Online Appendix for "Location Sorting and Endogenous Amenities: Evidence from Amsterdam"

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A.1 Institutional background

A.1.1 Policy changes in the Amsterdam real estate market

Change in Housing Point System (2011): Classification of a unit as social is determined by an annually updated national point system, with units below 143 points being classified as social. Until 2011, the number of points was based solely on the unit's physical attributes. In response to rental supply scarcity, the Dutch government designated 140 areas nationwide as having a "housing shortage" and implemented a 25-point increase for all rental units in these areas. As a consequence, this policy reduced the supply of social housing units and increased the supply of private rental units. In Amsterdam, it is estimated that 28,000 out of a total of 200,000 social housing units would shift to the private market (van Perlo, 2011).

Decrease in Default Lease Duration (2015): While landlords could historically terminate a rental contract based on certain legal grounds, the contract duration was by default "indefinite." The only way a landlord could increase rents was with a new lease—to an existing or to a new renter in the private market—or to index the initial lease to inflation. This left little room for landlords to increase rents within a lease. In 2015, a new law, "Wet Doorstroming Huurmarkt 2015", changed the standard duration of new contracts from indefinite to two years, with options to contract on even shorter duration (Koninkrijksrelaties, 2015). After the initial two years, the landlord had the option to offer the current tenant a new lease with a new price, but which had to be of indefinite duration. As a consequence, landlords had the incentive to find new tenants willing to pay higher prices for an initial two years, rather than renew an existing tenant's contract indefinitely (Koninkrijksrelaties, 2021), thus increasing private rental market supply.

Regulation of Vacation Rental Properties (2017): Due to the expansion of short-term rentals and tourism, the city of Amsterdam implemented strict regulations

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on the hospitality sector. First, the policy limited the construction of new hotels (Botman, 2021). Second, the city also required landlords to report all units they rented out as vacation rentals. Third, the city also set a maximum number of nights a property could be rented per year, initially set to sixty nights at the end of 2017 and tightened to only thirty nights in 2019. Together, these laws aimed to lower the incentives to rent short-term to tourists, and thus increase rental supply for locals.

A.2 Data

A.2.1 Residential histories and household characteristics

First, we construct an annual panel of location choices starting in 1995 using the registry (cadaster) data. The cadaster gives us a history of addresses for all individuals in the Netherlands from 1995-2020. For every individual, we pick their modal address each year. In terms of demographics, we keep individuals between 18-70 years old. We also observe country of origin of the household head, which we classify into four broad categories: Dutch, Dutch Indies, Western (OECD), and Non-Western. With regards to skill, we observe the graduation date and degree type for everyone completing a high school degree and beyond for 1999-2020. We classify households according to the highest achieved level of education into low, medium, and high skill for those with high school (VMBO) or less, vocation or selective secondary education (HAVO, VWO, MBO), or college and more (HBO, WO), respectively. Finally, we observe household-level tax returns for 2008-2020 with information on: gross and after-tax income, number of household members, an imputed measure of income per person, and household composition categories. The household composition data allows us to see whether the household has children. For our dynamic location choice estimation sample, we focus on heads of household as identified by the tax data. We keep those households who have lived at least one year in Amsterdam since 1995, household head's age is between 18-70 years, and have at least one year with reported tax return information.

A.2.2 Housing characteristics, tax appraisal values, and transaction prices

First, for every housing unit we observe the year it was built, the floor area in square meters, a categorical variable about the life stage of the property, and the usage category for 2011-2020. There are 11 usage types: residential, sport, events, incarceration, healthcare, industrial, office, education, retail, and other. There are six types of life-stage categories: constructed, not constructed, in process of construction, in use, demolished, and not in use. We also observe any changes to these characteristics. For example, we can see if a unit previously classified as residential is now considered commercial. With these transitions, we see that virtually no residential units convert to another usage type such as commercial and vice-versa. Given this segmentation, we only keep housing units classified as residential. Moreover, these data inform us about the extent of new construction. On average, new units make 1.2% of the residential housing stock on a yearly basis.

Table A1: Correlation between tax appraisal and transaction values.

	Transaction Value	
WOZ Value	1.069	(0.001)
Constant	-1,798.689	(441.983)
R^2	0.855	
N	128387	

Note: Table shows regression coefficients and fit of transaction values on tax appraisal (WOZ) values at the property level for Amsterdam 2005-2019. Standard errors in parenthesis.

Second, we observe a panel of housing values and characteristics for all properties in the Netherlands from 2006-2019. We observe annual tax appraisal values (WOZ) and geo-coordinates. These data are annually collected by the government to assess every property WOZ value and tax accordingly. The WOZ value of a property is constructed by comparing the value of nearby transacted properties in the neighbourhood and physical housing characteristics like size, house type, and construction year. We can compare WOZ appraisal values to the subset of properties that are transacted to see how well they track market values. Table A1 shows WOZ values correlate almost one-to-one with transaction prices and exhibit a high degree of predictive power. We take this as evidence that WOZ values are informative of market values. These data also contain information about the occupant's tenancy status: homeowner, private renter, or social housing renter. We use these categories to classify households across different segments of the housing market.

A.2.3 Linking households to housing units

We merge the housing unit panel to the household location panel through the property identifier. We can then see tenancy status and and number of occupants per unit. We keep housing units with less than six occupants—those below 99th percentile of occupant distribution—to eliminate residential units not inhabited by regular households, such as university student halls or nursing homes.

A.2.4 Rent imputation

Our microdata has information on physical characteristics and tax appraisal values for the universe of housing units in the Netherlands. However, we only observe rents for a subset of units. Because we need an annual panel of housing prices at the neighborhood level, we impute rents using tax valuations.

Table A2: Imputation results.

	In-sample fit					Out-of-sample fit			
	Hedonic Model		Random Forest			Hedonic Model		Random Forest	
	Rental Prices	Price/m^2	Rental Prices	Price/m^2		Rental Prices	Price/m^2	Rental Prices	Price/m^2
β	1.000	1.005	1.060	1.061	β	1.004	0.957	1.058	1.070
	(0.002)	(0.008)	(0.002)	(0.003)		(0.022)	(0.241)	(0.007)	(0.007)
constant	-0.795	-0.091	-73.653	-0.868	constant	5.118	0.764	-73.639	-0.965
	(9.364)	(0.117)	(3.356)	(0.037)		(25.746)	(0.347)	(9.698)	(0.107)
R^2	0.636	0.580	0.940	0.940	R^2	0.622	0.554	0.943	0.945
N	11408	11408	11408	11408	N	1268	1268	1268	1268

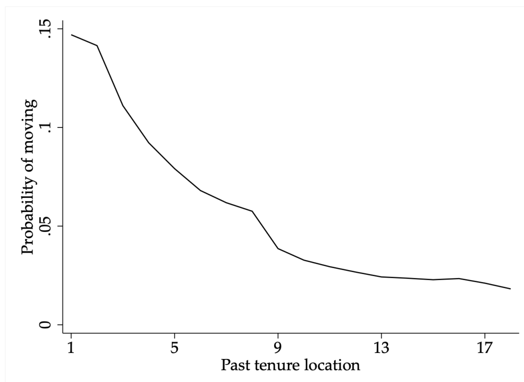
Notes: Table shows regression coefficients and fit of imputed rental prices on observed rental prices at the property level. We do so for a linear hedonic regression and a random forest, and for two different data samples, the training sample (left panel) to assess in-sample fit, and the testing sample (right panel) to asses out-of-sample fit. Standard errors in parenthesis.

First, we link microdata from the universe of housing units to a national rent survey which contains roughly 13,000 observations of units in the rental market between 2006-2019. We use the matched subset in the rental survey with their tax valuation information to predict rents for housing units that do not appear in the survey but do appear in the property value data as renter-occupied. We keep only properties that are rented in the private rental market and not in social housing. We predict total rental prices and rental prices by square meter on the properties that are classified as private rental units from the tax appraisal data. We use two methods: linear regression and random forest. In both cases we use tax-appraisal values, official categories for measures of quality, total floor area, number of rooms, latitude and longitude coordinates, time fixed effects, and wijk-code fixed effects. We train our algorithms in 90% of the sample and test out-of-sample predictive power in 10% of the sample. For the hedonic linear regression, the in-sample R^2 for total rental prices is 0.637 while the out-of-sample R^2 is 0.629.

