Location Sorting and Endogenous Amenities: Evidence from Amsterdam*

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Abstract

This paper argues that the endogeneity of amenities plays a crucial role in determining the welfare distribution across a city's residents. We quantify this mechanism by constructing a dynamic model of residential choice with heterogeneous households, where consumption amenities are the equilibrium outcome of a market for non-tradables. We estimate our model using Dutch microdata and leverage variation in Amsterdam's spatial distribution of tourists as a demographic shifter, finding significant heterogeneity across residents' preferences and in the responses of amenities to demographic composition. We show that the distributional effects of mass tourism hinge on this heterogeneity: after initial rent increases due to a reduction in housing supply, younger groups—the most similar to tourists—are compensated by having amenities tilt toward their preferences, while older families are additionally hurt by this amenity shift. Finally, we show that targeted regulations on amenities dominate housing market regulations when preferences over amenities are sufficiently heterogeneous.

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1 Introduction

Socioeconomic inequality is tightly linked to residential choice, both across and within cities (Moretti, 2013). Higher socioeconomic status households can afford to live in locations with more desirable amenities. Furthermore, amenities improve as residential composition changes, reinforcing the desirability of locations. This response of a location's amenities to demographic sorting has been shown to be a quantitatively important mechanism for amplifying welfare inequality (Guerrieri, Hartley and Hurst, 2013; Diamond, 2016). However, relatively little is understood about the nature of these *endogenous amenities*, as they are typically modeled as a one-dimensional object summarizing a wide variety of a location's characteristics.

It is natural to think that different types of households have diverse tastes across different types of consumption amenities, and that the firms providing such amenities cater to this heterogeneity (George and Waldfogel, 2003). For example, when neighborhoods gentrify, the initial increase in the share of young college-educated households is typically accompanied by an increase in the presence of bars and restaurants, and a reduction in mom-and-pop stores. While providing tractability, aggregating amenities into a single index does not allow for the *horizontal* differentiation of neighborhoods on the demand side, nor for differential supply-side responses to consumer heterogeneity. Moreover, if this heterogeneity plays an important distributive role, understanding its sources is crucial to design policies that alleviate urban inequality. For example, incumbent low-income residents living in gentrifying neighborhoods may not only suffer from higher housing prices, but also from the changes in neighborhood characteristics associated with the increase in higher-income households. Therefore, in this paper, we ask: How does preference heterogeneity over many endogenous consumption amenities shape within-city residential sorting and inequality?[1]

We build and estimate a dynamic spatial equilibrium model of a city with heterogeneity in household preferences over a *bundle of endogenous amenities*, whose supply caters to each neighborhood's demographic composition. To estimate our

[1]Recent work has focused on the role that *consumption amenities* play in neighborhood change (Couture, Gaubert, Handbury and Hurst, 2021; Hoelzlein, 2020; Miyauchi, Nakajima and Redding, 2021), differentiating households along income levels. By contrast, there is extensive work showing that many other demographics play a crucial role in residential decisions (Bayer, Ferreira and McMillan, 2007; Couture and Handbury, 2020).

model, we use restricted access census microdata from the Centraal Bureau voor de Statistiek (CBS), the statistics bureau of the Netherlands. From these data, we construct an annual panel of residential location choices for the universe of residents in the Netherlands. We complement these data with an annual panel of establishment counts for the city of Amsterdam, allowing us to track consumption amenities across time and space. Apart from the availability of high-quality data, Amsterdam provides an ideal laboratory to study the link between residential composition and endogenous amenities, as it has undergone significant changes due to the impact of mass tourism on local housing and amenity markets.

We start by presenting evidence that the expansion of tourism across Amsterdam is sufficiently important to affect both housing and local amenity markets. The number of overnight tourist stays in Amsterdam went from 8 million in 2008 to nearly 16 million in 2017, while commercially operated Airbnb listings grew to nearly 10% of the city's rental stock by 2017.[2] We show that the stark increase of short-term rentals, namely Airbnb, is spatially spread all over the city, in contrast to hotels which tend to be spatially concentrated in the city center. We then proceed to show that this expansion in short-term rentals has had a significant impact on Amsterdam rent prices. We continue by showing that this expansion of tourism is correlated with changes in the composition of neighborhood amenities. While amenities catering to tourists increase all over the city, their presence is negatively correlated with amenities catering exclusively to locals, such as private daycare facilities. Next, we show that different demographic groups respond differently to these neighborhood changes through their residential choices, suggesting different valuations for the changes taking place across Amsterdam.

In our model, amenities and residential choices are equilibrium outcomes and hence simultaneously determined. Therefore, to understand the relationship between them, we model and estimate the demand and supply sides of the amenities market and embed them into a residential choice model. On the demand side, households with heterogeneous preferences over location characteristics choose where to live. Because our micro-data track the residential locations of the universe of households over time, we can build and quantify a model of forward-looking households that face moving frictions (Bayer, McMillan, Murphy and Timmins,

[2]This corresponds to 2.5% of the total housing stock. We define commercial listings as entire-home listings that operate year-round, so locals are unlikely to live in them.

2016). These dynamic considerations are important for several reasons. First, moving decisions are infrequent in the short-run, suggesting large moving frictions. Failure to account for these frictions would make agents appear to be less responsive to changes in location characteristics than they actually are, leading to biased estimates toward zero and muted welfare effects from amenity changes. Second, we provide evidence that the probability of moving to a new location decreases in the time a household has been living in its current location. We capture this behavior by allowing agents to accumulate *location capital* that is lost upon moving. Therefore, households face an inter-temporal trade-off between moving and enjoying the benefits of a new preferred location or staying put and accumulating location capital.

Our model also endogenizes the supply of amenities and the supply of housing. On the housing supply side, we model atomistic absentee landlords who supply their housing unit to locals on traditional long-term leases or to tourists on short-term leases. On the amenity supply side, we endogenize the supply of different consumption amenities through a market where non-tradable services are provided by monopolistically competitive firms. These firms cater to tourists and to different types of local residents with heterogeneous preferences.[3] Our microfoundation of amenity supply has several advantages compared to models where amenities are modelled as a one-dimensional index. First, it provides a clear interpretation of how local amenities respond to demographics. Second, it allows us to study regulations that are targeted to specific amenities. Finally, given our model of demand and supply, the market's equilibrium conditions provide the mapping between the number of firms in each amenity category and the demographic composition of a location, which includes tourists.

We estimate our dynamic location choice model by building upon the Euler Equation in Conditional Choice Probability (ECCP) methodology (Aguirregabiria and Magesan, 2013; Scott, 2013; Kalouptsidi, Scott and Souza-Rodrigues, 2021) to estimate the preference parameters over neighborhood characteristics. We use an instrumental variable approach to deal with the endogeneity of rental prices and consumption amenities. Our estimation results reveal preference parameters that correlate with demographics in a reasonable way. Specifically, all households per-

[3]By non-tradable "service", we mean a broad sector of amenities, such as restaurants, which may have different "varieties" within it, e.g. Italian or Japanese.

ceive that moving is costly, with older households having the largest frictions. In terms of amenities, households with higher socioeconomic status perceive touristic amenities as dis-amenities. Single middle-aged households without children value restaurants the most, consistent with having the most leisure time among the demographic groups. By contrast, households with children value nurseries the most. On the amenity supply side, we find that the presence of tourists creates positive incentives for the entry of all type of firms except for private day-care facilities. We also find reasonable co-location results between residents and the entry of different types of services.

Given the estimated parameters, we use the model to run counterfactuals highlighting how preference heterogeneity and the endogeneity of amenities interact to determine spatial sorting and welfare inequality. In our first counterfactual, we compare the equilibrium outcome of a world where amenities are exogenous to one in which they endogenously respond to population composition, finding a significant increase in residential sorting across demographic groups. We find that despite the increased sorting across space, welfare inequality across demographic groups can decrease if preferences are heterogeneous. Intuitively, if preferences over amenities are misaligned between two demographic groups, then they would sort into different locations. This sorting increases the supply of their most preferred amenities while also avoiding competition with each other in the housing market. Thus, there are two mechanisms reducing the welfare gap across locations when preferences are heterogeneous: tailored amenities and lower housing prices. Our findings complement the existing literature on residential sorting by introducing heterogeneity in the relationship between households and amenities, which allows us to evaluate the role of preference heterogeneity on welfare inequality.

In our second counterfactual, we evaluate the effect of Airbnb entry on residents' welfare. We disentangle the welfare effects for residents into two components: changes in rent and changes in amenities. This decomposition allows us to separate the direct effect of Airbnb entry on rent via the reduction in housing supply, from the indirect effect via the endogenous response of amenities due to the increased tourist population. The key insight behind our results is that while all residents lose from higher rents, some lose and some win from the changes in amenities due to preference heterogeneity. In particular, residents whose preferences are similar to those of tourists benefit from these endogenous amenity changes.

Finally, in our third counterfactual we compare different forms of regulating mass tourism: either through housing markets or through amenity markets. Specifically, we compare a tax on short-term rentals to a tax on touristic amenities—the least preferred for residents.[4] First, we show that the distributional impact of both types of policies hinges on preference heterogeneity: households who most value touristic amenities lose the most. Second, we find that taxing touristic amenities is preferred to taxing short-term rentals. The reasoning is that the short-term rental tax reduces the tourist population and all the amenities they bring in an untargeted manner, including the subset of amenities they bring which are actually desired by locals. By contrast, the touristic amenity tax specifically targets a source of nuisance, and in doing so, it decouples the undesirable amenities brought by tourists, such as souvenir shops, from the desirable ones, such as restaurants. This targeting is therefore especially valuable to groups which value some—but also dislike some—of the amenities tourists bring.

Related literature. Spatial equilibrium models date back to Rosen (1979) and Roback (1982) and have experienced a recent comeback as the benchmark tool to study spatial inequality across and within cities (Moretti, 2013; Diamond, 2016; Couture and Handbury, 2020). A subset of the literature focuses on the within-city margin, developing methods to quantify residential agglomeration and dispersion forces, but typically remains silent on the exact mechanisms through which specific amenities are provided (Bayer et al., 2007; Guerrieri et al., 2013; Ahlfeldt, Redding, Sturm and Wolf, 2015; Davis, Hartley, Gregory et al., 2019; Su, 2022). Recent work imposes structure on amenity provision by building upon the trade literature, but often lack heterogeneity in residents' preferences over amenities or collapse amenities into a single quality index (Couture et al., 2021; Hoelzlein, 2020; Miyauchi et al., 2021). We contribute to the literature by incorporating preference heterogeneity over amenities into a dynamic model of residential choice, where the provision of consumption amenities is microfounded through a market mechanism. We build upon the notion of "preference externalities" (George and Waldfogel, 2003; Handbury, 2021) that proposes that demand-side preference heterogeneity translates into differences in the variety of products that are supplied in equilibrium. We show how the same insights can be used to interpret neighborhoods as differen-

[4] The city of Amsterdam is implementing both policies. A lodging tax on Airbnb was introduced in 2017, while a touristic amenity tax will be introduced in 2023. See here and here for details.

tiated products where amenities play the role of endogenous product attributes, and we highlight the implications for residential sorting and urban inequality.

