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

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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:** since 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.

Main 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.
- **Multiscale approach:** our main findings are robust to variations in our geographic unit of analysis, i.e., census tract and neighbourhood.

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. 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. 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 and housing information:** population, proportion of foreign population and number of rented houses in 2011 (Spain Population and Housing Census 2011 and Padrón municipal). ▸ Description of activities ▸ Descriptive statistics

Data

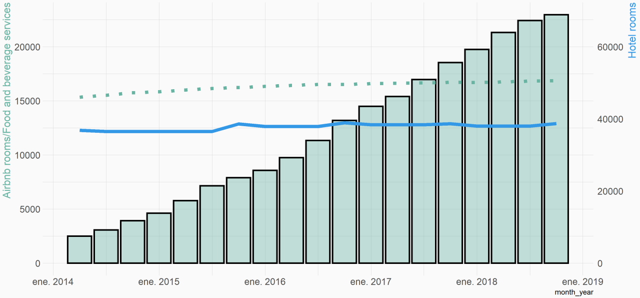


Figure 2: Restaurants (dots), Airbnb rooms (bars) and hotel rooms (solid) evolution.

Data

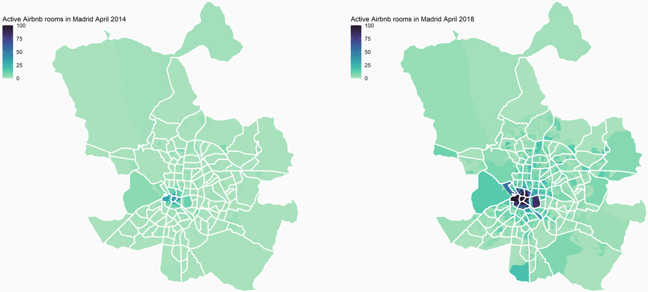


Figure 3: Spatial distribution of Airbnb rooms in April 2014 (left) and April 2018 (right).

Empirical strategy

Empirical strategy

Baseline specification

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

- **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.

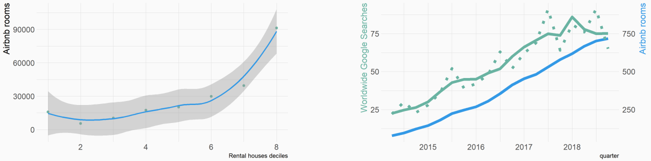
Empirical strategy

- **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) Worldwide Airbnb Google searches and Airbnb rooms in Madrid

(b) Airbnb rooms in 2016 and rental houses in 2011

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

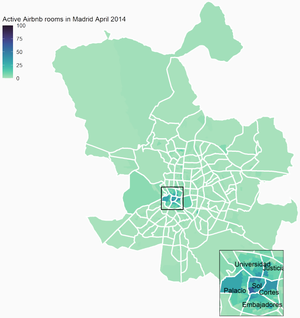


Figure 5: Spatial distribution of Airbnb rooms in April 2014 (left) and April 2018 (right), zooming the district "Centro".

▸ Descriptive statistics

Results

Results

Table 1: 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***
		(7.43×10^{-5})	(0.0002)		(6.78×10^{-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			Yes			Yes
Census tract			Yes			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: Cluster standard errors at the census tract level are shown in parentheses. Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively.

Results

Table 2: 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***	
	(9.8×10^{-5})		(2.95×10^{-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
R^2	0.87161	0.98943	0.82647	0.98232
KP *F-statistic*	90.371		73.253	

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

Results

Table 3: Impact of Airbnb on the food and beverage establishments employment and food and beverage establishments at the neighbourhood 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				
Neighbourhood	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	640	600	640	600
R^2	0.99864	0.99742	0.85980	0.97856

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

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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Go Back

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References

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Administrative units in Madrid