Similarly, the random forest delivers an in-sample R^2 of 0.813 and out-of-sample R^2 of 0.782. The random forest model has a substantially better performance in terms of predictive power, both in-sample and out-of-sample. Table A2 shows that when regressing imputed on observed rental prices, the random forest also outperforms classic linear regression.

A.2.5 Decreasing hazard rate of moving

Figure A2: Probability of changing residence, conditional on past location tenure.



Notes: Figure shows probability of moving out of the current location conditional on the number of years lived in the location. We take averages across individuals who are not social housing residents and across time. Moving probabilities and tenure are constructed using location choice panel derived from the CBS cadaster, described in section A.2.1.

Figure A2 shows the hazard rate of moving is decreasing in a household's tenure at the prior residence. This behavior can be rationalized by the inclusion of neighborhood-specific capital that accumulates over time and is lost upon moving.

A.2.6 Housing expenditure shares

With our rent imputation from section A.2.4 we can predict rental prices for all residential units of the city. We compute the share of income spent on housing for households in the private rental market by dividing the predicted rental price by their after-tax income. For households in social housing, we use instead the yearly maximum social housing rent. Finally, we estimate housing expenditures shares by taking the median observation conditional on demographic type and year. These housing expenditure shares map to the term $1 - \phi^k$ in Section A.3.1.

A.2.7 Constructing Airbnb supply and prices

A challenge with the web-scraped Inside Airbnb data is that some listings may be inactive, thus overstating Airbnb supply. To address this we focus on listings that are sufficiently "active". Using calendar availability data, we say a listing is "active" in month t if it has been reviewed by a guest or its calendar has been updated by its host in month t. Moreover, we want to separately identify listings in which the host lives in the unit and shares it with guests, from those in which there is no sharing. The former does not reduce housing stock for locals, while the latter does. We define a listing as "commercially operated" if it is an entire-home listing, has received new reviews over the past year, and has "sufficient booking activity" such that it is implausible a local is living in the unit permanently. A listing has "sufficient booking activity" if it satisfies any of the following three conditions:

1. It has been booked over 60 nights in the past year: this is equivalent to over 10 new reviews given an average review rate of 67% (Fradkin, Grewal and Holtz, 2018) and an average stay length of 3.9 nights (source: press.airbnb.com).
2. It shows intent to be booked for many nights over the upcoming year: the listing is available for more than 90 nights over the upcoming year and the "instant book" feature is turned on.
3. It has had frequent updates, reflecting intent to be booked even though it may not have the "instant book" feature turned on: the listing has been actively available for more than 90 nights over the upcoming year and this has happened at least twice within the past year.

A limitation of the data is webscrapes begin in 2015, so we impute listings pre-2015 using calendar and review data. We can only do this for listings that survived up to 2015, therefore our measure of pre- 2015 listings is a conservative lower bound.

A.3 Theory

A.3.1 Derivations of amenity demand

This section derives the amenity demand equation from section 4.1. We model the household decision of how much housing and amenities to consume conditional on living in a specific location. We omit time subscripts unless necessary.

Allocating expenditure between housing and consumption amenities. First, conditional on living in location j, a type k household with Cobb-Douglas preferences chooses how much of its wage w^k to spend on housing H_j and on a bundle of locally available consumption amenities C_j,

$$\max_{\{H_j, C_j\}} \quad A_j^k H_j^{1-\phi^k} C_j^{\phi^k} \quad \text{s.t.} \quad r_j H_j + P_{Cj} C_j = w^k, \tag{1}$$

where r_j is the rental price, P_{Cj} is the price of the consumption bundle, ϕ^k is the expenditure share parameter for consumption amenities, and A_j^k represents the household's valuation of the location's non-market attributes (A_j^k could represent public goods such as noise or pollution). The optimal choice of housing is $H_j^{*,k} = (1-\phi^k)\frac{w^k}{r_j}$. Therefore, the income left over for amenity consumption is $\phi^k w^k$.

Allocating expenditure across different consumption amenity sectors and varieties. Consumption amenities are classified into sectors indexed $s = 1, \ldots, S$ (e.g., "restaurants" is a sector), and firms/varieties are indexed i within each sector (e.g., an Italian restaurant is a firm/variety). The amenity consumption problem is,

$$\max_{\{q_{isj}^k\}_{is}} C_j^k \text{ s.t. } \sum_{is} p_{isj} q_{isj}^k = \phi^k w^k, \text{ where } C_j^k \equiv \prod_{s=1}^{S} \left[\left(\sum_{i=1,\ldots,N_{sj}} {q_{isj}^k}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s^k}. \tag{2}$$

C_j^k is the amenities bundle, q_{isj}^k is the quantity demanded of variety i in sector-location pair sj, N_{sj} is the number of firms/varieties in the sector-location, and p_{isj} is the price of variety i in sector-location sj. Note C_j^k aggregates consumption amenities across sectors and varieties in a way that is specific to each type k: it implies Cobb-Douglas preferences over amenity sectors (with weights α_s^k, such that $\sum_s \alpha_s^k = 1$) and CES preferences over varieties within an amenity sector (with substitution elasticity $\sigma_s > 1$).[3] Taking first order conditions with respect to q_{isj}^k, and then combining the FOC for two varieties i and i' in the same sector s we obtain,

$$\frac{q_{isj}^k}{q_{i'sj}^k} = \left(\frac{p_{isj}}{p_{i'sj}} \right)^{-\sigma_s}.$$

[3] Observe that expenditure shares in sector s are identical for households of type j across all neighborhoods j. However, type-k households' utility from consumption amenities differs due to the love-of-variety effect that stems from CES preferences.

Furthermore, total expenditure on sector s is $\alpha_s^k \phi^k w^k$ and equal to $\sum_{i\in s} p_{isj} q_{isj}^k$. Using this in the equation above, we obtain type k demand for variety i in sj, i.e., the amenity demand equation from section 4.1 of the main text,

$$q_{isj}^k = \frac{\alpha_s^k \phi^k w^k}{p_{isj}} \left(\frac{p_{isj}}{P_{sj}}\right)^{1-\sigma_s}, \quad \text{with } P_{sj} \equiv \left(\sum_{i=1}^{N_{sj}} p_{isj}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}},$$

A.3.2 Flow utility specification

This section derives the parametric form for flow utility used in estimation in section 5.3.1 of the main text and its connection to the amenity demand parameters.

Indirect utility from housing and amenity demand problem. Given our assumption that marginal costs are constant within a sector-location, the equilibrium of the firm-pricing game is symmetric within a sector-location, thus $p_{isj} = p_{sj}\ \forall i \in sj$. Hence, consumers buy an equal amount of amenities from every firm within the same sector-location. Type k demand for the individual firm i is,

$$q_{isj}^k = q_{sj}^k = \frac{\alpha_s^k \phi^k w^k}{p_{sj} N_{sj}}\ \forall i \in sj. \tag{3}$$