Our paper also contributes to the literature examining the recent rise of the short-term rental industry, as well as tourism more broadly. There is extensive reduced-form work on the effects of Airbnb entry on the housing market (Sheppard, Udell et al., 2016; Koster, Van Ommeren and Volkhausen, 2021; Garcia-López, Jofre-Monseny, Martínez-Mazza and Segú, 2020; Barron, Kung and Proserpio, 2021) as well as on hotel revenue (Zervas, Proserpio and Byers, 2017). Additionally, some papers quantify the industry's welfare impact through the lens of a structural model. Farronato and Fradkin (2018) study the effect of Airbnb entry on the competing hotels. Calder-Wang (2021) studies the distributional effects on the New York City rental market, focusing on rent effects but abstracting from amenity effects. Faber and Gaubert (2019) show the importance of tourism in the economic development of the coastline of Mexico. Finally, Allen, Fuchs, Ganapati, Graziano, Madera and Montoriol-Garriga (2021) study the effects of seasonal tourism on prices of goods and amenities borne by residents of Barcelona. We complement their work by simultaneously studying the effects of tourism on both residential and amenity markets, showing how they interact to shape urban inequality.

In terms of methodology, we use discrete-choice methods from the empirical industrial organization literature and show how they can be applied to urban residential markets (McFadden, 1974; Berry, 1994; Berry, Levinsohn and Pakes, 1995; Rust, 1987). Specifically, our 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., 2021). The method has been applied to several contexts where dynamics are first order: agricultural markets (Scott, 2013; Hsiao, 2021), occupational choice (Traiberman, 2019; Humlum, 2021), and residential choice (Diamond, McQuade and Qian, 2019; Davis et al., 2019; Davis, Gregory, Hartley and Tan, 2021).

2 Data

Individual-level data: residential histories and socioeconomic characteristics. Our restricted-access microdata comes from the statistical bureau of the Netherlands, Centraal Bureau voor de Statistiek (CBS). The key dataset for our dynamic model is the residential cadaster, which allows us to construct a panel of residential history for the universe of individuals in the Netherlands. We also observe household-level socioeconomic characteristics from tax return microdata: income, educational attainment, employment status, household composition, and ethnic background.[5] We classify households as low, medium, or high skill using educational attainment bins. Further details about how we restrict our estimation sample, which spans 2008-2020, are in Appendix A.2.1.

Housing unit data: rental prices, tax valuations, tenancy status, physical characteristics. Our restricted-access microdata includes several datasets at the housing unit level. First, we obtain property values from a panel of tax appraisal data for the universe of residential housing units for 2006-2020, which also includes geo-coordinates, quality measures, and the occupant's tenancy status (owner-occupied, rental, or social housing). Second, we obtain rental prices from a national rent survey for 2006-2019. Since the survey does not cover the universe of tenants, we impute rental prices by linking it to the tax appraisal data. We use a random forest to predict rental prices, which outperforms traditional linear hedonic models (Mullainathan and Spiess, 2017). Imputation details are in Appendix A.2.4.

Neighborhood-level data: amenities, demographics, tourist inflows. We use two levels of geographic units based on Amsterdam's administrative divisions: 99 "wijks" (neighborhoods) that belong to 25 larger "gebieds" (districts). We observe neighborhood-level outcomes at annual frequency from the publicly available Amsterdam City Data (ACD) from 2008 to 2018. This dataset contains neighborhood-level variables including sociodemographics (e.g., ethnic, income, and skill composition) as well as a rich set of consumption amenities (e.g., restaurants, bars, grocery stores). We distinguish between consumption amenities targeted to locals versus those targeted to tourists. To do so, we use ACD's definition of "touristic amenities", which encompasses lodging, passenger transport, travel agencies, and cultural and recreational retail. We also use ACD as our source for tourist inflows.[6]

Airbnb listings. We obtain Airbnb data from Inside Airbnb, an independent website that provides monthly web-scraped listings data for many cities around the

[5] Unfortunately, tax returns only include information about household income (pre- and post-tax), but not on workplace, occupations, or worked hours. For this reason, our papers focuses on outcomes in the residential market rather than the labor market.

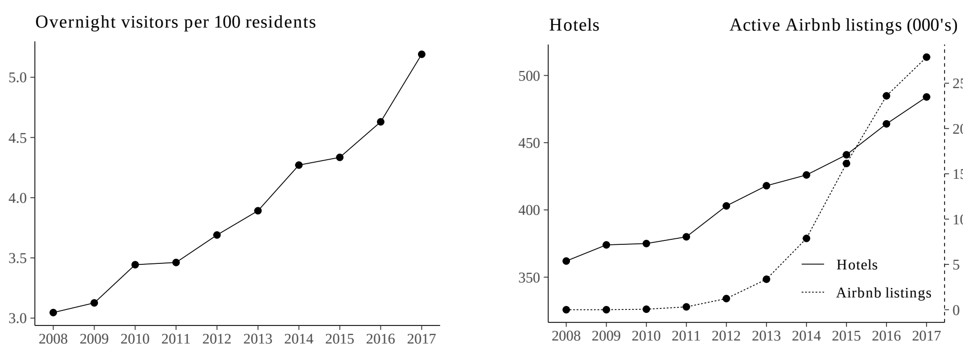
[6] The ACD wijk-level and Tourism data are publicly available at ACD BBGA and ACD Tourism.

world. Our data consist of listing-level observations with detailed information such as geographic coordinates, prices per night, calendar availability, and reviews. We use this information to separately identify "active" from "dormant" Airbnb listings, as well as to flag commercially-operated listings, those likely to be permanently rented to tourists year-round and are therefore removing housing stock away from locals. We define commercial listings as entire-home listings with sufficient booking activity. Full details of this classification are in Appendix A.2.5.

3 Stylized facts

This section presents the stylized facts that motivate our model's key features. We show how tourism volume and Airbnb penetration correlate with our outcomes of interest: rental prices, consumption amenities, and residential movements.

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

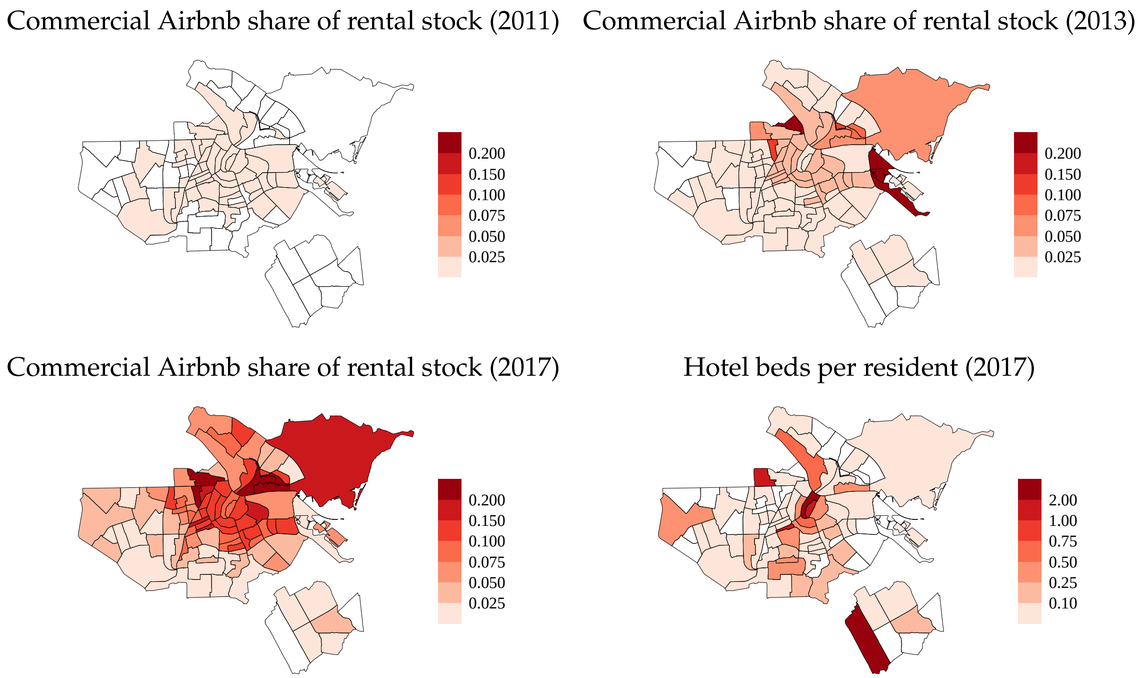


Notes: Figure shows the increase in overnight visitors and touristic lodgings (data source: ACD Tourism). Amsterdam population data is from ACD BBGA. We construct active Airbnb listings from Inside Airbnb data (procedure described in Appendix A.2.5).

Fact 1: Tourists and Airbnb listings have grown dramatically and sprawled across Amsterdam. Amsterdam has one of the highest tourist-to-local ratios in the world, slightly above Florence.[7] Figure 1 shows that between 2008 and 2017 the number of overnight visitors per resident nearly doubled, the stock of hotels grew from 362 to 484, while Airbnb listings grew from zero to over 25,000.

[7] Calculations based on 2018 tourist arrival and population data from ESTA.

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.

Figure 2 shows the spatial distribution of Airbnb has sprawled to cover most of the city. By contrast, the current distribution of hotels is concentrated in the city center. At the aggregate level, commercially-operated Airbnb listings represented 7% of Amsterdam's rental market in 2017, exceeding 20% in some central areas.[8] These trends suggest the increasing presence of tourists as part of the city's population is significant enough to alter local housing and amenity markets.

[8]Commercially-operated Airbnb listings amount to 3.2% of the market housing stock. Our definition of market housing stock excludes social housing units because they are not allocated to tenants through a market mechanism. See Appendix A.A.1 for institutional details on how social housing is allocated. For reference, home-owners, renters, and social housing represented 30%, 27%, and 42% of the total housing stock in 2017.

Table 1: Relationship between housing market outcomes and Airbnb listings

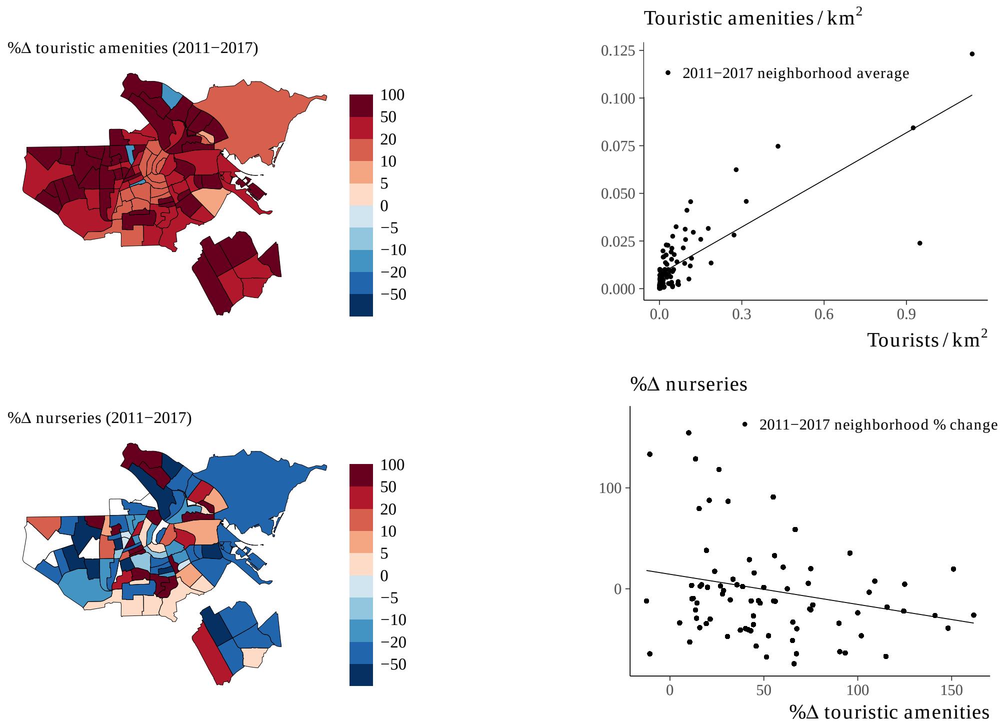
	Ln (rent/m2)			Ln (house sale value)		
	OLS	OLS	FE	OLS	OLS	FE
Ln (commercial Airbnb listings)	**0.066*****	**0.052*****	**0.115*****	**0.108*****	**0.031*****	**0.045****
	(0.008)	(0.006)	(0.018)	(0.016)	(0.006)	(0.022)
Ln (housing stock)		-0.056**	-0.111***		0.006	-0.045
		(0.027)	(0.028)		(0.027)	(0.032)
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.

