Location Sorting and Endogenous Amenities: Evidence from Amsterdam

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Motivation

The link has been found between inequality and sorting of households across locations

- Across cities: High-income households move to high-income and high-quality amenity cities
- Within cities: Concerns about housing affordability and gentrification of neighborhoods
  - High-income households move into previously low-income areas
  - Higher rental prices
  - Transformation of the neighborhoods to cater to this new demand due to the heterogeneous preferences among HHs and the nature of endogenous amenities
- Interaction between Location Choice and Amenities
  - Different amenities cater to different groups and respond differently

Research Question

- How does preference heterogeneity over multiple endogenous consumption amenities shape:
  - Sorting of demographic groups within a city?
  - Within-city spatial inequality?

Main Contributions to Literature

Spatial equilibrium models to study spatial inequality across and within cities.

- Many papers model endogenous amenities as a residual
  - Ahlfeldt, Redding, Sturm & Wolf (2015), Diamond (2016)
- Recent focus on endogenous consumption amenities with homogeneous households
  - Couture et al. (2021), Miyauchi et al. (2021)
- This paper contributes to the literature by incorporating preference heterog. over amenities into a dynamic model of residential choice.

Other Related Literature

- Examine the rise of the short-term rental industry and tourism more broadly
  - Farronato and Fradkin (2018), Calder-Wang (2021), Faber and Gaubert (2019)
  - This paper complements their work by simultaneously studying the effects of tourism on both residential and amenity markets, showing how they interact to shape urban inequality
- Empirical IO literature of discrete-choice methods and its applications to urban residential markets
  - dynamic estimation uses the Euler Equation in Conditional Choice Probabilities (ECCP) estimator
  - Hotz and Miller (1993), Arcidiacono and Miller (2011), Aguirregabiria and Magesan (2013), Scott (2013) Kalouptsidi et al. (2011)

Research Design

- Dynamic spatial equilibrium model of a city with three components:
  - On the demand side, heterogeneous, forward-looking households choose nbhds to live in within a city
  - On the amenity supply side, firms make entry decisions based on demographic composition and provide consumption amenities
  - On the housing supply side, absentee landlords make supply decision about their rental units
- Structural estimation using Netherlands Census micro-data + Amsterdam establishments and tourism data + short-term rentals (Airbnb listing data)
  - Tourism flows into Amsterdam as quasi-experimental variation in demographic composition
- Counterfactuals:
  - Welfare implications of the "tourism shock"
  - Role of endogenous consumption amenities in transmitting the shock
  - Evaluate taxes on tourism

Preview of Results I: Heterog. Preferences Matter

- Significant heterogeneity in preference parameters across demographic groups
- Two channels at play in equilibrium: amenities and prices
  - If different demographic groups have diff. preferences over amenities
    - sorting of demographic groups across locations $\rightarrow$ magnified by endogenous amenities
    - locations endogenously become more different $\rightarrow$ further polarizes demand for locations
    - Individual welfare is better off for each type of HHs: access to preferred amenities with less local competition for housing
  - Results may reverse if groups have very similar preferences for amenities

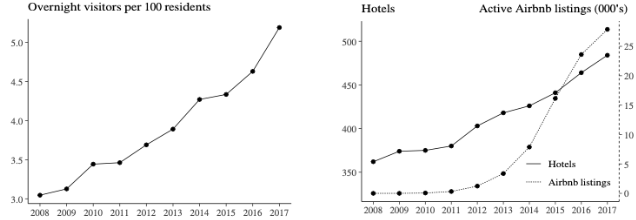
Preview of Results II

- Effects of the "tourism shock" when amenities are endogenous
  - While all residents lose from higher rent
  - some lose and some win from the changes in amenities due to preference heterog. (esp. how are these preferences correlated with those of tourists.)
- policies on regulating mass tourism: taxing short-term rentals vs. taxing touristic amenities
  - taxing amenities dominates taxing short-term rentals when the preferences of locals are sufficiently heterog. over the amenities tourists bring.

Data Patterns in Amsterdam

Fact 1: Tourists and Airbnb listings are dramatically increasing

Figure 1: Overnight visitors per resident, hotels, and Airbnb listings (2008-2017).

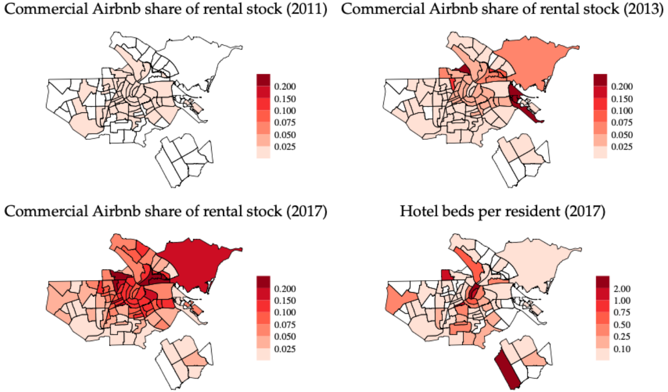


Notes: Figure shows the increase in overnight visitors and touristic lodgings (data source: ACD Tourism). Amsterdam population data is from ACD BBGA. We construct active Airbnb listings from Inside Airbnb data (procedure described in Appendix A.2.5).

Data Patterns in Amsterdam

Fact 2: The spatial distribution of Airbnb has expanded all over Amsterdam

Figure 2: Airbnb share of rental stock and hotel beds per resident (2011-2017).

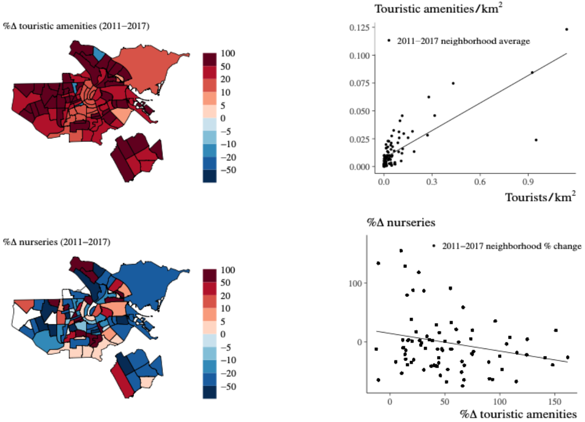


Notes: We construct commercial Airbnb listings from Inside Airbnb data (procedure described in Appendix A.2.5). Shares are shown at the neighborhood level ("wijk"). Rental housing stock, hotel beds, and population data is from ACD BBGA.

