Location Sorting and Endogenous Amenities: Evidence from Amsterdam*

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October 19, 2021

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Abstract

This paper argues the endogeneity of amenities plays a crucial role for the welfare distribution of a city's residents by reinforcing location sorting. We quantify this channel by leveraging spatial variation in tourism flows and the entry of home-sharing platforms, such as Airbnb, as shifters of location characteristics to estimate a dynamic model of residential choice. In our model, consumption amenities in each location are the equilibrium outcome of a market for services, which are supplied by firms and demanded by heterogeneous households. We estimate the model using detailed Dutch microdata, which allows us to track the universe of Amsterdam's residents over time and the evolution of a rich set of neighborhood amenities. Our results indicate significant heterogeneity across households in their valuation of different amenities, as well as in the response of amenities to demographic composition. We show that allowing for this endogenous response increases inequality between demographic groups whose preferences are closely aligned, but decreases it if substantially misaligned, suggesting heterogeneity in the two-way mapping between households and amenities plays a crucial distributive role. Finally, we highlight the distributional implications of our estimates by evaluating currently debated policies, such as price and quantity regulations in housing markets.

*We thank Christopher Flinn, Guillaume Fréchette, Alessandro Lizzeri, Elena Manresa, Tobias Salz, Paul Scott, and Sharon Traiberman for their guidance and support throughout this project. We also owe special thanks to Claudia Allende, Donald Davis, Michael Gilraine, Jessie Handbury, Pedro Mira, Martin Rotemberg, Lászlo Tétényi, and Daniel Waldinger for conversations that have substantially improved our paper. Finally, we thank participants at NYU's Applied Microeconomics Seminar, Econometrics Seminar, Stern IO Workshop, and Student IO Reading Group, as well as conference participants at Columbia, LSE, the FRB of Philadelphia, Washington University in St. Louis, and Universidad Torcuato Di Tella for their comments and suggestions. We gratefully acknowledge financial support from the C.V. Starr Center for Applied Economics. Any errors or omissions are our own.

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1 Introduction

The past decade has seen an increased interest in the spatial dimensions of inequality and its determinants. Recent work has argued these spatial disparities are driven by increased sorting of different types of workers into locations that differ in their employment opportunities. Moreover, part of the literature has focused on the endogenous response of a location's amenities to its demographics and its consequences for inequality through the reinforcement of residential sorting.[1]

Endogenous amenities are typically modeled as a one-dimensional object summarizing a wide variety of locally provided services. While providing tractability, this simplification does not allow locations to be horizontally differentiated in terms of their amenities. By contrast, allowing households to have heterogeneous preferences over a *set* of amenities and each amenity to respond to location demographics in its own way leads to richer sorting patterns than what the literature has found. In this paper, we ask: How does this two-way heterogeneity shape within-city residential sorting and inequality? To do so, we build and estimate a spatial equilibrium model of a city with household preference *heterogeneity* over a *bundle of amenities*, whose supply responds differentially to changes in neighborhood demographics.

To estimate our model, we exploit the substantial increase and spatial variation in tourism flows and the entry of short-term rental platforms in the city of our empirical application, Amsterdam. For our structural estimation, we complement our data on tourism, and short-term rental listings with restricted access microdata from the Centraal Bureau voor de Statistiek (CBS), the statistics bureau of the Netherlands. These data allows us to track the universe of residents in the Netherlands at every point in time, with which we construct a yearly panel of location choices for the universe of residents in the Netherlands. We also obtain data of yearly income and demographics by linking households to their annual tax returns. Using tax appraisal data from the universe of housing units in the Netherlands we are able to identify key housing characteristics as well as whether their occupants are homeowners or renters. We finally complement these data with a yearly panel of establishment counts for different type of services in the city of Amsterdam, that allows us to track changes in amenities over time and across space.

[1]See Moretti (2013), Diamond (2016), Baum-Snow and Hartley (2016), Couture and Handbury (2017), and Couture, Gaubert, Handbury and Hurst (2019).

We present reduced-form evidence that the expansion of tourism across Amsterdam is sufficiently important to affect housing markets and local amenities.[2] We start by linking web scraped Airbnb data to zipcode-level variables of interest from the Amsterdam city council's public database, and present evidence on how tourism volume co-varies with amenities and demographic composition over time and space. Next, to quantify the effect of short-term rentals on zipcode-level outcomes, we estimate a set of reduced-form models by leveraging shift-share instruments. We show Airbnb entry is a large enough shock to shift housing prices in Amsterdam. We find a 1% increase in commercially operated listings leads to a 0.111% increase in rent by square meter, which accounts for 12% of the average annual rent by square meter growth between 2008-2019. Similarly, a 10% increase in commercial listings leads to a 0.393% increase in house prices, accounting for 8.2% of the average growth in transaction values between 2008 and 2019.

The major obstacle in quantifying the effects of endogenous amenities on within-city inequality is that both amenities and residential choices are equilibrium outcomes and thus are simultaneously determined. To understand this relationship between residential choices and amenities, we build and estimate a dynamic model of the residential market, where amenities are the equilibrium outcome of a market for services, and heterogeneous forward-looking households choose where to live each period. The dynamic behavior of households should be taken into account for two reasons. First, the persistence in location decisions suggests the presence of moving costs. Failure to account for this dynamic behavior by estimating a static model would make agents appear to be less responsive to changes in location characteristics than they actually are, leading to biased estimates toward zero. Second, when households choose a location they form expectations about the evolution of amenities and prices in each locations. A consequence of such a dynamic model is that shocks to the city have very different effects if households perceive them as temporary as opposed to permanent, a feature that static models fail to capture.

In addition to fixed location characteristics, we model two types of endogenous amenities that vary over time: direct congestion effects from tourists and indirect effects through the market for different consumption amenities. To the best of our knowledge, existing work only models the

[2] The number of overnight stays in Amsterdam went from 8 million in 2008 to nearly 16 million in 2017, corresponding to 3 and 6 overnight stays per resident. In Amsterdam, commercially operated Airbnb listings grew to nearly 10% of the city's rental stock in 2017 (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.

endogenous supply of amenities as a one-dimensional function of a location's demographic composition. Instead, we contribute to the urban economics literature by providing a microfoundation for this mapping in a multi-dimensional case. Concretely, we endogenize different consumption amenities through a market where services are provided by monopolistically competitive firms and demanded by agents with heterogeneous preferences.[3] As a result, the market's equilibrium conditions provide the mapping between the number of firms in each service category and the demographic composition of a location, which includes tourists. Thus, markets supply different products as a function of the demographic composition of their consumers (Waldfogel, 1999; George and Waldfogel, 2003; Waldfogel, 2009). The purpose of this micro-foundation is two-fold. First, it provides a clear interpretation of how local amenities depend on demographics. Second, and most importantly, modeling amenities in this multidimensional way allows us to recover service-specific parameters, such as different operating costs. Hence, we can perform counterfactual simulations to study service-specific interventions, such as the zoning of certain consumption amenities.

Finally, in our model, absentee landlords supply their housing unit either to locals on traditional long-term leases or to tourists on short-term leases. We assume landlords are atomistic and do not internalize the fact that tourists create externalities that are borne by residents. More importantly, despite the total housing stock being fixed and inelastic, the option to rent short term to tourists endogenizes housing supply available for *locals*.

For our structural estimation, we build upon the Euler Equation in Conditional Choice Probability (ECCP) methodology borrowing tools from the empirical industrial organization literature (Aguirregabiria and Magesan, 2013; Scott, 2013; Kalouptsidi, Scott and Souza-Rodrigues, 2018). We also contribute to this literature in two ways. First, we introduce a new method to smooth conditional choice probabilities (CCP), which amounts to Bayesian smoothing with data-driven priors. Monte Carlo simulations show using our technique reduces the bias in the estimates of preference parameters caused by CCP measurement error by more than 50%. Lastly, one of the main empirical challenges in the estimation of residential demand is the presence of confounding unobservable factors. We employ a new identification strategy that combines the ECCP method-

[3] By "service", we mean a broad sector of amenities, such as restaurants, which may have different "varieties" within it. For example, Italian and Japanese restaurants would be different varieties within the restaurant service.

ology with Arellano-Bond instruments (Arellano and Bond, 1991) to construct a set of instruments whose statistical validity can be tested in the data.

Given the estimated parameters, we first evaluate the sorting and welfare consequences of the endogeneity of amenities. We compare the equilibrium outcome of a world where location characteristics are exogenous to one in which they endogenously respond to population composition, finding a significant increase in residential sorting across demographic groups. We find this increase in sorting leads to an increase in the welfare gap between demographic groups whose preferences for location characteristics are sufficiently aligned and a decrease for groups whose valuations are sufficiently misaligned. Intuitively, if preferences are misaligned between two groups, these groups sort into different locations, raising the supply of their most preferred amenities. Moreover, because amenities respond to demographics and preferences are misaligned, demand from the group in the other location decreases because amenities are tilting away from them, translating into lower prices. Thus, there are two effects reducing the welfare gap across locations when preferences are misaligned: each group obtains its preferred amenities and also faces lower housing prices. Our findings complement the existing literature on residential sorting by introducing heterogeneity in the two-way relationship between households and amenities, which allows us to explain richer patterns in the effects that endogenous amenities have on welfare inequality. We continue by evaluating policies that are currently being implemented across the world to regulate tourism and its effects on the housing market through the short-term rental industry.[4] First, we consider the most common policy regulation for short-term rentals: a lodging tax that is levied on the nightly rate that tourists pay. Second, we consider quantity regulations in the form of night caps: restrictions on how many nights per year a short-term rental host is allowed to book. This policy began to be implemented in Amsterdam in 2017, with enforcement being carried out directly from the Airbnb platform itself. Our counterfactual simulations show that this second policy generates larger welfare gains for the most disadvantaged groups, thus playing a greater redistributive role than the lodging tax.

The paper is organized as follows. Section 2 describes how this paper contributes to the existing literature. Section 3 describes our data. Section 4 presents the empirical evidence. Sections 5-6 present our model and estimation method. Section 7 describes our counterfactuals. Section 8

[4]Source: The Economist (October 27, 2018)

concludes.

2 Related literature

Spatial equilibrium models date back to Rosen (1979) and Roback (1982) and have experienced a recent comeback to address public finance questions concerning location sorting and inequality across cities (Moretti, 2013; Diamond, 2016). Although both employment opportunities and amenities are key determinants of residential choices across cities, we focus on within-city movements, thus abstracting away from labor market channels. Given that all households have access to the same labor market, observed location choices are driven by preferences for location characteristics rather than employment opportunities. In this way, we argue that we separate the two channels and explicitly focus on the identification of household preferences. An extensive literature studies within-city sorting (Bayer, McMillan and Rueben, 2004; Guerrieri, Hartley and Hurst, 2013; Ahlfeldt, Redding, Sturm and Wolf, 2015; Bayer, McMillan, Murphy and Timmins, 2016; Diamond, 2016; Davis, Gregory and Hartley, 2018) and delivers a tractable framework for quantifying residential agglomeration and dispersion forces, but is silent on the exact mechanisms that drive changes in endogenous amenities. To the best of our knowledge, only Couture et al. (2019) uses a similar micro-foundation of amenities by building on models from the trade literature, but with a one-dimensional amenity and households with homogeneous preferences. Another strand of the literature has documented how consumers with heterogeneous preferences show different spatial patterns of consumption (Davis, Dingel, Monras and Morales, 2019) and how such heterogeneity shapes the variety of products available in a market (Waldfogel, 1999; George and Waldfogel, 2003; Waldfogel, 2009). We add to both strands of this literature by constructing a micro-foundation of amenities, where the preference heterogeneity of local consumers shapes the composition of local amenities.

Our dynamic discrete-choice modeling approach has been previously used in the literature to estimate preferences for locations. Bayer et al. (2016) is the first paper that estimates a dynamic model of residential choice with heterogeneous preferences over price, racial composition, pollution, and crime rate. More recently, Davis, Hartley, Gregory and Tan (2017), Davis et al. (2018), and Diamond, McQuade and Qian (2018) estimate a dynamic discrete choice model of location choice to evaluate the effects of housing vouchers, low-income housing, and rent controls, respectively. More concretely, Davis et al. (2018) also include households that value endogenous characteristics, such as the share of black households and the share of low-income households. We add to their work by adding a market of endogenous consumption amenities that are valued by residents when making residential decisions.

In terms of methodology, our model borrows from the dynamic discrete-choice framework in the empirical industrial organization literature (Hotz and Miller, 1993; Arcidiacono and Miller, 2011; Aguirregabiria and Magesan, 2013; Scott, 2013; Kalouptsidi et al., 2018), which has been applied to several contexts where dynamics are first order, such as irreversible investment, occupational choice, and residential choice (Scott, 2013; Traiberman, 2018; Diamond et al., 2018). We add to this literature with a novel smoothing of the CCPs that are estimated in the first stage, and a new identification strategy in the presence of unobservable confounders that combines the ECCP methodology with Arellano-Bond instruments.

Finally, several recent papers examine the effects of short-term rentals and tourism. Zervas, Proserpio and Byers (2017) estimate the impact of Airbnb entry on the Texan hotel industry by using a difference-in-differences strategy, finding the impact on hotel revenue is in the -8% to -10% range, affecting low-end hotels most. Sheppard, Udell et al. (2016), Koster, van Ommeren and Volkhausen (2018), Barron, Kung and Proserpio (2018), and Garcia-López, Jofre-Monseny, Martínez-Mazza and Segú (2020) estimate the impact of Airbnb entry on housing prices in New York City, Los Angeles, the United States, and Barcelona, respectively, using different identification strategies. Farronato and Fradkin (2018) is the first paper that takes a structural approach to study the effect of Airbnb entry on the hospitality industry, showing that short-term rentals can flexibly expand supply when hotels become capacity constrained when demand peaks, thus keeping hotel prices low. However, they are silent on the effects on local residents through the housing or amenities channel, which seems to be a central concern for policymakers, especially in the European context. We complement their work by studying the effects on residents' welfare using a structural model of a city's housing market. Faber and Gaubert (2019) study the spillovers of tourism on manufacturing using a structural approach. By contrast, we contribute to this literature by studying the effects of tourism on the residential market. Finally, Calder-Wang (2019) presents a nuanced analysis of the distributional impact of Airbnb on New York City residents, focusing on welfare effects that operate through rental prices. We complement her work by studying welfare effects that arise from changes in neighborhood characteristics beyond prices.

