6.3 Robustness Checks

Table 11 shows that the effect of Airbnb on crime is robust across different measures of Airbnb activity in the block group. Column (2) reports that a 10% increase in maximum number of guests reduces crime per capita by 1.8%. Column (1) shows that as the number of Airbnb reservations increases by 10%, crime per capita also decreases by 1.8%. In column (3) we test the impact of the average daily rate per room. The impact on crime is still negative but is not estimated with enough precision. Overall, the results indicate that more Airbnb, but not necessarily how much it costs, helps to drive down the amount of crime in a neighborhood.

Table 12 examines how the impact of Airbnb varies for different types of crime. Following definitions from Bureau of Justice Statistics, we classify arson, burglary, criminal damage, locked vehicle, theft, and vehicle theft as property crime. Violent crime is defined as any incident related to homicide, assault, or sex offense. Columns (1) and (2) show that Airbnb reduces the prevalence of property and violent crime. Although the point estimates are different, they are statistically indistinguishable from each other. In column (3) we report the results for a linear probability model of homicide. Homicide is coded as 1 if at least one homicide occurred in the neighborhood and month, otherwise it is 0. This approach is used because the vast majority of observations do not have a homicide and in even fewer observations was there more than one homicide. The results indicate that Airbnb has no relation to the probability of a homicide. In summary, Airbnb reduces both violent and property crime by similar amounts. However, the most severe type of violent crime, homicide, is unrelated to Airbnb.

We also hypothesized that the impact of Airbnb rentals on crime would change across the seasons, because activity levels can change so much in the Milwaukee area. Winter is slow – the weather can be harsh, with an average low temperature of 13 degrees Fahrenheit in January, and there is relatively little activity to attract tourists. By contrast, summer is a very busy time, with a broad array of outdoor festivals that bring hundreds of thousands of visitors into the area throughout the summer months. Given this, it is somewhat surprising that Table 13 shows that Airbnb reduces crime by a similar order of magnitude in all seasons. The consistency of results suggests that the impact of Airbnb is permanent, supporting the theory that the dominant mechanism through which Airbnb reduces crime is long-term gentrification.

All the prior results used a monthly frequency. We interpolated the annual ACS data to fill in the monthly observations of crime and Airbnb. This mismatch of frequencies may lead to misspecification and potentially bias the results. In Table 14 we address this issue by transforming our data set into annual observations. For each observation we take the annual average. As a result, the number of observations is reduced to just over 4000. The annualized results show the same patterns and basic findings as the monthly data. This indicates that the results are robust when the frequency of observations is changed; and the prior results were not biased by any misspecification.

To guard against the concerns of self selection bias, we conduct Coarsened Exact Matching (CEM) and Propensity Score (PS) matching to improve causal inference. Matching observations prunes observations so that the Airbnb and non-Airbnb observations have more similar empirical support. This reduces the degree to which the causal effects are model dependent, reduces inefficiency, and reduces bias (Ho et al. (2007); Iacus et al. (2011)). Our first approach, CEM, is described in Iacus et al. (2008). CEM forces the matched observations to be relatively close to each other in key observables, allows an unbalanced match (one to many), and weights the matches. 356 matched buckets are created using key determinants of the crime rate (income, age, family, vacancy, public transit) and our preferred instrumental variable (IVcount90). For each bucket, each observation with Airbnb is matched with one or more observations without Airbnb. Our second approach, PS, matches observations that have similar probabilities of have Airbnb. The first stage calculates the propensity using a probit specification including all of continuous exogenous explanatory variables, including IVcount90, and year*month fixed effects. Each observation with Airbnb is matched with its 5 closest neighbors. Table 15 shows the results for the matched samples. Again the instrument performs well for all the samples and the results are consistent. In summary, the results are robust to additional controls for selection bias using a variety of matching techniques.

7 Conclusion

This paper examines the impact of the shared economy on neighborhood safety. We find consistent evidence that Airbnb meaningfully reduces crime. In particular, a 10% increase in Airbnb decreases the local or neighborhood level crime rate by approximately 2.7%. This result is very stable and is robust across different specifications. But this effect is more concentrated in higher income and higher cost areas of the city. We also find some evidence that the local crime reduction is mitigated by an increase in crime in nearby neighborhoods.

There is substantial concern in the popular press, local governments and the academic literature that Airbnb guests have negative spillovers in a neighborhood. There are perceptions and anecdotal stories that Airbnb guests behave badly while celebrating and enjoying their vacations. In terms of crime, Airbnb guests could both commit crimes themselves or be more easy victims of crime. On the other hand, we find suggestive evidence that Airbnb can help to gentrify a neighborhood by boosting the local economy and increasing the provisions of local amenities (restaurants, shops, galleries, pharmacies, and grocery stores, etc...). In addition, there is some evidence in prior research that short term rentals are maintained better than multifamily property. All of these factors likely play a role in reducing the prevalence of crime as around Airbnb host location. Our results suggest that, on balance, the positive forces of gentrification outweigh negative impacts: Airbnb helps improve neighborhood stability and safety.