Data Patterns in Amsterdam

Fact 3: Amenities are tilting towards tourists and away from locals

Figure 3: Changes in consumption amenities (2011-2017).

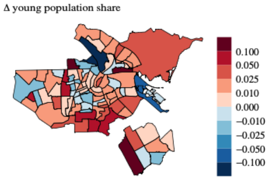


Notes: Data on neighborhood-level consumption amenities is from ACD BBGA. ACD has its own definition of "touristic amenities", which we use directly, and which encompasses lodging, passenger transport, travel agencies, and cultural and recreational retail.

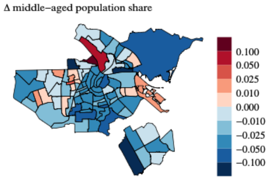
Data Patterns in Amsterdam

Fact 4: Differences in location choices across demographic groups

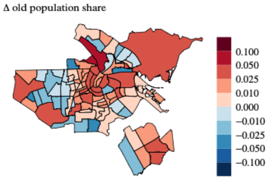
- Differences by age:



Note: Total growth for 2011-2017



Note: Total growth for 2011-2017



Note: Total growth for 2011-2017

Takeaway:

- Diff. demographic group would respond diff. to the same shock

Data Patterns in Amsterdam

Fact 5: Commercial Airbnb listings have a significant impact on local rental market

Table 1: Relationship between housing market outcomes and Airbnb listings

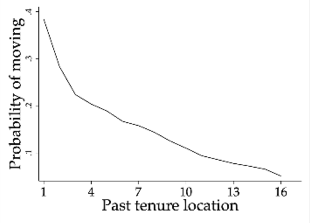
	Ln (rent/m2)			Ln (house sale value)		
	OLS	OLS	FE	OLS	OLS	FE
Ln (commercial Airbnb listings)	**0.066*****	**0.052*****	**0.115*****	**0.108*****	**0.031*****	**0.045****
	(0.008)	(0.006)	(0.018)	(0.016)	(0.006)	(0.022)
Ln (housing stock)		-0.056**	-0.111***		0.006	-0.045
		(0.027)	(0.028)		(0.027)	(0.032)
Ln (average income)		-0.492***	-0.353***		1.013***	0.953***
		(0.075)	(0.072)		(0.071)	(0.100)
Ln (high-skill population share)		0.330***	-0.014		0.356***	0.130
		(0.053)	(0.100)		(0.039)	(0.090)
District-year FE			X			X
Observations	780	773	773	746	745	745
R2	0.154	0.422	0.579	0.124	0.748	0.885

Notes: Standard errors clustered at the wijk level in parenthesis. We construct commercial Airbnb listings from the Inside Airbnb data. See Appendix A.2.5 for details. Rents and house sale values are from a combination of CBS surveys and transaction data, described in section 2. All other variables are from ACD BBGA.

Data Patterns in Amsterdam

Fact 6: Moving frictions increase over time

Figure 5: Probability of changing residence, conditional on past location tenure.



Notes: Figure shows the probability of moving out of the current location conditional on the number of years lived in the location. We take averages across individuals and across time. Moving probabilities and tenure are constructed using location choice panel derived from the CBS cadaster. More details can be found in sections 2 and A.2.1.

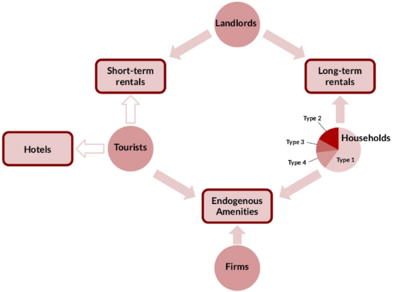
Takeaway:

- Neighborhood-specific capital accumulates over time and is lost upon moving (Diamond et al., 2019). Therefore, location capital creates another friction to moving beyond the standard fixed moving cost.

Model Preview

Motivated by the previous facts, they build a dynamic model of a city's rental market that consists of three parts:

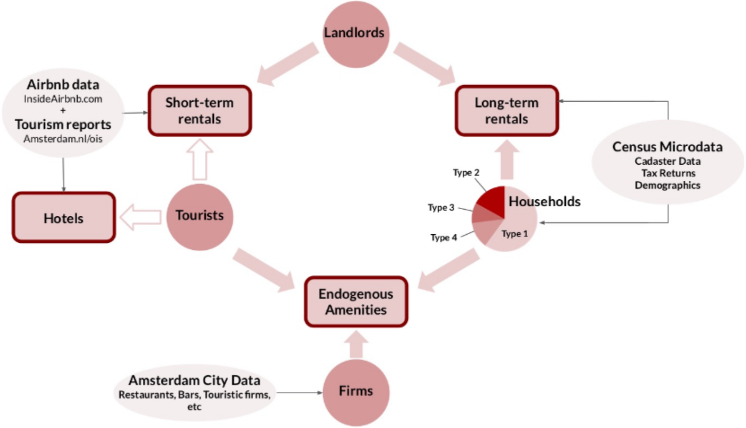
- Heterog. HHs with dynamic moving decisions across nbhds
- Landlords who can rent their units to locals or tourists
- A market for amenities that micro-founds how the composition of amenities endogenously responds to the composition of locals and tourists



Data

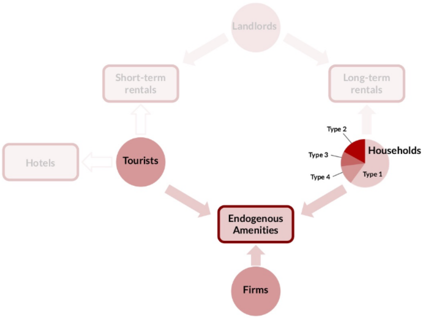
- **Individual-level data:**
  - from the Statistical Bureau of the Netherlands (CBS) from 2008-2020
  - a panel of residential history for individuals in the Netherlands.
  - household-level socioeconomic char.: income, educational attainment, employment status, household composition, and ethnic background.
- **Housing unit data:**
  - from a panel of tax appraisal data for 2006-2020 and a national rent survey for 2006-2019
  - property values, location, quality measures, the occupant's tenancy status, rental prices
- **Nbhd-level data:** amenities, demographics, tourist inflows from the Amsterdam City Data (ACD) from 2008 to 2018.
- **Airbnb listings:** monthly web-scraped listing data from Inside Airbnb website.