To obtain the indirect utility of living in j, we use the equation above to get the optimal amenity bundle C_j^*, which along with the optimal housing choice H_j^*, is substituted in equation 1. To take the indirect utility specification to the data we also reintroduce time subscripts, and impose a flexible form for A_{jt}^k,

$$A_{jt}^k \underbrace{\frac{w_t^k}{{r_{jt}}^{1-\phi^k}} \left(\prod_s \left[N_{sjt}^{\frac{1}{\sigma_s-1}} / p_{sjt}\right]^{\alpha_s^k}\right)^{\phi^k} \varphi^k}_{={H_j^*}^{1-\phi^k} {C_j^*}^{\phi^k}}, \text{ with } A_{jt}^k \equiv A_j A_t \left(\prod_s N_{sjt}^{\gamma_s^k}\right) b_{jt}^{\alpha_b^k} \tau_t^{\nu^k} \Xi_{jt}^k, \tag{4}$$

and where $\varphi^k \equiv (1-\phi^k)^{1-\phi^k} (\phi^k)^{\phi^k} \prod_s (\alpha_s^k)^{\alpha_s^k \phi^k}$ is a type-k constant. We assume the valuation of local non-market attributes A_{jt}^k is decomposed as follows: A_j is a fixed location attribute that is unobservable to the econometrician, A_t are unobservable shocks common to all locations in the city, $N_{sjt}^{\gamma_s^k}$ is a utility spillover derived from the nearby presence of amenities beyond the direct consumption itself (which could be dis-utility, such as noise from bars), $\tau_t^{\nu^k}$ is utility from location capital with $\nu^k > 0$, b_{jt} are exogenous time-varying location characteristics that are observable (such as the presence of public housing), and Ξ_{jt}^k are time-varying location attributes that are unobservable. The purpose of 4, especially specifying A_{jt}^k, is to take the theoretical choice problem to the data and be transparent about what the econometrician does and does not observe. Taking logs of 4, and adding a type I EV error ε_{ijt},

$$\mu_j^k + \mu_t^k - (1-\phi^k)\log r_{jt} + \sum_s \left(\frac{\alpha_s^k \phi^k}{\sigma_s - 1} + \gamma_s^k\right)\log N_{sjt} + \alpha_b^k \log b_{jt} + \nu^k \log \tau_t + \xi_{jt}^k + \varepsilon_{ijt},$$

where $\mu_j^k \equiv \log A_j^k + \log \varphi^k$, $\mu_t^k \equiv \log A_t^k + \log w_t^k$, and $\xi_{jt}^k \equiv -\phi^k \sum_s \alpha_s^k \log p_{sjt} + \log \Xi_{jt}^k$. Because the level of utility with type I EV errors is not identified, we normalize the variance of the shock to $\frac{\pi^2}{6}$ by dividing the equation above by σ_ε^k,

$$\delta_j^k + \delta_t^k + \delta_r^k \log r_{jt} + \sum_s \delta_s^k \log N_{sjt} + \delta_b^k \log b_{jt} + \delta_\tau^k \log \tau_t + \xi_{jt}^k + \epsilon_{ijt}, \tag{5}$$

where the δ coefficients are the normalized parameters after dividing by σ_ε^k. Finally, to get to the exact flow utility specification from section 5.3.1 of the main text, we define the indirect utility as 5 net of the type I EV shock, we introduce the moving cost, and rewrite $\sum_s \delta_s^k \log N_{sjt}$ in its vector-notation analogue $\delta_a^k \log a_{jt}$,[4]

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

Connection between flow utility parameters and amenity demand parameters. Observe that the flow utility parameters in the last equation above are a function of the parameters of the housing and amenity choice problem,

$$\delta_s^k = \left(\frac{\alpha_s^k \phi^k}{\sigma_s - 1} + \gamma_s^k\right) / \sigma_\varepsilon^k \quad \text{and} \quad \delta_r^k = -(1-\phi^k)/\sigma_\varepsilon^k.$$

Note the preference parameter for the sector s amenity, δ_s^k, can be positive or negative. The first term, $\frac{\alpha_s^k \phi^k}{\sigma_s - 1}$, is non-negative because the Cobb-Douglas preference parameter for amenity sector s α_s^k is non-negative (consuming the amenity cannot decrease utility). The second term, γ_s^k, can be positive or negative because it mea-

[4] Where $\delta_a^k \equiv [\delta_1^k, \ldots, \delta_S^k]$ and $\log a_{jt} \equiv [\log N_{1jt}, \ldots, \log N_{Sjt}]'$.

sures how the presence of amenity s impacts utility beyond direct consumption through spillovers that can be positive or negative (for example, noise from bars).

A.4 Simulation details

A.4.1 Outline of the equilibrium solver algorithm

We use a nested fixed-point algorithm to solve our model equilibrium. In the inner loop, we solve for the equilibrium vector of long- and short-term rental prices, given a fixed matrix of amenities. In the outer loop, we then solve for equilibrium amenities. The algorithm is as follows: fix parameters $\lambda \in (0,1)$ and $\delta_r, \delta_p > 0$. The outer loop proceeds as follows for step $t = 1, \ldots$

($\mathbf{O_1^t}$) Guess $\mathbf{a}^{(t)}$. The inner loop proceeds as follows for step $g = 1, \ldots$

($\mathbf{I}_1^g$) Guess $\mathbf{r}^{(g)}$ and $\mathbf{p}^{(g)}$

($\mathbf{I}_2^g$) Compute excess demand for long- and short-term housing:

$$\mathbf{z}^L(\mathbf{r}^{(g)}, \mathbf{p}^{(g)}, \mathbf{a}^{(t)}) \text{ and } \mathbf{z}^S(\mathbf{r}^{(g)}, \mathbf{p}^{(g)}, \mathbf{a}^{(t)})$$

($\mathbf{I}_3^g$) Update prices using excess demands,

$$\begin{aligned} \mathbf{r}^{(g+1)} &= \mathbf{r}^{(g)} + \delta_r \cdot \mathbf{z}^L(\mathbf{r}^{(g)}, \mathbf{p}^{(g)}, \mathbf{a}^{(t)}) \\ \mathbf{p}^{(g+1)} &= \mathbf{p}^{(g)} + \delta_p \cdot \mathbf{z}^S(\mathbf{r}^{(g)}, \mathbf{p}^{(g)}, \mathbf{a}^{(t)}) \end{aligned}$$

($\mathbf{I}_3^g$) Compute $d_{r,p}^{(g)} = \max \left\{ ||\mathbf{r}^{(g+1)} - \mathbf{r}^{(g)}||_\infty, ||\mathbf{p}^{(g+1)} - \mathbf{p}^{(g)}||_\infty \right\}$

Iterate until step G such that $d_{r,p}^{(G)} < \epsilon_{r,p}$ for a tolerance level $\epsilon_{r,p} > 0$. Denote,

$$\mathbf{r}^{(et)} \equiv \mathbf{r}^{(G)} \text{ and } \mathbf{p}^{(et)} \equiv \mathbf{p}^{(G)}$$

($\mathbf{O_2^t}$) Compute amenities the implied by equilibrium prices from inner loop,

$$\mathbf{a}_{js}^{(et)} = \frac{1}{F_{js}\sigma_s} \left(\sum_{k=1}^{K} \mathcal{Q}_j^{D,L,k}(\mathbf{r}^{(et)}, \mathbf{a}^{(t)}) \alpha_s^k \alpha_c^k w^k + \mathcal{Q}_j^T(\mathbf{p}^{(et)}, \mathbf{a}^{(t)}) \alpha_s^T \alpha_c^T w^T \right)$$

($\mathbf{O_3^t}$) Update amenities, $\mathbf{a}^{(t+1)} = (1-\lambda)\mathbf{a}^{(et)} + \lambda \mathbf{a}^{(t)}$

($\mathbf{O_4^t}$) Compute $d_a^{(t)} = ||\mathbf{a}^{(t+1)} - \mathbf{a}^{(t)}||_\infty$

Iterate until step T such that $d_a^{(T)} < \epsilon_a$ for a tolerance level $\epsilon_a > 0$.

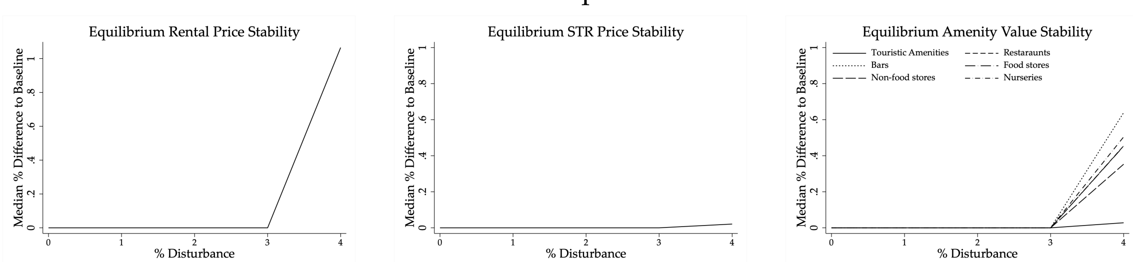
Algorithm settings. We construct the amenity supply equation using the estimates from section 5.2. We set the unobservable component of entry costs equal to the residuals of equation 24. For housing demand, we take the estimates from section 5.3, fix the exogenous characteristics of demand at their 2017 level, set unobservable demand shocks ξ_j^k equal to zero (their conditional mean), and sum across groups k to compute aggregate demand for long-term housing. We calibrate the differential costs of short- versus long-term rentals to match the number of STR tourists in each location in 2017. Finally, we start our solver at the observed prices and amenities in 2017. We define convergence when the infinite norm of the excess demand function for the vector of prices and amenities $(\mathbf{r}, \mathbf{p}, \mathbf{a})$ is less than 1E-10.

