# The Effect of Short-Term Rentals on Local Consumption Amenities: Evidence from Madrid

Sheffield Spatial Analysis Network Seminar

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## Motivation

- **A giant in the sector:** In a short period of time, Airbnb has grown from a few thousand of properties in 2009 to over seven million in 2020 in more than 100,000 cities worldwide.
- **Externalities:** The explosive increase of short-term rentals (STR) in urban areas has spurred a vigorous debate about its economic impacts (housing affordability, unfair competition with traditional accommodations and residents and tourists' welfare impact).

# Local consumption amenities

- **Economic landscape:** tourists are consumers with different needs and tastes, their arrival may change the geography of the economic activities.
- **Consumption amenities:** the business structure of the affected areas may have been transformed to satisfy the needs of the "new temporal residents".
- **Local effect:** As hotel costumers, Airbnb users are likely to spend a large share of the time budget in the immediate vicinity of the accommodation.

**Figure 1:** *"The restaurant business is booming in Madrid". Source: Europa Press.*

# This paper

- **Goal of the paper:** to study the impact of Airbnb entry in Madrid on the local consumption amenities. In particular, we evaluate how short-term rentals affect the number of establishments and employment of the food and beverage sector.

**Four conditions allow us to pinpoint the effect of short-term rentals on local consumption amenities:**

- Short-term rentals are more dispersed than traditional accommodations which are concentrated in the city center;
- The rapid adoption and diffusion of Airbnb;
- Food and beverage establishments quickly react to changes in the local demand due to their low startup cost;
- The urban geography shapes consumption pattern stressing the role of local consumption amenities.

# Research questions and identification strategy

**Research question I**

To what extent are local shops positively affected by Airbnb?

**Research question II**

Are the Airbnb economic spillovers the same across the urban geography or are there some areas more benefited than the others?

**Identification strategy**

To deal with the endogeneity of Airbnb activity (Airbnb listings do not distribute homogeneously across the territory), we use use a Bartik-like instrumental variable approach where we interact number of rented houses in 2011 (previous to Airbnb entry in Madrid) and the number of worldwide Airbnb Google searches as an instrument for the Airbnb activity.

# Preview of the results

- **Employment and number of establishments:** an increase in *ten* Airbnb rooms in a given census tract translates to one more restaurant and the same increase in a given neighbourhood generates *nine* new tourist-related employees.
- **Heterogeneous impact:**
  - **In the urban geography:** the effect of Airbnb on local consumption amenities is greater in less touristic areas, reinforcing the idea that peer-to-peer accommodations help to redistribute tourism consumption over the city.
  - **Within food and beverage services:** Airbnb-induced demand mainly in restaurants and coffees.
- **Mechanism:** neighbourhood demographic composition change (residents for tourists) and greater Airbnb economic spillover in areas outside downtown due to a downward-sloping commercial rent gradient.

# Outline of the presentation

1. **Literature review**
2. **Data**
3. **Empirical strategy**
4. **Results**
5. **Conclusions**

# Literature review

# Literature review

- **Related litertaure:**
  - **Short-term rentals externalities:** housing (Garcia-López et al., 2020; Barron et al., 2021), traditional accommodations (Zervas et al., 2017; Li and Srinivasan, 2019) and local economies (Xu and Xu, 2021; Bekkerman et al., 2021; Basuroy et al., 2020; Alyakoob and Rahman, 2019).
  - **Consumption amenities:** provision of food-related establishments in highly dense areas (Mazzolari and Neumark, 2012; Couture, 2013; Schiff, 2015; Couture and Handbury, 2020) and spatial frictions in urban consumption (Davis et al., 2019; Eizenberg et al., 2021; Miyauchi et al., 2021).

- **Contributions:**
  1. *Local effects:* Finer-grained data set for the universe of all economic activities which allow us to study the Airbnb economic spillover effects using small areas (census tracts) and differentiating from establishments typologies.
  2. *Identification strategy:* On the methodological ground, we contribute a new Bartik-like instrument to solve for the endogeneity in the Airbnb activity variable.