Fact 2: Rents have increased more in neighborhoods with more Airbnb entry. Motivated by the heterogeneity in Airbnb growth across the city, Table 1 shows how the intensity of Airbnb penetration is correlated with housing market outcomes: a 1% increase in commercial Airbnb listings is associated with a rent increase between .06-.12%. These magnitudes are sizable given the annual growth rate of rent between 2009-2019 was 1.02%, and are mostly in line with a recent literature estimating the effect of Airbnb on housing market prices.[9] However, this literature does not typically disentangle the underlying mechanisms driving the price effects: Airbnb's direct effect of reducing housing supply is combined with indirect equilibrium effects from changing amenities and resident composition. Given that our next facts highlight significant changes in Amsterdam's amenities and resident composition, the goal of our structural model is precisely to disentangle direct and indirect effects.

[9] Barron et al. (2021) estimate an Airbnb elasticity of rent of 0.018 and Garcia-López et al. (2020) find a value of 0.0098. In Appendix section A.5.1, we show how our results compare to these studies by using a shift-share identification strategy that is similar to what is typically used in this literature.

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

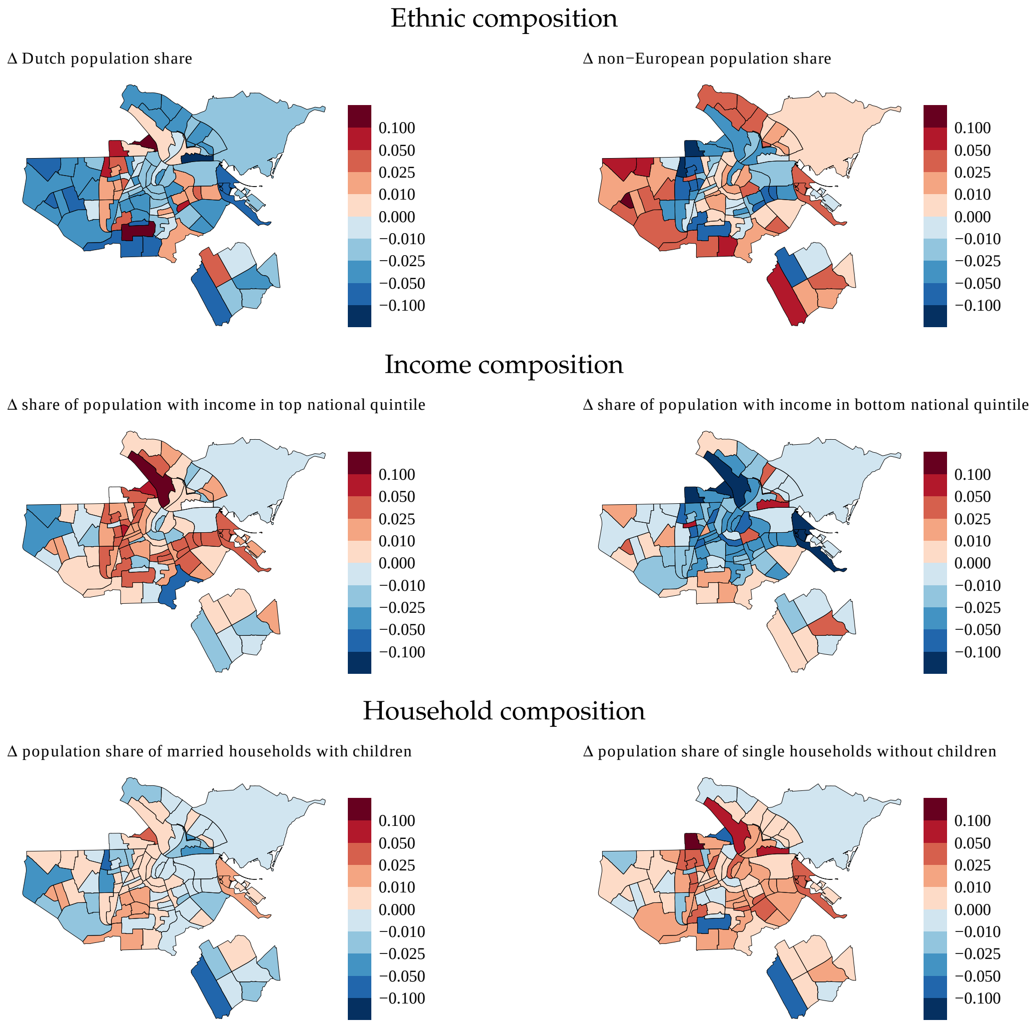


Notes: Data on neighborhood-level consumption amenities is from ACD BBGA. ACD has its own definition of "touristic amenities", which we use directly, and which encompasses lodging, passenger transport, travel agencies, and cultural and recreational retail.

Fact 3: Amenities have tilted towards tourists and away from locals. Beyond the impact of Airbnb on the housing market, the neighborhood amenities surrounding the housing units have also changed as tourists become an increasing share of the city's population. Figure 3 shows touristic amenities have grown across nearly all neighborhoods, although at different intensities, while amenities that cater exclusively to locals, such as nurseries, have declined. Furthermore, there is a negative relationship between changes in amenities targeted to locals and changes in amenities targeted to tourists. This substitution suggests heterogeneity on the demand as well on the supply side of the amenity market.

Fact 4: The composition of residents has changed heterogeneously across neighborhoods. Figure 4 shows that despite being exposed to the same city-level trends, different types of residents make different moving decisions, suggesting hetero-

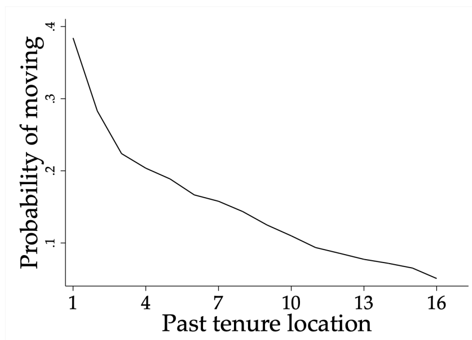
Figure 4: Changes in socioeconomic composition of neighborhoods (2011-2017).



Notes: Neighborhood-level population data comes from ACD BBGA.

geneity in the valuation of neighborhood characteristics. The top row of Figure 4 shows how moving decisions vary across ethnic groups. The clearest trend is a falling share of residents with Dutch background in most neighborhoods, except those immediately bordering the city center. While the share of immigrants with Western backgrounds has increased nearly everywhere, the share of non-European immigrants has only increased in the city's periphery and in a few central neighborhoods. In terms of heterogeneity along income, the middle row of Figure 4 shows the share of residents in the top 20% of the national income distribution has grown in central neighborhoods but not in the outskirts, indicating a rise in income inequality between the city core and periphery. Finally, the bottom row of Figure 4 shows heterogeneity along household composition: married households with children are leaving the city and are being replaced by single households without children. To summarize, the rich heterogeneity in moving decisions across households motivates rich heterogeneity in our model's demand primitives: moving costs, rent elasticities, and valuation of amenities.

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.

Fact 5: Moving frictions increase over time. The changes in neighborhood composition we have described are the result of individual moving decisions which occur infrequently and can be expected to have an important dynamic component (Bayer et al., 2016). Moreover, Figure 5 shows the hazard rate of moving is decreasing in a household's tenure at the prior residence.

This behavior can be rationalized through the inclusion of neighborhood-specific capital that accumulates over time and is lost upon moving (Diamond et al., 2019). Treated in such way, location capital creates another friction to moving beyond the standard fixed moving cost. Our structural model explicitly incorporates such dynamics by allowing for bilateral moving costs, forward-looking behavior as well as the accumulation of location capital.

4 A dynamic model of an urban rental market

Motivated by the previous facts, we build a dynamic model of a city's rental market that consists of three parts: i) heterogeneous households with dynamic moving decisions across neighborhoods, ii) landlords who can rent their units to locals or tourists, and iii) a market for amenities that microfounds how the composition of amenities endogenously responds to the composition of locals and tourists.

4.1 Endogenous amenities

Consumption amenities are classified into S sectors, each consisting of firms providing differentiated varieties. For example, if the sector is "restaurants", a firm corresponds to an individual restaurant supplying its own variety. Within each sector s and location j, there are N_{sj} firms supplying varieties in a monopolistically competitive setting with free entry. On the demand side, there are K types of consumers, each of which holds its own heterogeneous preferences over amenities.

Demand for amenities. Conditional on living in location j, a type-k household chooses how much of her budget to allocate across the locally available consumption amenities. We microfound the consumer's problem with *CES preferences over varieties within a sector* nested within *Cobb-Douglas preferences over sectors* as follows,

$$\max_{\{q^k_{isjt}\}_{is}} \quad \prod_s \left[\left(\sum_{i=1}^{N_{sjt}} {q^k_{isjt}}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha^k_s} \quad \text{s.t.} \quad \sum_{is} p_{isjt} q^k_{isjt} = I^k_t,$$

where q^k_{isjt} is the quantity of variety i in sector s and location j, p_{isjt} is the price, I^k_t is the consumer's after-rent income, α^k_s is the budget share spent on sector s, and $\sigma_s > 1$ is the elasticity of substitution across varieties within the sector. We assume all firms within a sector-location face the same costs, hence in equilibrium $p_{isjt} = p_{sjt}\ \forall i \in s, j$. The demand for a variety by each consumer type, q^k_{isjt}, and aggregate demand q_{isjt}, are respectively,

$$q^k_{isjt} = \frac{\alpha^k_s I^k_t}{p_{sjt} N_{sjt}}\ \forall i \in sj \implies q_{isjt} = \frac{\sum_k \alpha^k_s I^k_t M^k_{jt}}{p_{sjt} N_{sjt}}\ \forall i \in sj, \tag{1}$$

where M^k_{jt} is the number of type k consumers in location j. For the full derivation of the consumer problem, we refer the reader to Appendix section A.4.