A.4.2 Local uniqueness of equilibrium

To evaluate the extent of multiplicity, we experiment by perturbing the initial values supplied to the equilibrium solver described in section A.4.1.

Figure A2: Equilibrium deviations under a range of perturbations.

Rental Prices | STR prices | Amenities



Notes: The horizontal axes indicate perturbations (ranging from 0% to 4%) of the equilibrium solver's starting point. The vertical axes indicate how the equilibrium that results from the perturbed starting point deviates from the baseline unperturbed equilibrium (in percentage points). Deviations are measured as the mean percentage point gap in equilibrium outcomes across samples (where for each sample we take the median gap in rent, amenities, and STR prices). Values of zero on the vertical axes indicate the perturbation of the starting point leads to the same initial equilibrium. Positive values indicate convergence to a different equilibrium, with higher values indicating further distance from the initial equilibrium.

Note that given an amenities matrix $\mathbf{a}$, the equilibrium rent vector $\mathbf{r}$ is unique. Therefore, for our exercise it suffices to vary the initial values of $\mathbf{a}$. For the perturbation, we first fix the prices to those in the data, $(\mathbf{r^0}, \mathbf{p^0}) = (\mathbf{r}^{Observed}, \mathbf{p}^{Observed})$. Next, we draw an initial amenities matrix $\mathbf{a}^0$ from a neighborhood around observed amenities, $\mathbf{a}^{Observed}$, as follows: $\mathbf{a}^0 = \mathbf{a}^{Observed} + \mathbf{a}^{Observed} \cdot \epsilon$, where we randomly sample a matrix ϵ from a ring with inner radius ρ and outer radius $\rho + 0.01$, for $\rho = 0, 0.01, \ldots, 0.04$. For each ring, we draw 10 different starting values. Figure A2 shows that for any perturbation below $\epsilon = 0.04$ we obtain the same equilibrium. We take this as evidence that at least locally, the equilibrium is unique.

A.5 Welfare accounting details

A.5.1 Consumer surplus of renters

Following Train (2009), we define consumer surplus as a function of $EV^k_{j,\tau}$ when evaluated at vector $(\mathbf{r}, \mathbf{a})$. The expected consumer surplus for a type-k resident is a function of their marginal utility of income v_k and their choice over locations j':

$$\mathbb{E}\left[CS^k_{j,\tau}(\mathbf{r}, \mathbf{a})\right] = \frac{1}{v_k}\mathbb{E}^k\left[\max_{j'}\left(V^k_{j',j,\tau}(\mathbf{r}, \mathbf{a}) + \epsilon_{j'}\right)\right] = \frac{1}{v_k}EV^k_{j,\tau}(\mathbf{r}, \mathbf{a}) + C_k,$$

for some constant C_k. Integrating over the stationary distribution of households over locations, we obtain the following expression for consumer surplus:

$$CS^k(\mathbf{r}, \mathbf{a}) \equiv \frac{1}{v_k}\sum_{j,\tau} EV^k_{j,\tau}(\mathbf{r}, \mathbf{a})\pi^k_{j,\tau}(\mathbf{r}, \mathbf{a}) + C_k.$$

Following Section A.3.2, the expected value function for group k is,

$$EV^k_{j,\tau}(\mathbf{r}, \mathbf{a}) = \frac{1}{1-\beta}\frac{1}{\sigma^k}\log w^k + f(\mathbf{r}, \mathbf{a}),$$

for some function f and w^k is income of group k. Moreover, we can estimate $\sigma^k = -\frac{1-\phi^k}{\delta^k_r}$ where δ^k_r is the price coefficient and ϕ^k is the housing expenditure share of group k. Hence, the marginal utility of income for group k can be estimated as:

$$v^k = -\frac{1}{1-\beta}\frac{\delta^k_r}{1-\phi^k}\frac{1}{w^k}. \tag{6}$$

We treat Younger Families as renters, computing their surplus as specified above.

A.5.2 Consumer surplus of home-owners

Some of our household types (Older Families and Singles) are home-owners (i.e., owner-occupiers), whom we assume rent to themselves and receive back rental income. To compute how much rental income, we take a location's average rental income (based on r_j, the long-term rental price per square meter, and $size_j$, the average size of a housing unit) and weight it by the type-k home-owner population,

$$\bar{i}^{L,k}(\mathbf{r}, \mathbf{a}) \equiv \sum_j \frac{\mathcal{Q}_j^{D,L,k}(\mathbf{r}, \mathbf{a})}{\sum_j \mathcal{Q}_j^{D,L,k}(\mathbf{r}, \mathbf{a})} \cdot r_j \cdot size_j. \tag{7}$$

Consumer surplus of home-owners is the sum of i) their consumer surplus as renters, defined in section A.5.1, and ii) their rental income $\bar{i}^{L,k}(\mathbf{r}, \mathbf{a})$,

$$CS^k(\mathbf{r}, \mathbf{a}) \equiv \frac{1}{v_k} \sum_{j,\tau} EV_{j,\tau}^k(\mathbf{r}, \mathbf{a}) \pi_{j,\tau}^k(\mathbf{r}, \mathbf{a}) + \bar{i}^{L,k}(\mathbf{r}, \mathbf{a}) + C_k.$$

A.5.3 Consumer surplus of tourists

Following Train (2009), the consumer surplus of tourists is given by:

$$\frac{1}{v^T} \log \Big(\sum_j \exp(u_j^T(\mathbf{p}, \mathbf{a}) \Big) + C_T,$$

where $u_j^T(\mathbf{p}, \mathbf{a}) = \delta_j^S + \delta^S + \delta_p^S \log p_j + \delta_a^S \log a_j + \xi_j^S$, and $v^T = \sum_j \mathbb{P}_j^T(\mathbf{p}, \mathbf{a}) \cdot \frac{\delta_p^S}{p_j}$.

A.5.4 Absentee landlords.

The city-wide average surplus for absentee landlords is,

$$\sum_j \frac{H_j^A}{\sum H_j^A} \left[\frac{1}{\alpha} \log \Big(\exp(\alpha p_j + \kappa_j) + \exp(\alpha r_j) \Big) + C_L \right],$$

where the term in square brackets is the surplus of the average absentee landlord in location j, weighted by the housing stock owned in each location. We do not include the surplus of absentee landlords in the consumer surplus of residents.

A.5.5 Changes in surplus across counterfactuals

Given two equilibria $(\mathbf{r}_0, \mathbf{a}_0)$ and $(\mathbf{r}_1, \mathbf{a}_1)$, the change in type k consumer surplus is,

$$\Delta\mathbb{E}\left[CS^k\right] = \mathbb{E}\left[CS^k(\mathbf{r}_1, \mathbf{a}_1)\right] - \mathbb{E}\left[CS^k(\mathbf{r}_0, \mathbf{a}_0)\right],$$

where CS^k is defined as in the preceding sections for each household type.

A.5.6 Segregation measure

We use the entropy index (White, 1986) as our measure of segregation. First, we define the entropy index for a single location. Let d_j^k be type k share of location j population—if the type k population in location j is D_j^k, then $d_{jk} \equiv D_j^k / \sum_k D_j^k$. For location j, the entropy index is defined as $v_j \equiv -\sum_{k=1}^K d_j^k \log(d_j^k)$. Next, we define v as the entropy index for the whole city. To do so, we define: $D_j \equiv \sum_{k=1}^K D_j^k$, $D^k \equiv \sum_{j=1}^J D_j^k$, and $D \equiv \sum_{j=1}^J \sum_{k=1}^K D_j^k$, as well as,

$$\widehat{v} \equiv -\sum_{k=1}^{K} \frac{D^k}{D} \log\left(\frac{D^k}{D}\right) \qquad \text{and} \qquad \overline{v} \equiv \sum_{j=1}^{J} v_j \frac{D_j}{D} \qquad \Longrightarrow \quad v \equiv \frac{\widehat{v} - \overline{v}}{\widehat{v}}.$$

Note $v \in [0,1]$ and higher v means more segregation: v equals 0 if the share of each type in each location is equal to its population share in the whole population, and v equals 1 if each location is occupied by exactly one type.