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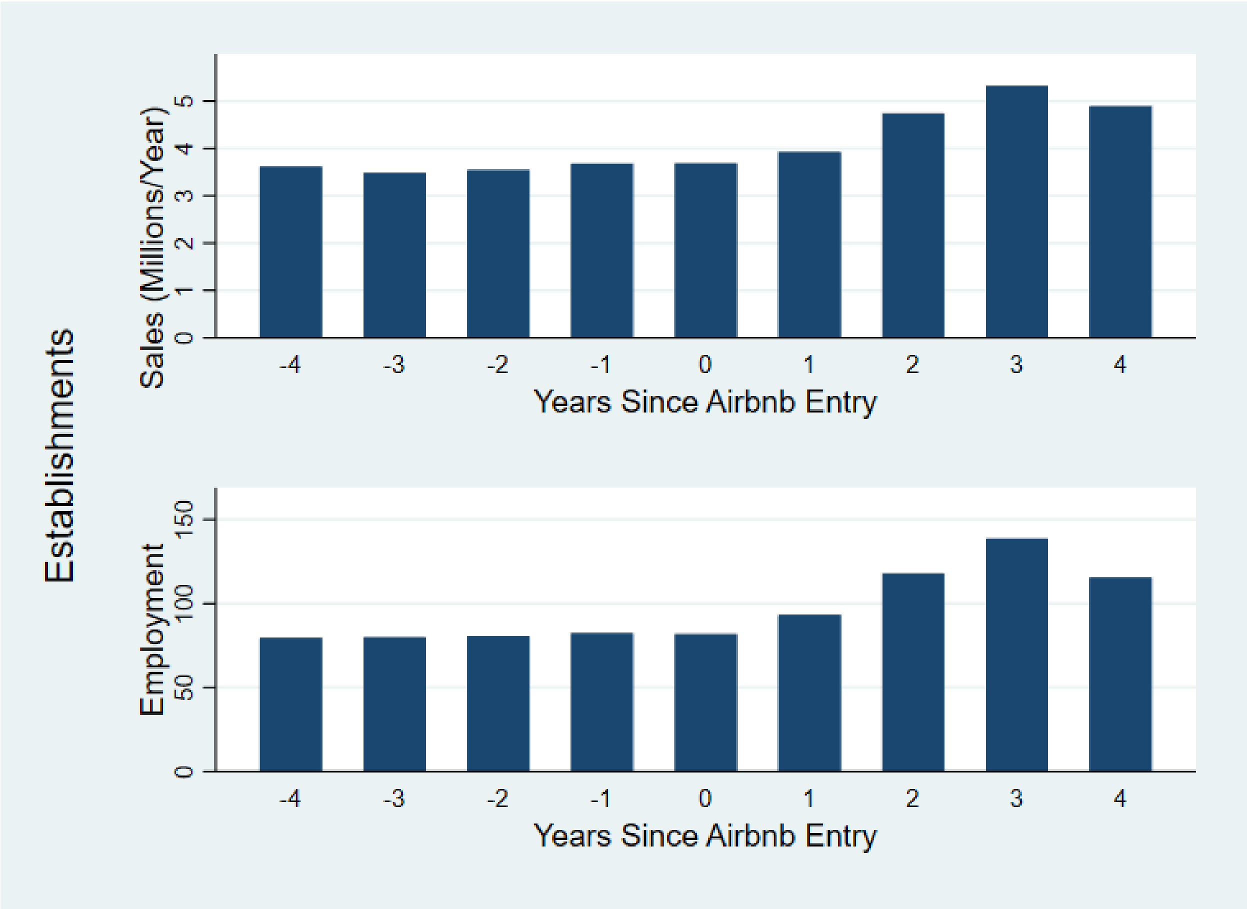
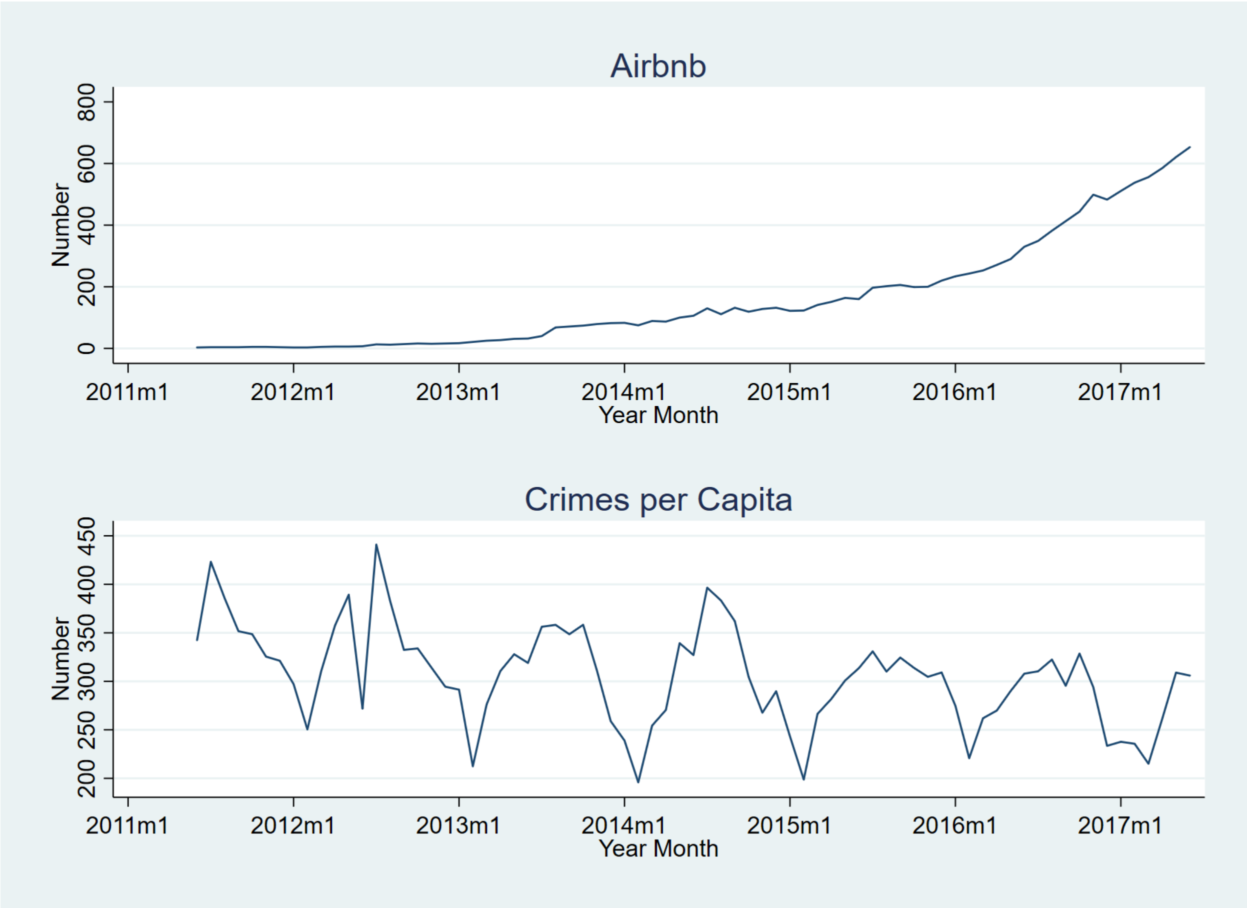
Figure 1: Establishments Sales and Employment

