reading group summer 24
Location Sorting and Endogenous Amenities: Evidence from Amsterdam (2024)

Milena Almagro and Tomas Domınguez-Iino

August 2024

Outline

Introduction

Data

Model - brace yourselves

Empirical Strategy and Results

Counterfactuals

Introduction

- build a model of residential choice with hetereogenous households - amenities improve in response to location sorting
- but nature of amenities has not been explored
- estimate the model using several data
- run counterfactual exercises

Context

- massive expansion in tourism in Amsterdam
- increased supply of private rentals, increased supply of STRs
- New regulation in Amsterdam severely restricting STR supply (hotels and Airbnbs)

Related Literature

- spatial equilirium models
- effects of STR entry on the housing market and hotel revenue
- discrete-choice tools from the empirical io literature applied to urban residential markets

Outline

Introduction

Data

Model - brace yourselves

Empirical Strategy and Results

Counterfactuals

Data

- individual-level microdata: Centraal Bureau voor de Statistiek, Netherlands they have complete residential histories, demographics
- housing data: panel on physical characteristics, occupancies, and values. impute rents
- neighbourhood data: Amsterdam City Data consists of demographics, tourist flows, and consumption amenities: restaurants, bars, food stores, non-food stores, nurseries, and "touristic amenities"
- STR data: Inside Airbnb. monthly data on listings, geo-coordinates, prices, reviews. need to identify preoperties that are permanently rented to tourists.

Fact 1: Tourists and STR listings have grown dramatically and sprawled across Amsterdam

Figure 1:

Fact 2: Rents have increased more in neighborhoods with more STR entry using OLS (likely biased) and IV (shift-share)

Table 1: Airbnb intensity and housing market outcomes

	Ln (rent/m2)					
	OLS	IV	OLS	IV	OLS	IV
Ln (commercial Airbnb listings)	**0.065*** **	**0.091*** **	**0.051*** **	**0.114*** **	**0.109*** **	**0.205* **
	(0.008)	(0.021)	(0.006)	(0.021)	(0.018)	(0.093)
Control variables			X	X	X	X
District-year FE					X	X
First stage F-stat		586.89		384.21		69.66
Observations	770	770	763	763	763	763

	Ln (house sale price)					
	OLS	IV	OLS	IV	OLS	IV
Ln (commercial Airbnb listings)	**0.109*** **	**0.290*** **	**0.034*** **	**0.149*** **	**0.037* **	**0.326** **
	(0.016)	(0.030)	(0.006)	(0.016)	(0.022)	(0.102)
Control variables			X	X	X	X
District-year FE					X	X
First stage F-stat		572.02		370.87		65.9
Observations	738	738	737	737	737	737

Notes: Observations are at the wijk (neighborhood) level. A "district" is a larger spatial unit than a neighborhood. Rent prices are neighborhood-average long-term rental prices constructed from CBS rent surveys. House sale prices are neighborhood average transaction values, constructed from CBS data covering the universe of housing transactions. Commercial Airbnb listings are constructed from the Inside Airbnb data (see Appendix A.2.7 for construction details). Neighborhood-level control variables are: housing stock, average income, high-skill population share, all from ACD BBGA. Standard errors are clustered at the wijk level in parenthesis.

Figure 2:

a 1% increase in a neighborhood's commercial STR listings is associated with a rent increase between .06-.11% and a house sale price increase between .04-.11%

Fact 3: Amenities have tilted towards tourists and away from locals

Figure 3:

Fact 4: The composition of residents has changed heterogeneously across neighborhoods

Figure 4:

Outline

Notation

- J locations $+1$ outside option
- M_{jt}^{k}: number of type k households in location j
- consumption amenities s in S sectors
- N_{sjt}: the number of varieties in sector s and location j at time t
- amenities $a_{jt} = [N_{1jt}, N_{2jt}, ..., N_{Sjt}]'$

Amenities Demand

- Demand: Cobb-Douglas over bundles H and C
- also Cobb-Douglas preferences over amenity sectors, CES over firms/varieties within sector

$$q^k_{isjt} = \frac{\alpha^k_s \phi^k w^k_t}{p_{isjt}} \left(\frac{p_{isjt}}{P_{sjt}}\right)^{1-\sigma_s}, \text{ with } P_{sjt} \equiv \left(\sum_{i=1}^{N_{sjt}} p_{isjt}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}} \quad q_{isjt} = \sum_k q^k_{isjt} M^k_{jt}.$$

Figure 5:

Amenities Supply

- Firms within s, j in monopolistic competition - same marginal cost, free entry
- fixed cost F_{sjt} - assumed to be increasing in N_{jt} (congestion costs)
- implies that firms choose same price $p_{sjt} = p_{ijst}$ and quantity $q_{sjt} = q_{isjt}$

$$(p_{sjt} - c_{sjt})q_{sjt} = F_{sjt}(N_{jt}), \quad \text{where } N_{jt} = \sum_s N_{sjt}.$$

Figure 6:

Amenities Market Clearing

- usual market clearing delivers equilibrium number of varieties/firm
- and a mapping from population composition to amenities

- total housing stock inelastic in the short run
- Landlords face a binary choice: long-term rentals or short-term rentals:

Figure 7:

Housing Supply

- total housing stock inelastic in the short run
- Landlords face a binary choice: long-term rentals or short-term rentals:

Figure 8:

Housing Demand

- moving costs and location capital

Figure 9:

$$\tau_{it} = \begin{cases} \min\{\tau_{it-1} + 1, \bar{\tau}\} & \text{if } j_{it} = j_{it-1} \\ 1 & \text{otherwise.} \end{cases}$$

Figure 10:

Housing Demand

- some macro...

$$V_t^k(x_{it}, \epsilon_{it}) = \max_{j \in \{0,1,\ldots,J\}} u_t^k(j, x_{it}) + \epsilon_{ijt} + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j, x_{it}, \epsilon_{it} \right].$$

Figure 11:

Housing Demand

- choice probabilities

$$\mathbb{P}_t^k(j|x_{it}) = \frac{\exp\left(u_t^k(j, x_{it}) + \beta \mathbb{E}_t\left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1})|j, x_{it}, \epsilon_{it}\right]\right)}{\sum_{j'} \exp\left(u_t^k(j', x_{it}) + \beta \mathbb{E}_t\left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1})|j', x_{it}, \epsilon_{it}\right]\right)}.$$

Figure 12:

Housing Demand

- transition matrix

$$\pi_t^k(j,\tau) = \begin{cases} \sum_{\tau'} \sum_{j' \neq j} \mathbb{P}_t^k(j|j',\tau')\pi_{t-1}^k(j',\tau') & \tau = 1 \\ \mathbb{P}_t^k(j|j,\tau-1)\pi_{t-1}^k(j,\tau-1) & \tau \in [2,\bar{\tau}) \\ \mathbb{P}_t^k(j|j,\bar{\tau}-1)\pi_{t-1}^k(j,\bar{\tau}-1) + \mathbb{P}_t^k(j|j,\bar{\tau})\pi_{t-1}^k(j,\bar{\tau}) & \tau = \bar{\tau}. \end{cases}$$

Figure 13:

- (population) demand for STRs

Figure 14:

$$\mathcal{H}_{jt}^{LT,D}(r_t, a_t) = \sum_{k=1}^{K} M_{jt}^{k}(r_t, a_t) f_{jt}^{k}.$$

Figure 15:

Housing Demand: tourists

- toursists' flow payoff from staying in STR

Figure 16:

Housing Demand: tourists

- toursists' demand for STR

Figure 17:

Housing Demand: tourists

- hotels are an outside option
- but no price or bookings data
- so use data on hotel capacity across locations

$$M_{jt}^{H}(p_t, a_t) \; = \; s_{jt}^{beds} \times M_t^{H}(p_t, a_t)$$

Figure 18:

Housing Equilibrium

- a stationary equilibrium
- a bunch of market clearing equations
- long-term rental markets clear, short-term rental markets clear, amenities markets clear

Outline

Amenity supply

- estimating equation:

Figure 19:

- X_{jt}^k total expenditure of the type k population in location j on consumption amenities
- β_s^k describes how this expenditure is allocated to each amenity sector s
- IV: something that shifts amenities demand

Amenity Supply

- IV: $Z_{jt}^k = w_t^k S_{jt}^{\gamma(k)}$, where S is housing stock by tenancy status
- GMM moment equation to idenfity βs: $E[\omega_{sjt} Z_{sjt}^k] = 0$

Amenity Supply

- results:

Figure 20:

-

Housing Demand: by locals

- "Euler Equations in Conditional Choice Probabilities" (ECCP) estimator: which I didn't understand and didn't have time to study in detail

Figure 21:

- interpret signs

- no IV here: they use reveiews of Airbnbs to create a score variable for every location

Figure 22:

Housing supply

- estimating equation:

Figure 23:

- OLS is biased - use shift-share IV that shifts demand
- shift: worldwide change in STR demand
- share: neighborhood-level exposure to the shift from the historic spatial distribution of touristic attractions
- relevance and exclusion are satisifed. (note: not mention of monotonicty, CALL IVAN)