Data


Landlords
Airbnb data
InsideAirbnb.com
+
Tourism reports
Amsterdam.nl/ois
Short-term rentals
Long-term rentals
Census Microdata
Cadaster Data
Tax Returns
Demographics
Type 2
Type 3
Type 4
Type 1
Households
Hotels
Tourists
Endogenous Amenities
Amsterdam City Data
Restaurants, Bars, Touristic firms, etc
Firms

Part I: Modelling Endogenous Amenities

- Consumption amenities are classified into S sectors, each consisting of firms providing differentiated varieties
- Within each sector s and location j, there are N_{sj} firms supplying varieties in a monopolistically competitive setting with free entry
- K types of consumers with heterog. preference over amenities



Demand for Amenities

Conditional on living in location j and time t, a type-k HH has after-rent income I_t^k and chooses how much of her budget to allocate across the locally available consumption amenities

- underlying assumption: Consumption of amenities only from residential location (Davis et al. (2019), Miyauchi et al. (2020))

Firms i supply differentiated products across diff. sectors s (bars, food stores, etc.)

The Consumer's Problem

A consumer of type k with rental r_t and after-rent income I_t^k maximizes utility choosing q_{is}:

$$\max_{\{q_{isjt}^k\}_{is}} \prod_{s \in S} \left[\left(\sum_{i=1}^{N_{sjt}} q_{isjt}^{k\ \frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s^k} s.t. \sum_{is} p_{isjt} q_{isjt}^k = I_t^k$$

- CES preferences across firms i: within a sectors there is equal substitution across firms
- Cobb-Douglas preferences across sectors s: different substitution across sectors

Amenity Supply I

- Within a sector s, a location j, and a time period t: Monopolistic competition with free entry
- Firms have identical MC $\Rightarrow$ identical pricing decisions
- Given Cobb-Douglas preferences, expenditure on sector s: $\alpha_s^k I_t^k$
- Given identical prices, consumers splits expenditure equally across N_{sjt} firms: $\frac{\alpha_s^k I_t^k}{N_{sjt}}$
- Denote M_{jt}^k as the number of type k consumers. Selling profits of each firm are: $\frac{1}{\sigma_s} \sum_k \frac{\alpha_s^k I_t^k}{N_{sjt}} M_{jt}^k$ ("Dixit-Stiglitz lite")

Amenity Supply II

- To operate in a sector-location, firms must pay a fixed cost each period. Assume unobservable cost has following functional form:

$$F_{sjt} = \Lambda_s \Lambda_j \Lambda_t N_{jt}^{\eta} \varphi_{sjt} \quad \forall i \in sj,$$

where Λ_s, Λ_j, and Λ_t are sector-, location-, and time-specific shifters, φ_{sjt} are remaining idiosyncratic cost shifters, and $N_{jt}^{\eta} > 0$ is an endogenous entry cost component, which acts as a congestion force aimed to capture competition for commercial real estate between firms in location j

- Under free-entry condition profits are equal to operational fixed cost F_{sjt}:

$$\frac{1}{\sigma_s N_{sjt}} \sum_k \alpha_s^k I_t^k M_{jt}^k = F_{sjt}$$

Equilibrium Amenities

Rearranging the previous equation arrives us at the equilibrium number of firms in s_j:

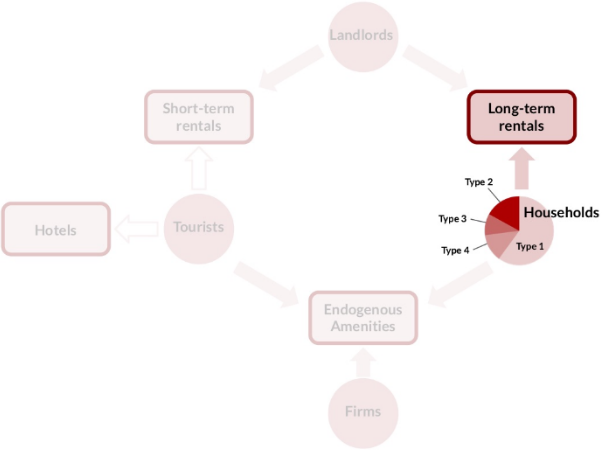
$$N_{sjt} = \frac{1}{\sigma_s F_{sjt}} \sum_k \alpha_s^k I_t^k M_{jt}^k$$

Define j-location's consumption amenities a_{jt} as follows,

$$a_{jt} \equiv [N_{1jt}, N_{2jt}, \ldots, N_{Sjt}]' = \mathcal{A}(M_{jt}^1, \ldots, M_{jt}^K, M_{jt}^T),$$

where M_{jt}^T denote the tourists as a "resident" type.
Therefore, the amenities composition is endogenously set up by the mapping $\mathcal{A}(\cdot)$ and the residential composition $[M_{jt}^1, \ldots, M_{jt}^K, M_{jt}^T]$.

