Urban Tourism, Location Sorting, and Residents' Welfare

Cayruã Chaves Fonseca

CEMFI

November 21, 2019

Motivation

- **Global tourism is on the rise:** 1.4 billion international travellers in 2018 (more than tripled since 1990)
- **Since 2009** a new factor plays a role in the increasing trends in tourism: **home-sharing** and **short-term rentals**
- Increase in tourism has attracted a lot of attention
  - Financial Times: Are **Airbnb** investors destroying **Europe's** cultural capitals?
  - The Atlantic: Too Many People Want to Travel
  - BBC: What Airbnb really does to a **neighbourhood**
  - The Guardian: **Residents** in tourism hotspots have had enough. So what's the answer?
  - Fortune: **Europe's** Vacation Hot Spots Have a Message for Tourists: Sorry, We're Full
- Most of the concerns relate to some form or another of **gentrification and pricing-out of locals**

This Paper

- Effects of **home-sharing and urban tourism** on the internal structure of a city:
  1. House prices
  2. Consumption amenities
  3. Residential mobility
- **House prices and rents:**
  - Tourists compete for floor space with local residents
- **Consumption amenities:**
  - Commercial environment may shift towards tourists' tastes
- **Residential mobility:**
  - As neighborhoods change, residents may choose to live elsewhere in the city
  - This feeds back into amenities and housing rents
- **Main interest:** sorting and welfare

Related Literature

- **Reduced-form studies of the effects of Airbnb:**
  - **Hotel Industry:** Zervas, Proserpio, and Byers (2017), Farronato and Fradkin (2018)
  - **Housing Market:** Garcia-López et al. (2019), Koster, Ommeren, and Volkhausen (2018), Barron, Kung, and Proserpio (2018)
- **Causes of gentrification and urban sorting:**
  - **Public safety:** Autor, Palmer, and Pathak (2017)
  - **Consumption amenities:** Couture and Handbury (2017)
  - **Rising value of time:** Su (2018)
  - **Rising top incomes:** Couture, Gaubert, et al. (2018)
- **Consequences of gentrification and urban sorting:**
  - **Displacement:** Ding, Hwang, and Divringi (2016)
  - **Individual well-being:** Brummet and Reed (2019)
  - **Welfare inequality:** Su (2018); Couture, Gaubert, et al. (2018)

Descriptive Patterns

Data and Sources

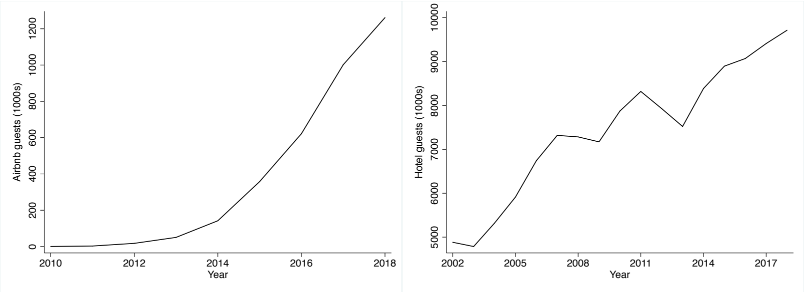
Data and sources for my (current) empirical context: **Madrid**

1. **Airbnb activity:**
   - **Source:** scraped from public facing information on the Airbnb website by the *Inside Airbnb* project
   - **Variables:** history of guest reviews (with exact date) and address of each Airbnb listing
2. **House prices:**
   - **Source:** publicly available from *Idealista*, the largest online real state marketplace in Spain
   - **Variables:** average offer price for second-hand homes at the neighborhood-year level
3. **Neighborhood characteristics:**
   - **Source:** aggregated by the Madrid City Council statistics department from different sources
   - **Variables:**
     - Establishment count by industry (Census of Establishments)
     - Neighborhood demographics and mobility flows (Municipal Population Register - *Padrón*)
     - Hotel guests at the city-year level (Hotel Occupancy Survey)

Tourism Growth

- Airbnb guest arrivals have been increasing rapidly
- Number of hotel guests are also on an increasing trend

Figure 1: Total visitors in Madrid staying in Airbnb (left) and hotels (right)