Supply of amenities. Within a sector-location, marginal cost is given by c_{sjt}. Therefore, optimal prices are given by:

$$p_{isjt} = \frac{c_{sjt}}{1 - \frac{1}{\sigma_s}} \quad \forall i \in sj. \tag{2}$$

To operate in a sector-location, firms must pay a fixed cost each period,

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

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. The number of firms in a sector-location N_{sjt} is therefore endogenously determined by a zero-profit condition,

$$(p_{isjt} - c_{sjt}) q_{isjt} = F_{sjt} = \Lambda_s \Lambda_j \Lambda_t N_{jt}^{\eta} \varphi_{sjt} \quad \forall i \in sj. \tag{3}$$

Equilibrium amenities. Given all firms in a sector-location sj make the same pricing decision, the equilibrium is symmetric: $q_{isjt} = q_{sjt}$ and $p_{isjt} = p_{sjt}$ $\forall i \in sj$. Given symmetry, and substituting 1 and 2 into 3 the equilibrium number of firms in sj,

$$N_{sjt} = \frac{1}{\sigma_s F_{sjt}} \sum_k \alpha_s^k I_t^k M_{jt}^k. \tag{4}$$

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

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

The second equality above stresses the role of the amenities model: to microfound a mapping $\mathcal{A}(\cdot)$ from residential composition $[M_{jt}^1, ..., M_{jt}^K, M_{jt}^T]$ to amenities a_{jt}. We include tourists M_{jt}^T as a type of "resident" because they are a relevant group of consumers for the firms supplying the amenities.

4.2 Housing demand

Choice set. At the beginning of every period t, household i chooses a residential location j_{it} among J different locations in a city, as well as an outside option of leaving the city altogether,[10]

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

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

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

State variables. The individual-level state variables are current location j_{it} and tenure length τ_{it}. The latter is key to rationalize the decreasing hazard rate of moving (Figure 5), and evolves as,

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

where we have assumed tenure can be accumulated up to a maximum absorbing state $\bar{\tau}$. In addition to individual-level state variables, there are aggregate-level state variables: the vector of rental prices across all neighborhoods r_t, the matrices of consumption amenities a_t and other non-consumption amenities b_t, as well as factors that are unobservable to the econometrician ξ_t. To condense notation, we denote x_{it} as the vector of individual state variables and ω_t as the vector of aggregate state variables,

$$x_{it} \equiv (j_{it-1}, \tau_{it-1}) \in \mathcal{X} \quad \text{and} \quad \omega_t \equiv (r_t, a_t, b_t, \xi_t) \in \Omega.$$

We denote with subscript t the functions that depend on the aggregate state ω_t, in particular the flow utility function and the value function,

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

[10] For simplicity, we assume that homeowners and renters face the same discrete choice problem. Concretely, homeowners are absentee landlords renting to themselves. Under this assumption, it is easy to compute the overall welfare of homeowners by adding up renters' consumer surplus to rental income in our counterfactual simulations.

Flow utility. Preference parameters differ by household type. The flow payoff for a household i of type k living in location j is a function of the individual i's state, x_{it}, location characteristics ω_{jt}, and location and time fixed effects, δ_j^k and δ_t^k:

$$u_t^k(j, x_{it}) = \delta_j^k + \delta_t^k + \delta_r^k \log r_{jt} + \delta_a^k \log a_{jt} + \delta_b^k \log b_{jt} + \delta_\tau^k \log \tau_{it} - MC^k(j, j_{it-1}) + \xi_{jt}^k, \tag{5}$$

which is micro-founded by the amenity demand system (see Appendix A.4).

Value function. Household i's value function is defined as,

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

where ϵ_{idt} is a type I EV idiosyncratic shock and the maximization is taken over policy functions $D : \mathcal{X} \times \Omega \times \mathbb{R}^J \to \{0, 1, ..., J\}$. Given the recursive nature of the problem, we can write,

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

Demand for each location. The probability a type k household in state x_{it} chooses location j is,

$$\mathbb{P}_t^k(j|x_{it}) = \frac{\exp\left(u_t^k(j, x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j, x_{it}, \epsilon_{it} \right] \right)}{\sum_{j'} \exp\left(u_t^k(j', x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j', x_{it}, \epsilon_{it} \right] \right)}. \tag{6}$$

Demand from all type k households for location j is,

$$\mathcal{D}_{jt}^{Lk} = \sum_x \mathbb{P}_t^k(j|s) M_{xt}^k Q_{xt}^k,$$

where M_{xt}^k is the number of households of type k with individual state x at time t and Q_{xt}^k is the demanded quantity of housing.[11] Total demand for location j is

[11] Following our microfoundation in Section A.4, we know that $Q_{xt}^{D,k} = \frac{(1-\phi^k) w_t^k}{r_{jt}}$, where $(1 - \phi^k)$ is housing expenditure shares that we compute using our microdata.

obtained by summing over all household types,

$$\mathcal{D}^L_{jt} = \sum_k \sum_x \mathbb{P}^k_t(j|s) M^k_{xt} Q^{D,k}_{xt}. \tag{7}$$

Evolution of population distribution. We denote $\pi^k_t(j,\tau)$ as a type-k household's probability of living in location j with tenure τ, conditional on the aggregate state at time t. Denote Π^k_t as the transition matrix across individual states, i.e., $\pi^k_{t+1} = \Pi^k_t \pi^k_t$, where each (j,τ) cell evolves as,

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

Stationary distribution. We denote $\Pi^k(\mathbf{r},\mathbf{a})$ as the transition matrix of type k households across individual states (j,τ), conditional on the aggregate state (the vectors of rental prices $\mathbf{r}$ and amenities $\mathbf{a}$) . A stationary distribution over individual states, $\pi^k(\mathbf{r},\mathbf{a})$, is therefore defined as $\pi^k(\mathbf{r},\mathbf{a}) = \Pi^k(\mathbf{r},\mathbf{a})\pi^k(\mathbf{r},\mathbf{a})$.

4.3 Housing supply

We denote by $\mathcal{H}_{jt}$ the total stock of housing (in units of floor space) in location j and year t. We assume that total housing stock is exogenous and determined outside our model. However, we endogeneize how $\mathcal{H}_{jt}$ is split between the long-term rental market (which caters to locals) and the short-term rental market (which caters to tourists) through the following landlord's problem.

Landlord problem. Absentee landlords make a binary choice between renting their unit in the long-term market (L) or in the short-term market (S).[12] Each unit has a given floor space of f_j square meters. The income obtained from long-term rentals is r_{jt}, and from short-term rentals is p_{jt}. In order to capture different matching and managerial costs involved in renting short- versus long-term, we allow for

[12] We can also allow for an outside option, that is, leaving the house empty. However, the number of empty houses in Amsterdam is essentially zero due to regulations that prevent housing units from being vacant for extended periods of time. See amsterdam.nl/en/housing/obligation-homeowner/ for more details.

a wedge in landlords' operating costs κ_{jt}, which is unobservable to the econometrician. The landlord's problem is therefore,

$$\max \left\{ \alpha r_{jt} + \epsilon_L, \quad \alpha p_{jt} - \kappa_{jt} + \epsilon_S \right\},$$

where α is the landlord's marginal utility of income and ϵ_L and ϵ_S are type I EV shocks.

Supply of housing at each location. The share of the housing stock allocated to the long- and short-term rental markets are,

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

4.4 Equilibrium

Our equilibrium definition departs slightly from standard definitions because we not only require market clearing in the housing market, but also in the market for consumption amenities.

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. a policy function $h(r_j, p_j; \kappa_j, \epsilon_l)$ for landlords,
3. a policy function $j^k(j_i, \tau_i, \mathbf{r}, \mathbf{a}; \epsilon_i)$ for each type k household,
4. a stationary distribution of types over locations and tenure, $\pi^k(\mathbf{r}, \mathbf{a})$

such that,

1. each landlord l supplies housing optimally to locals or tourists by choosing $h(r_j, p_j; \kappa_j, \epsilon_l)$. Long- and short-term rental supply in location j are,[13]

$$\mathcal{H}_j^L(r_j, p_j; \kappa_j) = \frac{\exp(\alpha r_j)}{\exp(\alpha r_j) + \exp(\alpha p_j - \kappa_j)} \mathcal{H}_j \quad \text{and} \quad \mathcal{H}_j^S(r_j, p_j; \kappa_j) = \mathcal{H}_j - \mathcal{H}_j^L(r_j, p_j; \kappa_j).$$

[13]Our assumption of a fixed total housing stock $\mathcal{H}_j$ implies short-term rental supply is determined as a residual from long-term rental supply.

2. each household i of type k demands housing optimally by choosing $j^k(j_i, \tau_i, \mathbf{r}, \mathbf{a}; \epsilon_i)$, so that demand for long-term rentals in location j is,

$$\mathcal{Q}_j^{D,L}(\mathbf{r}, \mathbf{a}) = \sum_k M^k \sum_\tau \left[\pi^k(\mathbf{r}, \mathbf{a}) Q_{j,\tau}^{D,k}(\mathbf{r})\right]_{j,\tau}$$

where M^k is the city-wide population of group k.

3. rental prices $\mathbf{r}$ clear the long-term rental market,[14]

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

4. equilibrium amenities are determined by the local composition of residents through the mapping $\mathcal{A}(\cdot)$, as microfounded by the amenities model,

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

where the total number of tourists M_j^T is the sum of tourists in hotels M_j^{HT} and tourists in short-term rentals $M_j^{ST} = \chi_j \mathcal{H}_j^S(r_j, p_j; \kappa_j)$, where χ_j is the mean number of tourists per rental unit in j. We take M_j^{HT} as exogeneous but endogenize M_j^{ST} through landlord's decisions.

Proof of equilibrium existence is in Appendix A.4.1. We discuss the issue of multiplicity of equilibria in Appendix A.6.2.

5 Estimation

Using the data described in Section 2, we construct an annual panel of location choices for 2008-2020 and an annual panel of location characteristics for 2008-2018.

5.1 Defining household heterogeneity

We first classify households into three categories based on modal tenancy status: homeowners, private market renters, and social housing renters. This ex-ante classification step is motivated by the fact that the average household belongs to its modal category more than 90% of the time, which suggests this margin of adjustment is minor in our context. It is also useful for several reasons. First, it allows

[14]Equilibrium short-term rental quantities are fully pinned down by supply (tourist demand is perfectly elastic at a vector of exogenously determined short-term prices $\mathbf{p}$).

us to abstract away from the homeownership decision. Second, it also allow us to cleanly and separately quantify welfare effects on homeowners and renters in our welfare analysis. Therefore, in what follows, we assume household tenancy status is determined outside our model and constant over time.

After the first classification step, we classify households into "types" using a k-means algorithm on demographics. Existing studies typically classify households into ex-ante groups based on observable demographics, such as race or income (Bayer et al., 2016; Davis et al., 2019). When defining such groups the practitioner faces a variance-bias trade-off. On the one hand, having more groups can capture more heterogeneity, but on the other hand there are fewer observations to estimate choice probabilities, which may lead to noisy estimates. The k-means approach allows us to solve this trade-off in a data-driven manner by reducing the dimension of observed characteristics through exploiting correlations across observables.[15] This dimensionality reduction is particularly useful when there is a large set of observable characteristics, as in our case. Moreover, the method admits heuristics to pin down the optimal number of groups. Further details are in Appendix A.5.2.

Results. Table 2 shows the household types that result from our classification algorithm, along with summary statistics of their average characteristics. We have given each group a label based on how prominent their demographic characteristics are. For example the "Student" group is characterized by being the youngest and low income. Overall, we consider the groups to be easily distinguishable in terms of age, income, skill level, ethnicity, and household composition.

5.2 Amenities

From equation 4, we derive our empirical model of amenity supply,

$$\log N_{sjt} = \lambda_j + \lambda_t + \eta \log N_{jt} + \log \left(\sum_k \beta_s^k X_{jt}^k \right) + \phi_{sjt}, \tag{8}$$

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, η is the congestion force in the commercial real estate market, λ_j and λ_t are location- and time-invariant compo-

[15]A clear example is income and skill: income is highly correlated with skill, so a classification including both dimensions separately may be redundant.

