## Do short-term rental platforms affect housing markets?

Evidence from Airbnb in Barcelona

Miquel A. García-López<sup>1</sup>, Jordi Jofre-Monseny<sup>2</sup>, Rodrigo Martínez-Mazza<sup>2</sup>, and Mariona Segú<sup>3</sup> Housing affordability: Policies in the rental market, November 20, Banco de España

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- Urban tourism has grown enormously
  - Between 1990 and 2017, the worldwide number of international tourist arrivals went from 400 to 1.300 millions (WTO, 2018)
- Increased tourism demand partly accommodated through short-term rental platforms
  - Airbnb is the largest platform worldwide, with over 2 million guest sleeping in an Airbnb every night and over 6 million listing worldwide. (Airbnb, 2019)
- Short-term rental platforms increase the overlap between tourism and housing markets
  - Efficiency improvement in markets where goods are not fully used (Barron, Kung, and Proserpio, 2018)
  - · New income source and tourism decentralization (Airbnb, 2019)

Short-terms rental platforms face neighbour's opposition: Gentrification





Short-term rental platforms face neighbors' opposition: Noise



- · Short-term rental platforms face neighbour's opposition
  - Gentrification (pecuniary externality)
  - Negative externalities (noise, insecurity, uncivil behaviours)
  - · Genuine home-sharing small
- Many cities worldwide have enacted regulations to limit the penetration of Airbnb (Amsterdam, Paris, New York, Berlin, San Francisco...)
- Limited (causal) evidence of the effects of short-term platforms on housing markets

Barcelona constitutes an ideal city to study the effects of Airbnb on local housing markets:

- Tourism boom: Airport passengers went from 20M to 47M between 2005 and 2017 (7th most visited city in Europe and 17th worldwide)
- · Airbnb in Barcelona is big
  - · Barcelona is 6th most popular Airbnb destination worldwide
  - · Airbnb is the largest platform in the city
  - Large profit gap between renting long-term versus short-term (10 days short-term vs monthly rent for residents)

## In this paper

We estimate the effect of Airbnb on housing rents and prices in Barcelona

- Exploit timing and geography of Airbnb penetration using:
  - Airbnb webscrapped data from InsideAirbnb
  - Posted ads for rentals and sales from a major real estate website Idealista -2007-2017
  - Transaction prices of second-hand apartments 2009-2016
- We find that 54 Airbnb listings (mean Nbrhd) leads to increases in rents of 1.75%, while for transaction (posted) prices the range is 5.3% (3.7%)
- Rents and transaction (posted) prices in Nbrhd's at the top decile of Airbnb activity increased by 7% and 19% (14%) respectively
- · Provide evidence that the mechanism is lower long-term rental supply.

### Literature and contribution

#### Earlier US studies

- Barron, Kung and Proserpio (2018) look at the impact of Airbnb on rents and house prices All US cities
- · Koster, van Ommeren and Volkhausen (2018) study Airbnb bans in LA County
  - · Borders provide clean identification but cannot identify supply effects

### Our paper

- First study for a European city, where housing markets might work differently (less excess capacity, no guest-houses)
- · High penetration: 2% of total dwellings and 7% of rented dwellings
- · High quality micro data on both rents and housing prices
- · Direct evidence on mechanism (household displacement)

# Roadmap...

- 1. Introduction
- 2. Theoretical framework
- 3. Data
- 4. Empirical Strategy
- 5. Alternative empirical strategies
- 6. Conclusion

- · Identical housing units across the city
- One central neighborhood *n*, with size *C*
- Supply: Absentee owners can rent short-term at (exogenous) rent T, or long-term at (endogenous) rent Q
  - Idiosyncratic cost to rent short-term,  $b_i \sim U(0,1)$
  - Marginal owner,  $T b_i^* = Q$
- Demand: Residents can rent in n with  $U_i^n = Y_i Q \alpha\left(F(b_j^*)\right) + a_i$  or rent elsewhere with  $U_i = Y_i$ 
  - $Y_i$  is nominal income and  $\alpha$  reflects externalities
  - Idiosyncratic attachment to neighborhood n,  $a_i \sim U(0,1)$
  - Marginal renter,  $Q(a_i^*) = -\alpha \left( F(b_j^*) \right) + a_i^*$