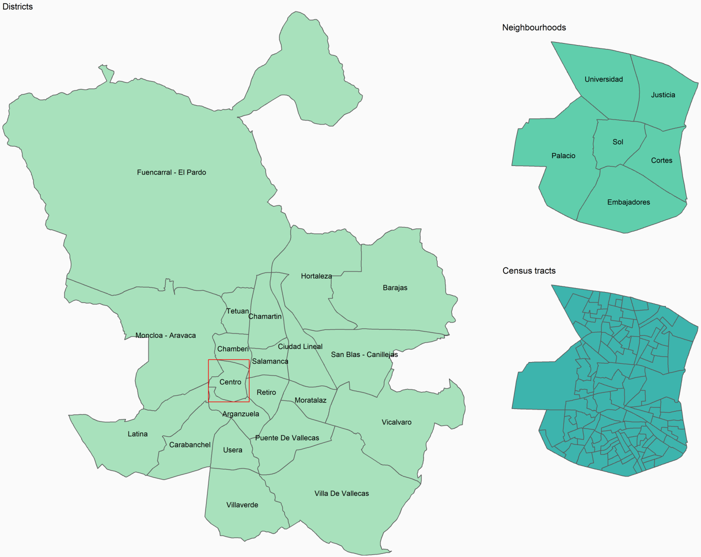

Figure 6: Administrative units in Madrid.

Go Back

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	

Go Back

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

Go Back

Intensive and extensive margin

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

- δ_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;
- ΔS is the variation in the establishment average employment;
- δ_N is the effect of Airbnb on the number of food and beverage companies;
- S_t, the establishment average employment.

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

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
R^2	0.97643	0.95433	0.94434	0.95951

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

Go Back

Specification form

Table 7: The Impact of Airbnb on the number of food and beverage establishments. Log-Log OLS and Poisson specification

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***
	(7.38×10^{-5})	(7.4×10^{-5})	(7.7×10^{-5})	(7.82×10^{-5})
Foreign Population (%)	-0.4339***	-0.4410***	-0.2509**	-0.2750*
	(0.0992)	(0.1038)	(0.1253)	(0.1484)
Hotel rooms	5.72×10^{-5}	4.38×10^{-5}	9.21×10^{-5}	7.23×10^{-5}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed-effects				
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.

Go Back

Falsification activities

Table 8: Impact of Airbnb on the number of professional, scientific and technical 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
R^2	0.96977	0.97049	0.96664	0.96378

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

Go Back

Alternative measures Airbnb activity

Table 9: Impact of Airbnb on the number of food and beverage establishments using alternative Airbnb measures

Dependent Variable:	Food and beverage establishments (Restricted sample, IV)			
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
R^2	0.98245	0.98232	0.98212	0.98227

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

Go Back

Parallel Pretrends

- **Parallel Pretrends:**

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

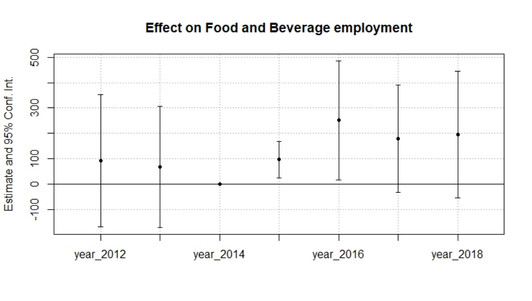

Figure 7: Event study plots for the top decile Airbnb Neighbourhoods.

Go Back

Alternative instruments

Table 10: Impact of Airbnb on the number food and beverage establishments using several instruments (IV)

Dependent variable:	Food and beverage establishments (Restricted sample, IV)			
Alternative Share Instruments:	Total dwellings	Empty houses	Share of rented houses	Share of rented + empty houses
Variables				
Airbnb rooms	0.0886**	0.0698	0.3799**	0.2948**
	(0.0438)	(0.0697)	(0.1813)	(0.1494)
Population	0.0033***	0.0034***	0.0031***	0.0032***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Foreign Population (%)	-1.261	-1.416	1.145	0.4425
	(1.088)	(1.228)	(1.562)	(1.303)
Hotel rooms	0.0022	0.0025	-0.0031	-0.0016
	(0.0021)	(0.0019)	(0.0044)	(0.0037)
Fixed-effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	39,691	39,691	39,691	39,691
R^2	0.98274	0.98286	0.97056	0.97610

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

Go Back

Spatial cross-regressive model

Table 11: Impact of Airbnb on the number of food and beverage establishments controlling for spillover effects.(IV, Census tracts, quarters)

Dependent variable:	Food and beverage establishments (Whole sample, IV)			
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 neighbours	-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
R^2	0.98890	0.98907	0.98900	0.98903

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

Go Back

Modifiable areal unit problem (MAUP)

Table 12: The Impact of Airbnb on the number of food and beverage establishments. (IV, Neighborhoods and Transport zones)

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
R^2	0.99850	0.99717	0.99722	0.99531

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.

Go Back