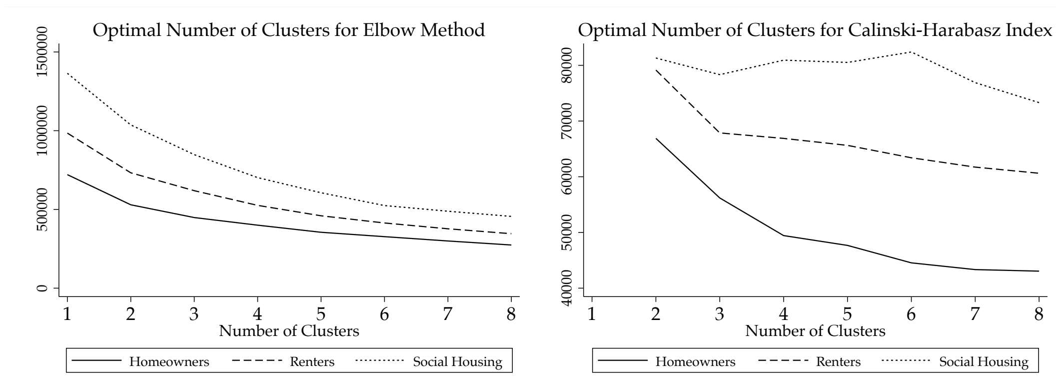
A.6 Estimation details

A.6.1 Classification by k-means clustering

First, given the high persistence in tenancy status, we classify households into three groups based on their modal tenancy status: homeowners, private renters, and renters in social housing. Second, we construct an invariant vector of demographics as follows. For time-varying data—age, disposable income (gross income net of tax), disposable income per person, presence of children—we take averages across years. We standardize all characteristics—skill, region of origin, age, disposable income, disposable income per person, children—because k-means is not invariant to scale and mechanically puts more weight on variables that have larger absolute values. We assign the categorical variables weights of $1/\sqrt{C-1}$, where the number of categories is C, so that each dimension has a weight of 1.[5] We finally run k-means on the transformed vector of demographics.

To choose the number of groups, we use a cross-validation method using two heuristics: the elbow method and the Calinski-Harabasz index. The optimal number of clusters as suggested by the elbow method is pinned down by the largest change of slope in the sum of squared errors curve. The Calinski-Harabasz index suggests that the optimal number of clusters is achieved when the ratio of the sum of between-clusters dispersion and of inter-cluster dispersion is maximized. Figure A2 shows the results of these heuristics for the three tenancy groups. For homeowners and private renters both methods suggest an optimal number of two clusters. For social housing renters, the first method suggests two clusters and the second method either two or six clusters. Putting both results together, we choose two as the final number of groups for social housing renters.

Figure A2: Heuristics for k-means classification



A.6.2 Discretization of a continuous state variable

We closely follow Rust (1987). To keep the number of states low, we discretize location tenure in two buckets: $\bar{\tau} = 1$ if $\tau \leqslant 3$ and $\bar{\tau} = 2$ otherwise. We assume that location tenure evolves using transition probabilities $\mathbb{P}_t(x'_{t+1}|j_t, x_t)$. In practice, we assume $\mathbb{P}_t(\tau_t = 1|j_t, x_t) = 1$ if $j_t \neq j_{t-1}$ and,

$$\mathbb{P}_t(\tau_t = 2|j_t, x_t) = \begin{cases} 1 & \text{, if } j_t = j_{t-1} \text{ and } \tau_{t-1} = 2 \\ p & \text{, if } j_t = j_{t-1} \text{ and } \tau_{t-1} = 1, \end{cases}$$

[5]That is, for skill, we retain two categories, one that belongs to low skill and one to medium skill. We divide the standardize dummies by $\frac{1}{\sqrt{2}}$. Four country of origin, we set Dutch as the baseline category and divide standardize dummies by $\frac{1}{\sqrt{3}}$.

where p is estimated using a frequency-based estimator.

A.6.3 Constructing the Expected Value Function

The value function is defined as follows:

$$V_t(x,\epsilon) = \max_j \left\{ \mathbb{E}_{x'|j,x}\Big[u_t(x',x)\Big] + \epsilon_j + \beta \mathbb{E}_t\Big[V_{t+1}(x',\epsilon')|j,x,\epsilon\Big] \right\}.$$

Under the assumptions in Section 5.3.1, we define the ex-ante value function as,

$$\begin{aligned} \mathbb{E}_t\left[V_{t+1}(x',\epsilon')|j,x,\epsilon\right] &= \int V_{t+1}(x',\epsilon')dF_t(x',\omega_{t+1},\epsilon'|j,x,\epsilon) && (8) \\ &= \int \Big(\int V_{t+1}(x',\epsilon')dF(\epsilon')\Big) dF_t(x',\omega_{t+1}|j,x) && (9) \\ &= \int V_{t+1}(x')dF_t(x',\omega_{t+1}|j,x) \equiv EV_t(j,x). && (10) \end{aligned}$$

We next define the conditional value function:

$$v_t(j,x) = \sum_{x'} \mathbb{P}_t(x'|j,x)\big(u_t(x',x) + \beta \bar{V}_t(x')\big) \equiv \bar{u}_t(j,x) + \beta EV_t(j,x).$$

If idiosyncratic shocks are distributed i.i.d. Type I EV, then:

$$\mathbb{P}_t(j|x) = \frac{\exp(v_t(j,x))}{\sum_{j'} \exp(v_t(j',x))}, \quad \text{and} \quad V_t(x) = \log\left(\sum_j \exp v_t(j,x)\right) + \gamma, \tag{11}$$

where γ is Euler's constant. Combining the two previous equations,

$$V_t(x) = v_t(j,x) - \ln(\mathbb{P}_t(j|x)) + \gamma. \tag{12}$$

A key observation is that equation 12 holds for any state x, and any action j.

Toward a demand regression equation. Our demand regression equation's starting point follows Hotz and Miller (1993), by taking differences on equation 11:

$$\ln\left(\frac{\mathbb{P}_t(j|x_t)}{\mathbb{P}_t(j'|x_t)}\right) = v_t(j,x_t) - v_t(j',x_t). \tag{13}$$

Substituting for the choice specific value function,

$$\ln\Big(\frac{\mathbb{P}_t(j|x_t)}{\mathbb{P}_t(j'|x_t)}\Big) = \bar{u}_t(j,x_t) - \bar{u}_t(j',x_t) + \beta\big(EV_t(j,x_t) - EV_t(j',x_t)\big). \tag{14}$$

Following Scott (2013) and Kalouptsidi, Scott and Souza-Rodrigues (2021), the realized expected value $V_t(x')$ can be decomposed between its expectation at time t and its expectational error, where uncertainty is on the aggregate state ω_{t+1}: $V_{t+1}(x') = \bar{V}_t(x') + \nu_t(x')$. Plugging in everything in equation 14 and using 12 to replace the continuation values V_{t+1} gives us,