Part II: Housing Demand



Part II: Housing Demand

- At the beginning of each period t, HH i chooses a residential location j_{it} among J diff. location in a city, as well as an outside option of leaving the city altogether,

$$j_{it} = \begin{cases} j & \text{if} \quad j \in \{1, \dots, J\} \\ 0 & \text{if the HH chooses a location outside of the city} \end{cases}$$

- Upon moving, households incur a moving cost MC^k that depends on the distance between the origin and destination location,

$$MC^k(j, j_{it-1}) = \begin{cases} 0, & j = j_{it-1} \\ m_0^k + m_1^k \text{dist}(j, j_{it-1}), & j \neq j_{it-1} \text{ and } j, j_{it-1} \neq 0 \\ m_2^k, & j \neq j_{it-1}, \text{ and } j = 0 \text{or} j_{it-1} = 0. \end{cases}$$

State Variables

- Individual state vector $x_{it} \equiv (j_{it-1}, \tau_{it-1}) \in \mathcal{X}$
  - j_{it-1}: current location
  - τ_{it-1}: tenure length
- Aggregate state vector $\omega_t \equiv (r_t, a_t, b_t, \xi_t) \in \Omega$
  - r_t: the vector of rental prices across all neighborhoods
  - a_t: the matrix of consumption amenities
  - b_t: the matrix of other non-consumption amenities
  - ξ_t: factors that are unobservable to the econometrician

Conditional Utility Function & Expected Value Function

Denote

$$u^k(j, x_{it}, \omega_t) \equiv u_t^k(j, x_{it}) \quad \text{and} \quad V^k(j, x_{it}, \omega_t) \equiv V_t^k(x_{it}, \varepsilon_{it})$$

HH i's indirect utility flow is given decision d is given by:

$$\begin{aligned} u_t^k(j, x_{it}) = \delta_j^k + \delta_t^k + \delta_r^k \log r_{jt} + \delta_a^k \log a_{jt} + \delta_b^k \log b_{jt} \\ + \delta_\tau^k \log \tau_{it} - MC^k(j, j_{it-1}) + \xi_{jt} \end{aligned}$$

HH i's expected value function is defined as:

$$V_t^k(x_{it}, \varepsilon_{it}) = \max_D \mathbb{E}_t \left[\sum_{s \geq t}^{\infty} u_s^k(j, x_{is}) + \varepsilon_{idt} \middle| j, x_{it}, \varepsilon_{it} \right],$$

where ε_{idt} is a type I EV idiosyncratic shock, D is the policy functions.

Demand for each Location

The recursive form:

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

Therefore, the probability of a type-k HH in state x_{it} chooses location j is,

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

Demand for each Location

Demand from all type k households for location j is,

$$\mathcal{D}_{jt}^{Lk} = \sum_{x} \mathbb{P}_t^k(j|x) M_{xt}^k \mathcal{Q}_{xt}^k,$$

where M_{xt}^k is the number of households of type k with individual state x at time t and $\mathcal{Q}_{xt}^k$ is the demanded quantity of housing, which can be pinned down from the household problem over housing and overall amenities expenditure problem and computed from the microdata.

Total demand for location j is obtained by,

$$\mathcal{D}_{jt}^{L} = \sum_{k} \sum_{x} \mathbb{P}_t^k(j|x) M_{xt}^k \mathcal{Q}_{xt}^k$$

Evolution of Population Dist. & Stationary Dist.

Denote $\pi_t^k(j,\tau)$ as a type-k HH's probability of living in location j with tenure τ, conditional on the aggregate state at time t. Write Π_t^k as the transition matrix across individual states, where each (j,τ) cell evolves as,

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

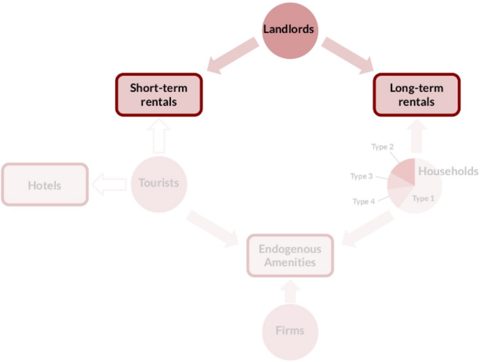
where the authors have assumed tenure can be accumulated up to a maximum absorbing state $\bar{\tau}$.

A stationary distribution is defined as

$$\pi^k(\mathbf{r},\mathbf{a}) = \Pi^k(\mathbf{r},\mathbf{a})\pi^k(\mathbf{r},\mathbf{a}).$$

Part III: Housing Supply

- The total stock of housing in location j and year t, $\mathcal{H}_{jt}$, is exogenous and determined outside the model.
- Absentee landlords make a binary choice between renting their unit in the long-term market (which caters to locals) or in the short-term market (which caters to tourists).



The Landlord's Problem

Suppose each unit is identical in location j. The income obtained from long-term rentals is r_{jt}, and from short-term rentals is p_{jt}. The relative matching and managerial costs involved in renting short- versus long-term is κ_{jt}, which is unobservable to the econometrician. The landlord's problem is:

$$\max\{\alpha r_{jt} + \varepsilon_L, \alpha p_{jt} - \kappa_{jt} + \varepsilon_S\},$$

where α is the landloard's marginal utility of income and ε's are type I EV shocks.

Supply of Housing at each Location

The shares of the housing stock allocated to the long- and short-term rental market are,

$$s_{jt}^{L} = \frac{\exp\left(\alpha r_{jt}\right)}{exp(\alpha r_{jt}) + exp(\alpha p_{jt} - \kappa_{jt})} \text{ and } s_{jt}^{S} = \frac{\exp\left(\alpha p_{jt} - \kappa_{jt}\right)}{exp(\alpha r_{jt}) + exp(\alpha p_{jt} - \kappa_{jt})}$$

Therefore, the long- and short-term rental supply in location j are,

$$\mathcal{H}_{jt}^{L}(r_{jt}, p_{jt}; \kappa_{jt}) = s_{jt}^{L}\mathcal{H}_{jt} \text{ and } \mathcal{S}_{jt}^{L}(r_{jt}, p_{jt}; \kappa_{jt}) = \mathcal{H}_{jt} - \mathcal{S}_{jt}^{L}(r_{jt}, p_{jt}; \kappa_{jt})$$