3 Data

Individual-level residential histories and socioeconomic characteristics

Our restricted-access microdata comes from the Centraal Bureau voor de Statistiek (CBS), the statistics bureau of the Netherlands. The key dataset for our dynamic residential choice model is the residential cadaster, which allows us to construct a panel of residential movements for the universe of individuals in the Netherlands.[5] We obtain socioeconomic characteristics of these individuals from tax return microdata.[6]

Housing unit characteristics, sale prices, and rental prices

Our restricted-access microdata also includes various datasets at the housing unit level, which we use to obtain sale prices and rental prices. First, we obtain property values from an annual panel of the universe of individual housing units with tax appraisals, as well as geo-coordinates, quality measures, and the occupant's tenancy status (owner-occupied, rental, or social housing). Second, we complement the tax appraisal values with sale prices from a dataset on the universe of house sale transactions. Third, we obtain rent data from a national rent survey. Since the survey does not cover the universe of tenants, we link it to the universal tax appraisal data and use the matched subset to impute rents for the housing units that do not appear in the rent survey. Our imputation uses two different imputation methods: a hedonic linear model and a random forest. The latter outperforms the classical linear hedonic approach as also found by Mullainathan and Spiess (2017) when predicting house values with different econometric methods. For rental prices, we find an out-of-sample R^2 of 0.617 and 0.743 for linear regression and random forest respectively. For rental

[5] Residential choice data at annual frequency and with universal coverage are rare. Decadal census data is often used to estimate static models (Diamond, 2016), while dynamic models use higher frequency data but usually focus on a restricted sample of individuals. For example, Bayer et al. (2016) work with a subset of home-owners and infer location choices from house transactions, whereas Davis et al. (2017, 2018) and Diamond et al. (2018) obtain non-governmental data from companies that purchase data from third parties or scrape public records.

[6] Unfortunately, tax returns only allow us to observe pre-tax and after-tax household income. We do not have data on work locations nor on the specific occupations of the household members.

prices by square meter we find an out-of-sample R^2 of 0.566 and 0.736 for linear regression and random forest respectively. Imputation details are in Appendix B.2.

Neighborhood-level outcomes

Our definition of a neighborhood is a "wijk" (there are 99 wijks in Amsterdam). We use publicly available data from Amsterdam City Data (ACD) at the wijk-level and at annual frequency to measure neighborhood-level outcomes over time.[7] The data contains over 700 neighborhood-level variables including sociodemographics (e.g., ethnic, income, and skill composition) as well as a rich set of publicly provided amenities (e.g., schools, hospitals, commuting access, green areas), non-market amenities (e.g., traffic and noise congestion, tourist congestion, crime, street cleanliness), and private-consumption amenities (e.g., bars, restaurants, hotels, tourist-oriented businesses). We also use ACD as our source for tourism data.[8]

Airbnb listings

We obtain Airbnb listings data from Inside Airbnb, a non-commercial, independent website that provides monthly web-scraped listings data for a host of cities around the world. Our web scrapes consist of listing-level observations with detailed information such as geographic coordinates, host identifiers, prices per night, calendar availability, and reviews. We define commercially operated listings as entire-home listings with sufficient booking activity such that a household cannot plausibly be living there permanently. Details of how we flag such listings are in Appendix B.

[7] The ACD data is publicly available at data.amsterdam.nl/datasets.

[8] All tourism reports are available at data.amsterdam.nl/dossiers/dossier/toerisme.

4 Stylized facts

In this section we present the stylized facts that motivate our model's key features. In particular, we show how tourism volume and Airbnb penetration correlate with our outcomes of interest: rents, house prices, consumption amenities, and residential movements.

Fact 1: Tourism flows and Airbnb listings have grown dramatically in Amsterdam

Amsterdam has one of the highest tourist-to-local ratios in the world, slightly above Florence and below Venice.[9] Figure 1 shows that the number of overnight visitors per resident nearly doubled between 2008-2017. To accommodate tourist inflows, the stock of hotels grew from 362 to 484, while Airbnb listings grew from zero in 2008 to over 25,000 in 2017.

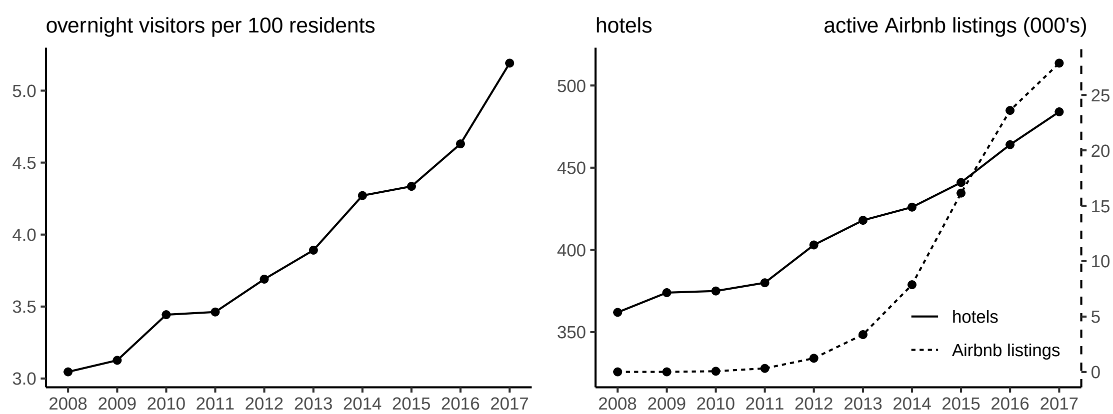


Figure 1: Tourists per resident, number of hotels, and active Airbnb listings.

Fact 2: The spatial distribution of Airbnb listings differs from that of traditional hotels

Airbnb listings are available in every neighborhood, while hotels are concentrated in the city center, partly due to zoning regulations. Figures 2 and 3 show how the spatial distribution of hotels and Airbnb has evolved. By 2017, commercially-operated Airbnb listings represented 5% of the rental stock in most neighborhoods, and over 20% in central areas.

[9] Own calculation based on 2018 tourist arrival and population data from ESTA.

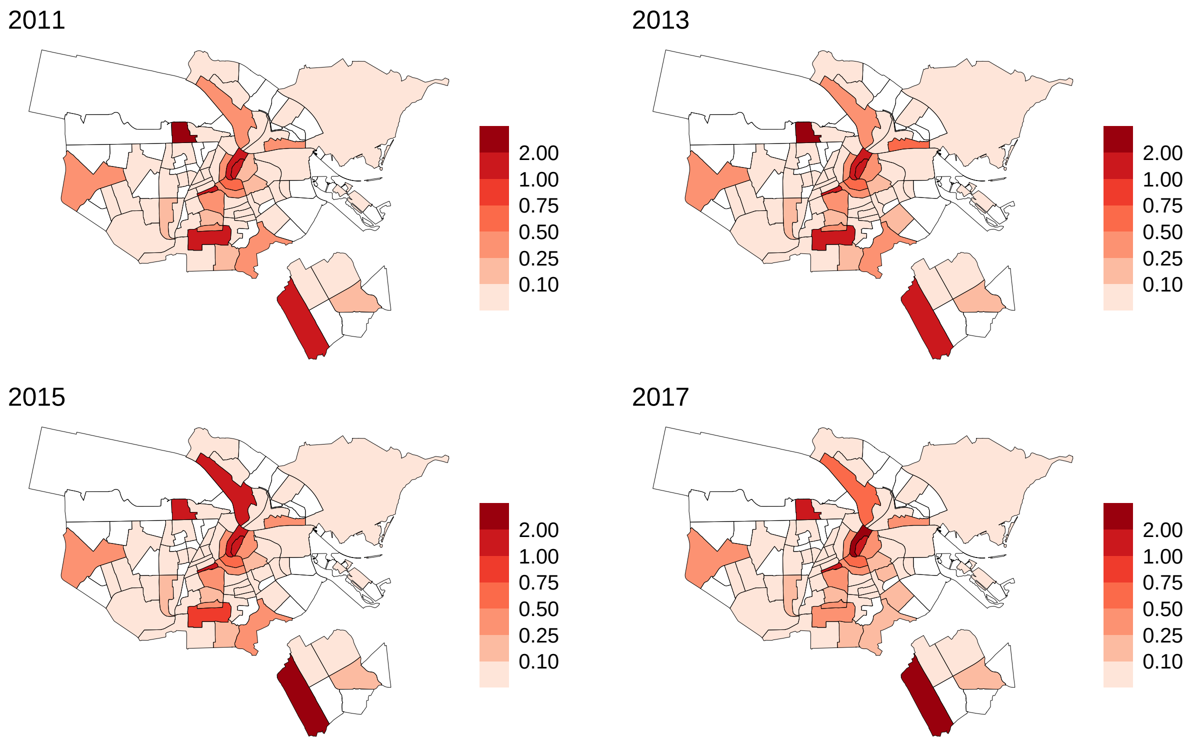


Figure 2: Number of hotel beds per resident (2011-2017)

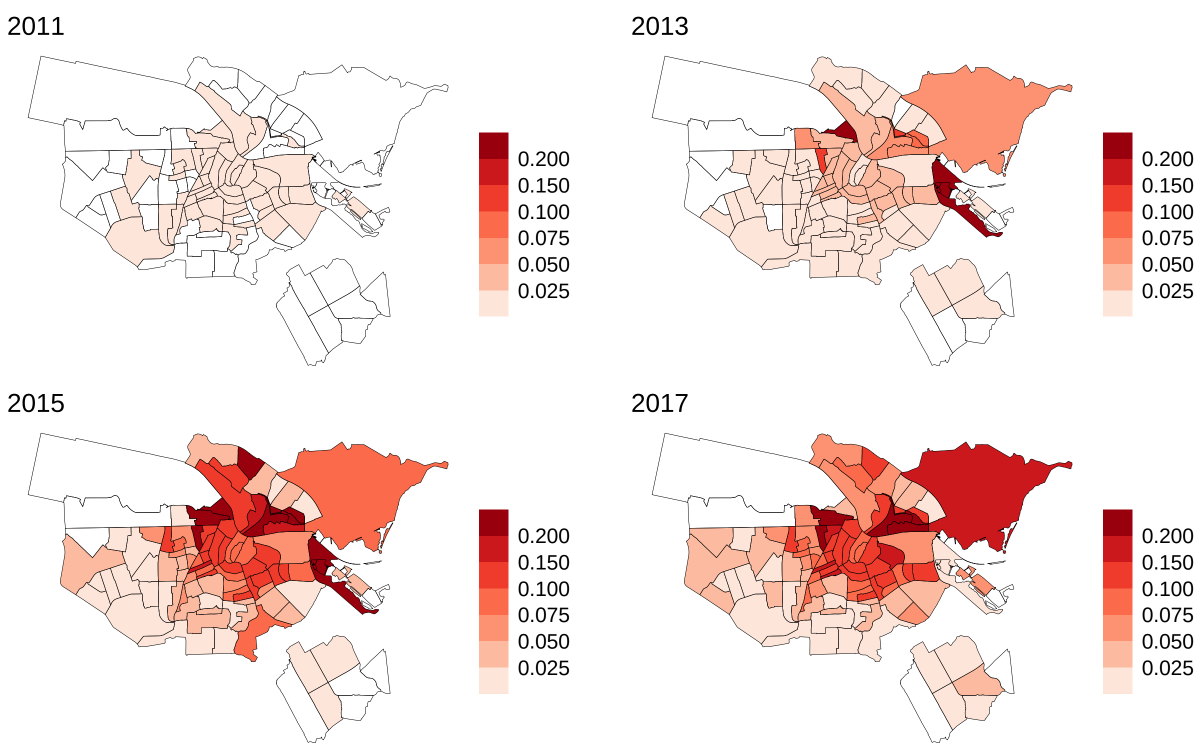


Figure 3: Commercial Airbnb listings as share of rental stock (2011-2017)

Fact 3: Amenities are tilting towards tourists

Figure 4 shows how different types of consumption amenities have evolved between 2008-2017. Touristic amenities have grown across nearly all neighborhoods, although at different intensities, while amenities that cater exclusively to locals, such as nurseries, have declined.[10]

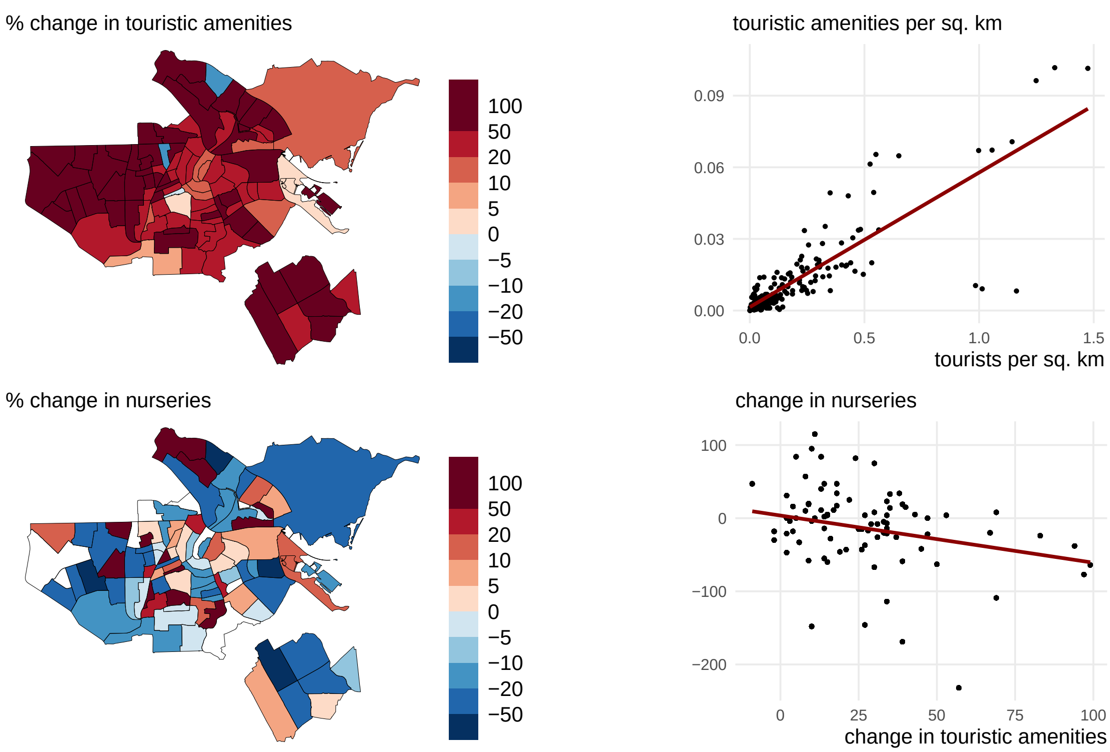


Figure 4: Growth of different types of consumption amenities (2011-2017)

Fact 4: Demographic composition is changing heterogeneously across neighborhoods

Figure 5 shows how the ethnic composition of each neighborhood has evolved. The clearest trend is a falling share of residents with Dutch or Dutch-colonial background in most neighborhoods. Simultaneously, the share of residents from non-Dutch Western and non-Western countries has increased. Regarding income segregation, Figure 6 shows the share of residents in the top 20% of the national income distribution has increased in most neighborhoods except those on the outskirts, suggesting a rise in income inequality between the core and periphery of the city.