$$\begin{aligned}
\ln\Big(\frac{\mathbb{P}_t(j|x_t)}{\mathbb{P}_t(j'|x_t)}\Big) &= \sum_x \mathbb{P}(x|j,x_t)u_t(x,x_t) - \sum_{x'} \mathbb{P}(x'|j',x_t)u_t(x',x_t) \\
&+\beta\Bigg[\sum_x \mathbb{P}(x|j,x_t)\bar{V}_t(x) - \sum_{x'} \mathbb{P}(x'|j',x_t)\bar{V}_t(x')\Bigg] \\
&= \sum_x \mathbb{P}(x|j,x_t)u_t(x,x_t) - \sum_{x'} \mathbb{P}(x'|j',x_t)u_t(x',x_t) \\
&+\beta\Bigg[\sum_x \mathbb{P}(x|j,x_t)\big(V_{t+1}(x) - \nu_{t+1}(x)\big) - \sum_{x'} \mathbb{P}(x'|j',x_t)\big(V_{t+1}(x') - \nu_{t+1}(x')\big)\Bigg] \\
&= \sum_x \mathbb{P}(x|j,x_t)u_t(x,x_t) - \sum_{x'} \mathbb{P}(x'|j',x_t)u_t(x',x_t) \\
&-\beta\Bigg[\sum_x \mathbb{P}(x|j,x_t)\big(v_{t+1}(\tilde{j},x) - \ln\mathbb{P}_{t+1}(\tilde{j}|x) - \nu_{t+1}(x)\big) \\
&- \sum_{x'} \mathbb{P}(x'|j',x_t)\big(v_{t+1}(\tilde{j},x') - \ln\mathbb{P}_{t+1}(\tilde{j}|x') - \nu_{t+1}(x')\big)\Bigg] \\
&= \sum_x \mathbb{P}(x|j,x_t)u_t(x,x_t) - \sum_{x'} \mathbb{P}(x'|j',x_t)u_t(x',x_t) \\
&-\beta\Bigg[\sum_x \mathbb{P}(x|j,x_t)\big(v_{t+1}(\tilde{j},x) - \ln\mathbb{P}_{t+1}(\tilde{j}|x)\big) \\
&- \sum_{x'} \mathbb{P}(x'|j',x_t)\big(v_{t+1}(\tilde{j},x') - \ln\mathbb{P}_{t+1}(\tilde{j}|x')\big)\Bigg] + \tilde{v}_{j,j',x_t},
\end{aligned}$$

where $\tilde{v}_{j,j',x_t} \equiv \beta\Big(\sum_x \mathbb{P}(x|j,x_t)\nu_{t+1}(x) - \sum_{x'} \mathbb{P}(x'|j',x_t)\nu_{t+1}(x')\Big)$ is a sum of expectational errors. Observe that if $\tilde{j}$ is a renewal action then:

$$v_{t+1}(\tilde{j}, x) = \bar{u}_{t+1}(\tilde{j}, x) + EV_t(\tilde{j}, 1) = u_{\tilde{j},x,t+1} + \delta_\tau \cdot 1 + MC(\tilde{j}, j) + EV_t(\tilde{j}, 1)$$

for all $x = (j, \tau)$, regardless of τ, where we decompose the per-period utility function, $\bar{u}_{t+1}(\tilde{j}, x)$, into a location specific component, $u_{\tilde{j},x_{t+1}}$, a location-tenure component δ_τ, and a moving cost component $MC(\tilde{j}, j)$. Substituting and re-arranging,

$$\begin{aligned}
&\ln\left(\frac{\mathbb{P}_t(j|x_t)}{\mathbb{P}_t(j'|x_t)}\right) + \beta\left[\sum_x \mathbb{P}(x|j, x_t)\ln \mathbb{P}_{t+1}(\tilde{j}|x) - \sum_{x'} \mathbb{P}(x'|j', x_t)\ln \mathbb{P}_{t+1}(\tilde{j}|x')\right] \\
&= u_{j,x_t} - u_{j',x_t} + \delta_\tau\Big(\sum_x \mathbb{P}(x|j, x_t)\tau(x) - \sum_{x'} \mathbb{P}(x'|j', x_t)\tau(x')\Big) \\
&+ MC(j, j_{t-1}) - MC(j', j_{t-1}) + \beta\Big(MC(\tilde{j}, j) - MC(\tilde{j}, j')\Big) + \tilde{v}_{j,j',x_t}.
\end{aligned}$$

A.6.4 First-stage estimation of Conditional Choice Probabilities.

We follow a similar procedure as in Traiberman (2019) and Humlum (2021). We depart from their approaches that use a linear probability model and use a multinomial logit on individual decisions to predict choice probabilities for several reasons. First, we can use individual variation. Second, our data reveal that the likelihood of not moving is approximately 85%, while the probability of moving to any other location remains close to zero. This bimodal nature of empirical distribution of choice probabilities suggests that an exponential relationship should be better suited to fit individual decisions compared to a linear model. Third, we find that many predicted probabilities of the linear model lie below zero or above one, a feature that requires an ad-hoc extra censoring step. For every individual i, we observe her individual state at time t $x_{it} = (j_{t-1}, \tau_{t-1})$, where j_{t-1} is the previous location, τ_{t-1} and type $k(i)$, as well as the moving decision variables for all j: $j_{it} = \mathbb{1}\{d(i)_t = j\}$. We define a base outcome 0, and estimate the following multinomial logit model for each group k:

$$\mathbb{P}(j_{it} = j) = \frac{\exp(\lambda^k_{j,t} + \alpha^k_{j,1}\tau_{t-1} + \alpha^k_{j,2}\tau^2_{t-1})}{1 + \sum_{j'=1}^{J} \exp(\lambda^k_{j',t} + \alpha^k_{j',1}\tau_{t-1} + \alpha^k_{j',2}\tau^2_{t-1}}.$$

Monte Carlo simulations. Through a Monte Carlo exercise, we compare the bias

Table A3: Parameters used in simulations

Variables		Parameters	
Name	Distribution (i.i.d.) / Value	Name	Value
u	$N(0, 0.05)$	α	- 0.05
v	$N(0, 0.05)$	β_1, β_2	0.1
ξ	$u + v$	γ_0, γ_1	-0.0025
b_{exo}	$LogN(0.5, 0.1)$	γ_2	-0.5
r	$0.75 \cdot b_{\text{exo}} + 0.25 \cdot v$	δ	0.1
a_{exo}	$LogN(1.5, 0.5)$	$N_{\text{households}}$	$\in [5 \cdot 10^5, 10^6]$
a	$0.75 \cdot a_{\text{exo}} + 0.25 \cdot v$	J	24
$\text{dist}(j, j'), j, j' \neq 0; \rho_d$	$LogN(1, 0.5)$	S	2
λ_j	$N(0, 0.1)$	$\bar{\tau}$	2
λ_t (Perfect foresight)	$N(0, 0.1)$	T	10
λ_t (Rational expectations)	0	tol in EV iteration	10^{-10}

in second-stage estimates when first-stage probabilities are predicted with a multinomial logit or with a standard frequency estimator. For our Monte Carlo exercise, we define the period flow utility function as:

$$u_t((d, \tau), x_t) = \alpha \log(r_{dt}) + \sum_s \beta_s \log N_{dst} + \xi_{dt} + \eta_t + \lambda_d + MC(d, j_{t-1}) + \delta_\tau \tau,$$

with table A3 showing the data generating process of each of the utility components. We also assume that agents have rational expectations. We compute the EV function for each time period as follows. Starting in the last period T, we assume that the economy is in steady-state. We define EV_T as:

$$EV_T(j_T, \tau_T) = \log \left(\sum_d \exp \left(\sum_{x'} \mathbb{P}_T(x'|d, x_T) \left[u_T(x', x_T) + \beta EV_T(d, x_T) \right] \right) \right) \quad (15)$$

For $t = 1, \ldots, T-1$, we compute EV_t using backward substitution as follows:

$$EV_t(j_t, \tau_t) = \log \Big(\sum_d \exp \big(\sum_{\tau'} \mathbb{P}_{t+1}(x'|d, x_t) \left[u_{t+1}(d, x_t) + \beta EV_{t+1}(d, x') \right] \big) \Big) \quad (16)$$

Assuming a uniform initial distribution of individuals across states, we simulate each individual forward for 10 time periods. We simulate 10 different samples. We take population sizes of 50 thousand—which roughly corresponds to the size of our groups—and 1 million— which provides insights about convergence properties of large samples. We test two first-stage estimates of conditional choice probabilities: (i) using a multi-nomial logit model and (ii)observed frequencies where we replace zero shares with a small $\epsilon = 10^{-5}$.

The results are presented in Table A4 and reveal that first-stage choice probabilities using a multi-nomial logit model yield a strictly dominant finite sample performance. The gap is most pronounced in small samples where the likelihood of observing zero flows between states in the data is higher, where the frequency-based estimator uses small but arbitrary values imputed by the researcher, which can be far from the true transition probabilities. The multi-nomial logit approximates the true probabilities well, reducing finite-sample bias in the final estimation stage. As we increase the sample size, the number of observed zero flows diminishes, and we observe convergence of both estimators to the performance of the first-best estimator using the true transition probabilities.