Equilibrium Definition

A *stationary equilibrium* is,

1. a vector of long-term rental prices $\mathbf{r} = (r_1, \ldots, r_J)$ and a matrix of amenities $\mathbf{a} = [a_1, \ldots, a_J]$
2. policy functions $h(r_j, p_j; \kappa_j, \varepsilon_l)$ for landlords, $j^k(j_i, \tau_i, \mathbf{r}, \mathbf{a}; \varepsilon_i)$ for each type-k household
3. a stationary distribution of types over locations and tenure, $\pi^k(\mathbf{r}, \mathbf{a})$

such that,

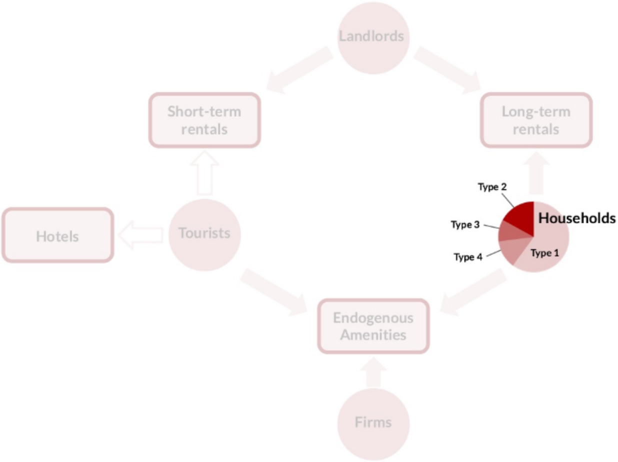
1. each landlord and each household supply and demand housing optimally, respectively
2. rental price $\mathbf{r}$ clear the long-term housing market in each location j,

$$\mathcal{H}_j^L(r_j, p_j; \kappa_j) = \mathcal{D}_j^L(\mathbf{r}, \mathbf{a}) \quad \forall j$$

3. the demand of amenities a_j is equal to the supply of amenities $\mathcal{A}_j$ in each location j,

$$a_j = \mathcal{A}(M_j^1, \ldots, M_j^K, M_j^T)$$

Define Heterog. HHs



Classify Heterog. HHs vis K-means Method

- They are interested in distributional effects ⇒ define household "types"
- Large number of demographics
  ⇒ country of origin, skill, income, housing tenancy, household composition
  ⇒ correlation" high income households tend to be high skill
- Classifying using arbitrary groups may lead to groups with few observations:
  ⇒ high income with low education
  ⇒ small groups lead to noisy estimates

Their approach: k-means exploits pre-existing correlations and avoids non-representative groups
⇒ minimize the number of groups while maximizing separation across groups

Clustering Results from K-means Algorithm

Table 2: Summary Statistics by Household Type

	Homeowners		Renters		Social Housing Tenants	
Group	Older Families	Singles	Younger Families	Students	Immigrant Families	Dutch Low Income
Age	44.59	37.84	40.56	28.42	55.12	38.52
Share Children	0.93	0.12	0.65	0.13	0.53	0.43
Share Low-Skilled	3.20%	2.42%	6.09%	5.40%	99.91%	0.02%
Share Medium-Skilled	3.01%	5.87%	2.28%	11.33%	0.09%	16.95%
Share High-Skilled	93.79%	91.71%	91.65%	83.27%	0.00%	83.02
Share Dutch Indies	6.92%	6.59%	4.12%	4.07%	13.22%	12.41%
Share Dutch	64.41%	58.74%	53.13%	61.44%	24.86%	49.36%
Share Non-Western	18.76%	21.43%	21.64%	19.48%	57.96%	30.37%
Share Western	9.91%	13.23%	21.12%	15.01%	3.96%	7.87%
Household Income (€)	62,031.39	30,611.41	47,441.08	16,821.48	21,243.24	27,714.85
Income Pctl.	77.04	45.49	64.64	23.23	33.41	42.17
Per Capita Income (€)	40,155.65	27,609.21	35,058.39	15,162.83	15,167.45	21,178.13
Income Pctl. per Person	73.42	52.84	65.83	26.34	26.69	42.10
Number of Households	106,388	78,561	105,712	124,112	83,117	174,203

Notes: This table presents the groups resulting from k-means classification on mean demographic characteristics over time. We report average characteristics across households in each group. Group names are provided to serve as an easy-to-remember label and are not an outcome of the data.

Amenity Supply: Estimation

Recall the equilibrium equation of endogenous amenities supply:

$$N_{sjt} = \frac{1}{\sigma_s F_{sjt}} \sum_k \alpha_s^k I_t^k M_{jt}^k$$

$$F_{sjt} = \Lambda_s \Lambda_j \Lambda_t N_{jt}^{\eta} \varphi_{sjt}$$

taking the log on both sides to derive the empirical model of amenity supply:

$$logN_{sjt} = \lambda_j + \lambda_t + \eta logN_{jt} + \log\left(\sum_k \beta_s^k X_{jt}^k\right) + \phi_{sjt}$$

where X_{jt}^k is the total expenditure of group k on all amenities, β_s^k determines how such expenditures are allocated to amenity sector s, and ϕ_{sjt} is the unexplained variation from entry cost.

Amenity Supply: Estimation

$$logN_{sjt} = \lambda_j + \lambda_t + \eta logN_{jt} + \log\left(\sum_k \beta_s^k X_{jt}^k\right) + \phi_{sjt}$$

Identification:

- calibrate η following Eckert et al.(2020), and set $\eta = -.33$.
  - There is virtually no remaining variation to identify η after controlling the location- and time- FEs.
  - N_{jt} is endogenous by construction $N_{jt} = \sum_s N_{sjt}$.
- X_{jt}^k also poses an simultaneity issue.
  - This is because the dist. of amenity expenditures by HH type, X_{jt}^k, is determined by the local population composition, which is the outcome of residential choices made based on the availability of amenities N_{sjt}.
  - any unobs. firm entry cost ϕ_{sjt} affecting N_{sjt} will be correlated with X_{jt}^k.