• In equilibrium, the long term rental market clears:

$$C(1 - F(b_i^*)) = 1 - F(a_i^*) \tag{1}$$

· The share of units that is rented short-term is

$$b_j^* = \frac{C - 1 + T}{1 + C - \alpha} \tag{2}$$

Which implies a positive relationship between  $b_i^*$  and T

• The effect of Airbnb on long-term rentals is:

$$\frac{dQ}{dT} = (C - \alpha) \frac{db_j^*}{dT} \tag{3}$$

• Following Barron et al. (2018) to relate rents and housing prices. Prices are the present value of discounted cash flows to the landlord:

$$P = \sum_{t=1}^{\infty} \delta^{t} \left[ (1 - b_{j}^{*})Q + \int_{0}^{b_{j}^{*}} (T - b_{j})db_{j} \right]$$
 (4)

According to the model, Airbnb:

- Increases housing prices more than rents
- Displaces residents
- Has strong redistributive impacts: Absentee owners benefit, while long-term residents lose.

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Data

#### Inside Airbnb data:

- · 21 data points between April 2015 and February 2018
- · Use reviews to measure active listings at the neighborhood/quarter level

### Rents and posted prices data:

• Idealista: Ads active in each December 2007 to 2017, with a rich set of unit characteristics.

#### Transaction sales data:

• ITP: Universe of second-hand apartments sold 2009-2016 from transaction tax records, similar set of characteristics.

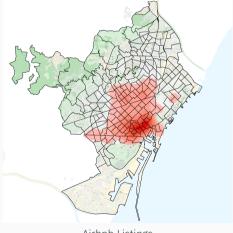
Basic Statistical Areas (BSA) - 233 small neighborhoods

# Data: Graphical Description

### Basic Statistical Areas in Barcelona and Airbnb's location:



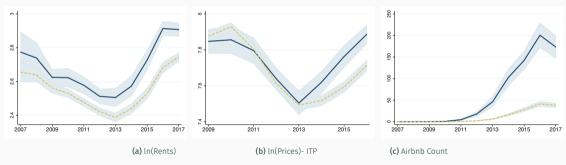
Basic Statistical Areas



Airbnb Listings

## **Graphical** evidence

Figure 1: Evolution of rents and prices, and Airbnb Activity



Notes: Averages (solid) and averages for the top decile of Airbnb activity in 2016 (dashed).



## **Main Strategy**

#### Nbrhd fixed-effects Model:

$$log(Y_{n,t}) = \alpha + \beta Airbnb_{n,t} + \gamma X_{n,t} + \mu_n + \tau_t + \varepsilon_{n,t}$$

- $log(Y_{n,t})$  are average residuals at BSA/time level of regressions of log of prices/rents on unit characteristics and time dummies
- $X_{n,t}$  includes mean age, log population density, average occupation, unemployment rate, relative income level, % foreign
- $\mu_n$  and  $\tau_t$  are nbrhd and time fixed effects
- Weighted observations by number of ads or sales at BSA level
- Standard errors clustered at BSA level

Table 1: Impact of Airbnb density on Rents and Prices with preferred specification

	Rents	Sales ITP	Sales Idealista
Airbnb Count (x100)	0.035*** (0.009)	0.097*** (0.019)	0.068*** (0.009)
N	2.138	7.018	2.247

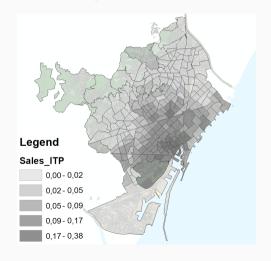
Notes: Significance is indicated by \* p < 0.1, \*\* p < 0.0.5, \*\*\* p < 0.01. Residuals are with respect to housing characteristics, there are time and BSA FE, as well as demographic controls.

- An increase of 54 listings (mean value) leads to increases in rents of 1.75% and in transaction (posted) prices of 5.3% (3.7%)
- An increase of 200 listings (mean in top decile) leads to increases in rents of 7% and in transaction (posted) prices of 19% (14%)

# Results: Implied impact

Figure 3: Rents Legend Rents 0,00-0,00 0,00-0,01 0,01-0,03 0,03-0,06 0,06-0,13

Figure 4: Sales ITP



#### Results: Robustness checks

#### Results are robust to:

- Demographic trends,  $X_{n,2012} \times t$  Demographic Trends
- BSA Specific Time Trends,  $\rho_n \times t$  BSA-Trends
- Detrended series with pre Airbnb data
- Alternative measures of Airbnb: Alternative Airbnb
  - Moving Average
  - Airbnb Density
  - · Log Airbnb Count
- Excluding Historical District (Ciutat Vella)