Table 2: Summary Statistics by Household Type

Group	Homeowners		Renters		Social Housing Tenants	
	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.

nents of firm entry costs, and ϕ_{sjt} captures any remaining unobservable cost.[16] Our main objects of interest are β_s^k and η, which we infer from the correlation between amenity composition, N_{sjt}, and residential composition, X_{jt}^k.

Identification. The main identification problem in identifying β_s^k from 8 is simultaneity. For a given location, the distribution of amenity expenditures by household 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}. Hence, any unobservable firm entry cost ϕ_{sjt} affecting N_{sjt} will be correlated with

[16]More precisely, to get from 4 to 8, we define $X_{jt}^k \equiv I_t^k M_{jt}^k$, where I_t^k is expenditure on total consumption amenities by a type k household and M_{jt}^k is the population of type k households. Under our micro-foundation in Appendix A.4, $I_t^k = \phi^k w_t^k$, where ϕ^k is the expenditure share on total consumption amenities and w_t^k is disposable income, both of which are directly observed in our data. Finally, we define $\lambda_j \equiv -\log \Lambda_j$, $\lambda_t \equiv -\log \Lambda_t$, $\phi_{sjt} \equiv -\log \varphi_{sjt}$, and $\beta_s^k \equiv \alpha_s^k / (\sigma_s \Lambda_s)$.

X_{jt}^k in equilibrium. Because ϕ_{sjt} is an amenity supply shock, we focus on instruments that are arguably an amenity demand shock. Following this intuition, we compute the total number of available units by tenancy status τ in location j, S_{jt}^{τ}, from the tax valuation registry and use those counts as shifters of the number of households by type k. We finally interact the wages of group k with their corresponding tenancy status counts to construct the following instruments:

$$Z_{jt}^k = w_t^k S_{jt}^{\tau(k)}.$$

The intuition behind our relevance condition is simple. Two identical neighborhoods with more social housing units should be home to more households that qualify for social housing assistance and, therefore, a larger total expenditure on amenities from this groups. A similar argument follow from other tenancy types, owner- and renter-occupied units. Similarly, if group k has higher income, we should expect higher total expenditures in amenity consumption. Because we are incorporating time fixed effects, our exclusion restriction only requires that the tenancy status counts are uncorrelated with unobservable entry costs:

$$\mathbb{E}[S_{jt}^{\tau(k)} \phi_{sjt} | \lambda_j, \lambda_t] = 0.$$

The previous exclusion restriction would be violated if changes in firm entry costs are correlated with changes in the composition of the housing stock. For example, neighborhoods with a higher presence of owner-occupied units could be more likely to impose local zoning restrictions on services.

We calibrate η following Eckert, Ganapati and Walsh (2020), who also estimate an endogenous entry cost. After the appropriate transformations, we set $\eta = -0.33$. We calibrate this parameter for two reasons. First, the model in equation 8 contains location j and time t fixed effects. When regressing $\log N_{jt}$ on those fixed effects, we obtain an $R^2 = 0.99$, so there is virtually no remaining variation to identify η. Second, the variable N_{jt} is also endogenous by construction as $N_{jt} = \sum_s N_{sjt}$, so the estimation of η would require an additional instrument.[17]

[17] For robustness, we also run a model with only time fixed effects, λ_t, and setting the instrument for N_{jt} as the number of non-residential units. We find $\eta = -0.11$, which is in line with the range of estimates derived from Eckert et al. (2020), [-0.33, -0.15], after appropriate transformations. We prefer a model that includes location fixed effects because it can capture important attributes that are constant over time but vary across locations, such as land-use restrictions or zoning regulations.

Implementation and results. We choose six consumption amenities: Touristic Amenities, Restaurants, Café Bars, Food Stores, Non-food Stores, and Nurseries.[18] We simultaneously estimate the parameters in equation 8 for all amenities.[19] To do so, we interact each of our instruments with a dummy variable for each amenity s, $Z^k_{sjt} = \mathbb{1}_s Z^k_{jt}$ to construct the following moment conditions,

$$\mathbb{E}\left[g^{sk}(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\right] = \mathbb{E}\left[Z^k_{sjt}\phi_{sjt}\right] = 0.$$

We identify fixed effects from the following moment conditions:

$$\mathbb{E}\left[g^{j}(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\right] = \mathbb{E}\left[\lambda_j\phi_{sjt}\right] = 0, \quad \text{and} \quad \mathbb{E}\left[g^{t}(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\right] = \mathbb{E}\left[\lambda_t\phi_{sjt}\right] = 0.$$

We stack all these moments together to form a final vector of moment conditions:

$$\mathbb{E}\left[g(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\right] = \mathbb{E}[Z_{sjt}\phi_{sjt}] = 0.$$

To ensure our optimization problem is well-defined, we impose the structural conditions that $\beta^k_s \geqslant 0$ so that $\log\left(\sum_k \beta^k_s X^k_{jt}\right)$ always exists. Concretely, we solve for the following constrained optimization problem:

$$\max_{\lambda_j, \lambda_t, \beta^k_s} \hat{g}(\lambda_j, \lambda_t, \beta^k_s)'_{sjt}\hat{W}\hat{g}(\lambda_j, \lambda_t, \beta^k_s)_{sjt} \quad \text{s.t. } \beta^k_s \geqslant 0 \;\; \forall s, k,$$

where $\hat{W} = (Z_{sjt}Z_{sjt}')^{-1}$. Because many of our estimates lie on the the boundary, $\hat{\beta}^k_s = 0$, standard inference does not apply. Therefore, we construct standard errors via a Bayesian bootstrap procedure using random weighting (Shao and Tu, 2012). Results are shown on Table 3.

Our estimates generally align with expected differences in consumption pat-

[18]For the first five amenities, we observe the number of establishments. However, for Nurseries we observe the number of available seats in a given location. We assume that the number of seats is constant across nursery establishments. Café bars in Amsterdam should not be confused with coffee shops. In the former, it is very common to order coffee, tea, or alcoholic beverages. The latter is meant for the consumption of cannabis products.

[19]Observe that the model is not fully identified. First, the full set of dummies corresponding to λ_j and λ_t is collinear. To avoid this collinearity, we set $\lambda_{j=1} = 0$. Second, observe that for any given c, the set of parameters

$$\tilde{\beta}^k_s = c\beta^k_c \quad \text{and} \quad \tilde{\lambda_t} = \lambda_t - c$$

is observationally equivalent. To avoid this issue, we normalize $\lambda_{t=T} = 0$.

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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

terns across demographic groups. First, Tourists have a positive and significant parameter for all consumption amenities except Nurseries. In terms of economic magnitudes, at the average neighborhood, increasing the number of tourists by one standard deviation, equal to a 250% increase, would increase the number of firms providing Touristic Amenities by 52%.[20] Second, Singles, Students and Tourists have the largest estimates for Touristic Amenities, although only significant for the last two groups. Similarly, incentives to enter for Restaurants is highest in the presence of Students and Tourists. Finally, only the three groups of families show positive estimates on Nurseries, and are significant for the first two.

5.3 Housing demand

We estimate household preference parameters using the "Euler Equations in Conditional Choice Probabilities" (ECCP) estimator, building on Aguirregabiria and Mira (2010), Scott (2013), and Kalouptsidi et al. (2021). The method allows us to recover parameters *without* solving value functions and without the need to spec-

[20]Because equation 8 is not linear, the effects depend on the point at which they are evaluated.

ify beliefs, thus reducing computational burden. In what follows, we describe the assumptions required for the estimation procedure.

Assumptions. We assume the state variables $\{x, \omega, \epsilon\}$ follow a Markov process, along with the following standard assumptions:

1. **Atomistic agents:** the market-level state ω evolves according to a Markov process that is unaffected by individual-level decisions j or states $\{x, \epsilon\}$,
$$p(\omega'|j, x, \omega, \epsilon) = p(\omega'|\omega).$$
2. **Conditional independence:** the transition density for the Markov process factors as,
$$p(x', \omega', \epsilon'|j, x, \omega, \epsilon) = p_x(x'|j, x, \omega)p_\omega(\omega'|\omega)p_\epsilon(\epsilon').$$
3. **Payoff to the outside option:** The flow payoff of living outside the city, excluding location capital, moving costs, and common time components, is normalized to zero:[21]
$$\delta_0^k + \delta_r^k \log r_{0t} + \delta_a^k \log a_{0t} + \delta_b^k \log b_{0t} + \xi_{0t}^k = 0.$$

The ECCP estimator is a two-step estimator. First, conditional choice probabilities (CCP) are estimated directly from the data. For this first stage, we predict CCPs using a multinomial logit that exploits information about the conditional state. We show in Appendix S.1.0.2 that this approach reduces the finite sample bias relative to a non-parametric approach that estimates CCPs using frequency estimators. Second, the CCPs are plugged into a regression equation that relates differences in the likelihood of two different paths to differences in their flow payoffs. To that end, we first introduce the concept of renewal actions.

Renewal actions. Two paths of actions are said to exhibit *finite dependence* if after a finite number of periods, the distribution of future states is the same (Arcidiacono

[21]This last assumption allows us to pin down utility levels, as in logit models adding a constant to all choices lead to the same probability. In other words, we can only identify differences in utility $\delta_j^k - \delta_{j'}^k$. Following a similar argument, utility components that are common across all choices for a given year t, captured by δ_t^k, cannot be identified. In what follows, we interpret δ_j^k as the time invariant component of group k utility for location j relative to the outside option.

and Miller, 2011). In our model, finite dependence appears whenever two households living in different initial locations, j and j', choose to move to the same new location $\tilde{j}$. We call such an action a *renewal action*, because the location tenure is reset, and hence the distribution of future states is the same for both households. Because expectations of future payoffs are unobservable to the econometrician, a key difficulty in estimating dynamic models is disentangling variation in current payoffs from continuation values. Renewal actions separate these two components by equalizing continuation values, thus leaving differences in choice probabilities being solely a function of differences in per-period payoffs.

Concretely, let $\tau(j, j_{t-1}, \tau_{t-1})$ be the function that maps action j and state $x_t = \left(j_{t-1}, \tau_{t-1}\right)$ to current location capital. Consider the following path represented by Figure 6: let j and j' denote actions chosen at state $x_t = \left(j_{t-1}, \tau_{t-1}\right)$, reaching states $x_{t+1} = \left(j, \tau(j, j_{t-1}, \tau_{t-1})\right)$ and $x'_{t+1} = \left(j', \tau(j', j_{t-1}, \tau_{t-1})\right)$, respectively, and let $\tilde{j}$ be a renewal action chosen at time $t+1$.