[10] ACD defines touristic amenities as "accommodation and lodging, other restaurants, passenger reorganization and mediation, culture and recreation, marinas, sailing schools and recreational retail."

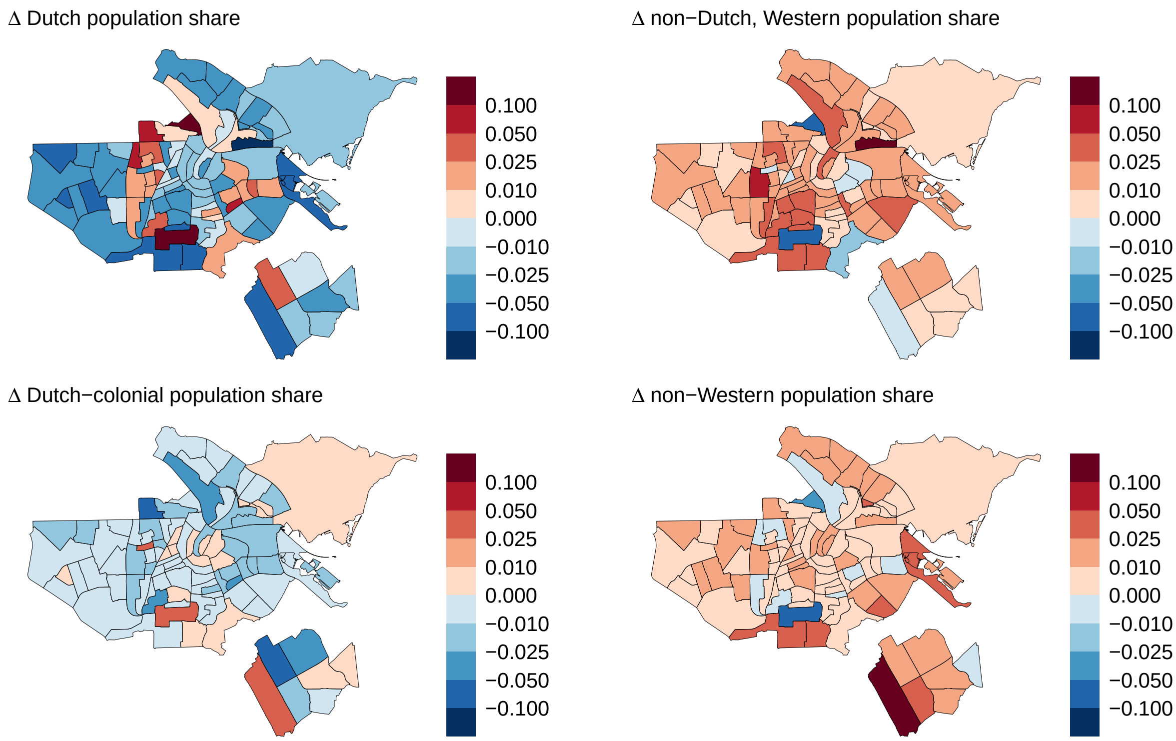


Figure 5: Changes in ethnic composition of neighborhoods (2011-2017). ACD defines "non-Western" as countries from Africa, Latin America, and Asia, and "Western" as countries from the rest of Europe, North America, Australia, and New Zealand. Our definition of "Dutch-colonial" consists of Suriname and the Netherlands Antilles.

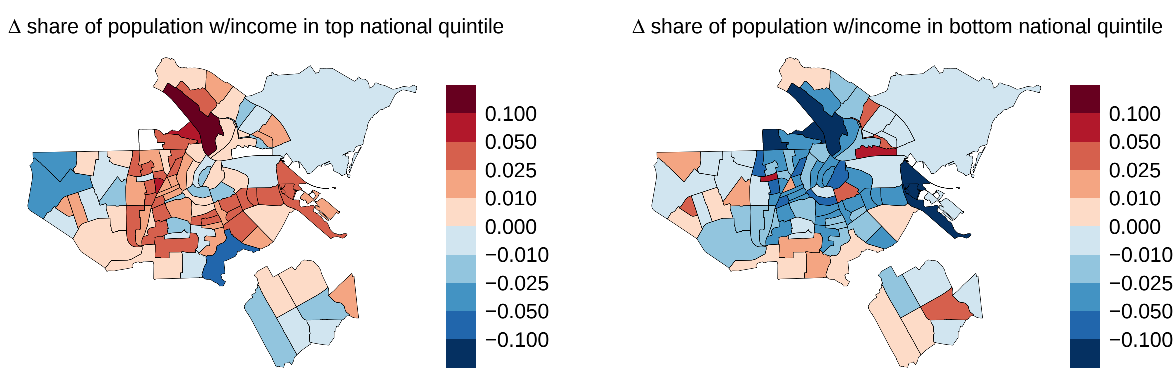


Figure 6: Changes in income composition of neighborhoods (2011-2017)

Regarding skill composition, Figure 7 shows an increase in the highest-skilled group, especially in central neighborhoods. As for age, the presence of middle-aged households has fallen nearly everywhere. This U-shaped relationship between age and urban residence seems to be explained by households leaving the city during their childbearing years, as shown in Figure 8.

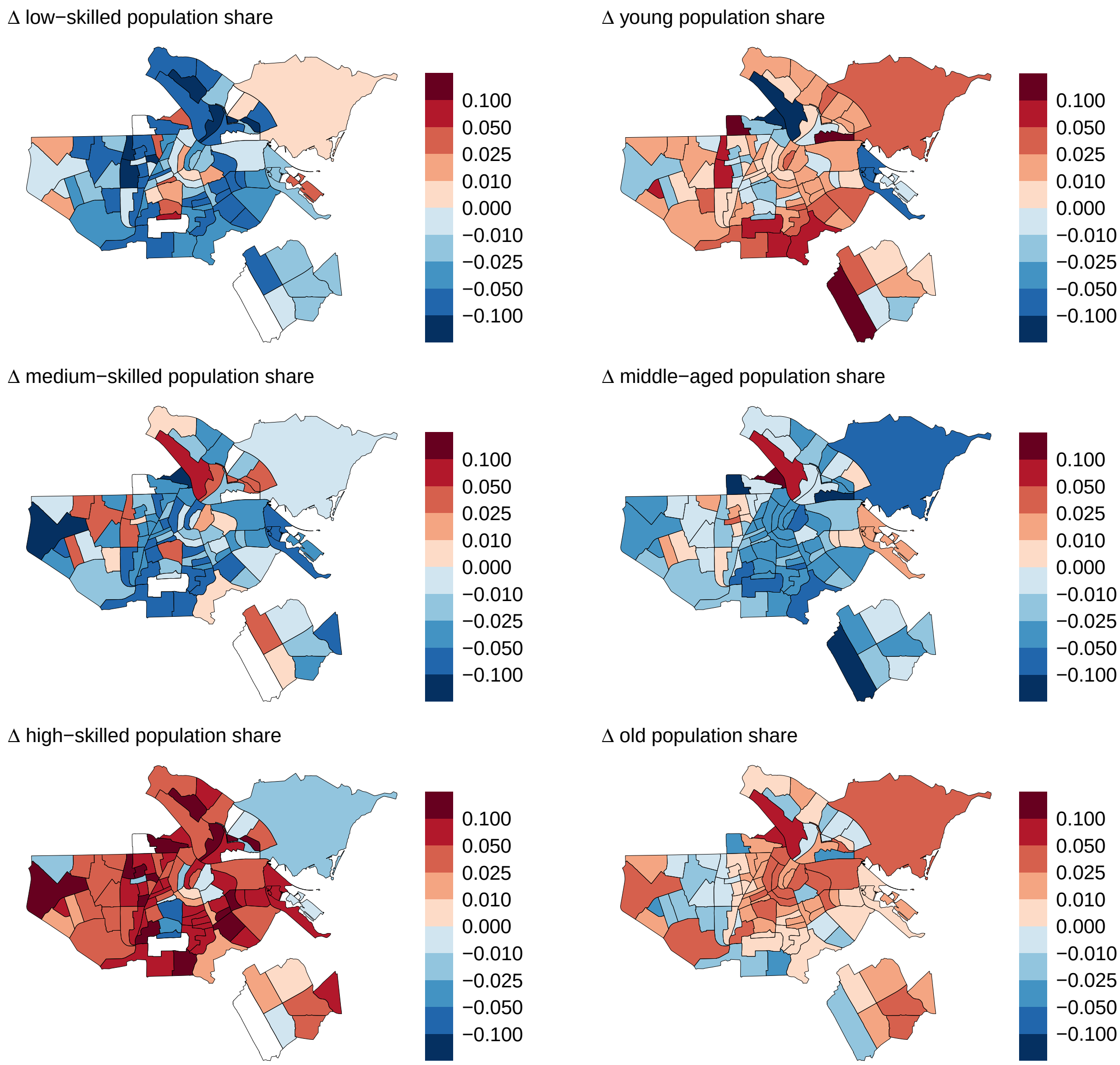


Figure 7: Changes in skill and age composition (2011-2017). Age groups are 15-34, 35-64, and 65+. Skill groups are divided into less than high school, complete high school, and complete college.

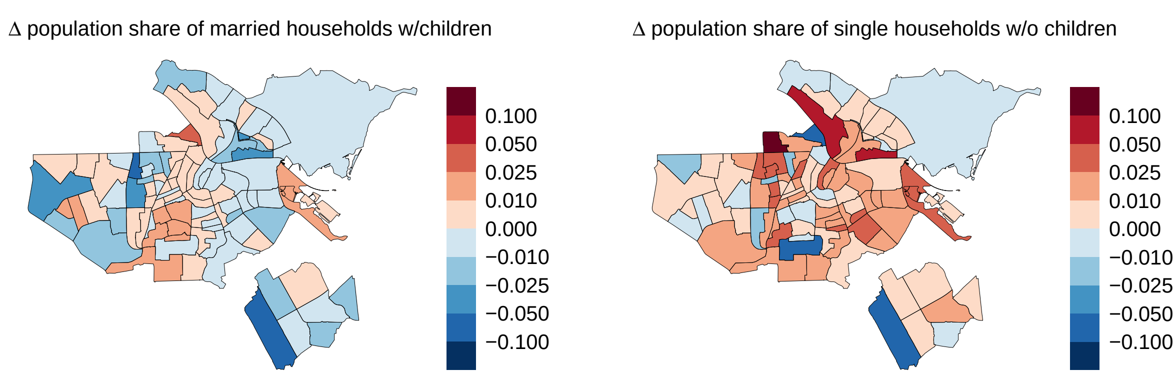


Figure 8: Changes in household composition of neighborhoods (2011-2017)

Fact 5: Rents have increased most in neighborhoods with higher Airbnb entry

By 2017, commercially-operated Airbnb listings represented 7% of Amsterdam's rental market and 3.2% of the market housing stock.[11] Table 1 shows that a 1% increase in commercial Airbnb listings is associated with an increase in rent ranging between .06-.12%, depending on the exact specification. Such magnitudes are sizable given the annualized growth rate of rent between 2009-2019 was 1.02%. These values are also broadly in line with a recent literature estimating the causal effect of Airbnb on the housing market by using shift-share identification strategies.[12] The estimates from this literature measure the total impact of Airbnb entry on rent without disentangling the underlying mechanisms: they combine the direct effect of reducing housing supply with indirect equilibrium effects arising from changing amenities and resorting of households across neighborhoods. Since our objective is to understand the heterogeneous welfare effects arising from amenity changes, in the following section we propose a structural model to disentangle such mechanisms.

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*****	**0.059*****	**0.125*****	**0.108*****	**0.053*****	**0.054*****
	(0.008)	(0.007)	(0.017)	(0.016)	(0.006)	(0.017)
Ln (housing stock)		-0.070**	-0.125***		-0.015	-0.038
		(0.029)	(0.028)		(0.024)	(0.029)
Ln (average income)		-0.482***	-0.316***		1.003***	0.988***
		(0.087)	(0.086)		(0.053)	(0.079)
Ln (high-skill population share)		0.291***	-0.083		0.281***	0.117
		(0.058)	(0.114)		(0.034)	(0.073)
District-year FE			X			X
Observations	780	659	659	746	634	634
R2	0.154	0.423	0.578	0.124	0.768	0.898

Notes: Standard errors clustered at the wijk level in parenthesis.

[11] Our definition of market housing stock excludes social housing units because they are not allocated to tenants through a market mechanism. See Appendix C 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.

[12] Barron, Kung and Proserpio (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.1 we show how our results change by using a similar shift-share identification strategy.

5 A dynamic model of a residential market

To rationalize the previous findings, we build a dynamic model of a city's rental market that consists of three parts: amenities, households, and landlords.

First, we describe how amenities in a location respond to its demographic composition. For endogenous consumption amenities, we start by modeling a competitive market for consumption amenities where firms supply services, and households with heterogeneous preferences demand them. Thus, using equilibrium conditions for that market, we construct a function from the socioeconomic composition of each location, which includes tourists, to the total supply of amenities in each location. In our model, we also include exogenous amenities, such as distance to the train station, and endogenous public amenities, such as congestion generated by tourists.

Our second objective is to understand the opposite direction of the first channel: the role of endogenous amenities in residential choice. Our model consists of forward-looking households who, at the beginning of every period, choose a residential location at the beginning of every period, taking prices and consumption amenities as given. Households accumulate location capital from living in the same location over many periods, and their utility directly depends on it. Intuitively, as residents become more familiar with their surroundings over time, or develop social networks, they obtain more utility from their residential location. Every time households move, they lose their location capital and incur a moving cost. Location tenure helps us rationalize two features of the data. First, we observe a decreasing hazard rate of moving conditional on living in the same location as shown in Figure 9.[13]

Second, the literature commonly finds unreasonably large moving costs to rationalize the acute persistence of location decisions.[14] As location tenure is lost upon moving it can equivalently be seen as part of the moving cost. Hence, including location tenure gives flexibility to the moving costs and helps rationalize the observed persistence with more reasonable one-time payment moving costs.