# Data

# Data

- **Data:**
  - **Unit of analysis**: census tracts and neighbourhoods; ▸ Madrid administrative units
  - **Time frame:** March 2014 to December 2018 (quarterly).

- **Variables:**
  - **Local consumption amenities**: establishment-level data under a four-digit NACE-based classification, location and activity status (Madrid City Council's census);
  - **Employment:** annual employment at the neighbourhood level (Social Security General Treasury);
  - **Short-term rentals:** user-faced web scrapped information from Airbnb (Inside Airbnb);
  - **Sociodemographic, housing and hotel information:** population, proportion of foreign population and number of rented houses in 2011 (Spain Population and Housing Census 2011 and *Padrón municipal)*. Hotel information coming from web scraped Expedia data. ▸ Description of activities ▸ Descriptive statistics

# Data

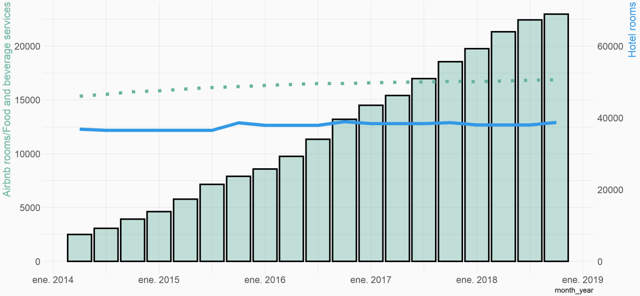



**Figure 2:** Number of food and beverage establishments, Airbnb and hotel rooms from the 2nd semester 2014 to 2nd semester 2018. Restaurants (dots), Airbnb rooms (bars) and hotel rooms (solid) evolution.

# Data

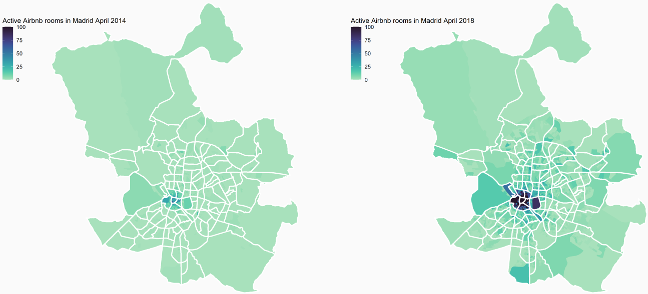



**Figure 3:** Spatial distribution of Airbnb rooms in April 2014 (left) and April 2018 (right). White lines delimit the administrative boundaries of neighborhoods, whereas the color intensity within neighborhoods re ects the number of Airbnb rooms in each census tracts.

# Empirical strategy

# Empirical strategy

**Baseline specification**

$$Y_{i,t} = \beta Airbnb_{i,t} + \rho X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}$$

- **Identification issues:**
  - **Identification problem I: Endogeneity.** Reverse causality and measurement error in our main variable of interest, the number of Airbnb rooms.
  - **Identification problem II: Airbnb non-random location.** Short-term rentals are mainly concentrated in the city center as traditional accommodations. Impossible to disentangle the effect of Airbnb from hotels.

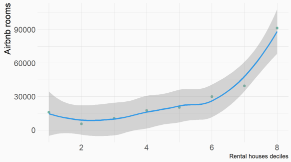
# Empirical strategy

- **Identification solution I: Instrumental variables** where we use as the initial shares, the number of rented houses in each census tract in 2011 (before Airbnb arrival to Madrid), and as the shift, the worldwide Airbnb Google searches.

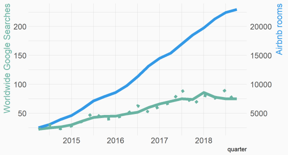
$$\textit{Shift-Share}_{i,t} = z_{i,2011} m_t$$

The number of rental houses prior to the entry of Airbnb in Madrid allow us to predict where tourist rentals will be located and with what intensity, while the number of global searches on Google for the word "Airbnb" predicts the *timing*.