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

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

From such a path we can derive our main regression equation,

$$\begin{aligned}
Y^k_{t,j,j',\tilde{j},x_t} = \; & u^k_t\left(j, x_t\right) - u^k_t\left(j', x_t\right) + \beta\left[u^k_t\left(\tilde{j}, x_{t+1}\right) - u^k_t\left(\tilde{j}, x'_{t+1}\right)\right] + \tilde{v}^k_{t,j,j',x_t} \\
\text{where,} \quad Y^k_{t,j,j',\tilde{j},x_t} \equiv \; & \log\left(\frac{\mathbb{P}^k_t(j, x_t)}{\mathbb{P}^k_t(j', x_t)}\right) + \beta \log\left(\frac{\mathbb{P}^k_{t+1}\left(\tilde{j}, x_{t+1}\right)}{\mathbb{P}^k_{t+1}\left(\tilde{j}, x'_{t+1}\right)}\right). \qquad (9)
\end{aligned}$$

On the left hand side, $Y^k_{t,j,j',\tilde{j},x_t}$ is the likelihood of path $\{x_t, x_{t+1}\}$ relative to path $\{x_t, x'_{t+1}\}$. On the right hand side, we have differences in flow payoffs for the two periods in which the paths diverge, as well as an expectational error $\tilde{v}^k_{t,j,j',x_t}$. The key observation is that at time $t+1$, when two agents of the same type k choose the renewal action $\tilde{j}$, they both move to the same individual state and hence their future expected payoffs are the same. Therefore, the value functions from each path cancel each other out at $t+1$. Equation 9 conveys that intuition: differences in the likelihood of path $\left(j_{t-1}, j, \tilde{j}\right)$ relative to path $\left(j_{t-1}, j', \tilde{j}\right)$ are explained solely by differences in utility flows and not in terms of expectations. Finally, if we choose $j' = 0$, substitute the functional form for flow utility into 9, and impose assumption 4, we obtain the parameterized version of our regression equation,

$$Y^k_{t,j,\tilde{j},x_{it}} = \delta^k_j + \delta^k_t + \delta^k_r \log r_{jt} + \delta^k_a \log a_{jt} + \delta^k_b \log b_{jt} + \delta^k_\tau \Delta\tau_{it} - \Delta MC^k_{it} + \tilde{\xi}^k_{t,j,x_{it}}, \tag{10}$$

where,

$$\begin{aligned}
\Delta\tau_{it} &\equiv \tau'(j, x_{it}) - \tau'(0, x_{it}), \\
\Delta MC^k_{it} &\equiv \left[MC^k(j, j_{it-1}) - MC^k(0, j_{it-1})\right] - \beta \left[MC^k(\tilde{j}, j) - MC^k(\tilde{j}, 0)\right],
\end{aligned}$$

and the last term is the sum of the unobservable time-varying location quality and an expectational error, $\tilde{\xi}^k_{t,j,x_{it}} = \xi^k_{jt} + \tilde{v}^k_{t,j,x_{it}}$.

Implementation. In practice, neighborhoods in our empirical application are defined as districts ("gebied"), of which there are 22 across Amsterdam.[22] We also define the outside option as any location outside Amsterdam. Our final location choice panel covers 2008 to 2020. We define our market as households that have been observed living in Amsterdam at least once between 2008 and 2020. We set our discount value β equal to 0.85 (De Groote and Verboven, 2019; Diamond et al., 2019). We discretize the location tenure space similar to Rust (1987). To keep the number of states low, we define two buckets of location capital corresponding to less than three years of tenure or more than four. Appendix A.5.4 shows the technical details of how to deal with such discretization of the state space. Overall, each group has a total of 46 states per year (23 past locations times two location capital states). We focus on the first three groups – Older Families, Single Households, and Younger Families—and abstract away from the location decisions of the last three groups—Students and both groups in social housing.[23] The reason for excluding Students is motivated by evidence that suggests that the housing market for students looks substantially different from the traditional housing market.[24] On the

[22]In 2020, there are 25 districts. However, we combine three districts at the border of the city with their closest district because they have few households living in them.

[23]Even though we do not endogenize the location choice of these groups, we still keep them as part of the locations' demographic composition as they represent a big part of the population.

[24]Amsterdam is a city with many college students. Some universities offer their own housing options but those tend to be limited. There are multiple popular websites

other hand, houses in the social segment of the market are not allocated through a market but through a centralized application wait list. Hence, we are unable to infer their preferences without further information.

Identification. First, the vector of neighborhood characteristics b_{jt} beyond rent and amenities contains the log of the average apartment size in square meters and the log of social housing units. We assume that the structural error $\tilde{\xi}^k_{t,j,x_{it}}$ is orthogonal to these housing characteristics, location fixed effects, tenure and moving costs:

$$\mathbb{E}\left[\tilde{\xi}^k_{t,j,x_{it}} | \delta^k_t, \delta^k_j, \log b_{jt}, \Delta\tau_{it}, \Delta MC^k_{it}\right] = 0 \ \forall k.$$

On the other hand, our equilibrium definition implies that the structural shocks $\tilde{\xi}^k_{t,j,x_{it}}$ are correlated with neighborhood prices r_{jt} and amenities a_{jt}. More generally, we may expect unobservable neighborhood trends, such as gentrification, to correlate with prices, amenities, and moving decisions. Therefore, we construct a vector of instruments, Z_{jt}, and estimate the demand parameters via two-step optimal GMM with the following moment conditions:[25]

$$\mathbb{E}\left[Z_{jt}\tilde{\xi}^k_{t,j,x_{it}}\right] = 0 \ \forall k.$$

Observe that under rational expectations, it follows that

$$\mathbb{E}\left[Z_{jt}\tilde{v}^k_{t,j,x_{it}} | \delta_j, \log b_{jt}, \Delta\tau_{it}, \Delta MC^k_{it}\right] = 0 \ \forall k,$$

as $\mathbb{E}[\tilde{v}^k_{t,j,x_{it}} | \mathcal{I}_t] = 0$ for all j, t, and x_{it}, where $\mathcal{I}_t$ is the set of variables that have been realized at time t or before. Therefore, it suffices to find instruments that are orthogonal to unobservable demand shocks:

$$\mathbb{E}\left[Z_{jt}\tilde{\xi}^k_{t,j,x_{it}} | \delta_j, \log b_{jt}, \Delta\tau_{it}, \Delta MC^k_{it}\right] = 0 \ \forall i, k, j, t.$$

For that reason, we consider Z_{jt} that can be interpreted as supply shocks. Because we have six amenities, we construct seven instruments in total. Three of those instruments are Bartik-type shocks that leverage three policy changes that can be effectively treated as supply shocks to the tenancy composition of the housing stock.

that function as student-specific platforms. Due to the tightness in the housing market, the municipality of Amsterdam recommends securing accommodation well in advance. See https://www.iamsterdam.com/en/study/steps-to-study-in-amsterdam/finding-housing-in-amsterdam.

[25] With A amenities, we need $A + 1$ number of instruments.

Concretely, new regulations on the rental market were introduced in 2011, 2015, and 2017 that changed the incentives of landlord and housing associations to supply their unit as social housing, a private market unit, or as a short-term rental, respectively. For full details, see Appendix A.1 for the institutional context and Appendix A.1.3 for details on the policy changes. To introduce spatial variation, we interact a dummy that turns one after the introduction of the policy and the log of the units in the housing market segment affected by the shock in the previous year. Additional instruments are the log number of housing units that are demolished inside the location j as well as outside the precinct, which we also interpret as supply shocks.[26] Finally, we follow Bayer et al. (2007) and construct two more instruments by using variation in changes of social housing units and the average apartment size in other areas of the city outside the precinct. Using these instruments, we find that the first stage regression of a 2SLS estimation has an F-stat of 139.1. See Appendix A.5.4 for full details on the demand estimation procedure.

Results. Table 4 shows estimates of preference over neighborhood characteristics, moving costs, and location capital for our main three groups. Overall, our results align with expected differences across demographics.

All groups exhibit that moving is costly with Older Families having the highest moving costs. All households derive positive utility from the accumulation of location capital. Estimates for rent are negative throughout, as is to be expected. Older families with children are the most sensitive to rent. In terms of amenities, the first two groups perceive a negative payoff from Touristic Amenities. In terms of economic magnitude, these two groups are willing to pay 0.1% and 0.2% more in rent to avoid a 1% increase in Touristic Amenities respectively.[27] Restaurants show a positive and significant coefficient for Singles, with a willingness to pay of 0.3% more in rent for a 1% in the number of firms offering that service, but they are not significant for the rest of the groups. Café Bars show a negative and significant coefficient for the first two groups. Non-food stores are positively valued by all groups. Finally, Nurseries are positive and significant for the two groups of families and are willing to increase their rent by roughly 0.14% for a 1% increase

[26] A precinct (stadsdeel) is a larger geographical unit containing districts (gebied). There are seven of them in Amsterdam.

[27] Willingness to pay of group k for amenity a is computed as the ratio $-\frac{\delta_a^k}{\delta_r^k}$.

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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in the number of childcare facilities.

5.4 Housing supply

Our estimating equation for the supply of long- relative to short-term units is,

$$\log s^L_{jt} - \log s^S_{jt} = \alpha \left(r_{jt} - p_{jt} \right) + \kappa_j + \kappa_t + \nu_{jt},$$

where we have parameterized the operating cost wedge κ_{jt} into location- and time-fixed effects, and ν_{jt} stands for any remaining unobservables varying at the jt level.

Instruments. OLS estimation leads to classic simultaneity bias from effectively regressing prices on quantities. The solution is an instrument that shifts relative demand for short- versus long-term units. We use predicted tourist demand from a shift-share research design: the "shift" part of the instrument exploits time variation in worldwide demand for Airbnb as proxied by online search volume (Barron et al., 2021), while the "share" part constructs neighborhood-level exposure to the shift from the historic spatial distribution of touristic attractions. The relevance condition is straightforward: higher demand from tourists raises short- relative to long-term rental prices. The exclusion restriction holds as long as changes in the predicted tourist demand is uncorrelated with cost shock changes affecting landlord's decisions. We claim that the historical nature of our shift components makes this assumption plausible, as historical monuments that were established decades and centuries ago are unlikely to be correlated with landlord's current costs.

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

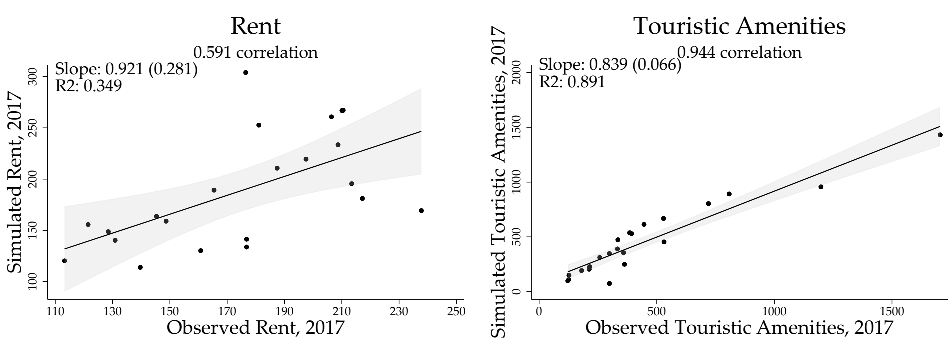
Notes: The table reports estimates of landlords' marginal utility of income for a discrete choice model between the short- and long-term rental markets. Data are a panel with 92 locations 2015-2017. Prices are instrumented using a "shift-share" instrument (Barron et al., 2021) that proxies for demand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

Results. Table 5 presents our estimates for α, the landlord's marginal utility of income, which are fairly stable across specifications. OLS estimates are downward-biased, as expected with simultaneity bias. Our preferred specification is the instrumental variable regression with two-way fixed effects.[28] In terms of economic significance, one standard deviation increase between Airbnb prices and long-term rental prices at the average neighborhood, a 28% increase, would increase the market share of the short-term relative to the long-term segment by 23%.