Last, absentee landlords supply units of housing to households. Assuming a fixed housing

[13] See also Diamond et al. (2018) for empirical evidence in the context of San Francisco.

[14] For example, we can calculate the income equivalent for the one-time payment of the psychological cost paid upon moving using the estimates found in Section 5.1 of Bayer et al. (2016). A back-of-the-envelope calculation leads to psychological costs of the order of 270,000 USD.

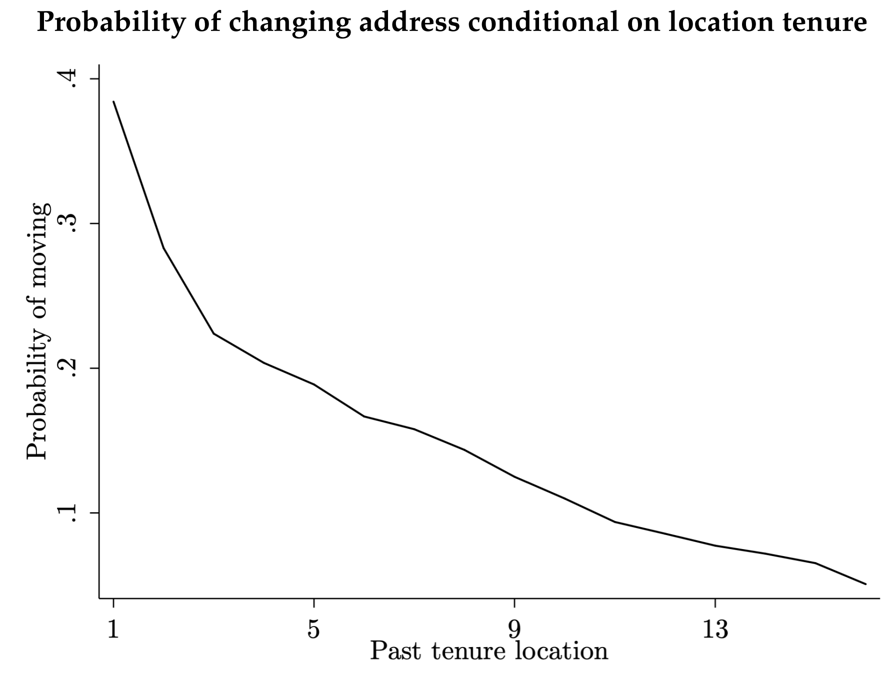


Figure 9: Decreasing hazard rate

stock, which we argue is reasonable in the context of Amsterdam, we allow tourism to have a direct effect on rental prices by splitting the rental market into two sub-markets: short-term rentals and long-term rentals. Every period, absentee landlords choose whether to rent their property full time to tourists in the former or to local residents in the latter. In this way, we endogenize housing supply available to locals through this binary decision. Finally, observe that both long-term housing prices as well as amenities are endogenous because they are determined in equilibrium for the residential market.

5.1 Endogenous amenities

In this section, we microfound how amenities respond to the demographic composition in each location. We assume S categories of services/consumption amenities (bars, restaurants, retail...) and K types of consumers representing different demographic groups, one of which is tourists. Each group has heterogeneous preferences over consumption amenities, and we assume they can only consume these amenities in their residential location.[15] Within a service category, location,

[15] Although this assumption is stark, evidence suggests urban residents disproportionately consume amenities, such as restaurants, that are located near their home. For example Davis et al. (2019) shows that commuting costs have a first order effect on restaurant consumption and that consumption segregation partly captures residential segregation. This

and time period, competitive firms offer products that are imperfect substitutes. In this way, residents experience "love-for-variety" as their indirect utility increases in the number of firms. We assume free entry, and that firms are small enough that individual pricing decisions do not affect the pricing decisions of other firms.

5.1.1 Amenities demand

In the following discussion, we fix the time period. Conditional on living in location j, a household of type k solves the following problem to maximize its utility over services:[16]

$$\max_{\{q_{is}\}_{is}} \prod_s \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_s^k} \quad \text{s.t.} \quad \sum_{is} p_{is} q_{is} = b_j^k, \tag{1}$$

where b_j^k is the budget that the household allocates to consumption amenities. We assume preferences are constant across time.

On the one hand, consumers have *CES preferences over products* with elasticity of substitution $\sigma_s \in (1, \infty)$. CES preferences imply a "love-for-variety" effect as utility increases in the number of firms. On the other hand, consumers have *Cobb-Douglas preferences over services*, which allows us to have different substitution patterns across different types of consumption amenities. Demand for firm i's good is,

$$q_i^k = \frac{\alpha_s^k b_j^k}{P_s} \left(\frac{P_s}{p_i} \right)^{\sigma_s},$$

where the price index is given by $P_s = \left(\sum_{i \in s} p_i^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}$. If we define $s(p_i, P)$ as the budget expenditure shares for firm i, we can rewrite the demanded quantity from firm i as,

$$q_i^k = \frac{\alpha_s^k b_j^k}{p_i} s(p_i, P).$$

Assuming M_j^k consumers of type k are living in location j, we can aggregate demand across consumers:

$$q_i = \sum_k M_j^k \frac{\alpha_s^k b_j^k}{p_i} s(p_i, P) = \frac{\sum_k M_j^k \alpha_s^k b_j^k}{p_i} s(p_i, P). \tag{2}$$

---

assumption can be relaxed by allowing for commuting costs but we refrain from doing so for tractability purposes and to keep the model as parsimonious as possible.

[16] We can also allow households to buy a tradeable good available at all locations with normalized price equal to 1 as in Couture et al. (2019)

Hence, aggregate demand can be represented by a representative consumer with total budget $\sum_k M_j^k \alpha_s^k b_j^k$ to spend on service s. From the previous expression, it is easy to see that all firms in a specific location and providing service s face the same demand curve.

5.1.2 Amenities supply

Firm i supplying service s solves the following profit-maximization problem:

$$\max_{p_i} q_i(p_i)(p_i - c_i),$$

where c_i is the marginal cost for firm i. We assume marginal costs c_i are constant across firms selling service s in the same location j, i.e., $c_i = c_{sj}$.[17] Therefore, all firms have the same pricing functions,

$$p_i = \frac{c_{sj}}{1 - \frac{1}{\mathcal{E}_i^D(p_i)}},$$

where $\mathcal{E}_i^D(p_i)$ is the price elasticity of aggregate demand for product i at price p_i. Provided a large number of firms are present, the pricing decision of one firm has negligible effects on the price index, and therefore,[18]

$$\mathcal{E}_{ik}^D(p_i) = \frac{\partial q_i^k}{\partial p_i} \frac{p_i}{q_i^k} = -\sigma_s.$$

Substituting, the pricing curve of firm i is finally given by,

$$p_i = \frac{c_{sj}}{1 - \frac{1}{\sigma_s}}.$$

Observe that prices do not depend directly on types because what matters for firms is aggregate demand that is summarized by the representative consumer.

[17] For example, if land prices (capital) as well as wages are location and service-specific, this assumption holds.

[18] If we include the effect of p_i on P, the elasticity of demand is given by:

$$\mathcal{E}_{ik}^D(p_i) = -\left((1-\sigma_s) \frac{\alpha_s^k b_j^k}{N_{js}} + \sigma_s \right),$$

where N_{js} is the number of firms in location j selling product s, so the first term is small when N_{js} is large. Under this more general form, we can also derive a mapping from the demographic composition to consumption amenities, but algebra becomes substantially more complicated, as the number of firms will be non-linear in the number of households for each type.

5.1.3 Amenities equilibrium

Given that all firms providing service s have the same pricing function and face the same demand curve, the unique equilibrium is symmetric,

$$q_i = q_s \quad \text{and} \quad p_i = p_s \quad \forall i \in s.$$

In the symmetric equilibrium, it follows that consumers buy equally from all firms offering the same service,

$$s(p_i, P) = \frac{1}{N_{sj}},$$

where N_{sj} are the number of firms in location j selling product s. Quantity demanded from firm i is given by,

$$q_i = \frac{\sum_k M_j^k \alpha_s^k b_j^k}{p_s N_{sj}}.$$

Denote location-service specific operational costs by F_{sj}. Due to competition and free-entry, firms enter until operational costs F_{sj} are equal to sale profits, and thus there are zero net profits in equilibrium,[19]

$$q_i(p_i - c_i) = F_{sj}.$$

Substituting aggregate equilibrium quantities, prices, and marginal costs gives us,

$$\frac{1}{p_i N_{sj}} \sum_k M_j^k \alpha_s^k b_j^k (p_i - c_i) = \frac{1}{\sigma_s N_{sj}} \sum_k M_j^k \alpha_s^k b_j^k = F_{sj}.$$

Thus, the number of establishments at location j providing service s is given by

$$N_{sj} = \frac{\sum_k M_j^k \alpha_s^k b_j^k}{F_{sj} \sigma_s}. \tag{3}$$

We define the vector of consumption amenities for each location as the vector of the number of firms in each service category:

$$a_j \equiv [N_{1j}, N_{2j}, \ldots, N_{Sj}] = \mathcal{A}(M_j^1, ..., M_j^K, M_j^T),$$

where $\mathcal{A}$ is the mapping derived by equilibrium conditions in the amenities market (equation 3). Observe that the previous mapping includes tourists, represented by M_j^T. For our application, this will include tourists staying in hotels as well as in short-term rentals.

[19] Given the competitive nature of our environment, we can treat firms' decisions as static given the absence of any future profits as in Desmet, Nagy and Rossi-Hansberg (2018).

A novel property of this mapping is that different sectors have their sector-specific market features such as the level of competition or entry costs. This heterogeneity across sectors is summarized by the parameters F_{sj} and σ_s. As σ_s increases, products become closer substitutes, so market power decreases, and incentives to enter decrease. Similarly, higher entry costs, F_{sj}, disincentivize entry.

5.2 Housing demand

We now present the location-choice problem for a type k household, following a similar exposition as in Scott (2013) and Diamond et al. (2018). For the marginal utility of money in our indirect utility function, we follow a similar specification as in Couture et al. (2019), where households earn annual income w_t^k, pay r_{jt} for a unit of housing, leaving them with total budget $b_{jt}^k = w_t^k - r_{jt}$ for consumption amenities.[20] At the beginning of every period t, a household i chooses where to live among J different locations, as well as an outside option of leaving the city.[21] We denote this decision by d_{it} and it is determined as follows:

$$d_{it} = \begin{cases} s & \text{if the household stays in the same housing unit, and thus location as in } t-1 \\ j & \text{if the household moves to a housing unit located in location } j \in \{1, ..., J\} \\ 0 & \text{if the household moves outside of the city.} \end{cases}$$

To be clear, if $d_{it} = j_{it-1}$ the household changes its housing unit but stays in the same location. The state variables j_{it} and location tenure τ_{it} evolve deterministically as follows

$$j_{it} = \begin{cases} j_{it-1} & \text{if } d_{it} = s \\ d_{it} & \text{otherwise,} \end{cases}$$

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

[20] This specification for the marginal utility of money has been widely used in the industrial organization literature, see for example Berry (1994), Berry, Levinsohn and Pakes (1995), or Nevo (2000). We can also assume that the budget spent in consumption amenities is a share of $w_t^k - r_{jt}$, $b_{sjt}^k = \lambda^k \alpha_s^k (w_t^k - r_{jt})$. In this case, our estimation procedure recovers the same coefficient but we cannot identify λ^k because it is absorbed by the location fixed effect.

[21] In our application, a location is a zipcode, "wijk," in Amsterdam.

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

Preference parameters differ by household type, which we index by k. A household i of type k living in location j pays rent r_{jt}, derives utility from location capital τ_{it}, a vector of endogenous amenities a_{jt}, which includes a vector of consumption amenities (services) $services_{jt}$, congestion from tourists $cong_{jt}$, a type-specific location fixed effect δ_j^k, and a type-specific time-varying location's underlying quality ξ_{jt}^k.[22] Upon moving, the household incurs a moving cost that depends on the distance between two locations $\text{dist}(j, j')$:[23]

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

To condense notation, we denote ω_t as the vector of global state variables,

$$\omega_t = (r_t, p_t, a_t, \xi_t),$$

and x_{it} as the individual state variables at the time of the decision,

$$x_{it} = (j_{it-1}, \tau_{it-1}).$$

Therefore, at time t, household i's indirect utility for decision d before the idiosyncratic shock is realized is,

$$u_t^k(d, x_{it}, \omega_t) = \delta_{j(d)}^k + \delta_\tau^k \tau_{it} + \delta_w^k \ln(w_t^k - r_{j(d)t}) + \delta_a^k \ln a_{j(d)t} - MC^k(d, j_{it-1}) + \xi_{jt}^k, \tag{4}$$

which can be micro-founded using utility function 1. See Appendix D.1 for more details.[24] In what follows, we denote with subscript t the functions that depend on the state variable ω_t. Household

[22]For our empirical application, we assume congestion effects $cong_{jt}$ are a linear function of the share of tourists in a location.

[23]We assume the geographic distance between neighborhoods is a good proxy for how similar those neighborhoods are given the spatial correlation across locations.