# Empirical strategy




(a) Airbnb rooms supply and rental houses in 2011




(b) Worldwide Airbnb Google searches and Airbnb rooms in Madrid

**Figure 4:** Shift-share instrument relevance

# Empirical strategy

- **Identification solution II: Sample restriction.** As we have a problem for identifying the effect of Airbnb on other effects such as traditional accommodations or tourist attractions from the city center, we decided to work with two samples: one complete with all census sections and one restricted where we eliminate those census sections belonging to the downtown district.

# Empirical strategy

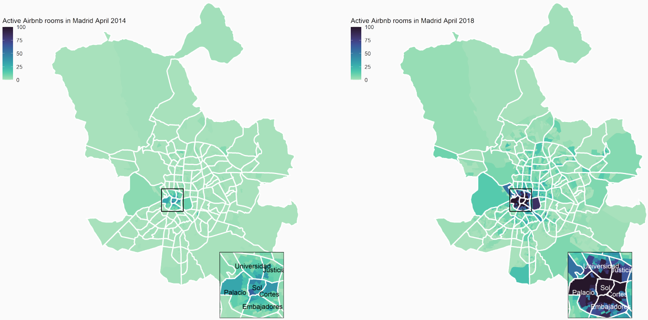



**Figure 5:** Spatial distribution of Airbnb rooms in April 2014 (left) and April 2018 (right), zooming the district "Centro".

Descriptive statistics

# Results

# Results

**Table 1:** THE IMPACT OF AIRBNB ON THE NUMBER OF FOOD AND BEVERAGE ESTABLISHMENTS (OLS).

| Dependent Variable: | Food and beverage establishments | | | | | |
|---|---|---|---|---|---|---|
| Model: | Whole sample | Whole sample | Whole sample | Restricted sample | Restricted sample | Restricted sample |
| *Variables* | | | | | | |
| (Intercept) | 5.679*** | 1.417*** | | 5.262*** | 1.013*** | |
| | (0.0398) | (0.1157) | | (0.0350) | (0.1067) | |
| Airbnb rooms | 0.3179*** | 0.2584*** | 0.0261*** | 0.4193*** | 0.3530*** | 0.0498*** |
| | (0.0071) | (0.0063) | (0.0018) | (0.0098) | (0.0100) | (0.0039) |
| Population | | 0.0021*** | 0.0034*** | | 0.0022*** | 0.0034*** |
| | | $(7.43 \times 10^{-5})$ | (0.0002) | | $(6.78 \times 10^{-5})$ | (0.0002) |
| Foreign Population (%) | | 7.652*** | -1.515*** | | 7.770*** | -1.581*** |
| | | (0.3394) | (0.3687) | | (0.2930) | (0.3723) |
| Hotel rooms | | 0.0308*** | 0.0032*** | | 0.0251*** | 0.0029*** |
| | | (0.0014) | (0.0009) | | (0.0016) | (0.0011) |
| *Fixed-effects* | | | | | | |
| Quarters | No | No | Yes | No | No | Yes |
| Census tract | No | No | Yes | No | No | Yes |
| *Fit statistics* | | | | | | |
| Observations | 41,800 | 41,800 | 41,800 | 39,691 | 39,691 | 39,691 |
| $R^2$ | 0.32040 | 0.42717 | 0.98984 | 0.10787 | 0.22286 | 0.98291 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Heteroskedasticity standard errors for columns 1-2 and 4-5 and cluster standard errors at the census tract level for columns 3 and 6. Time trend and distance to the center interaction in columns 3 and 6.