1.png



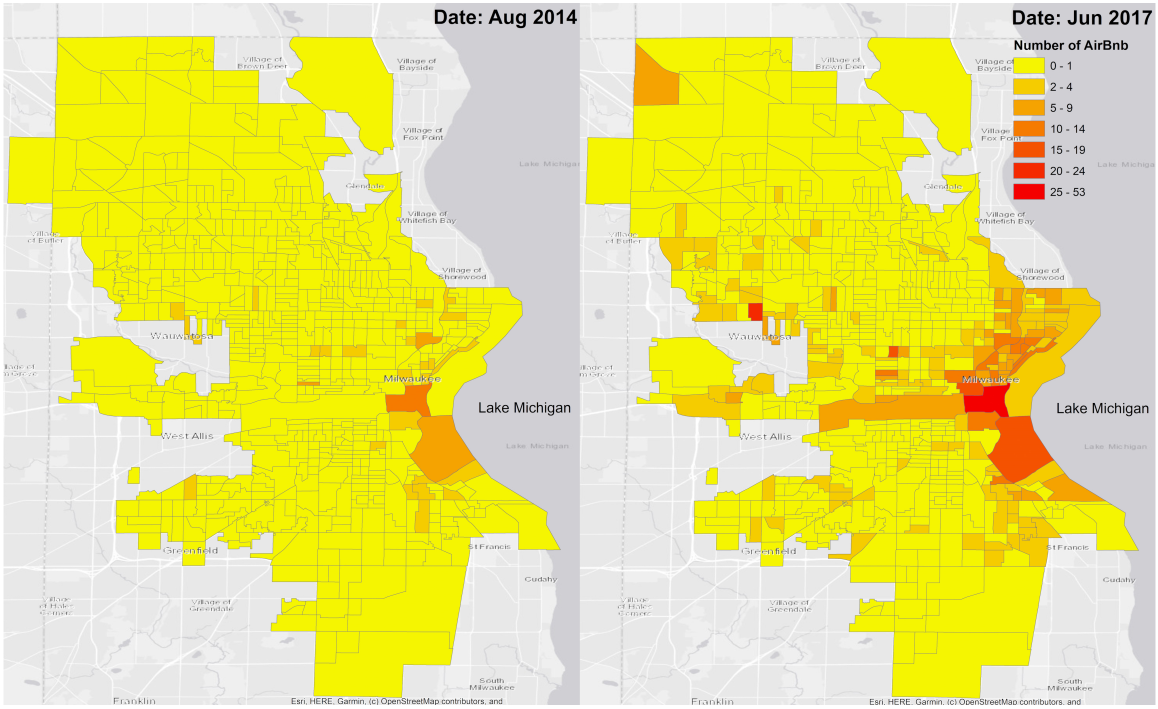
This graph shows average sales (in Millions per Year) and employment (Number of Employees) of amenity-producing establishments at the census block group level, pre and post Airbnb entry. Entry occurs in year 0 and is defined as the first time we observe an Airbnb in a location. These amenity-producing establishments include restaurants, bars, live music, movie theaters, aquariums, museums and other related establishments.

Figure 2: Number of Airbnb and Number of Crime



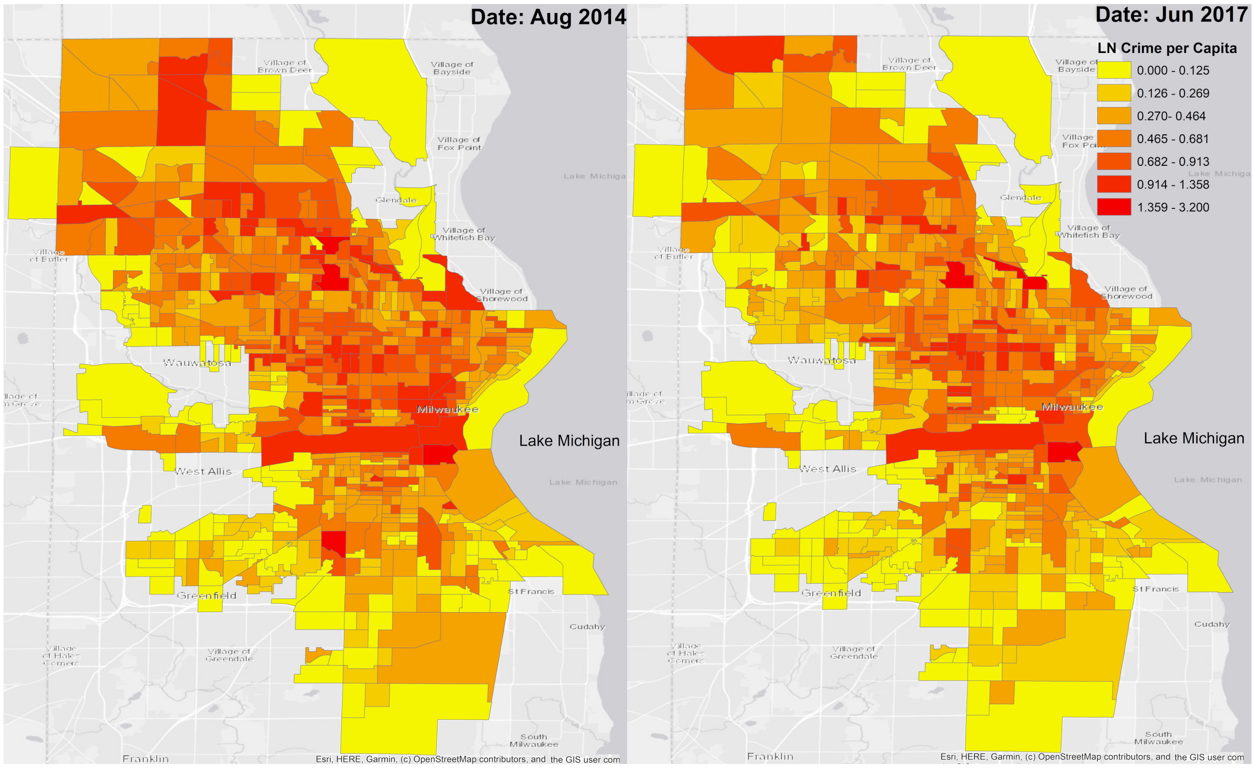
This graph shows the number of Airbnb properties available for rent in the city of Milwaukee in any given month from January 2011 until June 2017. The graph in the lower frame is the number of crimes in the city of Milwaukee per month. The crime data includes arson, assault offense, burglary, criminal damage, homicide, locked vehicle, sex offense, theft and vehicle theft.