Table A4: Monte Carlo simulations with location fixed effects only and an indicator for high location capital

			Mean of the absolute value of bias						
ξ	Pop (in 10^3)	Prob.	α	β_1	β_2	γ_0	γ_1	γ_2	δ
zero	50	T	1.2E-15	1.9E-16	3.2E-16	1.3E-15	8.2E-19	1.3E-15	1.8E-15
		L	2.3E-02	2.3E-03	4.5E-03	5.7E-02	1.4E-04	3.9E-02	1.0E-01
		F	6.1E-01	1.7E-01	1.7E-01	1.3E+00	2.9E-03	7.8E-01	1.3E+00
	1000	T	8.1E-16	2.5E-16	2.6E-16	1.2E-15	6.5E-19	9.4E-16	1.6E-15
		L	5.6E-03	1.2E-03	8.0E-04	3.3E-02	2.8E-05	3.6E-02	1.0E-01
		F	1.4E-02	3.9E-03	2.6E-03	1.3E-02	5.0E-05	1.4E-02	3.8E-02
exogenous	50	T	2.7E-02	3.8E-03	3.5E-03	7.2E-03	5.0E-06	1.4E-15	2.0E-15
		L	2.7E-02	3.5E-03	5.7E-03	5.9E-02	2.2E-04	2.8E-02	1.0E-01
		F	4.6E-01	2.2E-01	2.7E-01	7.7E-01	2.9E-03	5.2E-01	1.5E+00
	1000	T	4.2E-02	1.5E-02	1.4E-02	7.9E-02	3.6E-04	1.3E-15	2.0E-15
		L	4.4E-02	1.5E-02	1.4E-02	1.0E-01	3.7E-04	3.4E-02	1.0E-01
		F	4.8E-02	1.6E-02	1.4E-02	9.7E-02	4.7E-04	1.3E-02	4.3E-02
endogenous	50	T	2.5E-02	9.9E-03	1.1E-02	9.1E-03	1.3E-05	1.2E-15	2.0E-15
		L	2.8E-02	9.5E-03	1.0E-02	5.6E-02	1.6E-04	4.4E-02	1.0E-01
		F	4.3E-01	2.5E-01	2.4E-01	7.9E-01	2.8E-03	6.5E-01	1.0E+00
	1000	T	3.0E-02	6.8E-03	3.2E-03	1.1E-02	1.0E-05	1.1E-15	1.9E-15
		L	2.8E-02	6.9E-03	3.0E-03	2.5E-02	5.5E-05	3.7E-02	1.0E-01
		F	4.2E-02	8.3E-03	5.5E-03	2.8E-02	1.0E-04	9.2E-03	3.3E-02

Notes: Table presents averaged absolute distance between the estimated parameter and true parameter over 10 random draws of datasets. T represents estimation using the true transition probabilities; L using predicted probabilities by a multinomial logit model; and F using transition probabilities computed based on empirical shares.

A.7 Robustness exercises

A.7.1 Robustness of real estate supply elasticity

We test how different choices of supply elasticities and their implied congestion parameter η affect our main takeaways. First, Table A5 shows that choosing a supply elasticity equal to San Francisco, as estimated by Saiz (2010), delivers the best model fit in terms of matching the observed distribution of rental prices.

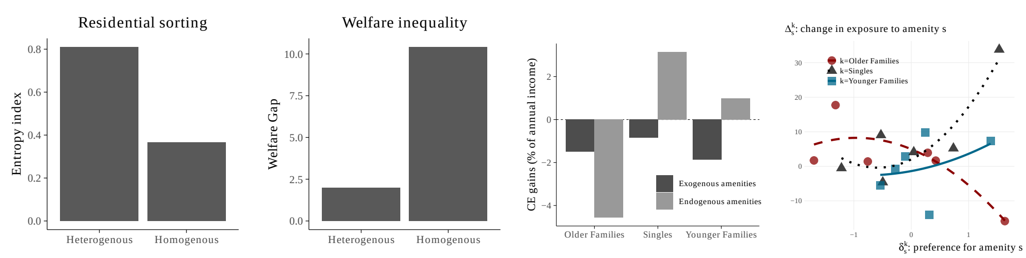
Table A5: Rent fit across a range of supply elasticities

	Parameters		Rent fit	
City	Supply Elasticity	η	R^2	β
San Franciso	0.66	1.52	0.578	1.229
New York	0.75	1.33	0.571	1.229
Boston	0.86	1.16	0.566	1.229
Portland	1.04	0.93	0.557	1.231
Detroit	1.24	0.81	0.549	1.234
Washington DC	1.61	0.62	0.524	1.252
Durham-Raleigh-Chapel Hill	2.11	0.47	0.476	1.291
Atlanta	2.55	0.39	0.473	1.288

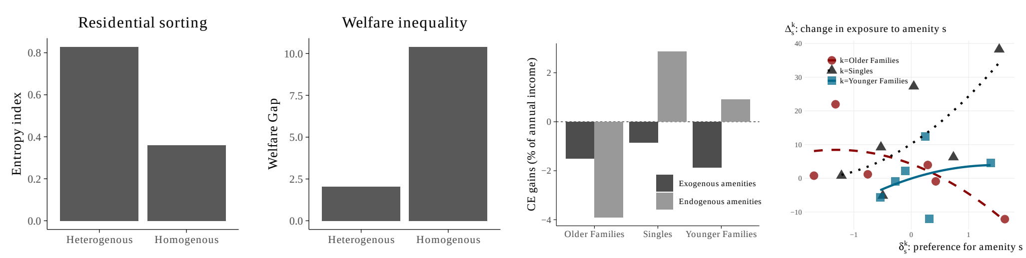
Notes: Table presents the R-square and slope of observed rents against our model equilibrium rents. Supply elasticities are from Saiz (2010) and inverted to obtain our amenity congestion parameter η.

Figure A5: Robustness of heterogeneity and STR-entry counterfactuals to η.

η = 1.52 (San Francisco baseline)



η = 0.93 (Portland)



η = 0.39 (Atlanta)

Second, Figure A5 shows the key takeaways from our main counterfactuals in sections 6.1-6.2 are robust to different supply elasticities, ranging from our baseline inelastic San Francisco case (η=1.52) to the highly elastic case of Atlanta (η=0.39). Figure A5 confirms that for the full range of η, the qualitative insight that preference heterogeneity can lead to more sorting but lower inequality is robust. It also confirms the qualitative insight that all households lose from STR entry due to higher rent, but some are partially compensated by amenity changes depending on how they value the amenities linked to tourism, is robust. In all cases, losses of older families are amplified by endogenous amenities, while those of other groups are compensated. Hence, the choice of η does not make a major difference for the mechanisms in our model, which instead depend on the correlation between preferences over amenities and amenity supply response across household types.

A.7.2 Robustness of amenity supply estimates to precinct-year fixed effects

We present estimation results for a version of equation 24 from the main text that allows for precinct-year fixed effects:

$$\log N_{sjt} = \lambda_j + \lambda_{p(j)t} - \eta \log N_{jt} + \log\left(\sum_k \beta_s^k X_{jt}^k\right) + \omega_{sjt}, \tag{17}$$

where $p(j)$ indicates the precinct where district j is located. Following the same procedure as in Section 5.2, estimation results are presented in Table A6.

We can test if the difference between the coefficients in Table A6 above and III in the main draft, respectively, are statistically indistinguishable. To do so, we can simply check whether confidence intervals overlap. It is easy to check that for the 95% confidence intervals reported in the tables, we can only reject that one coefficient is statistically different across the two specifications, namely, the coefficient for Tourists on Restaurants.[6] Moreover, to formally test for the difference between the two models, we conduct a joint multiple hypothesis test. The F statistic in that case is given by 0.8197, which is below 1.331—the critical value of an F distribution with 59 and 1319 degrees of freedom at the 5% level. Therefore, we conclude that the two models are not statistically different.

[6]We reject all statistical differences at the 99% level. We fail to reject four equalities at the 90% level.

Table A6: Estimates of amenity supply parameters.