# Results

**Table 2:** The impact of Airbnb on the number of food and beverage establishments (IV).

| Dependent Variable: | Food and beverage establishments | | | |
|---|---|---|---|---|
| Model: | Whole sample (First Stage) | Whole sample (Second Stage) | Restricted sample (First Stage) | Restricted sample (Second Stage) |
| *Variables* | | | | |
| Airbnb rooms | | 0.0563*** | | 0.1217*** |
| | | (0.0127) | | (0.0379) |
| Shift-share | 0.0009*** | | 0.0003*** | |
| | $(9.8 \times 10^{-5})$ | | $(2.95 \times 10^{-5})$ | |
| Population | -0.0004 | 0.0034*** | 0.0007*** | 0.0033*** |
| | (0.0006) | (0.0006) | (0.0002) | (0.0006) |
| Foreign Population (%) | -17.84*** | -0.8680 | -7.628*** | -0.9879 |
| | (6.214) | (0.9789) | (1.942) | (1.018) |
| Hotel rooms | 0.0381*** | 0.0019 | 0.0173** | 0.0016 |
| | (0.0131) | (0.0017) | (0.0073) | (0.0021) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 41,800 | 41,800 | 39,691 | 39,691 |
| KP *F-statistic* | 89.1 | | 105.4 | |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Shift-Share represents the interaction between the number of rented houses in 2011 and the worldwide Airbnb Google searches. Time trend and distance to the center interaction include in all specifications but not shown.

# Results

**Table 3:** The Impact of Airbnb on the food and beverage establishments employment and food and beverage establishments at the neighborhood level (IV).

| Dependent Variable: | Food and beverage establishments | | Employment | |
|---|---|---|---|---|
| Model: | Whole sample | Restricted sample | Whole sample | Restricted sample |
| *Variables* | | | | |
| Airbnb rooms | 0.0355*** | 0.0563*** | 0.4309* | 0.8972** |
| | (0.0051) | (0.0161) | (0.2272) | (0.3941) |
| Population | 0.0045*** | 0.0043*** | -0.0561* | -0.0201 |
| | (0.0009) | (0.0010) | (0.0322) | (0.0123) |
| Foreign Population (%) | -27.94 | -21.48 | 3,008.7 | 698.6 |
| | (34.52) | (34.56) | (2,206.1) | (780.6) |
| Hotel rooms | 0.0026 | 0.0081 | 0.0296 | -0.1622 |
| | (0.0049) | (0.0051) | (0.2830) | (0.1543) |
| *Fixed-effects* | | | | |
| Neighborhood | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 640 | 600 | 640 | 600 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Time trend and distance to the center interaction include in all specifications but not shown.

Intensive and extensive margin

# Further results

- **Complementary analysis:**
  - **Heterogeneous results:** Restaurants, bars, coffees and clubs. ▸ Heterogeneous results
- **Sensitivity analysis and robustness checks:**
  - **Specification form:** Log-log and Poisson model; ▸ Specification form
  - **Robustness checks:** Falsification activities and alternative ways of measuring Airbnb activity; ▸ Falsification activities ▸ Alternative measures Airbnb activity
  - **IV validity:** Parallel trend assumption and others instruments. ▸ Parallel trend ▸ Different instruments
- **Spatial analysis:**
  - **Spillovers:** Spatial cross-regressive model; ▸ Spatial econometric model
  - **Modifiable areal unit problem (MAUP):** Quarter neighbourhood analysis. ▸ Neighbourhood exercise

# Conclusions

# Conclusions

- **Local effects:** Airbnb's arrival in an area represents a positive externality, leading to an increase in the employment and number of food and beverage establishments.
- **Uneven impact across territory:** Airbnb's effect is higher in less touristy areas, which reinforces the idea that tourist accommodations can help redistribute economic activity derived from tourism in the city.
- **Regulation:** the model followed by Madrid and Barcelona of restricting the supply of tourist accommodations in the most affected areas can serve to decongest those areas of tourism and at the same time enhance the economic performance of other places.