[24]In Appendix D.1.1, renters can also choose to supply part of their unit to tourists by subletting a fraction of it, hence benefiting from the "sharing economy." In principle, this channel allows for redistributive effects of short-term rentals. We refrain from doing so here for two reasons. First, according to a CBRE 2017 report on the hospitality industry in America, 81% of the revenue from short-term rentals corresponds to commercial operators. This large share indicates most of the Airbnb usage comes from professional hosts. Second, from a theoretical point of view, in equilibrium, these effects are dampened as households' higher valuations for housing units increase housing demand, which finally translates into higher rental prices. Thus, the positive effects on households' welfare are diminished by higher rents, and these gains from the sharing economy will also be captured by landlords.

i's value function is defined as

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

where the maximization is taken over policy functions $D : \mathcal{X} \times \Omega \times \mathbb{R}^J \to \{s, 0, 1, ..., J\}$. Given the recursive nature of the problem, we can write

$$\begin{aligned} V_t^k(x_{it}, \epsilon_{it}) &= \max_D \mathbb{E}_t \left[\sum_{s \geq t}^{\infty} u_s^k(d, x_{is}) + \epsilon_{is} | d_{it}, x_{it}, \epsilon_{it} \right] \\ &= \max_{d \in \{s,0,1,...,J\}} u_t^k(d, x_{it}) + \epsilon_{it} + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | d, x_{it}, \epsilon_{it} \right]. \end{aligned}$$

Because idiosyncratic shocks are assumed to be i.i.d. type I EV errors, the probability that a type k household chooses neighborhood j has the following closed form:

$$\mathbb{P}_t^k(j|x_{it}) = \frac{\exp\left(u_t^k(j, x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j, x_{it}, \epsilon_{it} \right] \right)}{\sum_{j'} \exp\left(u_t^k(j', x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j', x_{it}, \epsilon_{it} \right] \right)}. \tag{5}$$

and long-term demand from type k households is given by,

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

where the sum is taken over individual states x, so M_{xt}^k is the number of households of type k with individual state x at time t. Total demand for neighborhood j is obtained by summing the previous expression over all types of households k,

$$\mathcal{D}_{jt}^L = \sum_k \sum_x \mathbb{P}_t^k(j|x) M_{xt}^k. \tag{6}$$

5.3 Housing supply

Every year, each location j has a fixed supply of housing units denoted by $\mathcal{H}_{jt}$.[25] Every period, absentee landlords choose to rent their unit in the traditional long-term market to locals, or in the

[25] While stark, we believe that lacking a housing developer sector is a credible hypothesis for the case of Amsterdam. Due to the soil quality and zoning regulations there is very little new construction. The annually average growth of housing stock is roughly 1% from 2009 to 2018 and mostly coming from conversion of commercial real estate into residential space.

short-term rental market to tourists.[26] The landlord's problem in location j is given by,

$$\max_{h\in\{L,S\}} \Big\{\alpha r_{jt} + \epsilon_L, \quad \alpha p_{jt} - \kappa_{jt} + \epsilon_S\Big\},$$

where:

- α is the landlord's marginal utility of rental income.
- p_{jt} is the short-term rental income and r_{jt} is the long-term rental income.
- κ_{jt} is the differential cost between the two markets, which we interpret as differential matching and managerial costs, and occupancy rates. This κ_{jt} is unobservable to the econometrician and rationalizes different long-term rental shares across time and space.
- ϵ_L, ϵ_S are idiosyncratic shocks assumed to be i.i.d. type I EV errors.

We index landlords by l. The total supply in the long- and short-term rental market in neighborhood j is given respectively by

$$\mathcal{H}^L_{jt} = \int_{l\in j} \mathbb{1}\{h_{lt} = L\}dl, \quad \text{and} \quad \mathcal{H}^S_{jt} = \int_{l\in j} \mathbb{1}\{h_{lt} = S\}dl.$$

where $\mathcal{H}^L_{jt} + \mathcal{H}^S_{jt} = \mathcal{H}_{jt}\ \forall t$. Since ϵ_L, ϵ_S are i.i.d. type I EV errors, the share of rental units in each market is respectively given by,

$$s^L_{jt} = \frac{\mathcal{H}^L_{jt}}{\mathcal{H}_{jt}} = \frac{\exp(\alpha r_{jt})}{\exp(\alpha r_{jt}) + \exp(\alpha p_{jt} - c_{jt})},$$

$$s^S_{jt} = \frac{\mathcal{H}^S_{jt}}{\mathcal{H}_{jt}} = \frac{\exp(\alpha p_{jt} - \kappa_{jt})}{\exp(\alpha r_{jt}) + \exp(\alpha p_{jt} - \kappa_{jt})}.$$

We assume locals demand long-term rentals given the demand function derived in (6). In addition to households, tourists also demand housing for short-term stays. As suggested by empirical evidence, we assume short-term rentals average yearly prices are optimally set slightly below the prices of three-star hotels, and that the effects of the short-term rental industry on the hotel industry is small.[27]

[26] 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 very strict regulations that prevent housing units from being vacant. See amsterdam.nl/en/housing/obligation-homeowner/ for more details. Regardless, our analysis remains valid for the subset of landlords who do not leave their housing unit empty.

[27] We argue this assumption is reasonable in the case of Amsterdam for two reasons. First, in 2016, the year with the largest amount of Airbnb listings, short-term rentals accounted for 15% of overnight stays. Second, consumers'

5.4 Equilibrium

A stationary equilibrium in this model is

- a set of price vectors $\{r, p\}$ and a matrix of endogenous amenities a,
- a policy function $h(r_j, p_j; \kappa_j, \epsilon_l)$ for landlords,
- a policy function $d^k(r, p, a, j_i, \tau_i; \epsilon_i)$ for each type k local, with associated value functions $V^k(x, \omega, \epsilon)$,
- a stationary distribution of agent types over locations and tenure lengths, $\pi^k(j, \tau)$, which delivers a socioeconomic composition vector M_j for each location,

such that,

- each landlord l supplies housing optimally to locals or tourists given prices $\{r_j, p_j\}$, by choosing $h_l = h(r_j, p_j; \kappa_j, \epsilon_l)$, so that long-term and short term rental supply in location j are given respectively by

$$\mathcal{H}_j^L(r_j, p_j; \kappa_j) = \int_{l \in j} \mathbb{1}\{h_l = L\} dl = \frac{\exp(\alpha r_j)}{\exp(\alpha r_j) + \exp(\alpha p_j - \kappa_j)} \mathcal{H}_j$$
$$\mathcal{H}_j^S(r_j, p_j; \kappa_j) = \int_{l \in j} \mathbb{1}\{h_l = S\} dl = \frac{\exp(\alpha p_j - \kappa_j)}{\exp(\alpha r_j) + \exp(\alpha p_j - \kappa_j)} \mathcal{H}_j,$$

- each household i of type k demands housing optimally by choosing $d_i = d^k(r, p, a, j_i, \tau_i; \epsilon_i)$ given market state variables $\omega = (r, p, a)$ and individual state variables $x_i = (j_i, \tau_i)$, so that long-term rental demand in location j is given by

$$\begin{aligned}\mathcal{D}_j^L(r, p, a, j, \tau) &= \int \mathbb{1}\{j(d_i, j_i) = j\} di \\ &= M \sum_k \sum_\tau \left[\mathbb{P}^k(s|j, \tau)\pi^k(j, \tau) + \sum_{j'} \mathbb{P}^k(j|j', \tau)\pi^k(j', \tau) \right],\end{aligned}$$

  where M is the market size.

- prices (r, p) clear the short- and long-term rental markets in each location j,

$$\mathcal{H}_j^L(r_j, p_j; \kappa_j) = \mathcal{D}_j^L(r, p, a, j, \tau) \quad \text{and} \quad \mathcal{H}_j^S(r_j, p_j; \kappa_j) = \mathcal{D}_j^S(p).$$

utility for up-scale Airbnb listings can be compared to the mean of mid-scale or economy hotels, so consumers perceive hotels as a different product of higher quality (Farronato and Fradkin, 2018). Given that hotels are not operating at full capacity, setting average prices above mid-scale hotels cannot be optimal for hosts. See Appendix C.2 for more details.

- equilibrium amenities are determined by the socioeconomic distribution through the mapping $\mathcal{A}(\cdot)$, as described in our amenities model,

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

6 Estimation

6.1 Defining heterogeneous households

Because we are interested in distributional effects, we need to define groups of households, and classify households into these groups. These groups are assumed to differ in their preference parameters, which we estimate.

Previous literature typically defines groups ex-ante based on observable demographics, such as race or income (Bayer et al., 2016; Davis et al., 2018). Given the large set of household characteristics that we observe, classifying on all observables would result in a large number of groups, some with very few observations. Having many small groups leads to poorly estimated parameters for two reasons. First, as the number of groups gets large, the number of observations for each group decreases, and therefore the variance of the estimates increases, presenting a classic bias-variance trade-off. More importantly, groups with a low number of individuals imply poorly estimated CCPs with large measurement errors. These poorly estimated CCPs lead to biases in the second step of the utility parameters in the demand estimation.

Our goal is to have a few groups as possible while capturing the relevant heterogeneity. In this paper, we group households using a *k-means* classification method, and we separately estimate demand for each group. Clustering on k-means allows us to reduce the dimensionality of demographics, while keeping groups that are significantly different from each other. See Appendix C.3 for the technical details of our classification method.

In Table 2, we show the average demographics for the resulting 12 groups in our k-means classification. In Figures 10, 11, and 12, we plot the change in composition share for these demographic groups across all zipcodes in Amsterdam. We observe an exodus from the city center for households in the social housing groups.[28] A similar, although less stark tendency, is evident for home-owners. On the other hand, renters are becoming more prevalent in the city center. Finally, in Figure 13 we present evidence of a decreasing hazard rate of moving conditional on location tenure.

[28]Households in the social housing groups are fully excluded from the demand estimation for locations.

Table 2: Average demographics by cluster

	Group	Name	Skill			Income				Share Children	Age	Background origin				N
			% L	% M	% H	Pctl. Tot. Inc.	Total Inc.	Pctl. Inc PP	Inc. PP			Dutch	Dutch Col.	Western	Non West.	
Home Owners	**1**	H skill, Young, Singles	0.01	0.03	0.95	0.34	24000	0.42	22100	0.13	32	0.57	0.08	0.17	0.18	47990
	2	L+M skill, Immigrant Families	0.40	0.58	0.01	0.50	32800	0.45	22500	0.78	47	0.37	0.22	0.11	0.29	18829
	3	H skill, High inc., Young EU Families	0.00	0.00	1.00	0.68	53700	0.67	36300	0.89	36	0.64	0.08	0.15	0.13	72568
	4	H skill, High inc., Old Dutch Families	0.01	0.00	0.99	0.77	72300	0.79	51600	0.77	55	0.79	0.09	0.08	0.04	43246
Renters	**5**	H Skill, Low inc., Young, EU, Singles	0.02	0.04	0.94	0.19	14900	0.23	14000	0.06	27	0.62	0.04	0.18	0.16	71805
	6	H Skill, Low inc., Young, Immigrant Families	0.04	0.07	0.88	0.33	22800	0.32	17500	0.80	31	0.50	0.06	0.22	0.22	39467
	7	H Skill, High inc., Old Dutch, Families	0.20	0.11	0.69	0.53	38400	0.56	30200	0.61	58	0.66	0.11	0.12	0.11	25740
	8	H Skill, High inc., Young, EU, Families	0.00	0.01	0.99	0.70	59000	0.74	44100	0.69	36	0.55	0.05	0.26	0.15	45855
Social Housing	**9**	H skill, Low inc., Young Singles	0.01	0.00	0.99	0.20	15300	0.23	13800	0.16	29	0.56	0.10	0.12	0.22	88002
	10	L skill, Low inc., Old Immigrant Families	1.00	0.00	0.00	0.40	26100	0.32	17100	0.75	50	0.17	0.12	0.10	0.61	41416
	11	M skill, Low inc., Mixed Background Families	0.00	1.00	0.00	0.37	24300	0.33	17600	0.65	40	0.29	0.37	0.06	0.28	42076
	12	H skill, Medium inc., Dutch Families	0.00	0.00	1.00	0.52	35100	0.51	25600	0.78	43	0.59	0.13	0.10	0.17	77416