### **Results: Mechanisms**

 Table 2: Impact of Airbnb on the number of households

	Outcome: log(Households)				
	(1)	(2)	(3)	(4)	
Airbnb	-0.018***	-0.028***	-0.016***	-0.010***	
Count (x100)	(0.005)	(0.006)	(0.005)	(0.004)	
Res wrt Housing	Х	Х	Х	Х	
Time FE	Χ	Χ	Χ	Χ	
BSA FE	Χ	Χ	Χ	Χ	
Dem Controls	-	Χ	Χ	Χ	
Time Trends	-	-	Dem	BSA	

Notes: Significance is indicated by \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. BSA-year level for 2009-2016. Standard errors clustered at the BSA level. N = 1,827 obs.

Alternative empirical strategies

## Alternative empirical strategies

#### Instrumental variables - Shift-share

- · Shift: Google Trends of worldwide searches of "Airbnb Barcelona"
- · Share: Proximity to touristic amenities weighted by their reviews in Google

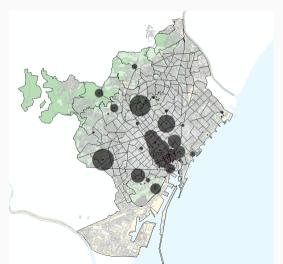
### **Event-Study**

### Sagrada Família case study

· A tourist amenity that is not an amenity for residents

## Instrumental variables: Location of tourist amenities

**Figure 5:** TripAdvisor Points of Interest, weighted by no of reviews



## Instrumental variables: Shift and share components

Figure 6: Airbnb activity and tourist amenities

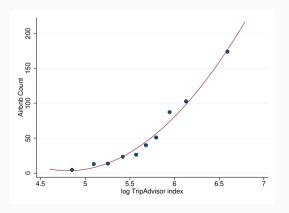
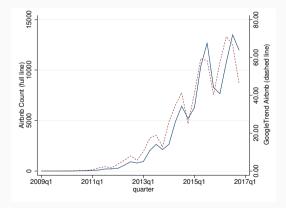
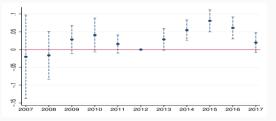


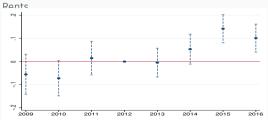
Figure 7: Airbnb activity and Google Trends searches

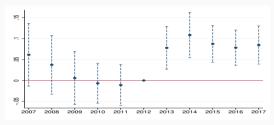


## Instrumental variables: Event study of the 'share' component

Figure 8: Event Study for touristic amenities index







Sales Idealista

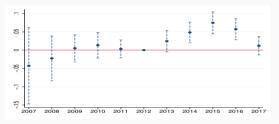
### Instrumental variables: results

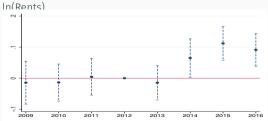
Table 3: Impact of Airbnb density on Rents and Prices with IV specification

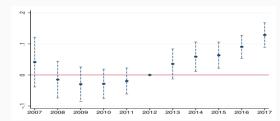
	Rents	Sales ITP	Sales Idealista
Airbnb Count (x100)	0.022*** (0.011)	0.158*** (0.024)	0.074*** (0.014)
Res wrt Housing	Х	Х	X
Time FE	Χ	Χ	Χ
BSA FE	Χ	Χ	Χ
Controls	Dem	Dem	Dem
N	2.138	7.018	2.247
F-Statistic	191.80	158.70	158.61