# Thank you!

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# Administrative units in Madrid

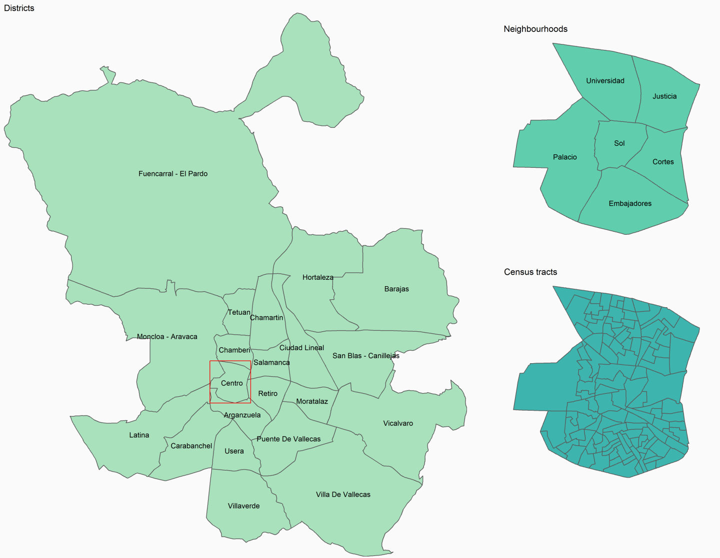


Figure 6: Administrative units in Madrid.

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# Description of activities

Table 4: Description of activities

| Food and beverage | Other professional, scientific and technical | Financial and insurance |
|---|---|---|
| Restaurant | Legal activities | Bank |
| Fast food restaurant | Law office | Activities of holding companies |
| Self-service restaurant | Accounting, bookkeeping and auditing activities; tax consultancy | Trusts, funds and similar financial entities |
| Bar restaurant | Law office (Accounting, bookkeeping and auditing activities; tax consultancy) | Other financial establishments |
| Bar with kitchen | Headquarters activities | Insurance |
| Coffee | Management consultancy activities | Reinsurance |
| Chocolate shop, tea room and ice-cream parlor | Architecture and engineering activities; technical testing and analysis | Pension fund |
| Retail sale of wine and spirits with consumption | Engineering and architecture office | Admin financial markets and other assets |
| Bar without performance | Research and development | Currency exchange |
| Bar with performance | Advertising, publicity, public relations and market research,. | Auxiliary insurance and pension funds |
| Tavern | Specialised design activities | Pension fund management activities |
| Bar without kitchen | Photo establishments | |
| Ciber-Coffee | Translation and interpretation activities | |
| Coffee with performance | Interpretation and translation office | |
| | Other professional, scientific and technical activities | |

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# Descriptive statistics

**Table 5:** DESCRIPTIVE STATISTICS, WHOLE AND RESTRICTED SAMPLES

| Year | 2014 | | | 2018 | | |
|---|---|---|---|---|---|---|
| Variable | Sum | Mean | S.d. | Sum | Mean | S.d. |
| Whole sample (N= 41,800, Census tracts = 2,200) | | | | | | |
| Food and beverage establishments | 15761 | 7.164 | 8.438 | 16867 | 7.667 | 9.2 |
| Airbnb listings | 2842 | 1.292 | 4.256 | 16128 | 7.331 | 15.424 |
| Airbnb rooms | 3921 | 1.782 | 6.015 | 22949 | 10.431 | 22.912 |
| Number of hotels | 298 | 0.135 | 0.652 | 307 | 0.14 | 0.675 |
| Hotel rooms | 36497 | 16.59 | 83.744 | 38685 | 17.584 | 88.554 |
| Foreign Population (%) | 342.1 | 0.156 | 0.102 | 389.1 | 0.177 | 0.117 |
| Population | 2918109 | 1326.413 | 465.802 | 2944446 | 1338.385 | 454.234 |
| Restricted sample (N= 39,691, Census tracts = 2,089) | | | | | | |
| Food and beverage establishments | 13068 | 6.256 | 6.166 | 13930 | 6.668 | 6.849 |
| Airbnb listings | 1062 | 0.508 | 1.115 | 9187 | 4.398 | 4.881 |
| Airbnb rooms | 1478 | 0.708 | 1.696 | 12853 | 6.153 | 7.375 |
| Number of hotels | 183 | 0.088 | 0.387 | 182 | 0.087 | 0.382 |
| Hotel rooms | 25805 | 12.353 | 67.304 | 26646 | 12.755 | 70.924 |
| Foreign Population (%) | 311.3 | 0.149 | 0.097 | 356.5 | 0.171 | 0.115 |
| Population | 2785762 | 1333.539 | 472.387 | 2811945 | 1346.072 | 459.965 |