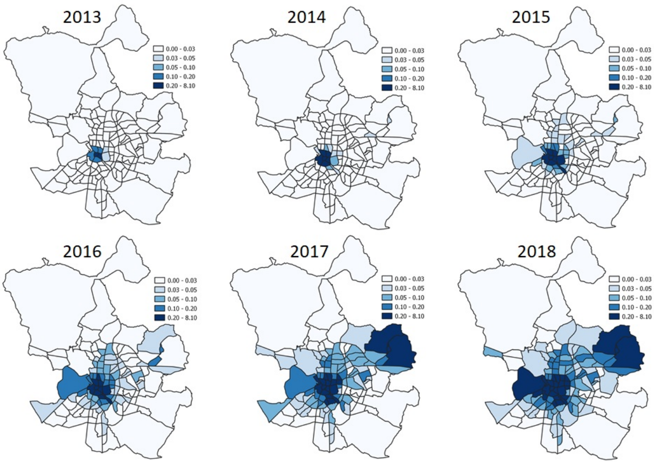


Notes: *i)* while the graph on the left starts in 2010 (first Airbnb guest reviews), the graph on the right starts in 2002 (first year for which hotel data is available). *ii)* note that y-axis values are very different on each graph and the share of overall tourists staying on Airbnb goes from less than 2% in 2014 to almost 12% in 2018

Spatial Distribution of Airbnb Activity

- Airbnb activity has expanded radially from the historic center, reaching almost all neighborhoods
- However, activity levels (number of listings and guests) are disproportionally concentrated in the historic center and areas surrounding the airport

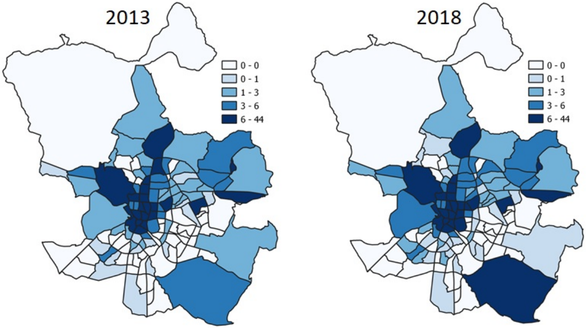
Figure 2: Number of Airbnb guest reviews per household



Spatial Distribution of Hotels

- Citywide hotel count has increased by 20% (496 to 595)
- Spatial distribution hasn't changed much
- Spatial correlation between number of hotels and Airbnb listings was 0.58 in 2013 and rose to 0.70 in 2018

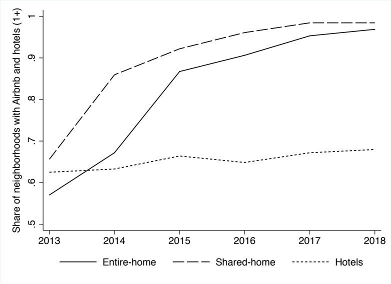
Figure 3: Number of establishments in the accommodation industry

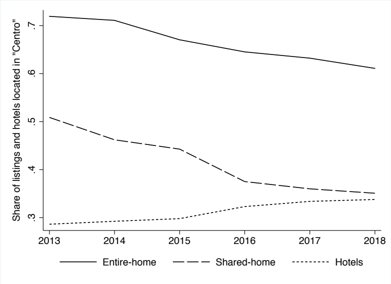


Diversification of Touristic Areas

- Can Airbnb bring tourism induced changes to areas that are not traditionally touristic?
  - **Yes:** Airbnb is present in more neighborhoods than hotels
  - **No:** Airbnb is more concentrated in the historic center than hotels

Figure 4: Fraction of neighborhoods with at least one tourist accommodation (left) and fraction of total accommodations located in “Centro” (right) by accommodation type





Tourists and Local Businesses

- Do local businesses benefit from increased Airbnb tourist demand?
- Regress changes in neighborhood share of restaurants reviews on changes in neighborhood share of Airbnb guest reviews
  - Areas increasingly concentrating more Airbnb guests also increased their share out of citywide restaurant reviews
  - Also true in an sample of non-touristic neighbrohoods

Dependent variable: fraction of Madrid Tripadvisor tourist reviews for restaurants

	Full Sample	Non-touristic
Frac. Airbnb Guest Reviews	0.195***	0.049***
	(0.033)	(0.017)
Frac. Restaurant Local Reviews	0.697***	0.431***
	(0.066)	(0.025)
Frac. of Madrid Hotels	0.496***	0.019***
	(0.059)	(0.007)
Year FE	Yes	Yes
Neighborhood FE	Yes	Yes
Observations	768	570
Number of Neighborhoods	128	95

Airbnb and House Prices

- Airbnb growth correlates with house price growth
- But it is hard to make causal claims