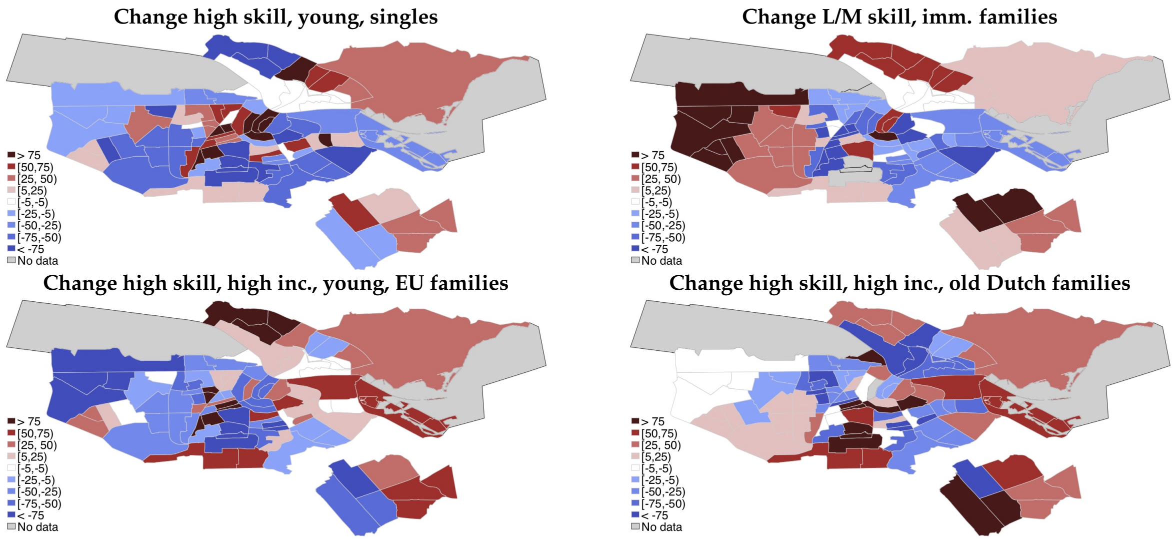


Figure 10: Percentage growth for shares of clusters of homeowners, 2011-2017

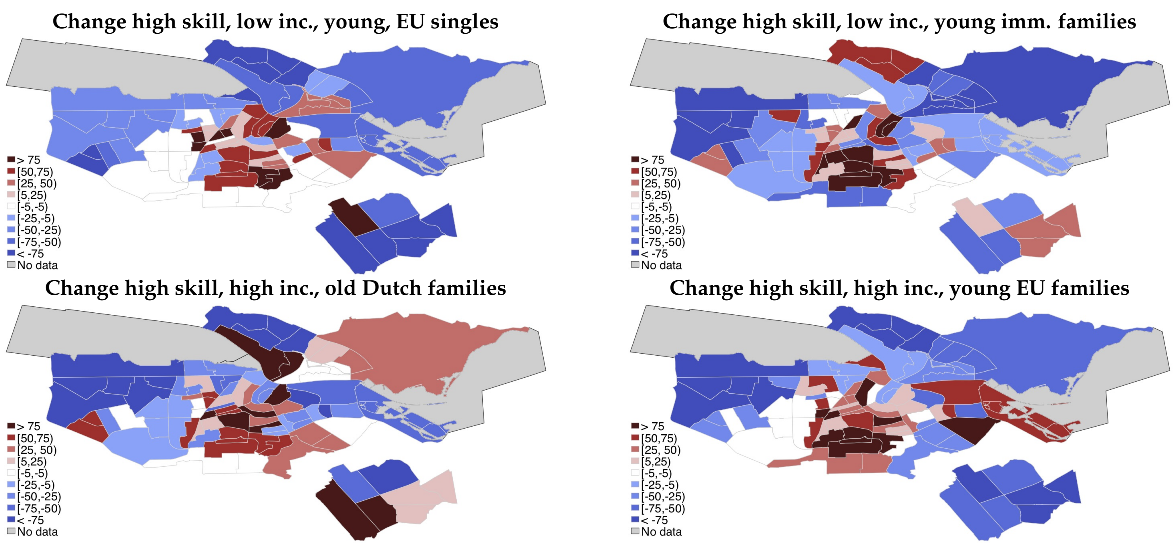


Figure 11: Percentage growth for shares of clusters of renters, 2011-2017

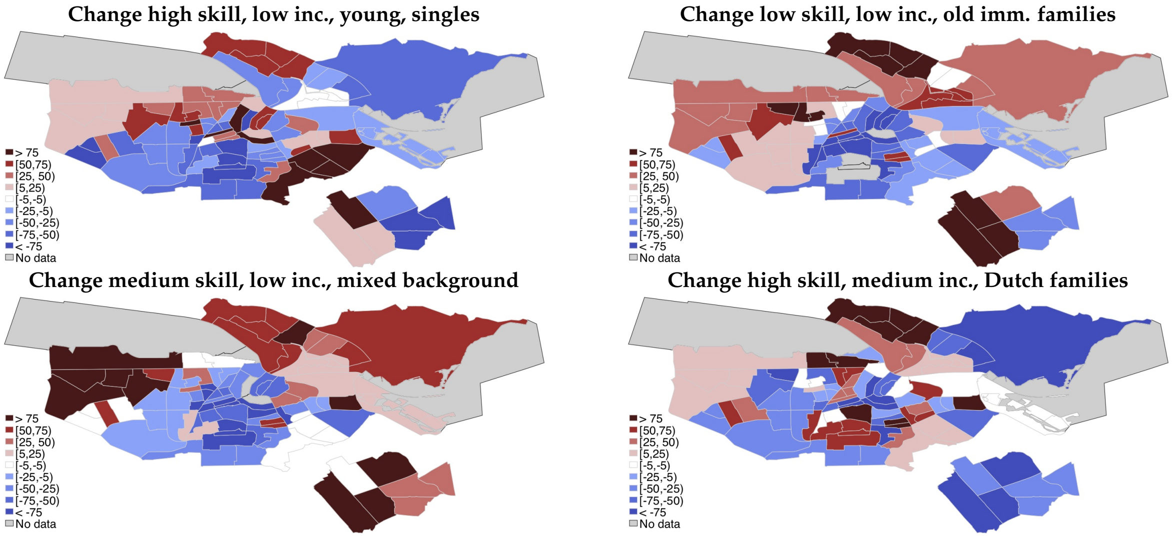


Figure 12: Percentage growth for shares of clusters for social housing, 2011-2017

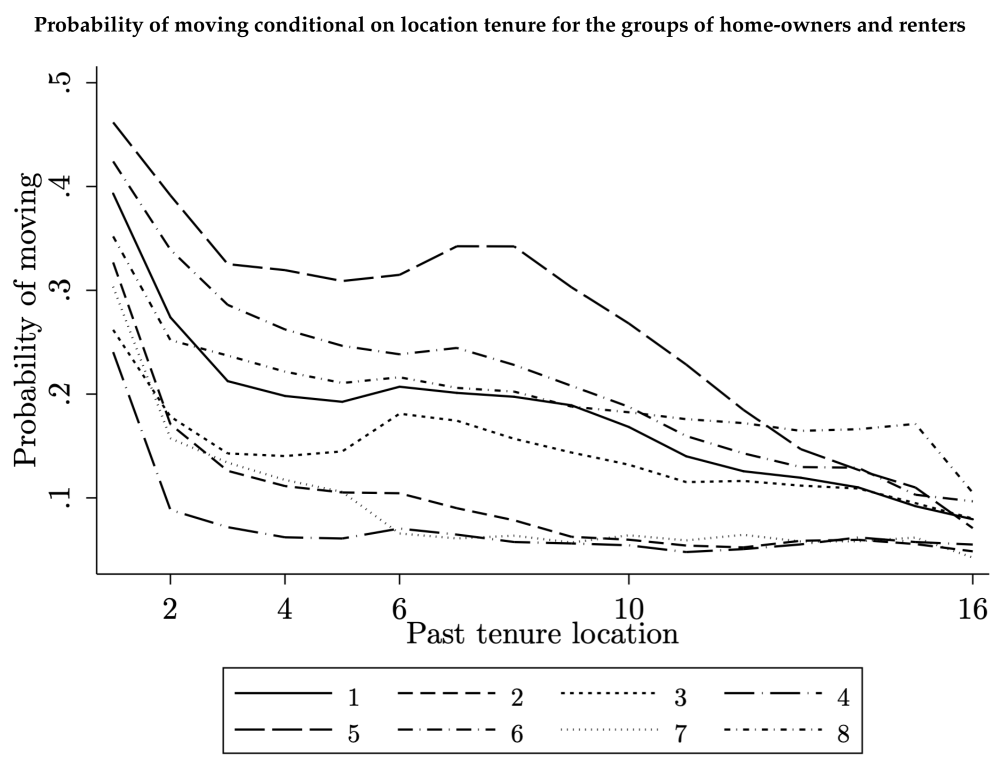


Figure 13: Decreasing hazard rate

6.2 Amenities

Following the derivation of equilibrium amenities in section 5.1, for every combination $n = (s, j, t)$, we can form the following equation:

$$N_{sjt} = \frac{1}{\sigma_s F_{sjt}} \sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}),$$

where individual types correspond to the k-means cluster types as well as tourists. We assume fixed costs can be represented in the following way:

$$F_{sjt} = \Lambda_s \Lambda_{jt} \Psi_{sjt},$$

where Λs and Λ_{jt} shift entry costs across sectors, locations, and time, respectively, and Ψ_{sjt} is an error term. In this cost specification the parameter Λ_s can be interpreted as entry barriers or the level of competition across firms providing service s while the parameter Λ_{jt} captures anything that is common to firms in location j at time t, such as wages or prices for commercial real estate. Taking logs of the previous equation, we obtain

$$\begin{aligned} \log N_{sjt} &= -\log \sigma_s - \log F_{sjt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) \\ &= \lambda_s + \lambda_{jt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) + \psi_{sjt}, \end{aligned} \tag{7}$$

where $\psi_{sjt} \equiv -\log \Psi_{sjt}$, $\lambda_s \equiv -\log \sigma_s - \log \Lambda_s$, and $\lambda_{jt} \equiv -\log \Lambda_{jt}$.[29]

The identifying assumption for the previous equation is that unobservables in ψ_{sjt} are not correlated with the total budget allocation of household k to service s for residents of location j, that is, to $M_{jt}^k(w_t^k - r_{jt})$. To address endogeneity concerns, we use a shift-share instrument, where the share component is motivated by the BLP instruments (Berry et al., 1995).[30] We take the share term as the average share of social housing *outside* of that zipcode, $sss_{-j,t}$. The shift term for every group is the total income for households in that group *across all* of Amsterdam, $M_t^k w_t^k$. The idea for the shift-share instrument, $sss_{-j,t} M_t^k w_t^k$, is that it predicts the share of group k's budget, $M_t^k w_t^k$, that is spent in neighborhood j. The reason is that as different demographic groups qualify or do not qualify for social housing, moving the share of social housing outside neighborhood j effectively moves the share of people of group k who live in neighborhood j. This construct is analogous to

[29]Observe that parameters $(\lambda_s, \alpha_s^1, ..., \alpha_s^K)$ are not separately identified. Therefore, to estimate equation 7 we make the normalization $\sum_k \alpha_s^k = 1$.

[30]Bayer, Ferreira and McMillan (2007) also use a similar instrument in a residential choice problem.

the BLP instruments where moving the characteristics of other products moves the demand for the product j through substitution between choices. Hence, we can expect the relevance condition to be satisfied,

$$Cov\Big(M_t^k w_t^k sss_{-j,t}, M_{jt}^k(w_t^k - r_{jt})\Big) \neq 0,$$

while the exclusion restriction requires

$$\mathbb{E}[M_t^k w_t^k sss_{-j,t}\psi_{sjt}] = 0.$$

The above is satisfied under the assumption that the total disposable income of group k at time t, $M_t^k w_t^k$, is orthogonal to the component of entry costs, ψ_{sjt}, and that both variables are independent from the average share of social housing outside j, $sss_{-j,t}$. We argue these assumptions are likely to be true. First, we do not expect the city's total budget for group k, $M_t^k w_t^k$, to be correlated with the entry cost of location j, ψ_{jt}, because $M_t^k w_t^k$ is a global trend that does not carry information about individual locations. Second, the share of social housing is determined by a point system that is defined *nationwide* and is *based on physical characteristics* of the housing unit.[31] Despite this exogenous definition, the share of social housing in j may correlate with unobservables in the entry cost; therefore, we construct the average social housing for a set of zipcodes different from j, $sss_{-j,t}$. We define this set as the zipcodes outside j's county ("Stadsdeel") to avoid spatial correlations.

To construct how many tourists "live" in each location, we take the number of hotel beds and multiply by the annual hotel bed occupancy rate. We also take the number of Airbnb commercial listings and multiply them by the average number of beds and the average commercial Airbnb occupancy rate.[32] We then sum both quantities. To compute expenses, we take total annual spending by tourists obtained from tourism reports and divide it proportionally to the number of tourists in each location. For local residents, the number of type k individuals can be directly computed from the micro-data. For income we use the average income by cluster and year.

Table 3 shows results for our non-linear IV specification, where we have pooled all sectors together with the appropriate interactions. The sectors chosen for this estimation are tourism services, food stores, general retail, education establishments, restaurants, cafes, and bars.[33]

[31] See Appendix C.1 for more details of the rental point system.
[32] The average number of beds in a commercial listing is four and the average occupancy rate is about 50%.
[33] The full definition of these services can be found in Appendix C.4.

Table 3: Amenity Supply Regressions

Panel A: General Retail, Food Stores, Touristic Amenities, and Bars

Dep. Var.:	Log Establishment Count							
	Retail		Food		Tourism		Bars	
Group 1	0.211***	(0.070)	0.160**	(0.063)	0.187***	(0.050)	0.403***	(0.094)
Group 2	0.161*	(0.092)	0.116	(0.093)	0.541***	(0.075)	−0.226***	(0.105)
Group 3	−0.029	(0.022)	−0.028	(0.019)	−0.012	(0.017)	0.020	(0.031)
Group 4	−0.003	(0.019)	−0.009	(0.015)	−0.012	(0.012)	−0.066***	(0.014)
Group 5	0.075	(0.072)	0.114	(0.077)	0.131***	(0.041)	0.079	(0.098)
Group 6	−0.470***	(0.144)	−0.45***	(0.148)	−0.578***	(0.092)	−0.282*	(0.164)
Group 7	0.605***	(0.069)	0.431***	(0.061)	0.290***	(0.041)	0.682***	(0.059)
Group 8	−0.131***	(0.030)	−0.058*	(0.031)	−0.058***	(0.018)	−0.345***	(0.036)
Group 9	0.110	(0.071)	0.192**	(0.081)	0.111*	(0.057)	−0.044	(0.064)
Group 10	−0.005	(0.027)	−0.048*	(0.025)	−0.013	(0.021)	0.13***	(0.028)
Group 11	0.176***	(0.060)	0.164***	(0.055)	0.129***	(0.044)	0.128**	(0.090)
Group 12	0.215**	(0.103)	0.388***	(0.111)	0.215**	(0.088)	0.351***	(0.124)
Tourists	0.085***	(0.013)	0.028***	(0.007)	0.070***	(0.011)	0.171***	(0.003)
λ_s FE	−11.3***	(0.190)	−11.858***	(0.195)	−10.605***	(0.200)	−12.771***	(0.210)
λ_{jt} FE	✓							
IV	✓							

Panel B: Cafes, Restaurants, Sport Establishments, and Educational Establishments

Dep. Var.:	Log Establishment Count							
	Cafe		Restaurant		Sport		Education	
Group 1	0.403***	(0.077)	0.188*	(0.100)	−0.075	(0.076)	−0.332***	(0.104)
Group 2	−0.226***	(0.060)	0.173*	(0.099)	0.630***	(0.092)	0.935***	(0.101)
Group 3	0.020	(0.026)	−0.015	(0.030)	0.013	(0.023)	0.090***	(0.033)
Group 4	−0.226***	(0.060)	0.173*	(0.099)	0.630***	(0.092)	0.935***	(0.101)
Group 5	−0.345***	(0.039)	−0.080**	(0.039)	0.060*	(0.031)	0.031	(0.033)
Group 6	−0.044	(0.068)	−0.003	(0.076)	−0.207***	(0.057)	−0.087	(0.069)
Group 7	0.130***	(0.035)	−0.028	(0.034)	−0.056**	(0.023)	−0.065**	(0.026)
Group 8	0.128**	(0.056)	0.381***	(0.090)	0.321***	(0.069)	0.568***	(0.097)
Group 9	−0.066***	(0.018)	−0.001	(0.022)	−0.002	(0.013)	0.001	(0.015)
Group 10	0.079	(0.073)	0.147	(0.098)	0.189**	(0.084)	0.182**	(0.088)
Group 11	−0.282*	(0.150)	−0.637***	(0.182)	−0.423***	(0.134)	−0.526***	(0.149)
Group 12	0.682***	(0.067)	0.468***	(0.075)	0.000	(0.048)	0.027	(0.057)
Tourists	0.351***	(0.090)	0.296***	(0.114)	0.538***	(0.113)	0.174	(0.115)
λ_s FE	−12.881***	(0.186)	0.197	−11.948***	−12.163***	(0.208)	−11.347***	(0.219)
λ_{jt} FE	✓							
IV	✓							

Note: *p<0.1; **p<0.05; ***p<0.01. SE in parenthesis.

We observe significant heterogeneity in how the supply of different amenities responds to the socioeconomic composition of the location as well as substantial heterogeneity across the barriers to entry for different services. For example, locations with an increase in tourists see an increase in the supply of touristic amenities, restaurants, bars, food stores, and general retail, and no effect in the supply of cafes, education establishments or sports amenities, holding the other demographic groups constant as shown in Figure 14.