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# Intensive and extensive margin

$$\delta_L \times \Delta Airbnb = \underbrace{N_t \times \Delta S}_{IntensiveMargin} + \underbrace{\delta_N \times \Delta Airbnb \times (S_t + \Delta S)}_{ExtensiveMargin}$$

- $\delta_L$ represents the effect of Airbnb on the employment (overall effect);
- $\Delta Airbnb$ is the variation in the number of Airbnb rooms;
- $N_t$, the number of food and beverage establishments;
- $\Delta S$ is the variation in the establishment average employment;
- $\delta_N$ is the effect of Airbnb on the number of food and beverage companies;
- $S_t$, the establishment average employment.

$$\Delta S = \frac{\Delta Airbnb \times (\delta_L - \delta_N \times S_t)}{N_t + \delta_N \times \Delta Airbnb}$$

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# Heterogeneous results

**Table 6:** Heterogeneous impact of Airbnb on the activities within the food and beverage industry (IV).

| Dependent Variables: | Restaurants | Bar | Coffee | Clubs |
|---|---|---|---|---|
| Model: | Restricted sample | Restricted sample | Restricted sample | Restricted sample |
| *Variables* | | | | |
| Airbnb rooms | 0.0606** | 0.0335 | 0.0503** | −0.0084 |
| | (0.0279) | (0.0240) | (0.0251) | (0.0171) |
| Population | 0.0021*** | 0.0010*** | 0.0008*** | 0.0003** |
| | (0.0004) | (0.0002) | (0.0002) | (0.0002) |
| Foreign Population (%) | -0.5550 | 0.3775 | -0.5510 | 0.2567 |
| | (0.8435) | (0.6964) | (0.7421) | (0.4992) |
| Hotel rooms | 0.0013 | 0.0019 | -0.0004 | -0.0011 |
| | (0.0013) | (0.0017) | (0.0010) | (0.0011) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 28,006 | 35,321 | 23,142 | 11,818 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Shift-share represents the interaction between the number of rented houses in 2011 and the worldwide Airbnb Google searches. Time trend and distance to the center interaction include in all specifications but not shown.

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# Specification form

**Table 7:** The Impact of Airbnb on the number of food and beverage establishments (Log-Log and Poisson model).

| Dependent Variables: | log(Food and beverage establishments+1) | | Food and beverage establishments | |
|---|---|---|---|---|
| Model: | Whole sample (OLS) | Restricted sample (OLS) | Whole sample (Poisson) | Restricted sample (Poisson) |
| *Variables* | | | | |
| log(Airbnb rooms+1) | 0.0127*** | 0.0118*** | | |
| | (0.0034) | (0.0034) | | |
| Airbnb rooms | | | 0.0003* | 0.0019*** |
| | | | (0.0001) | (0.0007) |
| Population | 0.0006*** | 0.0006*** | 0.0005*** | 0.0005*** |
| | $(7.38 \times 10^{-5})$ | $(7.4 \times 10^{-5})$ | $(7.7 \times 10^{-5})$ | $(7.82 \times 10^{-5})$ |
| Foreign Population (%) | -0.4339*** | -0.4410*** | -0.2509** | -0.2750* |
| | (0.0992) | (0.1038) | (0.1253) | (0.1484) |
| Hotel rooms | $5.72 \times 10^{-5}$ | $4.38 \times 10^{-5}$ | $9.21 \times 10^{-5}$ | $7.23 \times 10^{-5}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| *Fixed-effects* | | | | |
| Census tract | Yes | Yes | Yes | Yes |
| Quarters | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 41,800 | 39,691 | 41,800 | 39,691 |
| $R^2$ | 0.97987 | 0.97602 | 0.64035 | 0.55943 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level.