Figure 3: Airbnb Count per Census Block Group



These graphs show the count of airbnb in each Census block group, for two time periods in the sample.The graph on the left shows the values for August 2014 and the graph on the right the values for June 2017

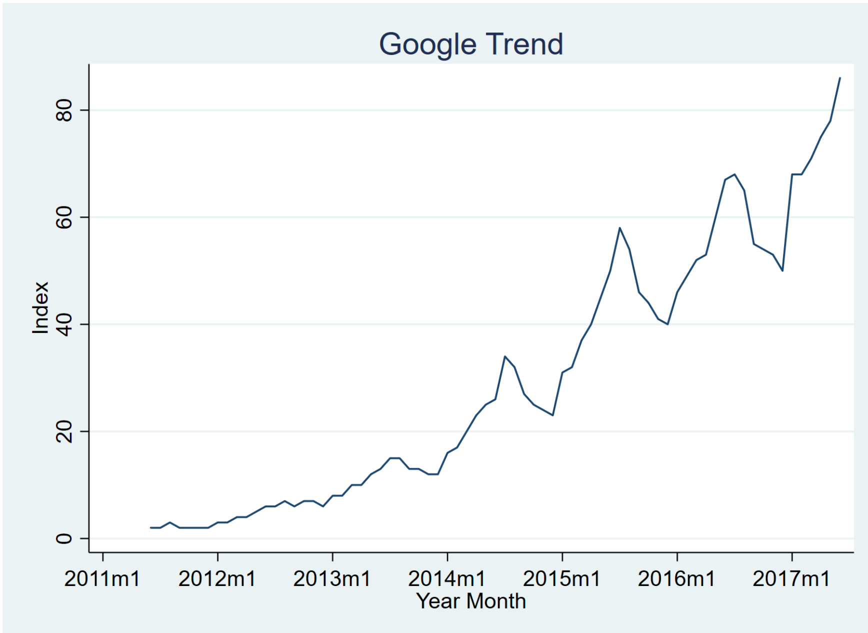
Figure 4: Crime per Census Block Group



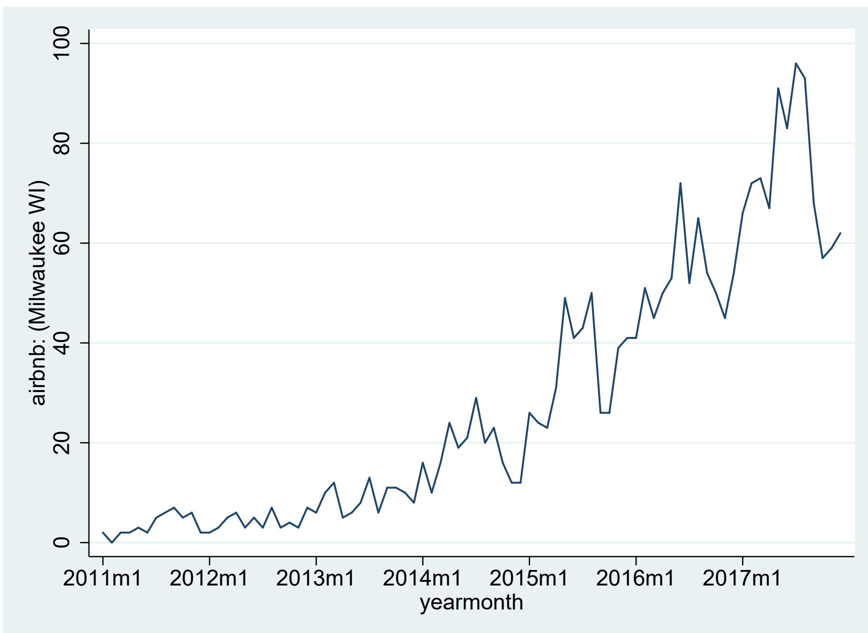
These graphs show the log value of the number of crimes per capita in each Census block group. The graph on the left shows the values for August 2014 and the graph on the right the values for June 2017

Figure 5: Airbnb Google Trends

(a) Worldwide Google Trends Search Index for Airbnb (Worldwide, 2011-2018)



(b) Milwaukee Google Trends Search Index for Airbnb (Milwaukee, 2011-2018)



This graph shows the Google trend index. This index captures the changes in the number of searches in Google for Airbnb.

Table 1: Variables Description

Name	Description	Geography	Source
ln(Crime)	Natural lograthim of the total number of crime related incidences per capita (1,000 people). Total crime includes arson, assault offense, burglary, criminal damage, homicide, locked vehicle, sex offense, theft and vehicle theft.	Block Grp.	MPD
ln(Airbnb)	Natural lograthim of then umber properties available for rent.	Block Grp.	AirDNA
Reservations	Number of the reservations.	Block Grp.	AirDNA
Maximum Guest	Maximun number of guest that are allowed to stay in the properties available for rent.	Block Grp.	AirDNA
ln(Income)	Natural logarithm of the median household income.	Block Grp.	ACS
Poverty	Percentage of the population under the poverty line in the past 12 months.	Block Grp.	ACS
Urate	Unemployment rate calculated by the count of unemployed divided by the population over age 16.	Block Grp.	ACS
Black	Population of black race over total population.	Block Grp.	ACS
College	Percentage of the population with some college and more. This includes people with less than 1 year of college, more than a year but no degree, associate, bachelor's, master's, professional and doctorate degree.	Block Grp.	ACS
Family	Median number of children in the household.	Block Grp.	ACS
ln(Age)	Natural lograthim of median age of the population	Block Grp.	ACS
Renter	Fraction of the housing units that are renter occupied	Block Grp.	ACS
Transit	Fraction of the population that uses public transit as means of transportation (Excluding Taxicab).	Block Grp.	ACS
Vacancy	housing units with a vacant status over all housing units. units.	Block Grp.	ACS
Income Ratio	Ratio of block group median household income to census tract median household income.	Block Grp.	ACS
Gini	Gini Coefficient for household income.	Tract	ACS
Google Trend	Represent worldwide search interest for Airbnb. A value of 100 is the peak popularity. A value of 50 means that the term ”Airbnb” is half as popular. A score of 0 means there was not enough data for the term ”Airbnb”.	Worldwide	Google
Count 1990	The number of establishments in 1990 that increase the appeal of a location to tourists. This includes establishments involved in restaurants, bars, entertainment (for example, music and theater establishments), lodging, sports and athletics, gambling, zoos, aquariums, museums, and others	Block Grp.	DB
Zoning	Represents the percentage of square feet dedicated to residential use in 2005.	Block Grp.	ITMD

Note: MPD(Milwaukee Police Department) data link - https://data.milwaukee.gov/dataset/wibr; AirDNA (Airbnb dats provider) link - https://www.airdna.co/; Google (Google Trend) Trend - https://trends.google.com/trends/explore?date=all&q=airbnb; ACS (American Community Survey) link - https://factfinder.census.gov; DB(Dun and Bradstreet National Establishment Time Series) link - https://www.kauffman.org/entrepreneurship/research/data-resources/; ITMD (City of Milwaukee master poperty file) link - https://data.milwaukee.gov/dataset/mprop