Dependent variable: Ln of House Prices

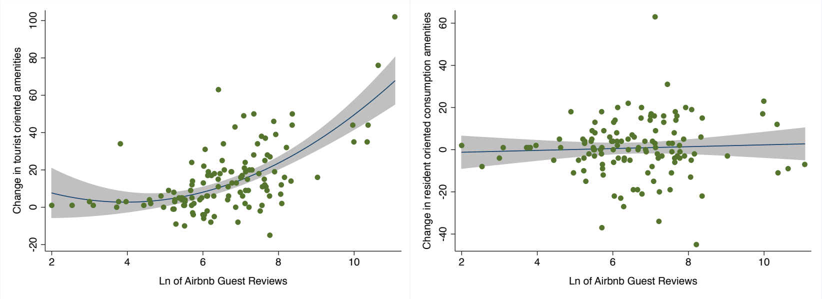
	(1)	(2)	(3)	(4)	(5)
Airbnb Density (EH)	0.072***	0.028***	0.019***	0.010***	0.011***
	(0.018)	(0.006)	(0.005)	(0.002)	(0.004)
Ln Population		0.024	0.006	0.143	0.151
		(0.027)	(0.021)	(0.182)	(0.183)
Perc. College		0.021***	0.018***	0.023***	0.023***
		(0.001)	(0.001)	(0.003)	(0.003)
Perc. Aged 20-39		0.008**	0.004	-0.001	-0.001
		(0.003)	(0.003)	(0.003)	(0.003)
Perc. Employed		0.010***	0.001	0.001	0.001
		(0.002)	(0.002)	(0.001)	(0.001)
Year FE	No	No	Yes	Yes	Yes
M-30 Trends	No	No	Yes	Yes	Yes
Neighborhood FE	No	No	No	Yes	Yes
IV	No	No	No	No	Yes
Observations	795	795	795	795	795

Econ. Significance

Tourists and Consumption Amenities

- Airbnb activity **positively correlates** with changes in the number of **restaurants and entertainment venues**
- But it **doesn't correlate** with changes in the number of businesses in activities that **cater more to locals**

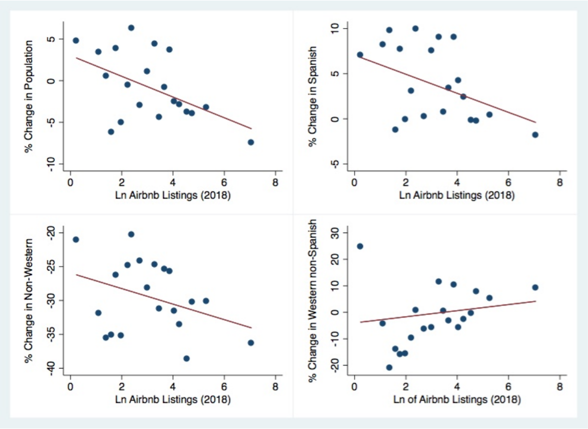
Figure 5: Change in the number of tourist oriented businesses (bars, restaurants, entertainment) and resident oriented businesses (clothing, butcheries, fruit stores)



Airbnb and Population Growth (I)

- Airbnb activity is associated with lower rates of population growth
- If we divide the population by region of birth, the only exception to the rule are non-Spanish Westerners

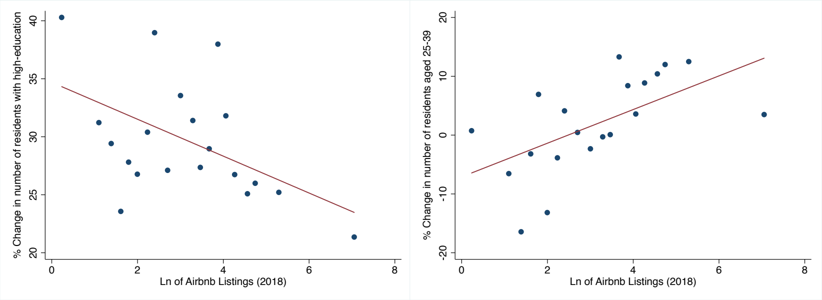
Figure 6: Percentage change in population from 2010 to 2018 and Airbnb listings



Airbnb and Population Growth (II)

- **Education:** growth rate of college educated population is lower in areas with high Airbnb activity
- **Age:** growth rate of young adult population is larger in areas with high Airbnb activity

Figure 7: Percentage change in population from 2010 to 2018 for college educated population (left), and for residents aged between 25-39 (right)



A Pattern and a Puzzle (I)

- Guerrieri, Hartley, and Hurst (2013) document a consistent pattern in within-city spatial variation in house price growth:
  - Growth rates are higher in areas with low baseline prices
- Madrid followed the same rule both during the boom previous to the financial crisis and during the widespread price decreases up to 2014