Amenity Supply: Estimation

$$logN_{sjt} = \lambda_j + \lambda_t + \eta logN_{jt} + \log\left(\sum_k \beta_s^k X_{jt}^k\right) + \phi_{sjt}$$

Identification:

- calibrate η.
- X_{jt}^k endogenous object. Address this concern by constructing demand shifters:
  - Housing stock available across household types: owner-occupied, rental, social housing, S_{jt}^k
  - Interact each group's available housing stock with income group, w_t^k
  - Instruments constructed as follows:

$$Z_{jt}^k = w_t^k S_{jt}^k$$

Amenity Supply: GMM results

Table 3: Estimates of Amenity Supply Parameters

Group	Touristic Amenities	Restaurants	Café Bars	Food Stores	Non-Food Stores	Nurseries
Older families	59.944	0.0	0.0	0.0	2.271	415.243***
	[0.0,218.18]	[0.0,16.297]	[0.0,0.0]	[0.0,11.998]	[0.0,25.707]	[186.264,837.487]
Singles	364.062	59.441	0.0	52.182	0.0	0.0
	[0.0,833.441]	[0.0,148.899]	[0.0,0.0]	[0.0,167.529]	[0.0,43.415]	[0.0,0.0]
Younger families	0.0	0.0	3.543	29.255**	107.138***	387.489*
	[0.0,0.0]	[0.0,13.121]	[0.0,21.808]	[0.729,58.678]	[50.957,158.689]	[0.0,672.534]
Students	488.828*	199.533***	21.44	54.437	0.0	0.0
	[0.0,1072.092]	[76.883,288.674]	[0.0,40.371]	[0.0,129.194]	[0.0,0.0]	[0.0,729.872]
Immigrant Families	0.0	0.0	7.33***	38.676	43.796*	153.907
	[0.0,0.0]	[0.0,9.443]	[0.942,29.473]	[0.0,76.667]	[0.0,147.762]	[0.0,663.999]
Dutch Low-Income	0.0	0.0	0.0	0.0	0.0	0.0
	[0.0,137.308]	[0.0,22.976]	[0.0,0.0]	[0.0,36.584]	[0.0,0.0]	[0.0,0.0]
Tourists	435.917***	200.103***	113.284***	71.219***	368.742***	0.0
	[328.271,582.922]	[163.424,240.117]	[76.9,130.32]	[42.979,93.96]	[276.691,430.773]	[0.0,0.0]

Note: This table presents estimates of coefficients β_s^k from Equation 8 for seven household types and six types of services using a three-way panel of 22 districts in Amsterdam for 2008-2018. Parameters are estimated via GMM, where we restrict parameters to be weakly positive as implied by the microfoundation of the model in Section A.4. The estimation procedure is outlined in section 5.2. Bayesian-bootstrap 95% confidence intervals with random Dirichlet weights are reported in brackets. We omit estimates of the location and time fixed effects. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Housing Demand: DDC Estimation

Recall the Dynamic discrete choice problem of housing demand:

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

Several identification issues:

- Continuation values are unobservable and are a function of prices and amenities $(\mathbf{r}, \mathbf{a})$
- Simultaneity bias for prices and amenities $(\mathbf{r}, \mathbf{a})$ due to unobservable demand shocks ξ_{jt}

$$\begin{aligned} u_t^k(j, x_{it}) = \delta_j^k + \delta_t^k + \delta_r^k \log r_{jt} + \delta_a^k \log a_{jt} + \delta_b^k \log b_{jt} \\ + \delta_\tau^k \log \tau_{it} - MC^k(j, j_{it-1}) + \xi_{jt} \end{aligned}$$

Identification: Euler Equations in Conditional Choice Probability (ECCP)

They use Euler Equations in Conditional Choice Probability (ECCP)

- Aguirregabiria and Mira (2010), Scott (2013), Kalouptsidi et al. (2021), Arcidiacono and Miller (2011)
- Finite dependence property. In this context, it is called Renewal Actions.

Identification: ECCP

Figure 6: Depiction of path combinations used in the estimation.

$$\begin{tikzcd}
 & (j, \tau(j, j_{t-1}, \tau_{t-1})) \arrow[dr] & \\
(j_{t-1}, \tau_{t-1}) \arrow[ur] \arrow[dr] & & (\tilde{j}, 1) \\
 & (j', \tau(j', j_{t-1}, \tau_{t-1})) \arrow[ur] &
\end{tikzcd}$$

For any two agents of the same type k, moving to a new location $\tilde{j}$ is a renewal action
$\Rightarrow$ Their future flows look the same (finite dependent) and can cancel out continuation values

With a bit of algebra and some assumptions, they get to the ECCP estimator:

$$ln\left(\frac{\mathbb{P}_t^k(j, x_t)}{\mathbb{P}_t^k(j', x_t)} \frac{\mathbb{P}_{t+1}^k(\tilde{j}, x_{t+1})^\beta}{\mathbb{P}_{t+1}^k(\tilde{j}, x'_{t+1})^\beta}\right) = u_t^k(j, x_t) - u_t^k(j', x_t) \\ + \beta\left[u_t^k(\tilde{j}, x_{t+1}) - u_t^k(\tilde{j}, x'_{t+1})\right] + \tilde{v}_{t,j,j',x_t}^k$$

Identification: ECCP

Figure 6: Depiction of path combinations used in the estimation.

$$\begin{tikzcd}[column sep=small]
 & (j, \tau(j, j_{t-1}, \tau_{t-1})) \arrow[dr] & \\
(j_{t-1}, \tau_{t-1}) \arrow[ur] \arrow[dr] & & (\tilde{j}, 1) \\
 & (j', \tau(j', j_{t-1}, \tau_{t-1})) \arrow[ur] &
\end{tikzcd}$$

$$ln\left(\frac{\mathbb{P}_t^k(j, x_t)}{\mathbb{P}_t^k(j', x_t)}\frac{\mathbb{P}_{t+1}^k(\tilde{j}, x_{t+1})^\beta}{\mathbb{P}_{t+1}^k(\tilde{j}, x'_{t+1})^\beta}\right) = u_t^k(j, x_t) - u_t^k(j', x_t)$$
$$+ \beta\left[u_t^k(\tilde{j}, x_{t+1}) - u_t^k(\tilde{j}, x'_{t+1})\right] + \tilde{v}_{t,j,j',x_t}^k$$

Intuition:

- After renewal action $\tilde{j}$, same future flows after $t+2$
- Relative likelihood of j over j' only depends on differences in utility flows along those paths

Identification: IVs

Recall Euler Equation:

$$ln\left(\frac{\mathbb{P}_t^k(j,x_t)}{\mathbb{P}_t^k(j',x_t)}\frac{\mathbb{P}_{t+1}^k(\tilde{j},x_{t+1})^\beta}{\mathbb{P}_{t+1}^k(\tilde{j},x'_{t+1})^\beta}\right) = u_t^k(j,x_t) - u_t^k(j',x_t) + \beta\left[u_t^k(\tilde{j},x_{t+1}) - u_t^k(\tilde{j},x'_{t+1})\right] + \tilde{v}_{t,j,j',x_t}^k$$

and utility flows:

$$u_t^k(j,x_{it}) = \delta_j^k + \delta_t^k + \delta_r^k \log r_{jt} + \delta_a^k \log a_{jt} + \delta_b^k \log b_{jt} + \delta_\tau^k \log \tau_{it} - MC^k(j,j_{it-1}) + \xi_{jt}$$