	Touristic Amenities	Restaurants	Bars	Food Stores	Non-Food Stores	Nurseries
Older Families	251.65	15.284	0.0	3.042	18.097	1268.765***
	[0.0,619.269]	[0.0,46.657]	[0.0,0.0]	[0.0,27.438]	[0.0,85.227]	[497.721,2397.678]
Singles	619.613	62.969	0.0	160.705	13.632	6.78
	[0.0,1989.024]	[0.0,404.971]	[0.0,0.0]	[0.0,530.939]	[0.0,198.9]	[0.0,0.001]
Younger Families	0.0	5.07	22.95	96.491***	331.003***	1506.579***
	[0.0,0.0]	[0.0,41.273]	[0.0,68.748]	[12.003,186.982]	[161.975,560.076]	[349.155,2863.146]
Students	1891.545**	713.637***	33.078	174.087	0.68	313.761
	[179.018,3749.272]	[354.964,1135.771]	[0.0,164.968]	[0.0,561.47]	[0.0,0.001]	[0.0,2317.864]
Immigrant Families	0.0	0.328	16.918	64.158	67.804	321.911
	[0.0,0.0]	[0.0,0.001]	[0.0,61.799]	[0.0,170.987]	[0.0,249.827]	[0.0,1431.537]
Dutch Low Income	19.156	1.032	0.302	15.877	0.0	0.001
	[0.0,171.662]	[0.0,16.112]	[0.0,2.647]	[0.0,86.375]	[0.0,0.0]	[0.0,0.007]
Tourists	1332.384***	656.306***	342.083***	240.882***	1151.567***	0.0
	[963.408,1732.815]	[522.936,817.854]	[248.024,443.765]	[157.747,308.077]	[880.522,1457.284]	[0.0,0.0]

Note: Table reports bootstrap results for coefficients β_s^k from Equation 17 for seven population types and six types of services. Parameters β_s^k along with fixed effects λ_j and $\lambda_{p(j)t}$ are estimated via GMM, where we restrict $\beta_s^k \geqslant 0$. The estimation procedure is outlined in section 5.2 and follows a Bayesian-bootstrap with random Dirichlet weights across 100 draws. Top rows indicate average estimates of the bootstrap samples. Results inside square brackets indicate 95% confidence intervals. We omit estimates of the location and time fixed effects. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.7.3 Comparison of static and dynamic model estimates

We show how our demand estimates change in the static version of our model: we remove forward-looking behavior (by setting $\beta = 0$) and location capital, i,.e., the dynamic state-dependent component of moving costs. We keep the bilateral moving costs since they are a static component of moving costs and are common in static models of migration (Bryan and Morten, 2019).

Table A7: Preference parameter demand estimation results in the static model.

	Older Families		Singles		Younger Families	
Rent	-17.207***	(4.968)	-11.268***	(4.138)	-14.575***	(4.316)
Tourism Offices	-2.863***	(0.920)	-1.656**	(0.766)	-0.261	(0.799)
Restaurants	2.530	(1.543)	2.990**	(1.285)	1.838	(1.340)
Bars	-0.956**	(0.427)	-0.671*	(0.356)	-0.513	(0.371)
Food Stores	-1.437	(1.359)	0.114	(1.132)	1.120	(1.180)
Nonfood Stores	-1.401	(1.584)	-0.992	(1.320)	-0.225	(1.376)
Nurseries	3.162***	(0.728)	1.629***	(0.607)	2.741***	(0.633)
N	11132		11132		11132	

Notes: Table shows results of preference parameters for a static location choice model for 22 districts for 2008-2019. We estimate preference parameters separately for three groups via GMM. The dependent variable is differences in path likelihoods, after normalizing with respect to the outside option. Each type has 46 possible states, and 22 possible choices over 11 years, leading to 11,132 state-choice combinations. We omit exogenous controls moving costs for ease of exposition. Two-step efficient GMM standard errors in parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7 shows the demand estimates in the static model. Table A8 compares the static estimates to our baseline dynamic estimates by performing a t-test of differences for the willingness to pay for amenities—the amenity preference parameters normalized by the rent coefficient. Most of the coefficients are significantly different across specifications, and in several cases even change sign. We take these differences as evidence that failing to account for dynamic considerations can severely bias preference coefficients, in line with the findings of similar studies (Bayer, McMillan, Murphy and Timmins, 2016).

Table A8: Comparison of dynamic and static estimates.

		Dynamic		Static		Difference		
Group	Amenity	WTP	sd	WTP	sd	Mean	sd	t-test
Older Families	Touristic Amenities	-0.1212	0.0151	-0.1664	0.0396	0.0452	0.0170	2.6667
	Restaurants	0.0265	0.0347	0.1470	0.0896	-0.1206	0.0389	-3.0967
	Bars	-0.0695	0.0091	-0.0556	0.0209	-0.0139	0.0099	-1.4065
	Food Stores	-0.1557	0.0303	-0.0835	0.0746	-0.0721	0.0336	-2.1484
	Nonfood Stores	0.0392	0.0359	-0.0814	0.0980	0.1206	0.0409	2.9518
	Nurseries	0.1498	0.0087	0.1838	0.0267	-0.0340	0.0102	-3.3151
Singles	Touristic Amenities	-0.2148	0.0708	-0.1470	0.0489	-0.0679	0.0699	-0.9702
	Restaurants	0.3183	0.1751	0.2653	0.1313	0.0530	0.1733	0.3057
	Bars	-0.2285	0.0880	-0.0595	0.0268	-0.1690	0.0861	-1.9620
	Food Stores	-0.5266	0.2284	0.0101	0.1017	-0.5368	0.2242	-2.3936
	Nonfood Stores	0.6637	0.3140	-0.0881	0.1256	0.7518	0.3080	2.4412
	Nurseries	0.0190	0.0588	0.1446	0.0276	-0.1256	0.0578	-2.1748
Younger Families	Touristic Amenities	0.1612	0.1676	-0.0179	0.0513	0.1791	0.1641	1.0909
	Restaurants	-0.1426	0.1947	0.1261	0.0907	-0.2687	0.1912	-1.4055
	Bars	-0.0529	0.0379	-0.0352	0.0216	-0.0177	0.0373	-0.4741
	Food Stores	-0.2748	0.1664	0.0769	0.0911	-0.3516	0.1637	-2.1478
	Nonfood Stores	0.7044	0.3846	-0.0154	0.0952	0.7198	0.3763	1.9128
	Nurseries	0.1252	0.0384	0.1881	0.0282	-0.0629	0.0380	-1.6557

References

Bayer, P., McMillan, R., Murphy, A. and Timmins, C. (2016). A dynamic model of demand for houses and neighborhoods. *Econometrica* 84(3):893–942.

Botman, M. (2021). Wet toeristische verhuur van woonruimte maakt regulering vakantieverhuur mogelijk.

Bryan, G. and Morten, M. (2019). The aggregate productivity effects of internal migration: Evidence from Indonesia. *The Journal of Political Economy* 127(5):2229–2268.

Fradkin, A., Grewal, E. and Holtz, D. (2018). The determinants of online review informativeness: Evidence from field experiments on Airbnb. *Available at SSRN 2939064* .

Hotz, V.J. and Miller, R.A. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies* 60(3):497–529.

Humlum, A. (2021). Robot adoption and labor market dynamics. *Working Paper* .

Kalouptsidi, M., Scott, P.T. and Souza-Rodrigues, E. (2021). Linear IV regression estimators for structural dynamic discrete choice models. *Journal of Econometrics* 222(1):778–804.

Koninkrijksrelaties, M.v.B.Z.e. (2015). Wet doorstroming huurmarkt 2015.

Koninkrijksrelaties, M.v.B.Z.e. (2021). Evaluatie Wet doorstroming huurmarkt 2015.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica: Journal of the Econometric Society* pp. 999–1033.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics* 125(3):1253–1296.

Scott, P.T. (2013). Dynamic discrete choice estimation of agricultural land use. *Toulouse School of Economics Working Paper* 526.

Traiberman, S. (2019). Occupations and import competition: Evidence from Denmark. *American Economic Review* 109(12):4260–4301.

Train, K.E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press.

van Perlo, B. (2011). Alle sociale huren 120 euro omhoog. *Het Parool* Section: Voorpagina.

White, M.J. (1986). Segregation and diversity measures in population distribution. *Population index* pp. 198–221.