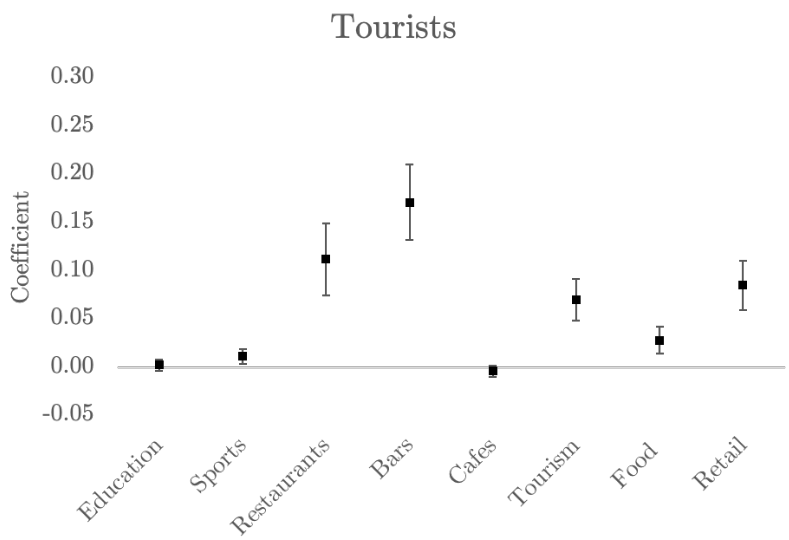


Figure 14: Amenities supply in response to tourists

Moreover, Figure 15 shows how different amenities respond to different demographic groups of local residents. For example we can compare group 1, the group of high skill, young, home owners with no children, to group 2, the group of immigrant families that are also home owners, but without college education. We see that bars respond positively while educational establishments respond negatively to the presence of young professionals (group 1) but we observe the opposite patterns for the group of immigrant families.

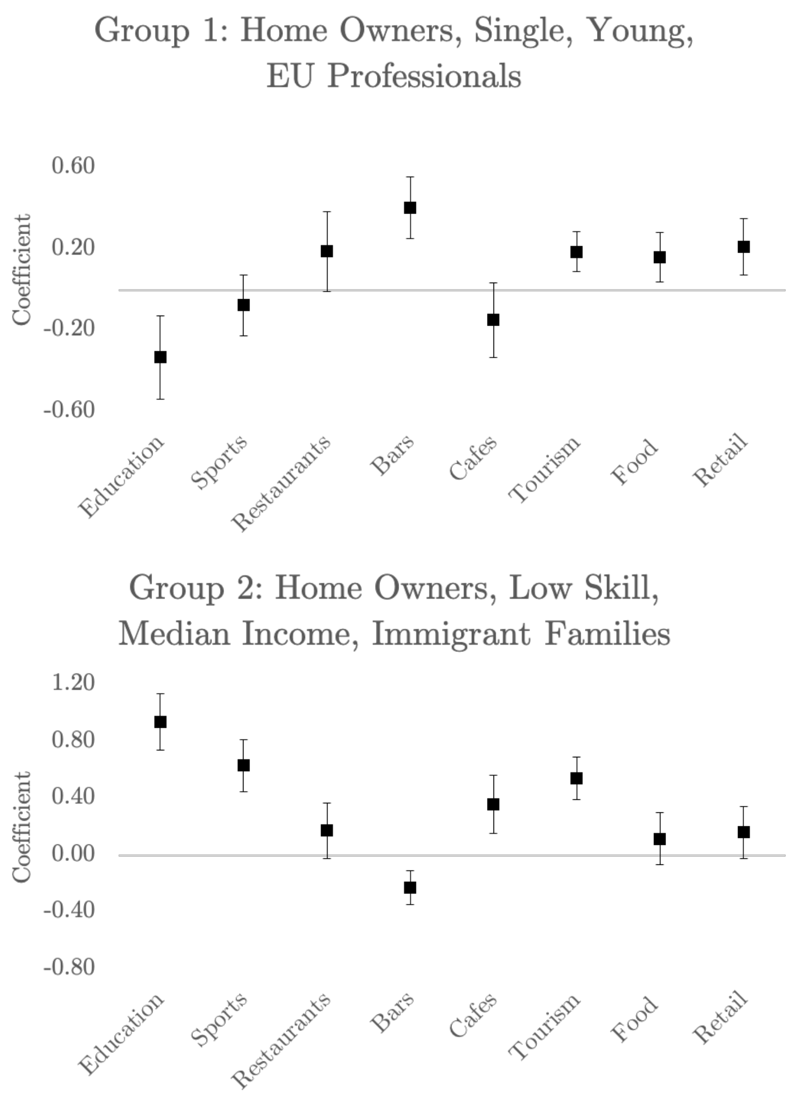


Figure 15: Amenity supply parameters of young professionals and immigrant families

6.3 Housing demand

In this section, we describe how we estimate the preference parameters for households. We do so by building upon the Conditional Choice Probability Estimator following Aguirregabiria and Mira (2010), Scott (2013), and Kalouptsidi et al. (2018). The ECCP estimator is particularly well suited for our application where we can leverage the assumption that location capital is lost whenever a household moves. The ECCP estimator allows us to recover parameters *without* solving value functions and without the need to specify beliefs.

The ECCP estimator is the discrete-choice analogue of inter-temporal Euler equations with continuous choice variables. Derivatives are replaced by differences, and the envelope theorem is replaced by results on finite dependence in the household dynamic problem as defined by Arcidiacono and Miller (2011). A dynamic problem exhibits finite dependence if two different sequences of choices starting from the same state lead to the same distribution of future states after n periods. If agents have rational expectations, value functions are substituted with their observable realizations plus an expectational error. Combining rational expectations with finite dependence, our household dynamic model maps to an equation in observables and an expectational error. This mapping allows us to estimate the structural model using regression equations. Moreover, this methodology does not require us to specify beliefs about the evolution of future states nor solve for value functions, exponentially reducing the computational burden.

The ECCP estimator is a two-step estimator. First, CCPs are estimated directly from the data. We use a novel smoothing approach that can reduce the bias of the second-stage preference parameter estimates by more than 50% based on the results of our Monte Carlo simulations. See Appendix D.2.4 for more details about our smoothing methodology. Second, model parameters are estimated using the CCPs obtained from the first stage. The key regression equation compares differences in the log likelihood of two different paths with a common starting and finishing point with differences in utility flows along those paths. The intuition for identification follows from these two paths having a common future state, and therefore the same expected future returns from that point onward. Therefore, continuation values are the same for both paths, so that value functions cancel out. Therefore, the relative likelihood of one path compared to the other has to be explained solely by differences in the (parameterized) utility flows along those two paths until that common point is finally reached.

6.3.1 Assumptions

We assume that states follow a Markov process. We also make the following standard assumptions:

Assumption 1 ***Atomistic agents****: The market states evolve according to a Markov process that is unaffected by individual decisions and states*

$$p(\omega'|d, x, \omega, \epsilon) = p(\omega'|\omega),$$

$\forall i \in I$ *and* $\forall d \in J$.

Assumption 2 ***Conditional independence assumption***: *The transition density for the following Markov process factors as*

$$p(x', \omega', \epsilon' | d, x, \omega, \epsilon) = p_x(x'|x, \omega, d) p_\omega(\omega'|\omega) p_\epsilon(\epsilon').$$

Assumption 3 ***Type I Extreme-Value errors***: ϵ_{ijt} *are i.i.d, type I Extreme-Value errors.*

6.3.2 Renewal actions

As defined by Arcidiacono and Miller (2011), two paths of action exhibit finite dependence if after a finite number of periods, the distribution of future states is the same. In our housing demand model, finite dependence appears whenever two households living in different locations, j and j', choose to move to the same new location $\tilde{j}$,

$$j \to \tilde{j} \quad \text{and} \quad j' \to \tilde{j},$$

because their location tenure clock is reset, and hence the distribution of future states is the same for both of them. These type of actions are known as *renewal actions*, and are a subset of actions with finite dependence. Renewal actions are a common component of recent papers in the literature using ECCP estimators (Scott, 2013; Diamond et al., 2018; Traiberman, 2018).

Because expected future payoffs are unobservable to the econometrician, one of the main difficulties in the estimation of dynamic models is disentangling variation in current payoffs from continuation values. Renewal actions help separate these two components of utility, because after playing them, continuation values are equalized. Hence, variation in choices up to the renewal action should reflect variation in utility flows.

More concretely, our main regression equation is,

$$Y^k_{t,d,d',\tilde{d},x_{it}} = u^k_t(j(d), x_{it}) - u^k_t(j(d'), x_{it}) + \beta\big(u^k_t(j(\tilde{d}), x_{it+1}) - u^k_t(j(\tilde{d}), x'_{it+1})\big) + \tilde{\varepsilon}_{t,d,d',x_{it}}, \tag{8}$$

where

$$Y^k_{t,d,d',\tilde{d},x_{it}} \equiv \ln\Big(\frac{\mathbb{P}^k_t(d, x_{it})}{\mathbb{P}^k_t(d', x_{it})}\Big) + \beta \ln\Big(\frac{\mathbb{P}^k_{t+1}\big(j(\tilde{d}), x_{it+1}\big)}{\mathbb{P}^k_{t+1}\big(j(\tilde{d}), x'_{it+1}\big)}\Big),$$

with d and d' being actions played at state x_{it}, reaching states x_{it+1} and x'_{it+1}, respectively, and $\tilde{d}$ being a renewal action played at time $t+1$. In what follows, we denote $j = j(d), j' = j(d')$, and

$\tilde{j} = j(\tilde{d})$ to simplify notation. Following our indirect utility specification,

$$u_t^k(d, x_{it}) = \delta_j^k + \delta_\tau^k \tau_{it} - \delta_r^k \log\left(w_t^k - r_{jt}\right) + \delta_a^k \ln a_{jt} - MC^k(j, j_{it-1}),$$

and so our regression equation is,

$$\begin{aligned} Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta_j^k - \delta_{j'}^k + \delta_\tau^k \Big(\tau(d, x_{it}) - \tau(d', x_{it}) \Big) \\ &+ \delta_a^k \Big(\ln a_{jt} - \ln a_{j't} \Big) - \delta_r^k \Big(\log\left(w_t^k - r_{jt}\right) - \log\left(w_t^k - r_{j't}\right) \Big) \\ &- \Big(MC^k(j, j_{it-1}) - MC^k(j', j_{it-1}) \Big) - \beta \Big(MC^k(\tilde{j}, j) - MC^k(\tilde{j}, j') \Big) \\ &+ \tilde{\varepsilon}_{t,d,d',x_{it}}. \end{aligned} \tag{9}$$

We can interpret $Y^k_{t,d,d',\tilde{d},x_{it}}$ as the log likelihood of path $(x_{it}, x_{it+1}, x_{it+2})$ relative to path $(x_{it}, x'_{it+1}, x_{it+2})$. The intuition of the previous equation goes as follows: The relative likelihood of $(x_{it}, x_{it+1}, x_{it+2})$ compared to $(x_{it}, x'_{it+1}, x_{it+2})$, that is, $Y^k_{t,d,d',x_{it}}$, has to be solely explained by the relative discounted utility flow of path $(x_{it}, x_{it+1}, x_{it+2})$ compared to $(x_{it}, x'_{it+1}, x_{it+2})$, because after playing renewal action $\tilde{d}$ tenure location resets and the problem from then on is identical for both paths. For full details on how to obtain this equation, see Appendix D.2.

6.3.3 Identification

First, as in any logit inversion trying to recover utility parameters, only differences

$$\delta_j - \delta_{j'}$$

in utility are identified. To separately identify the levels δ_0, we make the following assumption:

Assumption 4 ***Payoff to the outside option****: The utility payoff of living outside the city, excluding moving costs and location capital, is normalized to zero.*

The previous assumption implies

$$\delta_0 + \delta_a^k \ln a_{0t} + \delta_w^k \log\left(w_t^k - r_{0t}\right) = 0.$$

Second, equation (9) requires controlling for location fixed effects δ_j. Taking care of fixed effects by demeaning the dependent variable with respect to j will lead to biased estimates. The reason is that when demeaning, we are including variables from all time periods, because the mean is precisely taken over all t. The required identifying assumptions on expectational errors $\tilde{\varepsilon}_{t,d,d',x_{it}}$ in this case should be

$$\mathbb{E}\left[\left(\log\left(w_t^k - r_{jt}\right) - \log\left(w_t^k - r_{j't}\right)\right)\tilde{\varepsilon}_{t',d,d',x_{it}}\right] = 0 \quad \forall t', t,$$

and

$$\mathbb{E}\left[(\ln a_{jt} - \ln a_{j't})\tilde{\varepsilon}_{t',d,d',x_{it}}\right] = 0 \quad \forall t', t,$$

which is likely to fail because one can expect expectational errors at time t to be correlated with future variables $t' > t$ of rent and amenities.[34] Following a similar argument as in Scott (2013) and Kalouptsidi et al. (2018), we proceed to estimate equation 9 by taking differences with the previous time period with respect to the same state, $x_{it} = x_{it-1} = x = (j, \tau)$, and for the same action path. In this way, everything that is time-invariant cancels out, and the final regression equation is

$$\begin{aligned}
\nabla Y^k_{t,d,d',\tilde{d},x} = {} & \delta^k_j - \delta^k_{j'} + \delta^k_\tau\Big(\tau(d,x) - \tau(d',x)\Big) \\
& - \left(\delta^k_j - \delta^k_{j'} + \delta^k_\tau\Big(\tau(d,x) - \tau(d',x)\Big)\right) \\
& + \delta^k_a \nabla\Big(\ln a_{jt} - \ln a_{j't}\Big) + \delta^k_w \nabla\Big(\log\left(w^k_t - r_t\right) - \log\left(w^k_t - r_{j't}\right)\Big) \\
& - \Big(MC^k(j, j_{it-1}) - MC^k(j', j_{it-1})\Big) - \beta\Big(MC^k(\tilde{j}, j) - MC^k(\tilde{j}, j')\Big) \\
& + \left(MC^k(j, j_{it-1}) - MC^k(j', j_{it-1}) + \beta\Big(MC^k(\tilde{j}, j) - MC^k(\tilde{j}, j')\Big)\right) \\
& + \nabla\tilde{\varepsilon}_{t,d,d',x},
\end{aligned}$$

where ∇ is the first difference operator $\nabla x_t = x_t = x_{t-1}$. Simplifying, the first difference regression equation that we take to the data is

$$\nabla Y^k_{t,d,d',\tilde{d},x} = \delta^k_a \nabla\Big(\ln a_{jt} - \ln a_{j't}\Big) + \delta^k_w \nabla\Big(\log\left(w^k_t - r_{jt}\right) - \log\left(w^k_t - r_{j't}\right)\Big) + \nabla\tilde{\varepsilon}_{t,d,d',x}. \tag{10}$$

Inspection of equation 10 reveals that the unobservable component $\nabla\tilde{\varepsilon}_{t,d,d',x}$ is correlated with regressors as the previous period expectational error $\tilde{\varepsilon}_{t-1,d,d',x}$ is correlated with contemporary variables $\ln a_{jt}$ and $\ln(w^k_t - r_{jt})$. More importantly, one of the main challenges of estimating demand parameters in residential choice is that many unobservables, beyond the expectational error, are correlated with regressors and location choices. For example, gentrification trends will push up rents as well as the probability of certain sociodemographic groups to live in specific locations.