## **Event Study results**

Figure 9: Event study, Top decile AirbnbCount







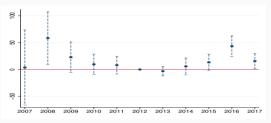
ln(Prices)- Sales Idealista

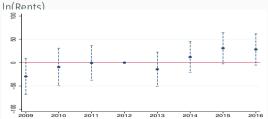
▶ Continuous Airbnbcour

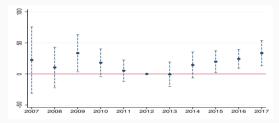
In(Prices) - ITP Sales

# Sagrada Família case study: results

Figure 10: Event study, Sagrada Familia







ln(Prices)- Sales Idealista

In(Prices) - ITP Sales

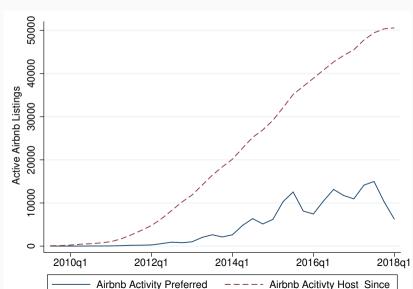


Conclusion

### Conclusion

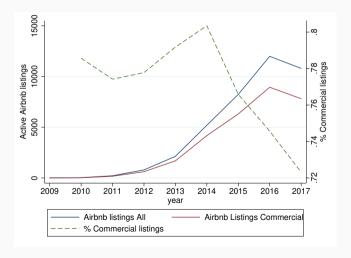
- Several regression-based approaches exploiting timing and geography of Airbnb entry indicate that Airbnb has led to an increase in both rents and prices
- Effects are larger for prices than for rents
- · Average effects are small but impacts in some parts of the city are significant
- · Airbnb cannot explain the housing affordability problem in Barcelona

Figure 11: Comparing different approaches to Airbnb Activity



### Commercial vs Casual Back

Figure 12: Commercial: If owned by a multihost or with an average of more than five reviews per active quarter



## **Results Other Specifications**

Table 4: Impact of Airbnb density on Rents

	Baseline	Robustness		
	(1)	(2)	(3)	(4)
Airbnb Count (x100)	0.035*** (0.009)	0.041*** (0.010)	0.058*** (0.020)	0.034* (0.018)
Res wrt Housing	Χ	Χ	Χ	Χ
Time FE	X	X	X	X
BSA FE	Χ	X	X	X
Controls	Dem	Dem	Dem	-
Time Trends	-	Dem	BSA	-
Detrended	-	-	-	Χ
N	2.138	2.144	2.123	2.144

## **Results Other Specifications**

Table 5: Impact of Airbnb density on ITP Sales

	Baseline		obustness	- [
	(1)	(2)	(3)	(4)
Airbnb Count (x100)	0.097***	0.080***	0.065***	0.084***
	(0.019)	(0.021)	(0.024)	(0.026)
Res wrt Housing	Χ	Χ	Χ	Х
Time FE	Χ	Χ	Χ	Χ
BSA FE	X	X	X	X
Controls	Dem	Dem	Dem	-
Time Trends	-	Dem	BSA	-
Detrended	-	-	-	X
N	7.018	7.022	7.005	7.018

# Results Other Specifications • Back

Table 6: Impact of Airbnb density on Sales Idealista

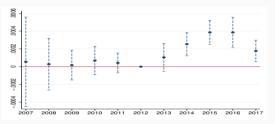
	Baseline	Robustness		
	(1)	(2)	(3)	(4)
Airbnb Count (x100)	0.068***	0.045*** (0.011)	0.022 (0.019)	0.085*** (0.021)
	(0.009)	(0.011)	(0.019)	(0.021)
Res wrt Housing	Χ	Χ	Χ	Χ
Time FE	X	Χ	X	Χ
BSA FE	X	X	X	X
Controls	Dem	Dem	Dem	-
Time Trends	-	Dem	BSA	-
Detrended	-	-	-	Χ
N	2.247	2.251	2.229	2.247

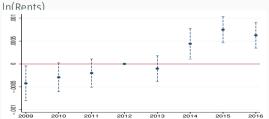
## Alternative Airbnb Measures • Back

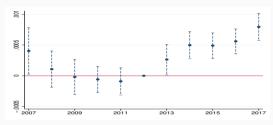
Table 7: Impact of Airbnb on rents and prices - Alternative Airbnb Measures Baseline AbnbCount MA AbnbDens log AbnbCount No CV (1)(2)(3)(4)(5)Panel A: Rents Airbnb 0.035\*\*\* 0.029\*\*\* 0.0098\*\*\* 0.053\*\*\* 0.0068 (0.009)(0.008)(0.005)(0.003)(0.010)Panel B: Transaction Prices (ITP) 0.097\*\*\* 0.107\*\*\* 0.039\*\*\* 0.034\*\*\* 0.093\*\*\* Airbnb (0.019)(0.023)(0.005)(0.006)(0.025)Panel C: Posted Prices (Idealista) Airbnb 0.068\*\*\* 0.070\*\*\* 0.019\*\*\* 0.017\*\*\* 0.096\*\*\* (0.009)(0.010)(0.004)(0.004)(0.025)Mean 402016 56 49 1.57% 1.76% 43

# Results: Event Study Continuous Variable • Back

Figure 13: Event study, Continuous AirbnbCount







ln(Prices)- Sales Idealista

In(Prices) - ITP Sales