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max
Crime	6.21	5.32	0.00	233.46
Airbnb	0.31	1.09	0.00	33.22
Number of Reservations	0.61	3.26	0.00	118
Maximum Number of Guests	1.02	4.76	0.00	140
Daily Rate	70.89	65.47	9.45	2122.09
Income	40,267.08	17,640.97	6,702.00	204,000.00
Poverty	0.27	0.17	0.00	0.89
Urate	0.08	0.05	0.00	0.43
Black	0.38	0.35	0.00	1.00
College	0.29	0.09	0.00	0.79
Family	1.03	0.44	0.00	4.12
Age	248.54	131.94	14.9	741.00
Renter	0.53	0.22	0.00	1.00
Transit	0.09	0.09	0.000	0.77
Vacancy	0.11	0.10	0.00	0.81
Income Ratio	5.98	254.78	0.11	25,396.83
Gini	0.43	0.06	0.29	0.70
IV count90	25.63	37.414	0.00	336.43
Google Trend	29.25	23.67	2.00	86.00
Establishments 1990	2.76	5.68	0.00	52.00
Observations	39,079			

Note: This table provides the descriptive statistic for our sample. Crime is the number of crimes per 1,000 people; Airbnb is measured by the number of Airbnb listings; Number of Reservations is the number of reservations booked in a month; Maximum number of guests is sum of the maximum capacity of all the properties available for rent; Daily rate is the average daily rate of the properties available, only 2,801; Income is median income; Poverty is measured by the fraction of population below poverty line; Urate is the unemployment rate; Black is the fraction of black population; College is the fraction of people has college or graduate degree; Family is the fraction of family with children; Age is the median age of the population; Renter is the fraction of population that are renters; Transit is the fraction of population taking public transit; Vacancy is the property level vacancy rate, which is calculated as one minus owner occupancy rate; Income ratio is the median income ratio of tract to block group; Gini is the gini coefficient of income at the tract level; Google trend is the index of searches of Airbnb in google; Establishments 1990 is the number of tourist related establishments in 1990. For more detail please refer to Table 1.

Table 3: AirBnb Funding Rounds

Type	Date	Amount Raised	Post-money Valuation	Investors
Seed	Jan-09	$20.0 k	$2.5 m	Y Combinator
Seed	Apr-09	$615.0 k		Sequoia Capital, Y Ventures
Series A	Nov-10	$7.2 m	$70.0 m	Ashton Kutcher, Elad Gil, Greylock Partners, Jeremy Stoppelman, Keith Rabois, SV Angel, Sequoia Capital, Y Ventures
Series B-1	Jul-11	$114.9 m	$1.3 b	Andreessen Horowitz, Ashton Kutcher, CrunchFund, DST Global, General Catalyst, Jeff Bezos, Oliver Jung, Sequoia Capital
Series B-2	Jul-11	$2.1 m		A-Grade Investments, Andreessen Horowitz, CF, DST Global, General Catalyst, General Catalyst Partners, Jeff Bezos, Oliver Jung, Sequoia Capital
Series C	Oct-13	$200.0 m	$2.9 b	Airbnb, Ashton Kutcher, CF, Founders Fund, Sequoia Capital
Series D	Apr-14	$519.7 m	$10.5 b	Andreessen Horowitz, Dragoneer Investment Group, Sequoia Capital, Sherpa Capital, T. Rowe Price, TPG
Unattributed	Jun-14			137 Ventures
Series E-1	Jun-15	$1.6 b	$25.5 b	Baillie Gifford, China Broadband Capital, Fidelity Investments, GGV Capital, General Atlantic, Groupe Arnault, Hillhouse Capital Group, Horizons Ventures, Kleiner Perkins Caufield & Byers, Sequoia Capital, T. Rowe Price, Temasek Holdings, Tiger Global Management, Wellington Management
Series E-2	Nov-15	$100.0 m		FirstMark
Debt	Jul-16	$1.0 b		Brand Capital, Citigroup, JP Morgan Chase & Co, Morgan Stanley
Series F	Sep-16	$1.0 b	$31.0 b	Altimeter Capital, CapitalG, Eniac Ventures, Geodesic Capital, Glade Brook Capital Partners, TCV
Secondary	Oct-16			All Blue Capital

Source: https://craft.co/airbnb/funding-rounds

Table 4: IV Validation Test: Correlation Between Instruments and Crime

	(1) Total Establishments	(2) Venture Capital	(3) Food and Restaurant Establishment	(4) Zoning
IV	0.000	-0.048	-0.001	-0.019*
	(0.002)	(0.037)	(0.002)	(0.012)
Poverty	0.452	0.505	0.458	0.505
	(0.635)	(0.621)	(0.631)	(0.649)
Urate	1.664	1.679	1.660	1.857
	(1.195)	(1.197)	(1.194)	(1.187)
Black	0.121	0.081	0.124	0.121
	(0.957)	(0.959)	(0.957)	(0.936)
College	0.431	0.526	0.436	0.517
	(0.905)	(0.916)	(0.903)	(0.872)
Family	-0.374	-0.401*	-0.374	-0.372
	(0.244)	(0.237)	(0.243)	(0.249)
ln(Age)	0.336	0.327	0.339	0.364
	(0.406)	(0.404)	(0.405)	(0.405)
Renter	0.823	0.789	0.826	0.856
	(0.629)	(0.630)	(0.633)	(0.607)
Transit	-0.514	-0.466	-0.519	-0.477
	(1.088)	(1.081)	(1.094)	(1.083)
Vacancy	0.226	0.264	0.239	0.056
	(1.222)	(1.241)	(1.219)	(1.189)
Income Ratio	0.000**	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Gini	-0.070	-0.115	-0.070	-0.114
	(1.118)	(1.146)	(1.121)	(1.058)
Block groups FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Instrumental Variable	N	N	N	N
Observations	935	935	935	935

Note: Standard errors are clustered at the block group level. Each column is a regression for block groups that never had Airbnb listing. The dependent variable, which is the log of total crime per capita, is regressed on the instrumental variable and demographic control variables. In column (1), the instrument is our preferred instrumental variable, which is the interaction between google trends and the total number of establishments. In Column (2), the instrument is the interaction of venture capital funding rounds with the total number of establishments. In Column (3), the instrument is the interaction of google trend with the number of food and accommodation establishments. The instrument in the last column is the interaction of google trend with residential zoning.