5.5 Model fit

In this section, we show how our model fits the data and simulate a steady-state equilibrium for 2017. We assume that agents have perfect foresight. We find our equilibrium using a nested fixed-point algorithm outlined in Section A.4.2. We take our preferred housing supply estimate from Section 5.4 and calibrate the landlords' differential costs to match the number of Airbnb tourists in each location in 2017. Further details are in Section A.6.1. Figure 7 plots the simulated endogenous objects—rents and amenities—against the observed objects in the data. Recall that while we use rent and amenity variation, we are not directly targeting the fit of our simulated vectors against the observed vectors in our estimation.

Figure 7: Model fit.



Notes: The figure presents scatter plots, linear fit, and 95% confidence intervals of the simulated objects, rents and touristic amenities, against the observed objects. We simulate our dynamic model of residential choice for Amsterdam in 2017 using the estimated parameters in Section 5 and using the nested fixed-point algorithm outlined in Section A.4.2. We omit the remaining endogenous amenities for the ease of exposition, but those can be found in Section 4.

There are several reasons why our simulated economy may differ from the observed data. First, we assume that 2017 is in steady state and that people have

[28]We believe that the lack of significance arises from little within-neighborhood variation due to only three years of data. Reassuringly, the estimates across specifications appear rather stable.

perfect foresight, which is not necessarily true in the data.[29] Second, there could be estimation error. Third, the model can be mis-specified. However, despite these possible sources of divergence, we generally see that our simulated equilibrium is able to reproduce the observed equilibrium with high precision. We take these results as evidence that our model, estimated parameters, and equilibrium assumptions are a good approximation of the economic forces present in the real world.

6 Counterfactuals

In this section, we quantify the importance of different model components, such as preference heterogeneity, and evaluate the welfare implications of different counterfactual scenarios. In general, we focus on renter's consumer surplus (CS), in log wages, and measure welfare changes for type k as her *Consumption Equivalent*, CE^k. Concretely, we define CE^k as the monetary compensation required to leave a type-k household on the same ex-ante utility level as the baseline scenario.[30]

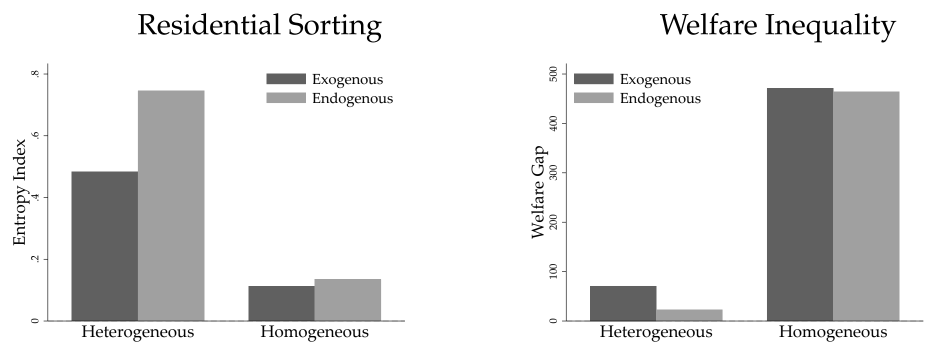
6.1 Role of preference heterogeneity for sorting and inequality

We first evaluate how preference heterogeneity interacts with the endogeneity of amenities to determine spatial sorting and welfare inequality. We solve the model using our estimated parameters and compare equilibrium outcomes with exogenous amenities to those with endogenous amenities. We repeat this exercise under the assumption that households hold the same preferences over amenities.

[29] Observe that our estimation method does not impose any of these assumptions.

[30] A positive CE^k means that the average type-k household is worse off in the counterfactual relative to the baseline scenario and vice versa. See Appendix A.6.4 for details on welfare measures.

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.

Table 6: Neighborhood differentiation as spatial dispersion of amenities

	Homogeneous preferences			Heterogeneous preferences		
Amenity	Exogenous	Endogenous	Δ	Exogenous	Endogenous	Δ
Touristic amenities	0.38	0.44	0.06	0.38	0.38	0
Restaurants	0.54	0.54	0	0.54	0.53	-0.01
Bars	0.66	0.65	-0.02	0.66	0.67	0.01
Food stores	0.46	0.47	0.01	0.46	0.51	0.05
Non-food stores	0.58	0.56	-0.01	0.58	0.65	0.07
Nurseries	0.29	0.43	0.14	0.29	0.49	0.2

Notes: Columns labelled "Exogenous" and "Endogenous" report the Gini index (across neighborhoods) for each characteristic. "Δ" reports the difference between these two columns. Positive values imply that the spatial distribution of characteristic becomes more unequal.

The left panel of Figure 8 shows residential sorting increases when amenities are endogenous, and more so when preferences are heterogeneous. The right panel of Figure 8 shows that despite the increased sorting across space, welfare inequality across household types can *decrease* when amenities are endogenous, especially if preferences are heterogeneous. The intuition is that heterogeneous preferences lead to more sorting, and as a result neighborhoods become more differentiated in terms of their amenities. Concretely, Table 6 shows the spatial distribution of almost every amenity becomes more concentrated. Differences in preferences over amenities implies household types do not compete with each other for the same locations, thus keeping rental prices low while obtaining their preferred amenities.

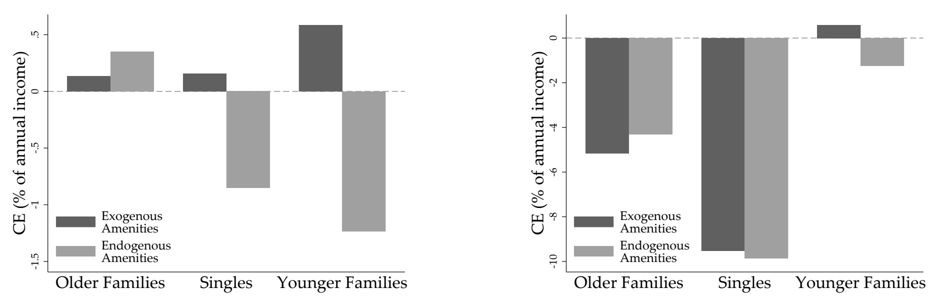
6.2 Decomposing welfare effects of the short-term rental industry

Next, we use our model to evaluate the effect of short-term rental entry on welfare as measured by renter's surplus. We model this entry as a landlord's cost reduction of renting in the short-term market, due to a better technology to match with guests. Our goal is to disentangle the welfare effects for residents into two components: changes in rent and changes in amenities. This decomposition allows us to separate changes in rent due to the direct effect, through the reduction in housing supply, from the indirect effect, through the amenity adjustment due to the increased tourist population. To separate these effects, we run a restricted version of the counterfactual where amenities are kept exogenously fixed at baseline. The key insight behind our results is that, while all residents lose from higher rent, some lose and some win from the changes in amenities due to preference heterogeneity.

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

Renters

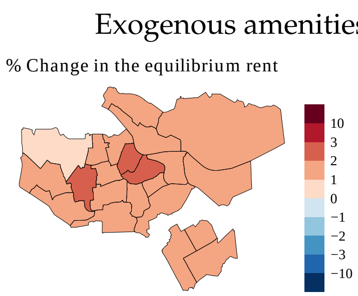
Homeowners



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 rebateing 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.

Our main results are presented in Figure 9, which reports welfare effects in consumption equivalent terms: how much extra income a household must be given in the counterfactual with short-term rentals in order to be just as well off as in the baseline equilibrium without them. The dark grey bars in Panel (a) of Figure 9 show by how much each household needs to be compensated in the exogenous amenities counterfactual. Every household loses because Airbnb entry reduces housing supply and raises rents, as shown in the left panel of Figure 10. However, the effects are regressive: Older Families, which are predominantly Dutch and higher-income, lose the least. Younger Families, which tend to be poorer and of immigrant background, lose the most. Hence, by only taking into account rent effects, we would conclude that the entry of short-term rentals increases inequality.

Figure 10: Rent changes under exogenous and endogenous amenities

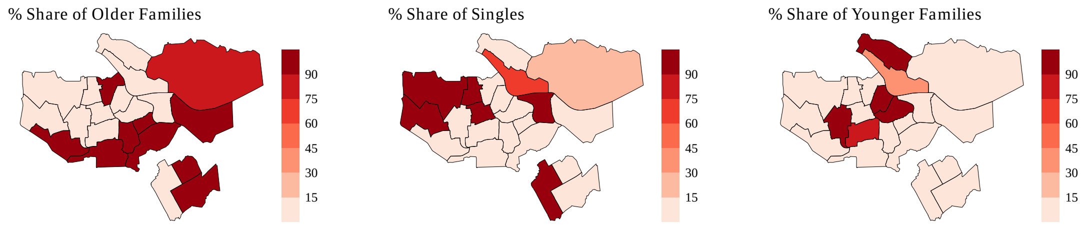


Notes: The figures show the percentage change in a neighborhood's equilibrium rent when we simulate short-term rental entry, for the case of exogenous and endogenous amenities. In both cases, we fix the baseline amenities levels to the no-Airbnb endogenous equilibrium levels.

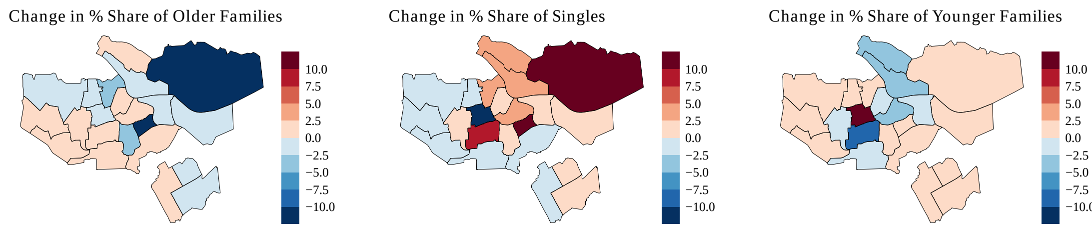
The light grey bars in Figure 9 Panel (a) show the welfare effects when amenities are allowed to endogenously respond to residential composition. Older Families lose more than when amenities were exogenous because on top of facing higher rent they also lose the amenities they value most. Singles and Younger Families now obtain welfare gains because they face an increase in the amenities they like, and this is large enough to outweigh the welfare losses from higher rent. Thus, as we move from exogenous to endogenous amenities our qualitative results are reversed: the entry of short-term rentals now *reduces* welfare inequality.

So far, we have discussed welfare as renter surplus, ignoring whether households gain from an increase in rental income as homeowners. We now relax this restriction by considering the Older Families and Singles to be homeowners while keeping Younger Families as renters. We adjust our simulations by having homeowners pay rent as before, but receiving it back as a lump sum transfer (see Appendix A.6.4 for details). Panel (b) of Figure 9 shows that homeowners now gain from Airbnb entry. As expected, the entry of short-term rentals increases inequality between homeowners and renters mostly driven by gains in rental income.