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# Falsification activities

**Table 8:** The Impact of Airbnb on the number of "Professional, scientific and technical" activities and "Finance and insurance activities" (IV).

| Dependent Variable: | Professional, scientific and technical | | Finance and insurance | |
|---|---|---|---|---|
| Model: | Whole sample | Restricted sample | Whole sample | Restricted sample |
| *Variables* | | | | |
| Airbnb rooms | 0.0048 | 0.0094 | −0.0094 | −0.0332 |
| | (0.0042) | (0.0142) | (0.0082) | (0.0286) |
| Population | 0.0006*** | 0.0006*** | 0.0008*** | 0.0008*** |
| | (0.0001) | (0.0001) | (0.0002) | (0.0002) |
| Foreign Population (%) | 0.2338 | 0.2476 | 0.1534 | 0.1588 |
| | (0.3813) | (0.4239) | (0.6618) | (0.7542) |
| Hotel rooms | 0.0003 | 0.0001 | 0.0022 | 0.0032 |
| | (0.0007) | (0.0008) | (0.0017) | (0.0022) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 41,800 | 39,691 | 41,800 | 39,691 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Time trend and distance to the center interaction include in all specifications but not shown.

▸ Description of activities

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# Alternative measures Airbnb activity

**Table 9:** The impact of Airbnb on the number of food and beverage establishments using alternative measures of Airbnb activity (IV).

| Dependent Variable: | Food and beverage establishments (Restricted sample) | | | |
|---|---|---|---|---|
| Alternative Airbnb measure: | Listings | Rooms | Beds | Guests |
| *Variables* | | | | |
| Airbnb listings | 0.1638*** | | | |
| | (0.0509) | | | |
| Airbnb rooms | | 0.1217*** | | |
| | | (0.0379) | | |
| Airbnb beds | | | 0.0840*** | |
| | | | (0.0269) | |
| Airbnb guests | | | | 0.0525*** |
| | | | | (0.0168) |
| Population | 0.0033*** | 0.0033*** | 0.0033*** | 0.0033*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Foreign Population (%) | -1.045 | -0.9879 | -1.106 | -1.130 |
| | (1.009) | (1.018) | (1.012) | (0.9991) |
| Hotel rooms | 0.0017 | 0.0016 | 0.0017 | 0.0015 |
| | (0.0021) | (0.0021) | (0.0022) | (0.0021) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 39,691 | 39,691 | 39,691 | 39,691 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Time trend and distance to the center interaction include in all specifications but not shown.

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## Parallel Pretrends

- **Parallel Pretrends:**

$$Y_{i,t} = \sum_{t \neq 2014} \lambda_t \times \delta Airbnb\ high\ activity + \rho X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}$$

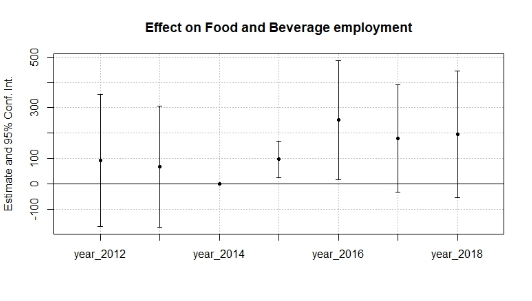


**Figure 7:** Event study plots for the top decile Airbnb Neighbourhoods.

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# Alternative instruments

**Table 10:** The impact of Airbnb on the number food and beverage establishments using alternative instrumental variables (IVs).