Table 5: IV Validation Test: Placebo Test

	(1) IV	(2) Venture Capital	(3) Food and restaurant establishment	(4) Zoning
ln(Airbnb)	0.5870	0.9944	0.7253	0.9239
	(0.446)	(1.160)	(0.657)	(0.783)
ln(Income)	0.1204	0.1914	0.1445	0.1797
	(0.160)	(0.280)	(0.194)	(0.235)
Poverty	0.2788	0.291	0.2829	0.2916
	(0.371)	(0.549)	(0.428)	(0.517)
Urate	0.6367	1.2541	0.8462	1.1473
	(0.985)	(2.118)	(1.317)	(1.466)
Black	-0.0624	-0.1033	-0.0762	-0.095
	(0.374)	(0.551)	(0.430)	(0.509)
College	-0.103	-0.0685	-0.0913	-0.0762
	(0.349)	(0.539)	(0.407)	(0.491)
Family	-0.1498	-0.0686	-0.1222	-0.0835
	(0.125)	(0.264)	(0.163)	(0.207)
ln(Age)	0.6678*	0.9374	0.7593	0.8907
	(0.364)	(0.811)	(0.491)	(0.599)
Renter	0.2432	0.2086	0.2315	0.2181
	(0.330)	(0.471)	(0.372)	(0.439)
Transit	-0.3862	-0.3258	-0.3657	-0.3341
	(0.539)	(0.774)	(0.616)	(0.748)
Vacancy	0.6161	0.2597	0.4952	0.3192
	(0.548)	(1.125)	(0.704)	(0.891)
Income Ratio	0.0001***	0.0001*	0.0001***	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
Gini	0.3746	0.5478	0.4334	0.5162
	(0.528)	(0.831)	(0.605)	(0.775)
Block groups FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Instrumental Variable	Y	Y	Y	Y
KP (F-stat)	2.688	0.798	1.497	1.459
Observations	6,147	6,147	6,147	6,139

Note: Standard errors are clustered at the block group level. ln(Airbnb) is measured by the log of the randomly generated number of Airbnb listings. In column (1), the instrument is our preferred instrumental variable, which is the interaction between google trend and the total number of establishments. In Column (2), the instrument is the interaction of venture capital funding rounds with the total number of establishments. In Column (3), the instrument is the interaction of google trend with the number of food and accommodation establishments. The instrument in the last column is the interaction of google trend with zoning. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 6: The Effects of Airbnb on Crime: OLS Estimates

	(1: OLS)	(2: OLS)	(3: OLS)	(4: OLS)
ln(Airbnb)	-0.024***	0.001	0.006	0.003
	(0.008)	(0.015)	(0.015)	(0.014)
ln(Income)			-0.066**	-0.112***
			(0.030)	(0.035)
Urate			0.090	0.219
			(0.179)	(0.167)
College			-0.123	-0.100
			(0.105)	(0.100)
Black			0.054	0.013
			(0.054)	(0.053)
Poverty				0.031
				(0.092)
Family				-0.043
				(0.028)
ln(Age)				0.388***
				(0.058)
Renter				-0.146**
				(0.072)
Transit				0.198*
				(0.113)
Vacancy				0.566***
				(0.104)
Income Ratio				(0.000)
				0.000
Gini				-0.001
				(0.212)
Block groups FE	N	Y	Y	Y
Year-month FE	N	Y	Y	Y
Instrumental Variable	N	N	N	N
Observations	39,079	39,079	39,079	3,9079

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. ln(Airbnb) is measured by the log of one plus the number of Airbnb listings. ln(Income) is the log of median income; Urate is the unemployment rate; College is the fraction of people has college or graduate degree; Black is the fraction of black population; Poverty is measured by the fraction of population below poverty line; Family is the fraction of family with children; ln(Age) is the log of the median age of the population; Renter is the fraction of population that are renters; Transit is the fraction of population taking public transit; Vacancy is the vacancy rate; Income ratio is the median income ratio of tract to block group; Gini is the gini coefficient at the tract level.

Table 7: The Effects of Airbnb on Crime: Instrument Variable Estimates

	(1: IV)	(2: IV)	(3: IV)
ln(Airbnb)	-0.266***	-0.271***	-0.268***
	(0.097)	(0.102)	(0.099)
ln(Income)		-0.044	-0.080**
		(0.031)	(0.038)
Urate		0.145	0.273
		(0.184)	(0.172)
College		-0.208*	-0.172
		(0.117)	(0.112)
Black		0.000	-0.042
		(0.058)	(0.056)
Poverty			0.020
			(0.098)
Family			-0.076**
			(0.032)
ln(Age)			0.349***
			(0.066)
Renter			-0.103
			(0.076)
Transit			0.243**
			(0.116)
Vacancy			0.620***
			(0.107)
Income Ratio			(0.000)
			0.000
Gini			0.078
			(0.225)
Block groups FE	Y	Y	Y
Year-month FE	Y	Y	Y
Instrumental Variable	Y	Y	Y
Kleibergen-Paap F Statistic	21.288	20.37	19.511
Observations	39,079	39,079	39,079

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. ln(Airbnb) is measured by the log of one plus the number of Airbnb listings. ln(Income) is the log of median income; Urate is the unemployment rate; College is the fraction of people has college or graduate degree; Black is the fraction of black population; Poverty is measured by the fraction of population below poverty line; Family is the fraction of family with children; ln(Age) is the log of the median age of the population; Renter is the fraction of population that are renters; Transit is the fraction of population taking public transit; Vacancy is the vacancy rate; Income ratio is the median income ratio of tract to block group; Gini is the gini coefficient at the tract level. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 8: Alternative Instrument Variables

	(1) Venture Capital	(2) Food and Accommodation	(3) Zoning
ln(Airbnb)	-0.219***	-0.283**	-0.251**
	(0.083)	(0.110)	(0.113)
ln(Income)	-0.086**	-0.079**	-0.083**
	(0.037)	(0.039)	(0.039)
Urate	0.263	0.276	0.267
	(0.170)	(0.173)	(0.173)
College	-0.159	-0.176	-0.172
	(0.108)	(0.113)	(0.109)
Black	-0.032	-0.045	-0.041
	(0.055)	(0.057)	(0.058)
Poverty	0.022	0.020	0.024
	(0.096)	(0.099)	(0.097)
Family	-0.070**	-0.078**	-0.073**
	(0.030)	(0.032)	(0.032)
ln(Age)	0.356***	0.347***	0.352***
	(0.064)	(0.066)	(0.066)
Renter	-0.111	-0.101	-0.108
	(0.075)	(0.077)	(0.075)
Transit	0.235**	0.246**	0.234**
	(0.115)	(0.117)	(0.117)
Vacancy	0.611***	0.623***	0.618***
	(0.105)	(0.107)	(0.108)
Income Ratio	0.000	0.000	0.000
	0.000	0.000	0.000
Gini	0.064	0.083	0.071
	(0.220)	(0.227)	(0.226)
Block groups FE	Y	Y	Y
Year-month FE	Y	Y	Y
Instrumental Variable	Y	Y	Y
Kleibergen-Paap F Statistic	19.65	16.031	13.929
Observations	39,079	39,079	38,967

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. ln(Airbnb) is measured by the log of one plus the number of Airbnb listings. All other explanatory variables are the same as in the prior table. The instrumental variable for Column (1) is the interaction of venture capital funding data with total number of establishments in year 1990.The instrumental variable in Column (2) is the interaction of google trend index with the number of food and accommodation establishment. Instrumental variable in Column (3) is the interaction of google trend index with fraction of properties zoned as residential in 2005.