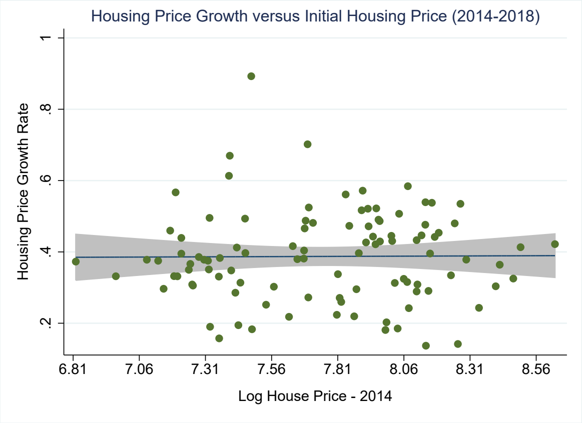
Figure 8: House price growth rate as a function of initial prices during the boom (left) and the bust (right)

▸ House Prices in Madrid ▸ U.S. cities recently

A Pattern and a Puzzle (II)

- **Puzzle:** house price growth rates in recent years do not correlate with baseline price levels

Figure 9: Growth rate in house prices as a function of baseline prices



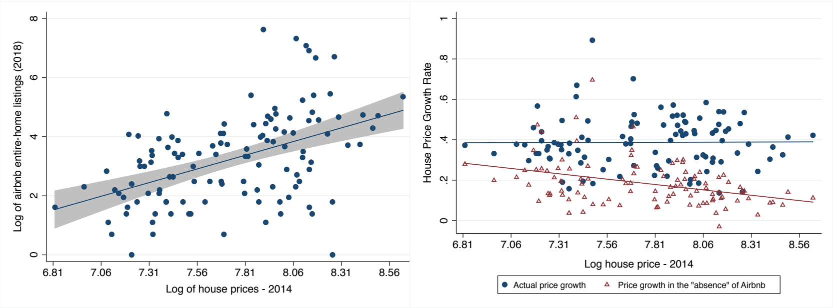
Accounting for Tourist Influx

- We can plot house price growth after accounting for Airbnb's effect:

$$\frac{\Delta price_{it}}{price_{it-1}} = ln(price_{it-1}) + \Delta ln(Airbnb_{it}) + \varepsilon_{it} \qquad (1)$$

- Airbnb activity tends to concentrate in areas with high initial house prices
- Since Airbnb activity tends to increase house prices, it creates a force against the general pattern

Figure 10: Airbnb listings as function of initial house prices (left) and price growth rate after controlling for Airbnb listings (right)



A Residential Location Model

Note: the model presented in the following slides is borrowed from Almagro and Dominguez-Iino (2022)

The Model in a Nutshell

- **Agents and decisions:**
  - **Residents** of different types (low-skill, high skill) choose a location to live and how much to consume of private amenities
  - **Firms** in different categories of consumption (e.g. restaurants, groceries) choose prices
  - **Landlords** choose whether to allocate their housing unit to the long-term (residents) or short-term market (Airbnb tourists)
  - **Tourists** choose how much to consume of private amenities (but their location decision and hotel supply are exogenous)
- **Sorting mechanism:**
  - As **tourist influx** increases, tourist attractive neighborhoods experience increases in **house prices** and a shift in their **commercial landscape**
  - Residents **less sensitive** to rents and/or with preference for private amenities more **aligned** with the ones of tourists sort into these locations (reinforces the cycle)
- **Equilibrium:**
  - Spatial distribution of population, housing rents, and level of consumption amenities is determined in equilibrium

Residential Location (Preview)

- Residents have to pay a rent to live in a given neighborhood
- Utility from private consumption and from non-rival amenities
- In each period, locals choose one neighborhood to live in taking housing rents and access to amenities as given
- Local resident r, of demographic group d, living in neighborhood j, gets utility

$$U_j^{rd} = A_j^{\theta^d} \prod_{c=1}^{C} \left[\left(\sum_{i=1}^{E_c} q_{ic}^{\frac{\sigma_c - 1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c - 1}} \right]^{\gamma_c^d} exp(\epsilon_j^{rd})$$

$$s.t. \quad \sum_{ic} p_{ic} q_{ic} = w^d - r_j = m_j^d$$

- First focus on the decision of the optimal consumption of private amenities conditional on being in a location
- Then come back to the indirect utility of choosing each location for each demographic type

Consumption Amenities

Set-up

- There are three D different types of consumers (e.g. high skill local, low skill local, tourist) with heterogeneous preferences
- There are C types (categories) of private consumption amenities (e.g. restaurants, groceries, other retail...)
- In each neighborhood and within a consumption category, many firms offer imperfectly substitutable products/services

Demand

- Conditional on being in location j, consumer type d chooses quantities to consume from each firm (in all categories)

$$\max_{q_{ic}} \prod_{c=1}^{C} \left[\left(\sum_{i=1}^{E_c} q_{ic}^{\frac{\sigma_c - 1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c - 1}} \right]^{\gamma_c^d} \quad s.t. \ \sum_{ic} p_{ic} q_{ic} = m_j^d$$