Identification of endogenous variables:
(with 6 amenities, they need 7 number of instruments)

- Three Bartik-type supply shifters motivated by local policy
- Demolition of housing stock
- Three BFM/BLP instruments

They also calibrate β from the literature and set $\beta = .85$ (De Groote and Verboven, 2019; Diamond et al., 2019)

Preference Estimation Results

Table 4: Preference parameter demand estimation results

	Older Families	Singles	Younger Families
Intra-City Moving Cost	-5.492***	-4.969***	-5.026***
	(0.015)	(0.011)	(0.012)
Bilateral Moving Cost	-0.169***	-0.148***	-0.118***
	(0.001)	(0.001)	(0.001)
In/Out of City Moving Cost	-4.408***	-4.012***	-4.044***
	(0.012)	(0.009)	(0.010)
High Location Capital	0.185***	0.211***	0.263***
	(0.017)	(0.013)	(0.013)
Log Rent	-11.769***	-2.523**	-2.340**
	(1.201)	(0.987)	(1.045)
Log Tourism Offices	-1.193***	-0.449***	0.299**
	(0.169)	(0.143)	(0.144)
Log Restaurants	0.281	0.729***	-0.195
	(0.284)	(0.251)	(0.242)
Log Café Bars	-0.822***	-0.547***	-0.081
	(0.092)	(0.079)	(0.082)
Log Food Stores	-2.000***	-1.314***	-0.600**
	(0.324)	(0.280)	(0.289)
Log Nonfood Stores	0.700**	1.626***	1.429***
	(0.341)	(0.299)	(0.296)
Log Nurseries	1.763***	0.076	0.316**
	(0.172)	(0.141)	(0.148)
Location FE	✓	✓	✓
Time FE	✓	✓	✓
Neighborhood Controls	✓	✓	✓
N	233772	233772	233772

Notes: This table presents regression results of preference parameters for a dynamic location choice model for 22 districts in Amsterdam for 2008-2019. We estimate preference parameters separately for three groups via two-step optimal GMM. The dependent variable is differences in path likelihoods, after normalizing with respect to the outside option. After this normalization, each type has 46 possible states (23 past locations and two location capital categories), 22 possible actions, and 21 possible renewal actions over 11 years, which leads to 233,772 possible states and two-step path combinations. We omit exogenous controls—the log of social housing units and the log of the average apartment in square meters—for the ease of exposition. Two-step efficient GMM standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Housing Supply: Estimation

Recall the market shares of the housing stock allocated to the long- and short-term rental market:

$$s^L_{jt} = \frac{\exp(\alpha r_{jt})}{exp(\alpha r_{jt}) + exp(\alpha p_{jt} - \kappa_{jt})} \text{ and } s^S_{jt} = \frac{\exp(\alpha p_{jt} - \kappa_{jt})}{exp(\alpha r_{jt}) + exp(\alpha p_{jt} - \kappa_{jt})}$$

Combining and Rearranging:

$$lns^L_{jt} - lns^S_{jt} = \alpha(r_{jt} - p_{jt}) + \underbrace{\kappa_j + \kappa_t + v_{jt}}_{=\kappa_{jt}}$$

where v_{jt} stands for any remaining unob. varying at the jt level.
Instrument for price gap $(r_{jt} - p_{jt})$ using demand shifter:

- Proxy of worldwide Airbnb popularity P_t $\times$ Touristic establishments pre-Airbnb entry T_j^{2008}

Housing Supply: Estimation Results

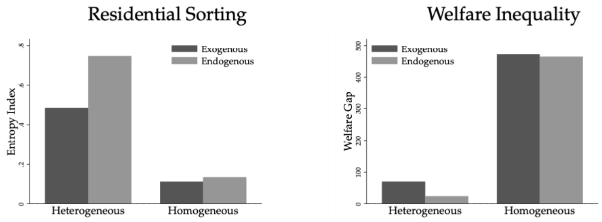
Table 5: Long-term (LT) relative to short-term (ST) housing supply elasticities

	Dependent variable: ln (LT share) - ln (ST share)							
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
LT price - ST price	**0.144***	**0.354*****	**0.140***	**0.360*****	**0.096**	**0.341*****	**0.020**	**0.241**
	(0.081)	(0.104)	(0.083)	(0.112)	(0.084)	(0.089)	(0.106)	(0.495)
Year FE			X	X			X	X
Wijk FE					X	X	X	X
First stage F-stat		69.22		23.94		14.72		15.82
Observations	271	271	271	271	271	271	271	271

Notes: The table reports estimates of landlords' marginal utility of income for a discrete choice model between the short- and long-term rental markets. Data are a panel with 92 locations 2015-2017. Prices are instrumented using a "shift-share" instrument (Barron et al., 2021) that proxies for demand shocks. Construction of the variables is described in Section A.2. Wijk-level clustered standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Endogenous Amenities and Preference Heterogeneity

Figure 8: Residential sorting and welfare inequality



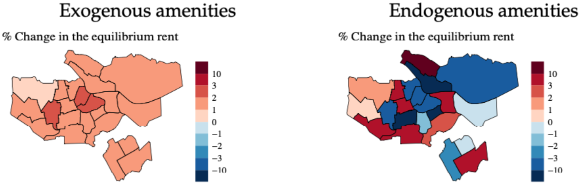
Notes: The panel on the left reports the entropy index, a commonly used measure of segregation of household types across districts (see Appendix S.2.1 for a formal definition). The panel on the right reports the welfare gap across household types, measured as the ratio of the consumer surplus in log wages of the highest-welfare household type relative to the lowest-welfare household type.