| Dependent variable: | Food and beverage establishments (Restricted sample) | | | |
|---|---|---|---|---|
| Alternative Share Instruments: | Total dwellings | Empty houses | Share of rented houses | Share of rented + empty houses |
| *Variables* | | | | |
| Airbnb rooms | 0.0955** | 0.0709 | 0.1427*** | 0.1068*** |
| | (0.0421) | (0.0696) | (0.0385) | (0.0411) |
| Population | 0.0033*** | 0.0034*** | 0.0033*** | 0.0033*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Foreign Population (%) | -2.269 | -2.542 | -1.744 | -2.144 |
| | (1.646) | (1.849) | (1.542) | (1.579) |
| Hotel rooms | 0.0020 | 0.0025 | 0.0012 | 0.0018 |
| | (0.0020) | (0.0019) | (0.0023) | (0.0022) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 39,691 | 39,691 | 39,691 | 39,691 |
| KP *F-statistic* | 103.9 | 26.27 | 75.5 | 97.1 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Time trend and distance to the center interaction include in all specifications but not shown.

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# Spatial cross-regressive model

**Table 11:** THE IMPACT OF AIRBNB ON THE NUMBER OF FOOD AND BEVERAGE ESTABLISHMENTS CONTROLLING FOR SPILLOVER EFFECTS (IV).

| Dependent variable: | Food and beverage establishments (Whole sample) | | | |
|---|---|---|---|---|
| Spatial matrix: | Cut-off distance | Inverse distance | Rook | Queen |
| *Variables* | | | | |
| Airbnb rooms | 0.0974*** | 0.0860* | 0.0886* | 0.0867* |
| | (0.0362) | (0.0457) | (0.0495) | (0.0450) |
| Airbnb rooms neighbors | -0.0540 | -0.0372 | -0.0394 | -0.0379 |
| | (0.0343) | (0.0446) | (0.0480) | (0.0435) |
| Population | 0.0033*** | 0.0034*** | 0.0034*** | 0.0034*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Foreign Population (%) | -0.8902 | -1.030 | -1.056 | -1.049 |
| | (0.9894) | (0.9483) | (0.9450) | (0.9468) |
| Hotel rooms | 0.0014 | 0.0017 | 0.0016 | 0.0017 |
| | (0.0017) | (0.0017) | (0.0017) | (0.0017) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Census tract | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 41,800 | 41,800 | 41,800 | 41,800 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level. Cut-off distance set at 300m. Rook criterion restrict the potential neighbors to those which share common sides of the polygons. Queen criterion is built upon Rook criterion but also including common vertices. Time trend and distance to the center interaction include in all specifications but not shown.

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# Modifiable areal unit problem (MAUP)

**Table 12:** The Impact of Airbnb on the number of food and beverage establishments (IV).

| Dependent Variable: | Food and beverage establishments | | | |
|---|---|---|---|---|
| Model: | Whole sample (Neighborhood) | Restricted sample (Neighborhood) | Whole sample (Transport zones) | Restricted sample (Transport zones) |
| *Variables* | | | | |
| Airbnb rooms | 0.0386*** | 0.0718*** | 0.0555*** | 0.0952*** |
| | (0.0075) | (0.0249) | (0.0090) | (0.0147) |
| Population | 0.0049*** | 0.0047*** | 0.0037*** | 0.0034*** |
| | (0.0010) | (0.0011) | (0.0005) | (0.0005) |
| Foreign population (%) | -27.68 | -16.01 | 0.9345 | 0.7268 |
| | (36.17) | (38.00) | (5.929) | (5.808) |
| Hotel rooms | 0.0008 | 0.0035 | -0.0013 | 0.0005 |
| | (0.0043) | (0.0049) | (0.0034) | (0.0032) |
| *Fixed-effects* | | | | |
| Quarters | Yes | Yes | Yes | Yes |
| Neighborhood | Yes | Yes | | |
| Transport zones | | | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 2,432 | 2,318 | 9,025 | 8,531 |

*Notes*: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the census tract level.Time trend and distance to the center interaction include in all specifications but not shown.

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