Consumption Amenities

- CES preferences for different firms/products i within the same consumption category c (elasticity of substitution σ_c)
- Cobb-Douglas preferences for consumption categories
- Demand for product i in category c is (implicit assumption)

$$q_i = \frac{\gamma_c^d m_j^d}{p_i^{\sigma_c} \sum_{i \in c} p_i^{1-\sigma_c}} = \frac{\gamma_c^d m_j^d}{p_i} \frac{p_i^{1-\sigma_c}}{\sum_{i \in c} p_i^{1-\sigma_c}} = \frac{\gamma_c^d m_j^d}{p_i} s(p_i, P_c)$$

- If there are N_j^d consumers of type d in location j, aggregate demand for firm i in category c is

$$Q_i = \sum_d N_j^d \frac{\gamma_c^d m_j^d}{p_i} s(p_i, P_c) = \frac{s(p_i, P_c)}{p_i} \sum_d N_j^d \gamma_c^d m_j^d$$

- All firms in the same (j, c) pair face the same demand curve

Consumption Amenities

Supply

- Firm i in category c and location j, maximizes profits:

$$\max_{p_i} Q_i(p_i - c_i)$$

- Optimal price will depend on marginal costs and price elasticity of aggregate demand

$$p_i^* = \frac{c_i}{1 - \frac{1}{\eta}}\,, with \;\; \eta(p_i) = -\frac{\partial Q_i}{\partial p_i}\frac{p_i}{Q_i}$$

- **Assumptions:**
  1. Firms in the same location j and consumption category c have the same marginal costs
  2. Price of firm i has negligible effects on price index $\sum_{i \in c} p_i^{1-\sigma_c}$

$$p_i^* = \frac{c_{jc}}{1 - \frac{1}{\sigma_c}}$$

Consumption Amenities

Equilibrium

- Since all firms in the same location and consumption category have the same costs

$$p_{ijc} = p_{jc} \quad \forall i \in c$$

- Equal prices imply that consumers buy equally from all firms in the same category-location

$$Q_{ijc} = Q_{jc} = \frac{s(p_i, P_c)}{p_i} \sum_d N_j^d \gamma_c^d m_j^d = \frac{\sum_d N_j^d \gamma_c^d m_j^d}{p_{jc} E_{jc}} = \frac{\left(1 - \frac{1}{\sigma_c}\right) \sum_d N_j^d \gamma_c^d m_j^d}{c_{jc} E_{jc}}$$

- If entry costs are location-category specific, free entry implies

$$Q_{jc}(p_{jc} - c_{jc}) - F_{jc} = 0$$

- With delivers the number of firms in each category-location

$$E_{jc} = \frac{\sum_d N_j^d \gamma_c^d m_j^d}{F_{jc} \sigma_c}$$

Consumption Amenities

Taking Stock

- Number of firms in different categories in each neighborhood is a function of size and composition of "local" consumers

$$E_j = [E_{j1}, ..., E_{jC}] = \Gamma\left(N_j^1, ..., N_j^D\right), \quad e.g.\ \Gamma\left(N_j^{RL}, N_j^{RH}, N_j^T\right)$$

- That's how spatially heterogeneous **tourist influx** as well as **residential decision** of locals generates differential densities of **each type of consumption amenity** across the city
- Tourists here are **both hotel guests and Airbnb visitors**
- Potential improvements:
  1. Consumers only buy in the same neighborhood where they live (residents) or stay (tourists)
  2. Two neighborhoods with the same number of restaurants are equally attractive (quality?)

Residential Location

- Back to the utility presented earlier
- In each period, locals choose where to live taking housing rents and access to amenities as given
- Local resident r, of demographic type d, living in location j, gets the following utility

$$U_j^{rd} = A_j \prod_{c=1}^{C} \left[\left(\sum_{i=1}^{E_c} q_{ic}^{\frac{\sigma_c - 1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c - 1}} \right]^{\gamma_c^d} exp(\epsilon_j^{rd})$$

$$s.t. \quad \sum_{ic} p_{ic} q_{ic} = w^d - r_j = m_j^d$$

- In the model, only local residents make this choice
- Tourists' location decision is not endogenous so far (like a "shock" in tourism demand)