Intuitions:

- Heterog. preferences lead to more sorting, and as a result, nbhds become more differential in terms of their amenities
- Welfare inequality across HH types can decrease when amenities are endogenous, esp. if preferences are heterogeneous

Short-term Rental Entry: Changes in Rents

Figure 10: Rent changes under exogenous and endogenous amenities



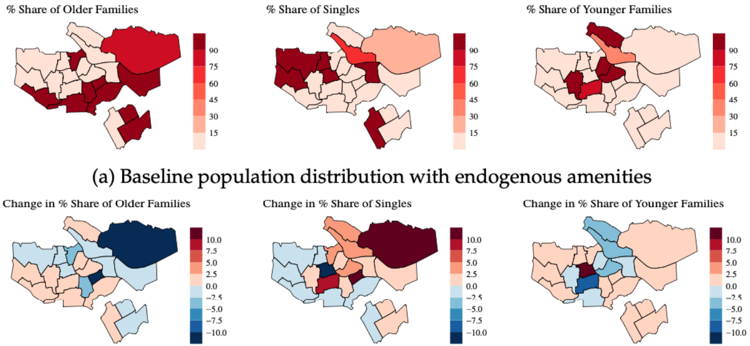
Notes: The figures show the percentage change in a neighborhood's equilibrium rent when we simulate short-term rental entry, for the case of exogenous and endogenous amenities. In both cases, we fix the baseline amenities levels to the no-Airbnb endogenous equilibrium levels.

Intuitions:

- HH types do not compete with each other for the same locations
  $\Rightarrow$ lower rental prices while preferred amenities

Short-term Rental Entry: Changes in Residents

Figure 11: Spatial distribution at baseline and after short-term rental entry



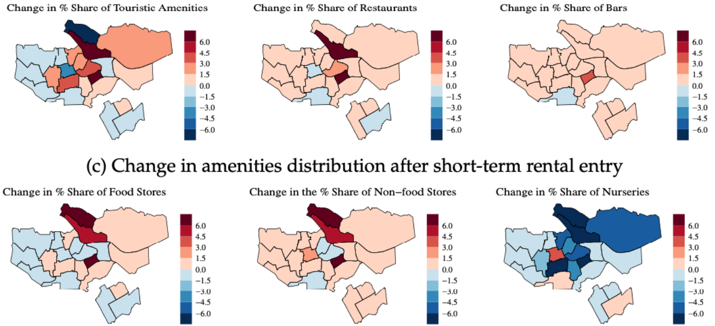
(a) Baseline population distribution with endogenous amenities

(b) Change in population distribution after short-term rental entry

Takeaways:

- After Airbnb entry, the Older Families leave the center-south and -eastern districts, Singles leave the west and move towards the center, and Younger Families move west of the center

Short-term Rental Entry: Changes in Amenities



(c) Change in amenities distribution after short-term rental entry

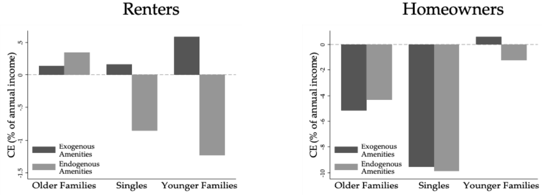
Notes: Figures correspond to the model described in Section 4.4. The top row shows the neighborhood population share of each household type in the equilibrium without short-term rentals. The second, third, and forth rows show the changes in population shares, and neighborhood amenity share after short-term rental entry. To facilitate comparison between the equilibria, we always initialize our equilibrium solver in Section A.4.2 from the observed vectors of rents and amenities.

Takeaways:

- Older Families ↓ ⇔ nurseries ↓ and touristic amenities ↑
- Singles ↑ ⇔ restaurants and non-food stores ↑
- Younger Families ↑ ⇔ non-food stores and nurseries ↑

Short-term Rental Entry: Welfare Decomposition

Figure 9: Decomposition of welfare effects from the entry of short-term rentals.



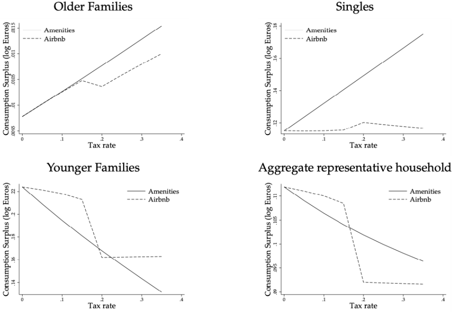
Notes: The consumption equivalent is computed as how much extra income a household must be given in the counterfactual equilibrium to keep utility as in the baseline equilibrium. Positive values indicate a welfare loss. Left and right panels report changes in renter's and homeowner's welfare respectively. "Home ownership-adjusted" consumption equivalent is computed by rebating rental income back to homeowners as a city-wide uniform lump sum transfer and is reported as a percentage of the household's income. See Appendix for A.6.4 for details.

Takeaways:

- If amenities are exogeneous, everyone loses and inequality increases as Airbnb entry reduces the housing supply and raises rents
- If amenities are endogenous, the effect of short-term rentals reduces welfare inequality
- Considering the Older and Singles to be homeowners while keeping Younder Faminies as renters, the entry of short-term rentals increases inequality between homeowners and renters

Policy Implications for Targeting of Touristic Amenities

Figure 13: Short-term rental tax vs. Touristic amenity tax (welfare effects)



Notes: The figure reports consumer surplus (in log Euros) for each household type under each type of tax. The exception is the bottom right panel, which reports a representative household aggregated across types, where each type is weighted by population share. Implementation details are in Appendix S.2. Kinks in the Airbnb tax counterfactuals occur due to tipping points in the demographic composition of a few selected neighborhoods, described in Appendix A.6.3.

Takeaways:

- Welfare gains from targeting amenities are larger when households hold very heterog. tasks across the various amenities tourists bring.
- For example, Singles dislike touristic amenities, while enjoying other amenities that tourists bring, such as restaurants.

Conclusion

This paper estimates a spatial equilibrium model of a city's residential market with,

- Heterogeneous demographic groups of households who make forward-looking residential choices
- A multi-dimensional provision of endogenous amenities
- Endogenous housing supply through the short-term rental industry

The endogeneity of amenities with heterogeneous preferences matters

- Important implications on sorting, welfare and inequality
- Effects across groups depend on how preferences are aligned