Table 9: The Effect of Airbnb by Neighborhood Type

	(1) Low Income	(2) Middle Income	(3) High Income	(4) Low Rent	(5) Middle Rent	(6) High Rent
ln(Airbnb)	-0.268	-0.084	-0.336***	-0.441	-0.441	-0.177**
	(0.439)	(0.107)	(0.119)	(0.354)	(0.354)	(0.076)
ln(Income)	-0.178***	-0.126	0.114	-0.160	-0.160	-0.014
	(0.061)	(0.088)	(0.075)	(0.122)	(0.122)	(0.062)
Urate	0.248	0.185	-0.369	0.265	0.265	-0.17
	(0.227)	(0.294)	(0.448)	(0.317)	(0.317)	(0.283)
College	0.061	-0.069	-0.213	-0.073	-0.073	-0.182
	(0.162)	(0.197)	(0.207)	(0.186)	(0.186)	(0.169)
Black	-0.098	0.14	0.042	0.062	0.062	-0.056
	(0.104)	(0.096)	(0.104)	(0.118)	(0.118)	(0.088)
Poverty	-0.142	0.223	0.095	-0.178	-0.178	0.052
	(0.165)	(0.166)	(0.239)	(0.211)	(0.211)	(0.167)
Family	-0.042	-0.128***	-0.100	-0.126**	-0.126**	-0.021
	(0.047)	(0.049)	(0.072)	(0.063)	(0.063)	(0.054)
ln(Age)	0.269***	0.332***	0.458***	0.095	0.095	0.436***
	(0.103)	(0.087)	(0.149)	(0.114)	(0.114)	(0.113)
Renter	-0.279*	-0.133	0.007	-0.126	-0.126	-0.036
	(0.143)	(0.123)	(0.148)	(0.155)	(0.155)	(0.120)
Transit	0.385**	0.234	0.282	-0.047	-0.047	0.170
	(0.158)	(0.197)	(0.319)	(0.197)	(0.197)	(0.206)
Vacancy	0.720***	0.767***	0.447**	0.592**	0.592**	0.397**
	(0.149)	(0.193)	(0.212)	(0.232)	(0.232)	(0.156)
Income Ratio	-0.000***	-0.000***	0.000***	0.059	0.059	-0.000***
	0.000	0.000	0.000	(0.094)	(0.094)	0.000
Gini	0.052	0.616*	-0.301	-0.087	-0.087	-0.508
	(0.389)	(0.319)	(0.489)	(0.404)	(0.404)	(0.352)
Block groups FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
Instrumental Var.	Y	Y	Y	Y	Y	Y
KP (F-stat)	1.909	14.478	12.897	2.573	2.573	15.112
Observations	14,084	13,148	11,845	12,464	12,464	13,503

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. Each column is a different regression. Low is the bottom one-third of the distribution. Middle is the middle third, of the distribution. High is the top one-third of the distribution. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 10: Spillover Effects of Airbnb

	(1: IV)	(2: IV)	(3: IV)
ln(Airbnb)	-0.333***	-0.339***	-0.336***
	(0.11)	(0.11)	(0.11)
ln (Airbnb tract)	0.132***	0.137***	0.132***
	(0.03)	(0.03)	(0.03)
ln(Income)		-0.049	-0.090**
		(0.03)	(0.04)
Urate		0.096	0.219
		(0.19)	(0.17)
College		-0.211*	-0.179
		(0.12)	(0.11)
Black		0.034	-0.010
		(0.06)	(0.05)
Poverty			0.030
			(0.10)
Family			-0.075**
			(0.03)
ln(Age)			0.346***
			(0.07)
Renter			-0.133*
			(0.07)
Transit			0.261**
			(0.12)
Vacancy			0.602***
			(0.11)
Income Ratio			0.000
			0.00
Gini			0.077
			(0.23)
Block groups FE	Y	Y	Y
Year-month FE	Y	Y	Y
Instrumental Variable	Y	Y	Y
Kleibergen-Paap F Statistic	10.117	10.02	9.655
Observations	39,079	39,079	39,079

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. Independent variable of ln(Airbnb tract) is the log of one plus the number of Airbnb in the neighboring blocks within the same census tract. The instrumental variable used for Airbnb tract is the interaction of google trend with the number of establishments in 1990 for the neighboring block groups within the same census tract. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 11: Alternative Airbnb Measures

	(1) Reservations	(2) Max Guest	(3) Daily Rate
ln(Airbnb)	-0.188***	-0.182***	-0.439
	(0.067)	(0.069)	(1.309)
ln(Income)	-0.089**	-0.080**	-0.199
	(0.037)	(0.039)	(0.876)
Urate	0.268	0.266	0.864
	(0.169)	(0.178)	(5.545)
College	-0.17	-0.178	-1.051
	(0.110)	(0.115)	(2.690)
Black	-0.032	-0.056	-0.709
	(0.055)	(0.059)	(1.582)
Poverty	0.026	0.010	-0.487
	(0.097)	(0.101)	(2.708)
Family	-0.068**	-0.076**	-0.225
	(0.030)	(0.032)	(0.226)
ln(Age)	0.368***	0.352***	0.159
	(0.062)	(0.067)	(0.856)
Renter	-0.103	-0.091	-0.021
	(0.075)	(0.078)	(1.461)
Transit	0.248**	0.255**	-1.151
	(0.116)	(0.119)	(2.313)
Vacancy	0.609***	0.622***	1.412
	(0.105)	(0.109)	(1.042)
Income Ratio	0.000	0.000	0.000
	0.000	0.000	0.000
Gini	-0.024	0.067	-0.342
	(0.224)	(0.232)	(4.280)
Block groups FE	Y	Y	Y
Year-month FE	Y	Y	Y
Instrumental Variable	Y	Y	Y
KP (F-stat)	22.095	17.647	0.152
Observations	39,079	39,079	3,830

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. The alternative measures for Airbnb include the log of one plus the number of reservations, log of one plus the number of maximum guests, and the log of one plus the daily rate per room. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 12: The Effect of Airbnb by Type of Crime