Residential Location

- The first order condition for q_{ic} is

$$A_j \prod_{c' \neq c} \left[\left(\sum_{i=1}^{E_{c'}} q_{ic'}^{\frac{\sigma_{c'}-1}{\sigma_{c'}}} \right)^{\frac{\sigma_{c'}}{\sigma_{c'}-1}} \right]^{\gamma_{c'}^d} \gamma_c^d \left[\left(\sum_{i=1}^{E_c} q_{ic}^{\frac{\sigma_c-1}{\sigma_c}} \right)^{\frac{\sigma_c}{\sigma_c-1}} \right]^{\gamma_c^d-1} \ldots$$

$$\ldots \left(\sum_{i=1}^{E_c} q_{ic}^{\frac{\sigma_c-1}{\sigma_c}} \right)^{\frac{1}{\sigma_c-1}} q_{ic}^{\frac{-1}{\sigma_c}} exp(\epsilon_j^{rd}) = \lambda p_{ic}$$

- We know from before that $p_{ic} = p_c$ and that consumers equally from all suppliers in the same location-category, q_c^d
- Using this fact and combining two FOCs for different categories, we get

$$\frac{\gamma_c^d}{\gamma_{c'}^d} = \frac{p_c E_c q_c^d}{p_{c'} E_{c'} q_{c'}^d} = \frac{p_c Q_c^d}{p_{c'} Q_{c'}^d} \quad \longrightarrow \quad p_{c'} Q_{c'}^d = \frac{\gamma_{c'}^d}{\gamma_c^d} p_c Q_c^d$$

Residential Location

- Summing the expenditure across all consumption categories

$$\sum_{c' \in C} p_{c'} Q_{c'}^d = \frac{p_c Q_c^d}{\gamma_c^d} \sum_{c' \in C} \gamma_{c'}^d = \frac{p_c Q_c^d}{\gamma_c^d} = \frac{p_c E_c q_c^d}{\gamma_c^d}$$

- And substituting in the budget constraint

$$\frac{p_c E_c q_c^d}{\gamma_c^d} = (w^d - r_j) \;\; \longrightarrow \;\; q_c^d = \frac{1}{E_c} \frac{\gamma_c^d}{p_c} (w^d - r_j)$$

- The indirect utility is

$$\bar{U}_{jt}^{rd} = A_{jt}(w_t^d - r_{jt}) \prod_c \left[\frac{\gamma_c^d \left(1 - \frac{1}{\sigma_c}\right)}{c_{jct}} E_{jct}^{\frac{1}{\sigma_c - 1}} \right]^{\gamma_c^d} exp(\epsilon_{jt}^{rd})$$

Residential Location

- The term A_{jt} represents non-market amenities
- Utility individuals receive simply by leaving in neighborhood j

$$A_{jt} = exp(\beta_a^d a_{jt} + \mu_j^d + \xi_{jt}^d)$$

- μ_j^d are time invariant characteristics of a neighborhood that make it attractive (proximity to the coast)
- ξ_{jt}^d are time-varying unobserved non-market amenity levels (time-varying unobserved neighborhood quality)
- a_{jt} also represent non-market amenities but I explicitly estimate preference parameters for them because they either
  - Are directly related to tourist influx: congestion from tourists
  - Are allowed to endogenously respond to forces within the model: skill mix of local residents (not captured in the commercial environment but also respond to local skill mix)

Residential Location

- Takings logs, indirect utility is

$$\log \bar{U}_{jt}^{rd} = \mu^d + \mu_j^d + \xi_{jt}^d + \beta_a^d \log a_{jt} + \log(w_t^d - r_{jt}) + \\ + \sum_{c=1}^{C} \frac{\gamma_c^d}{\sigma_c - 1} \log E_{jct} - \sum_{c=1}^{C} \gamma_c^d \log c_{jct} + \epsilon_{jt}^{rd}$$

Mean utility and moving costs

- We can write the utility of resident r of demographic group d living in neighborhood j at time t as

$$\log \bar{U}_{jt}^{rd} = \mu^d + \mu_j^d + V_{jt}^d + \epsilon_{jt}^{rd}$$

- If moving from location l to j involves a cost k_{ljt}^d, the residential location decision of each period is

$$\max_j \left\{ V_{jt}^d + \epsilon_{jt}^{rd} - k_{ljt}^d \right\}$$

Residential Location

- Assuming ϵ_{jt}^{rd} is distributed EV-1, probability of choosing j for those who started in l is

$$\pi_{ljt}^{d} = \frac{exp(V_{jt}^{d} - k_{ljt}^{d})}{\sum_{j'} exp(V_{j't}^{d} - k_{lj't}^{d})}$$

- Given a initial distribution of population across space in period $t-1$, then period's t population in each neighborhood j is

$$N_{jt}^{d} = \sum_{l=1}^{L} \pi_{ljt}^{d} \, N_{l,t-1}^{d}$$

Housing Supply

- Total housing in each neighborhood H_j is fixed
- Absentee landlords choose whether to rent to residents in the long-term market or to tourists in the short-term market
- Landlords owning a housing unit in neighborhood j at time t face the following decision

$$\max_{h=\{L,S\}} \{\beta ln(r_{jt}) + \nu_h \ , \ \beta ln(p_{jt}) - \kappa_{jt} + \nu_h\}$$