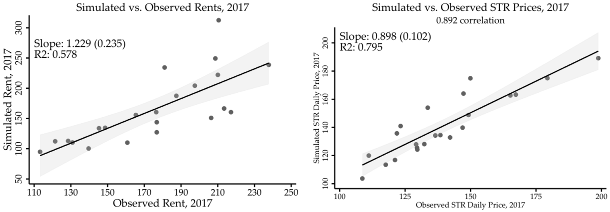
Housing supply

- IV results: increase in the gap between STR prices and LTR prices of one standard deviation (29%) would raise the market share of the ST relative to the LT segment by 13.6%

Figure 24:

- pretty well!

Figure 7: Model fit: Rents and STR prices



Notes: The figure presents scatter plots, linear fit, and 95% confidence intervals of simulated rents and STR prices, against observed rents and prices for 22 districts. Rents are in $Euros/m^2$ per year. STR prices are average daily prices.

Figure 25:

Outline

Introduction

Data

Model - brace yourselves

Empirical Strategy and Results

Counterfactuals

Counterfactual 1: Preference heterogeneity vs homogeneity

- set preference parameters for consumption amenities to the average value across all household types, weighted by the size of groups
- segregation is higher when households have heterogeneous preferences for amenities

Figure 26:

- ... but inequality is lower when preferences are heterogeneous

Counterfactual 1: Preference heterogeneity vs homogeneity

- ... but inequality is lower when preferences are heterogeneous

Table 7: Neighborhood differentiation as spatial dispersion of amenities.

	Gini index for each preference specification		
Amenity	Homogenous (HO)	Heterogenous (HE)	HE-HO
Touristic amenities	0.34	0.37	0.03
Restaurants	0.43	0.56	0.13
Bars	0.59	0.66	0.07
Food stores	0.32	0.57	0.25
Non-food stores	0.53	0.67	0.14
Nurseries	0.51	0.43	-0.08

Notes: Columns "Homogeneous" and "Heterogeneous" report the Gini index for each amenity sector: how concentrated the number of establishments in each sector is across locations. Higher values indicate most of the sector's establishments are clustered in a few locations. Column HE-HO reports the difference between the "Heterogeneous" and "Homogeneous" columns. Positive values in the HE-HO column indicate the spatial distribution of the amenity becomes more clustered across space when preferences are heterogeneous.

Figure 27:

- because high income groups do not compete with low income groups for the same locations, allowing low income groups to obtain their preferred amenities without having the high income groups bid up their rents

Counterfactual 2: Decomposing welfare effects of the STR industry

- STR entry reduces rent & change amenity composition
- disentangle: pre-entry baseline, allow STR keeping amenities fixed, then allow amenities to adjust

Counterfactual 2: Decomposing welfare effects of the STR industry

- touristic amenities grow the most in areas populated by old people

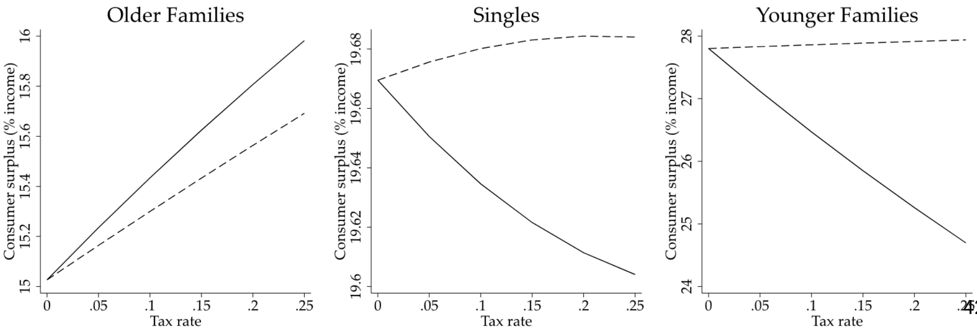
Figure 28:

- Older Families are the highest-income group and face largest welfare losses: so STR entry is progressive

Counterfactual 3: Taxing STRs and/or Touristic amenities

- tax short-term rentals - directly reduces rent
- vs tax touristic amenities
- taxing STR has monotonically increasing effects (in tax rates) on welfare

Figure 12: Welfare effects: short-term rental tax vs. touristic amenity tax.



Conclusion

- studied the role of preference heterogeneity over a set of endogenous location amenities in shaping within-city sorting and welfare inequality
- there exists hetereogenity preference over amenities
- leads to increased sorting but welfare effects are ambiguous

See ya