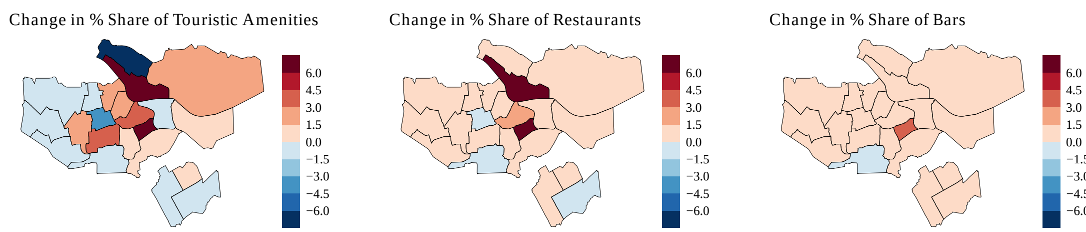
Figure 11: Spatial distribution at baseline and after short-term rental entry



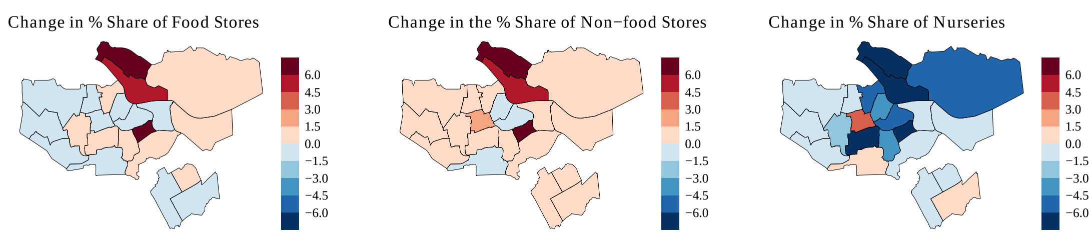
(a) Baseline population distribution with endogenous amenities



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



(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.

Figure 11 shows residential movements and amenity changes. The top row shows that in the baseline equilibrium with endogenous amenities, Older Families tend to live in the south/eastern districts, Singles live mostly in western districts, and Younger Families live in central-western districts. The second row shows that after Airbnb entry, the Older Families leave the center-south, Singles leave the west and move towards the center, and Younger Families move west of the center. The third and fourth rows show that these location changes are correlated with amenity changes. Older Families especially leave districts where there is a decline in nurseries (the amenity they value most) and an increase in touristic amenities, which they dislike the most. Hence, on top of higher rent, Older Families lose the amenities they value most in these districts. Singles move to the south-central districts, where there is an increase in the amenities they value most (restaurants and non-food stores). Finally, Younger Families move slightly west, where there is an increase in non-food stores and nurseries, both of which they value.

6.3 Policy implications for targeting of amenities

Section 6.2 highlights the importance of preference heterogeneity when evaluating the distributional incidence of shocks to the residential market. In this section, we consider normative implications for policies in both housing and amenity markets.

Concretely, we leverage the micro-foundation of our amenity market and compare a tax on short-term rentals to a tax on touristic amenities. The short-term rental tax is a housing policy: its main goal is to increase the housing supply available for locals and improve welfare through more affordable rent. However, it may also have indirect equilibrium effects on amenities via the reduction in the tourist population and re-sorting of locals. In particular, it reduces all types of amenities tourists bring, some of which may be valued by locals. By contrast, the tax on touristic amenities is an amenity-market policy: it targets specifically the amenities locals dislike without altering the remaining beneficial amenities. It may also indirectly affect the housing market by changing residents' valuation of locations.[31]

Figure 13 compares the welfare levels across household types for a range of tax rates. Older Families and Singles gain from both policies, with effects increasing in the tax rate. The opposite pattern holds for Younger Families. This contrasting result is because the first two types dislike touristic amenities, while Younger Families enjoy them. Observe that the gap between the two types of taxes is not

[31] Models with a single amenity cannot evaluate the effects of a tax targeted to a specific service.

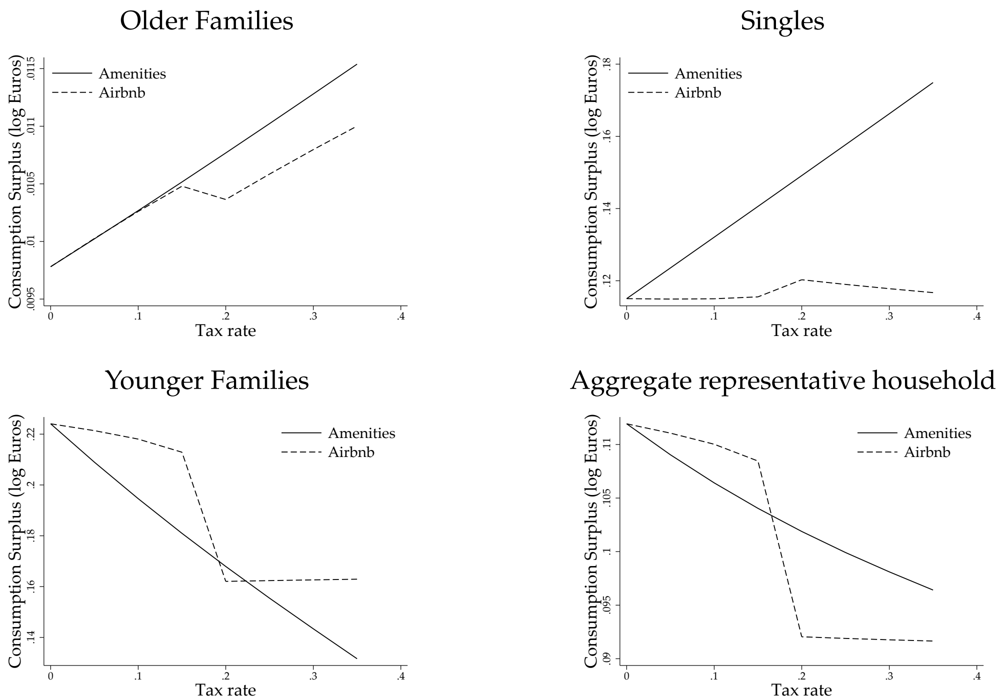
the same across household types. For Singles, the amenity-tax leaves them much better off than the short-term rental tax, but less so for Older Families. The reason is that although Singles dislike touristic amenities, they enjoy other amenities that tourists bring, such as restaurants. Because the amenity-tax specifically targets touristic amenities, it decouples the undesirable amenities from the desirable ones. By contrast, the short-term rental tax reduces the tourist population and all the amenities that come with them in an un-targeted manner. On the other hand, Older Families mainly value Nurseries, which tourists do not bring. Hence, for Older Families there is little welfare gain from differentially targeting the amenities brought by tourists, because all such amenities are relatively undesirable for them. Thus, a short-term rental tax delivers relatively similar welfare gains to a touristic amenity tax for them. To conclude, the desirability of regulating the housing market versus the amenity market hinges on household's preference heterogeneity. Concretely, the welfare gains from targeting amenities are larger when households hold very heterogeneous tastes across the various amenities tourists bring, because it allows policymakers to specifically target the source of nuisance.

7 Discussion

While our model is rich along many dimensions—dynamic location choices, heterogeneity in demand for neighborhoods and in the endogenous supply of differentiated amenities—it is tailored to answer a specific set of research questions while remaining silent on others. In this section, we discuss the limitations of our analysis and suggest potential extensions for future work.

Unified labor market. Our model assumes households obtain their income from a city-wide integrated labor market rather than neighborhood-level labor markets. We consider this assumption reasonable for a city as compact as Amsterdam (less than 10 km at its widest) and with first-world public transport infrastructure (which has not experienced major changes during our sample period). Furthermore, our microdata do not specify occupation nor work location, which prevents us from incorporating labor markets into our model in a more explicit way. In that sense, our main goal is to emphasize the role that housing and amenity markets play for spatial inequality, focusing on location choice within a city and abstracting away from employment opportunities as major drivers of location choice.

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.

Effects of tourism on the labor market. We have leveraged Amsterdam's tourism boom as a demand shifter in housing and amenity markets to quantify the distributional effects on residents in their role as consumers. However, tourism may also affect residents by creating employment opportunities (Faber and Gaubert, 2019). If tourism raises wages mostly in non-tradable service sectors, typically employing lower-skilled workers, then it could have a progressive effect that might counterbalance regressive effects in housing and amenity markets. In a unified labor market, we would expect a tourism shock to create a uniform rise in tourism sector wages across the city, but not to have differential effects across neighborhoods. As mentioned in the prior paragraph, we only observe wage trends for the household types used in our welfare analysis, which we reassuringly find to be mostly flat during our sample period.[32,33]

Consuming amenities outside the residential location. We assume consumers can only access amenities from the location in which they live in. This assumption can be relaxed by allowing for commuting across locations. However, an empirical application would require data on consumption trips across neighborhoods, which we do not have for Amsterdam. To the extent smartphone-based evidence from other cities indeed confirms urban residents tend to consume amenities located near their home (Miyauchi et al., 2021; Allen et al., 2021), our qualitative insights should not significantly change since our mechanisms ultimately depend on amenity consumption choices being correlated with residential location.

8 Conclusion

In this paper, we study the role of preference heterogeneity over a set of endogenous location amenities in shaping within-city sorting and welfare inequality. To do so, we build a model of residential choice where heterogeneous, forward-looking households consume a set of amenities provided by firms in a market for non-tradable services. We leverage increasing tourism flows and the spatial variation in the entry of short-term rentals in Amsterdam as events that shift the demographic composition of neighborhoods, and thus alter local amenities.

First, we show tourism flows and the entry of short-term rental platforms have led to a significant impact on rents, amenities, and within-city migration in Amsterdam. Second, to rationalize our findings, disentangle different mechanisms, and conduct policy counterfactuals, we build a dynamic spatial equilibrium model of a city's rental market with heterogeneous forward-looking households, and show how to estimate it using tools from the empirical industrial organization literature. We endogenize and microfound housing supply through landlords' decisions to rent to locals on traditional leases or full-time to tourists through the short-term rental market. Furthermore, in contrast to most work that collapses amenities into a one-dimensional quality index, we also microfound how different consumption amenities arise in each neighborhood as an equilibrium outcome of a market where

[32] See Appendix A.1.2. The tourist sector has a moderate employment share—around 11%— in the city of Amsterdam. Financial services and the public sector are bulk of the city's employment.

[33] The omission of a labor market does not affect our estimation exercise, which relies on across-neighborhood variation under the assumption of a city-wide unified labor market.

firms supplying amenities cater to households that demand them through their perception of neighborhoods as horizontally differentiated products.

We estimate our three-part model borrowing tools from the empirical industrial organization literature. On the housing supply side, we find that landlords respond positively to monetary incentives. On the demand side, we estimate location preferences, finding substantial heterogeneity across households in their utility parameter that correlates in a reasonable way with sociodemographic status. Finally, the structural parameters of amenity supply indicate important differences in how different services respond to changes in their location demographics.

Armed with our estimated parameters, we explore the role of endogenous amenities in shaping within-city inequality. We find this endogeneity reinforces sorting but has ambiguous effects on welfare inequality. Concretely, the welfare effects depend on how similar preferences for amenities are across groups, with the welfare gap increasing between households whose preferences are substantially aligned and vice versa. In quantifying the welfare effects followed by Airbnb entry, we find that while all residents lose from higher rent, some lose and some win from the changes in amenities due to preference heterogeneity, in particular how their preferences are correlated with those of tourists. Finally, we use our model to compare different forms of regulating mass tourism: taxing short-term rentals or taxing touristic amenities. We show that taxing amenities dominates taxing short-term rentals when the preferences of locals are sufficiently heterogeneous over the amenities tourists bring. In cases of wide heterogeneity, the targeted feature of a tax on touristic amenities is especially welfare-enhancing because it decouples the undesirable amenities brought by tourists from the desirable ones.

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