- Since I assume total housing is fixed $H_{jt}^L + H_{jt}^S = H_j \ , \ \forall t$
- And assuming ν_h are type I EV shocks, the share of housing allocated to visitors and residents in each neighborhood is

$$s_{jt}^L = \frac{exp(\beta ln\ r_{jt})}{exp(\beta ln\ r_{jt}) + exp(\beta ln\ p_{jt} - \kappa_{jt})}$$
$$s_{jt}^S = \frac{exp(\beta ln\ p_{jt} - \kappa_{jt})}{exp(\beta ln\ r_{jt}) + exp(\beta ln\ p_{jt} - \kappa_{jt})}$$

Equilibrium

- At every t, moving rates from l to j and population in j are

$$\pi^{\star d}_{ljt} = \frac{exp(V^{\star d}_{jt} - k^{d}_{ljt})}{\sum_{j'} exp(V^{\star d}_{j't} - k^{d}_{lj't})} \ ,$$

$$N^{\star d}_{jt} = \sum_{l=1}^{L} \pi^{\star d}_{ljt} \ N^{\star d}_{l,t-1}$$

- Number of firms providing consumption amenity category c in location j and time t is

$$E^{\star}_{jct} = \frac{\sum_d N^{\star d}_{jt} \gamma^{d}_{c} m^{\star d}_{jt}}{F_{jct}\sigma_c}$$

- Housing supply in the short and long term markets are

$$s^{\star L}_{jt} = \frac{exp(\beta ln \ r^{\star}_{jt})}{exp(\beta ln \ r^{\star}_{jt}) + exp(\beta ln \ p^{\star}_{jt} - \kappa_{jt})} H_j$$

$$s^{\star S}_{jt} = \frac{exp(\beta ln \ p^{\star}_{jt} - \kappa_{jt})}{exp(\beta ln \ r^{\star}_{jt}) + exp(\beta ln \ p^{\star}_{jt} - \kappa_{jt})} H_j$$

Estimation - Housing Supply

- Taking logs and subtracting short-term from long-term share of housing in each neighborhood we get

$$ln\, s^S_{jt} - ln\, s^L_{jt} = \beta(ln\, p_{jt} - ln\, r_{jt}) - \kappa_{jt}$$

- Expressing extra cost of short-term renting in location j time t as $\alpha_j + \alpha_t + \vartheta_{jt}$ and taking first-differences

$$ln\, s^S_{jt} - ln\, s^L_{jt} = \beta(ln\, p_{jt} - ln\, r_{jt}) + \alpha_j + \alpha_t + \vartheta_{jt}$$

$$\Delta\left(ln\, s^S_{jt} - ln\, s^L_{jt}\right) = \beta\Delta\left(ln\, p_{jt} - ln\, r_{jt}\right) + \Delta\left(\alpha_t\right) + \Delta\left(\vartheta_{jt}\right)$$

- β: relative utility gain from relative increase in rental income
- **Instrument:** shift-share predicted tourists (or population)
  - **Relevance:** predicted tourist inflow should increase $(p_{jt} - r_{jt})$
  - **Exclusion:** not correlated to neighborhood specific time varying shocks to extra cost of short-term renting

Estimation - Consumption Amenities

- Firms fixed costs are a combination of location, time, and category effects: $F_{jct} = \lambda_j \lambda_c \lambda_t \phi_{jct}$
- Take logs of the eq. condition in the amenities market

$$log\ E_{jct} = \delta_j + \delta_t + \delta_c + log\left(\sum_d \gamma_c^d N_j^d m_{jt}^d\right) + \xi_{jct}$$

$$where\ \ \delta_j = -log\lambda_t\ ,\ \ \delta_t = -log\lambda_t,\ \ \delta_c = -log\lambda_c - log\sigma_c$$

$$and\ \ \xi_{jct} = -log\phi_{jct}$$

- Error term are category-location-time specific component of fixed-costs
- Term δ_c is a combination of category specific fixed costs and level of competition
- Challenges:
  1. Non-linearity in parameters
  2. Endogeneity
  3. IV needs to correlate with aggregate budget group d has to spend on

Estimation - Residential Location

- 2-step approach
  1. Use observed moving rates to estimate mean utility separately from moving costs
  2. Use change in mean utility of different destinations to estimate parameters that determine quality of life in each neighborhood (consumption amenities, housing rents...)
- First step:

$$log\ \pi^d_{ljt} = V^d_{jt} - k^d_{ljt} - log\left(\sum_{j'} exp(V^{\star d}_{j't} - k^d_{lj't})\right)$$