	(1) Violent Crime	(2) Property Crime	(3) Homicide
ln(Airbnb)	-0.156**	-0.174*	0.004
	(0.070)	(0.092)	(0.027)
ln(Income)	-0.075***	-0.055	-0.008
	(0.029)	(0.036)	(0.008)
Urate	0.074	0.341**	0.043
	(0.147)	(0.169)	(0.036)
College	-0.131	-0.122	-0.012
	(0.092)	(0.105)	(0.021)
Black	0.029	-0.070	0.000
	(0.041)	(0.055)	(0.011)
Poverty	-0.059	0.063	-0.003
	(0.078)	(0.096)	(0.020)
Family	-0.037*	-0.063**	-0.003
	(0.022)	(0.031)	(0.006)
ln(Age)	0.167***	0.359***	0.000
	(0.050)	(0.065)	(0.011)
Renter	-0.041	-0.112	-0.015
	(0.057)	(0.072)	(0.014)
Transit	0.247***	0.153	0.004
	(0.089)	(0.124)	(0.020)
Vacancy	0.364***	0.572***	0.038
	(0.081)	(0.103)	(0.024)
Income Ratio	0.000	0.000	0.000
	0.000	0.000	0.000
Gini	0.170	-0.017	0.078
	(0.166)	(0.219)	(0.052)
Block groups FE	Y	Y	Y
Year-month FE	Y	Y	Y
Instrumental Variable	Y	Y	Y
KP (F-stat)	19.511	19.511	18.67
Observations	39,079	39,079	44,874

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. The Homicide regression is run as a linear probability regression, where the dependent variable is 1 if there was a homicide in the month and 0 otherwise. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 13: The Seasonal Effect of Airbnb on Crime

	(1) Jan-Mar	(2) Apr-Jun	(3) Jul-Sep	(4) Oct-Dec	(5) Festivals
ln(Airbnb)	-0.341***	-0.228**	-0.291**	-0.202	-0.291**
	(0.129)	(0.102)	(0.122)	(0.123)	(0.122)
ln(Income)	-0.052	-0.046	-0.098**	-0.135***	-0.098**
	(0.055)	(0.042)	(0.046)	(0.051)	(0.046)
Urate	0.322	0.314	0.205	0.317	0.205
	(0.271)	(0.193)	(0.205)	(0.248)	(0.205)
College	-0.243	-0.072	-0.097	-0.339**	-0.097
	(0.157)	(0.118)	(0.125)	(0.144)	(0.125)
Black	-0.131	0.000	-0.051	-0.015	-0.051
	(0.086)	(0.058)	(0.063)	(0.082)	(0.063)
Poverty	0.017	0.142	0.002	-0.114	0.002
	(0.142)	(0.110)	(0.114)	(0.144)	(0.114)
Family	-0.088*	-0.035	-0.063*	-0.134***	-0.063*
	(0.046)	(0.036)	(0.036)	(0.040)	(0.036)
ln(Age)	0.242***	0.439***	0.431***	0.304***	0.431***
	(0.067)	(0.082)	(0.100)	(0.067)	(0.100)
Renter	0.019	-0.057	-0.188**	-0.154	-0.188**
	(0.104)	(0.086)	(0.085)	(0.099)	(0.085)
Transit	0.349**	0.210*	0.151	0.304*	0.151
	(0.162)	(0.125)	(0.125)	(0.162)	(0.125)
Vacancy	0.481***	0.656***	0.731***	0.530***	0.731***
	(0.156)	(0.114)	(0.122)	(0.140)	(0.122)
Income Ratio	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gini	0.185	0.312	-0.158	-0.129	-0.158
	(0.297)	(0.241)	(0.276)	(0.306)	(0.276)
Block groups FE	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
Instrumental Var.	Y	Y	Y	Y	Y
KP (F-stat)	17.817	20.086	16.339	17.429	16.339
Observations	9,395	10,239	9,765	9,680	9,765

Note: Standard errors are clustered at the block group level. The dependent variable is the log of one plus total crime per capita. The Festival season is July, August and September. KP (F-stat) represents the Kleibergen-Paap F Statistic.

Table 14: The Effect of Airbnb: Annual Data

	(1: OLS)	(2: OLS)	(3: OLS)	(4: OLS)	(5: IV)	(6: IV)	(7: IV)
ln(Airbnb)	-0.051**	-0.001	0.001	-0.003	-0.365***	-0.390***	-0.392***
	(0.025)	(0.022)	(0.023)	(0.021)	(0.125)	(0.133)	(0.131)
ln(Income)			-0.071*	-0.107**		-0.030	-0.050
			(0.041)	(0.047)		(0.042)	(0.049)
Urate			0.072	0.177		0.158	0.259
			(0.234)	(0.220)		(0.233)	(0.220)
College			-0.21	-0.176		-0.341**	-0.287**
			(0.137)	(0.130)		(0.149)	(0.142)
Black			0.005	-0.026		-0.095	-0.134*
			(0.077)	(0.074)		(0.080)	(0.078)
Poverty				0.081			0.074
				(0.122)			(0.124)
Family				-0.046			-0.102**
				(0.035)			(0.040)
ln(Age)				0.556***			0.486***
				(0.080)			(0.089)
Renter				-0.178*			-0.101
				(0.095)			(0.096)
Transit				0.17			0.245*
				(0.136)			(0.136)
Vacancy				0.758***			0.858***
				(0.135)			(0.134)
Income Ratio				0.000			0.000
				0.000			0.000
Gini				0.03			0.137
				(0.278)			(0.281)
Block groups FE	N	Y	Y	Y	Y	Y	Y
Year FE	N	Y	Y	Y	Y	Y	Y
Instrumental Variable		N	N	N	Y	Y	Y
Kleibergen-Paap F Statistic					19.341	18.581	17.615
Observations	4,024	4,024	4,024	4,024	4,024	4,024	4,024

Note: Each variable is the annual average and matches the frequency of the ACS data with the crime and Airbnb data.

Table 15: The Effect of Airbnb: Matched Sample

	(1) CEM	(2) PS: 1 to 5
Airbnb	-0.213*	-0.223*
	(0.119)	(0.133)
Income	-0.089	0.019
	(0.084)	(0.107)
Urate	0.282	0.407
	(0.333)	(0.448)
College	-0.064	-0.461
	(0.188)	(0.342)
Black	0.083	-0.008
	(0.137)	(0.213)
Poverty	0.002	0.143
	(0.201)	(0.239)
Family	-0.121*	-0.244***
	(0.064)	(0.076)
Age	0.277**	0.142
	(0.119)	(0.161)
Renter	-0.270	0.123
	(0.171)	(0.203)
Transit	0.394*	-0.151
	(0.232)	(0.303)
Vacancy	0.482	0.981***
	(0.344)	(0.256)
Income Ratio	-0.000***	0.000
	0.000	0.000
Gini	0.105	0.444
	(0.417)	(0.432)
Block groups FE	Y	Y
Year-month FE	Y	Y
Instrumental Variable	Y	Y
Kleibergen-Paap F Statistic	7.671	13.135
Observations	17,195	11,781

Note: The results in the first column use the coarsened exact matching method. The results in the second column us the propensity scoring matching method (1 to 5 nearest neighbors). Standard errors are clustered at the block group level.