- Imposing moving costs to be a function of distance we get

$$log\ \pi^d_{ljt} = V^d_{jt} + \Omega^d_t + \Omega^d_{fix}\left[\mathbb{1}\{l \neq j\}\right] + \Omega^d_{dist}(dist_{lj}) + \Gamma^d_{lt} + \zeta^d_{ljt}$$

Estimation - Residential Location

- Second step:

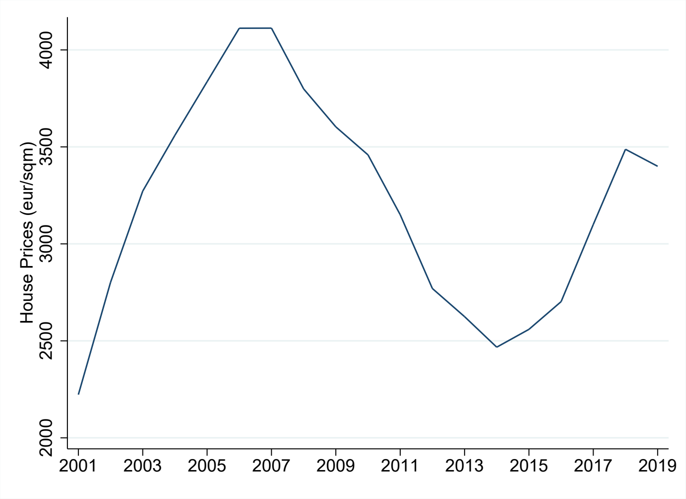
$$\hat{V}_{jt}^{d} = \sum_{b=1}^{B} \theta_b^d log\ b_{jt} + log(w_t^d - r_{jt}) +$$
$$\sum_{c=1}^{C} \frac{\gamma_c^d}{\sigma_c - 1} log\ E_{jct} + \sum_{c=1}^{C} \gamma_c^d log\ c_{jct}$$

- **To be continued........ (work in progress)**

Extra Slides

Evolution of House Prices in Madrid

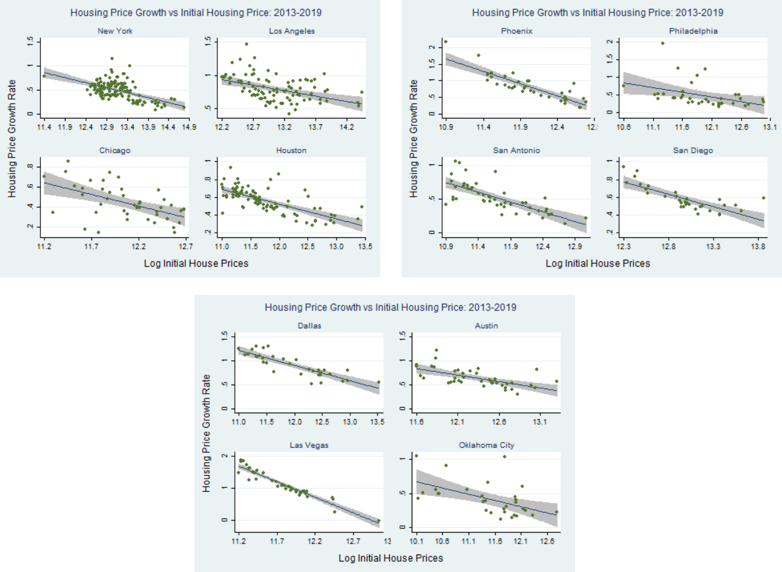
Figure 11: Average of second-hand house prices offered in Idealista.com



▸ Motivation

U.S. Cities: House Price Growth and Baseline Prices

Figure 12: House price growth as a function of baseline prices in U.S. cities



Effect of House Prices: Economic Significance

Pctile Airbnb Density Grow	Neighborhood	Estimated Airbnb Effect	Actual House Price Growth	Explained by Airbnb
20	Estrella	0.24%	29.34%	0.83%
40	Pueblo Novo	0.41%	18.70%	2.20%
60	Rejas	0.69%	21.71%	3.20%
80	Puerta del Angel	1.32%	38.53%	3.44%
90	Almagro	2.03%	25.82%	7.87%
94	Embajadores	11.19%	55.79%	20.06%
95	Palacio	11.90%	38.48%	30.92%
96	Universidad	11.35%	56.90%	19.95%
97	Justicia	12.86%	49.46%	26.00%
98	Cortes	15.73%	37.44%	42.02%
99	Sol	27.58%	49.64%	55.55%

House Prices