[34] Rational expectations only impose $\mathbb{E}\left[z_{t'}\tilde{\varepsilon}_{t,d,d',x_{it}}\right] = 0$ for all $t' \leq t$.

Moreover, these types of unobserved components tend to be time persistent. To deal with this type of endogeneity, we propose a new identification strategy that combines the ECCP methodology with instruments in the spirit of the exclusion restrictions of Arellano and Bond (1991). First, we assume the unobserved component in equation 10 follows an ARMA structure, which allows us to capture time persistence in time-varying unobservables. Second, this assumption delivers internally consistent estimators following the same reasoning as in Arellano and Bond (1991). Appendix D.2 contains a more detailed discussion of this new approach.

Finally, to recover the time-invariant parameters, we construct the residuals from the levels in equation (9) using the parameters obtained by the first-difference regression of equation (10). We then estimate these residuals on the time-invariant components, moving costs, and location tenure. To recover location fixed-effects, δ_j, we simply follow the standard approach of taking averages over residuals across all observations with the same location j.

6.3.4 Estimation results

This section provides an overview of our preliminary demand-estimation results for the eight groups of renters and home-owners.[35] Given that the estimation requires some extra exclusion restrictions (see section D.2.5 for details), we present basic OLS estimates in Table 4. In this estimation, we have included education establishments, sport amenities, touristic services, restaurants, bars, and cafes as our set of consumption amenities. As public amenities, we include congestion effects generated by tourists in hotels and in Airbnb listing defined as the number of each divided by the local population. We also include population density as well as location fixed effects. Finally, given the discussion in C.2, many hotel developments are being built over time. We include the number of hotels as a proxy to control for unobservable trends that are correlated with these

[35] We exclude the demographic groups in social housing as well as all the observations of households living in social housing for the other two groups because the choice of moving to social housing is very different from moving choices in the private market.

new constructions. Recall the regression equation that we estimate is

$$
\begin{aligned}
Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta^k_j - \delta^k_{j'} + \delta^k_\tau \Big(\tau(d, x_{it}) - \tau(d', x_{it}) \Big) \\
&+ \delta^k_a \Big(\ln a_{jt} - \ln a_{j't} \Big) + \delta^k_w \Big(\log \big(w^k_t - r_{j(d)t} \big) - \log \big(w^k_t - r_{j't} \big) \Big) \\
&- \Big(MC^k(j, j_{it-1}) - MC^k(j', j_{it-1}) \Big) - \beta \Big(MC^k(\tilde{j}, j) - MC^k(\tilde{j}, j') \Big) \\
&+ \tilde{\varepsilon}_{t,d,d',x_{it}}.
\end{aligned}
$$

For specific details about the estimation procedure, see section D.2.3. All moving costs and tenure location have the expected sign, where we observe significant heterogeneity across groups. For example, home-owners have on average larger effects from location capital accumulation than renters. This result can be explained by home-owners feeling more attached to their neighborhoods than renters. All groups have the expected sign on adjusted income, except for one group that corresponds to home-owners in the top-income group. This negative sign is not uncommon in the literature and usually captures unobservable neighborhood time-varying characteristics that positively correlate with price, such as gentrification trends. We also see significant heterogeneity across income parameters. Renters are on average more sensitive to adjusted income, disposable income minus the price of housing, than home-owners, as expected. It also appears that the coefficient on adjusted income correlate with the original disposable income, with lower-income households being more sensitive than higher-income households for the two groups. Group 5, the one formed by young, high-skill, European renters without children, is an exception to this relationship, but this result can be rationalized by these households putting more weight on the characteristics of the location than on price of housing. Our income-price coefficients are of larger magnitude as those found in Diamond (2016), an expected result given that we estimate a *dynamic* model whereas Diamond (2016) estimates a *static* model. Finally, we find significant heterogeneity across coefficients for different amenities and location characteristics. For example, older households tend to value more education establishments and less touristic services, while groups with a higher share of Dutch descendant households value more restaurants than groups with a higher share with a non-Western origin. See Figure 16 for more details.

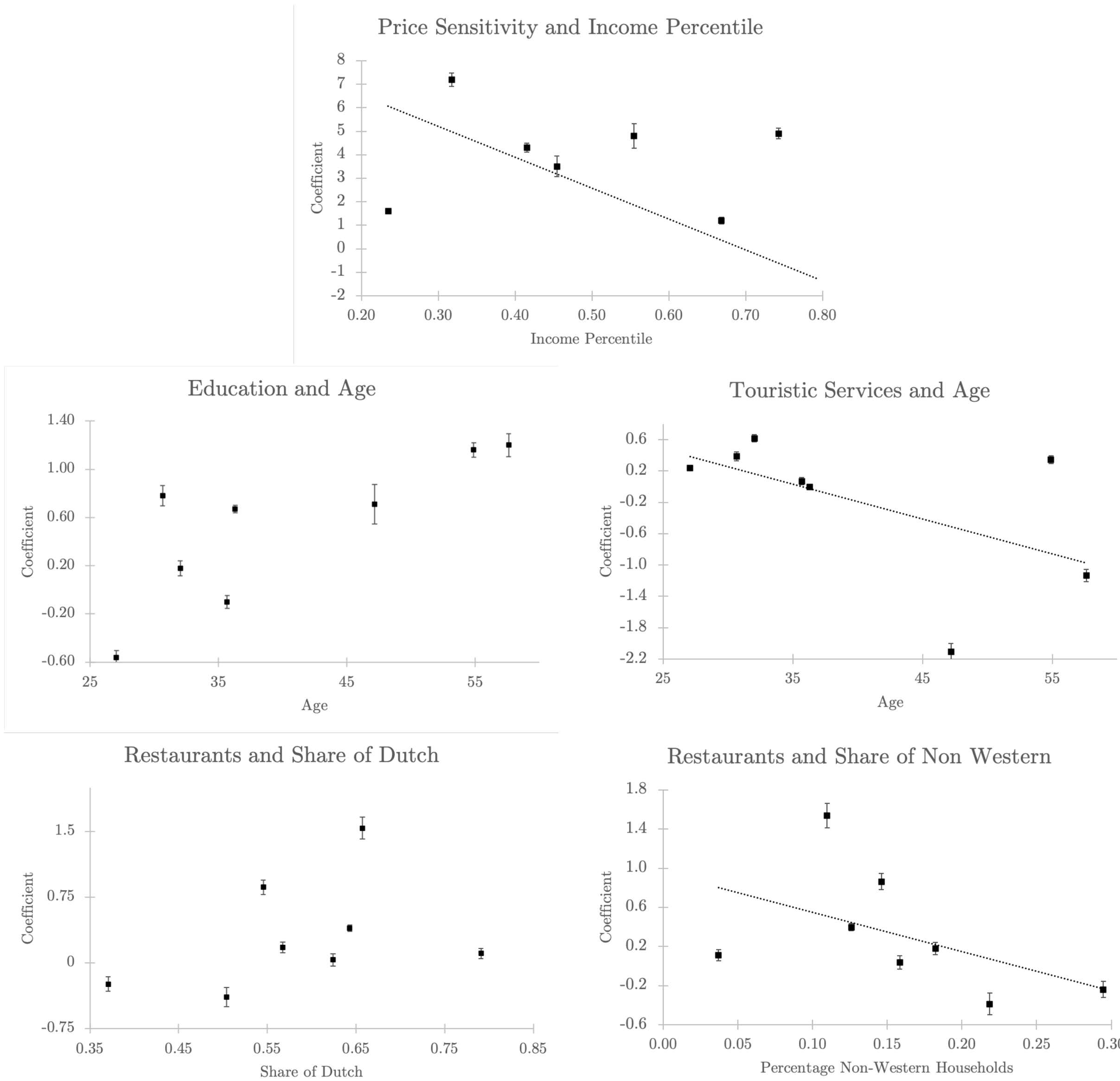


Figure 16: Relationship between demand estimation coefficients and demographics

Table 4: Dep. var.: Log likelihood ratio of action paths for eight household groups

	Home owners				Renters			
	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8
Adjusted Income	4.325***	3.511***	1.234***	−9.301***	1.564***	7.185***	4.834***	4.874***
Education est.	0.176***	0.708***	0.668***	1.164***	−0.561***	0.781***	1.209***	−0.098***
Sport Est.	−0.023	0.645***	0.238***	1.000***	0.319***	0.286***	0.380***	0.124***
Hotel	0.181***	−0.737***	0.285***	0.137***	0.314***	0.158***	0.554***	0.211***
Restaurant	0.179***	−0.240***	0.398***	0.109***	0.036	−0.387***	1.538***	0.864***
Bars	−0.140***	−0.168***	−0.203***	−0.089***	0.160***	0.381***	0.068**	0.097***
Cafes	0.237***	−0.044**	0.014*	0.409***	0.171***	−0.170***	−1.057***	−0.023
Touristic services	0.617***	−2.104***	−0.005	0.343***	0.236***	0.389***	−1.136***	0.070***
Food stores	−0.115***	−2.135***	0.094***	−1.14***	0.148***	0.910***	0.580***	0.453***
Retail	−0.292***	−1.86***	−0.047***	−0.502***	−0.903***	0.036	0.912***	−0.949***
Pop. Density	−1.88***	13.846***	−2.624***	−1.337***	1.819***	−2.855***	1.887***	−1.891***
Congestion Hotels	−0.007**	0.034***	0.036***	0.112***	−0.050***	−0.002	0.035***	−0.047***
Congestion Airbnb	−0.147***	−0.077***	0.100***	0.134***	−0.046***	−0.196***	−0.185***	0.005
Share social housing	0.163***	0.776***	0.228***	−0.323***	0.058***	−0.224***	−0.145***	0.024***
$MC_{0,O}$	−1.164***	−2.123***	−2.081***	−2.937***	−4.430***	−3.781***	−2.527***	−1.845***
$MC_{0,I}$	−1.912***	−1.648***	−2.564***	−3.228***	−3.370***	−3.243***	−2.303***	−2.765***
$MC_{1,dist}$	−0.093***	−0.183***	−0.135***	−0.185***	−0.288***	−0.135***	−0.142***	−0.075***
Dummy τ_2	2.380***	1.216***	2.053***	1.118***	0.454***	0.700***	0.966***	1.610***
Dummy τ_3	2.374***	1.183***	1.517***	0.672***	0.711***	0.860***	0.902***	1.337***
Location FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2 1st-stage	0.041	0.091	0.037	0.078	0.054	0.081	0.055	0.063

Note: *p<0.1; **p<0.05; ***p<0.01

6.4 Housing supply

Because the supply model is static, differences in the short- and long-term market shares of housing map directly to a regression equation,

$$\ln s_{jt}^{L} - \ln s_{jt}^{S} = \alpha r_{jt} - \left(\alpha p_{jt} - \kappa_{jt}\right) + \nu_{jt},$$

where ν_{jt} is measurement error or unobservables not included in κ_{jt}. We parametrize $\kappa_{jt} = \gamma_j + \gamma_t$, where γ_j and γ_t are fixed effects:

$$\ln s_{jt}^{L} - \ln s_{jt}^{S} = \alpha(r_{jt} - p_{jt}) + \gamma_j + \gamma_t + \nu_{jt}.$$

Running OLS in the previous equation may lead to biased estimates because we are, in effect, estimating a supply equation using equilibrium outcomes, which are a function of unobserved demand and supply shocks. To correctly identify supply elasticities, we need to find an appropriate instrument. The natural instrument for supply elasticities is a demand shifter. We construct a demand shifter with predicted tourist demand, using a shift-share approach as in our reduced-form exercise of section 4. The relevance condition is satisfied because higher demand from tourists will increase the gap between short- and long-term rental prices $p - r$. We expect the exclusion restriction to be satisfied because predicted tourist demand is unlikely to be correlated with time-varying supply shocks. Table 5 presents estimates for the supply-side parameters. Under both OLS and IV specifications, the coefficient on price is positive and significant. Higher price gaps between long-term and short-term prices naturally lead to higher long-term market shares.

Table 5: Dependent variable: Log long-term share - Log short-term share

	OLS		IV	
Price gap	0.919^{***}	(0.077)	1.646^{***}	(0.232)
Location FE	✓		✓	
Time FE	✓		✓	
R^2	0.849		0.828	
Observations	655		655	
F Statistic	453.042^{***}		352.12^{***}	
1 stage F Stat	-		1033.82^{***}	
Note:	*p<0.1; **p<0.05; ***p<0.01. SE clustered at zipcode-level.			

7 Simulations and Counterfactuals

7.1 The role of heterogeneous preferences for endogenous amenities

The objective of our first exercise is to evaluate the role of the endogeneity of amenities and consumer heterogeneity for the model's equilibrium outcomes. In this simplified exercise there are two types of agents, high and low income (H and L), and two type of amenities (also H and L). H agents prefer amenity H four times as much as amenity L. H agents earn 25% more than L agents, and are 33% less sensitive to rental prices than L agents. There are also two locations (L1 and L2), with location L1's exogenous characteristics being more desirable than L2's for both agents. We simulate two worlds: one in which both type of agents have the same preferences over amenities, denoted by case A, and one in which they have opposite preferences over amenities (L agents value amenity L four times as much), denoted by case M. Figures 17 and 18 plot the equilibrium outcomes for each location (population composition and amenities) under both worlds.

From Figure 17 we observe that when preferences are misaligned there is more segregation of agents types across locations than when preferences are aligned. Notice that in both cases the type H agents outprice the type L agents when competing for the exogenously better location, L1. Under misaligned preferences, L agents benefit from living together in the exogenously worse location L2, since the lack of competition from type H agents means they pay a lower rental price, while amenities endogenously tilt towards their specific tastes (Figure 18). Both lower prices and endogenous amenities compensates for the bad ex-ante characteristics of L2. Under aligned preferences, L agents want to consume more of type H amenities than of type L. This is why they demand to live close to agents of type H, because type H agents bring in type H amenities.

The equilibrium outcome for amenities also follows the segregation patterns of agent types. Under misaligned preferences, neighborhoods become more horizontally differentiated in the type of amenities that they offer compared to the case of aligned amenities.

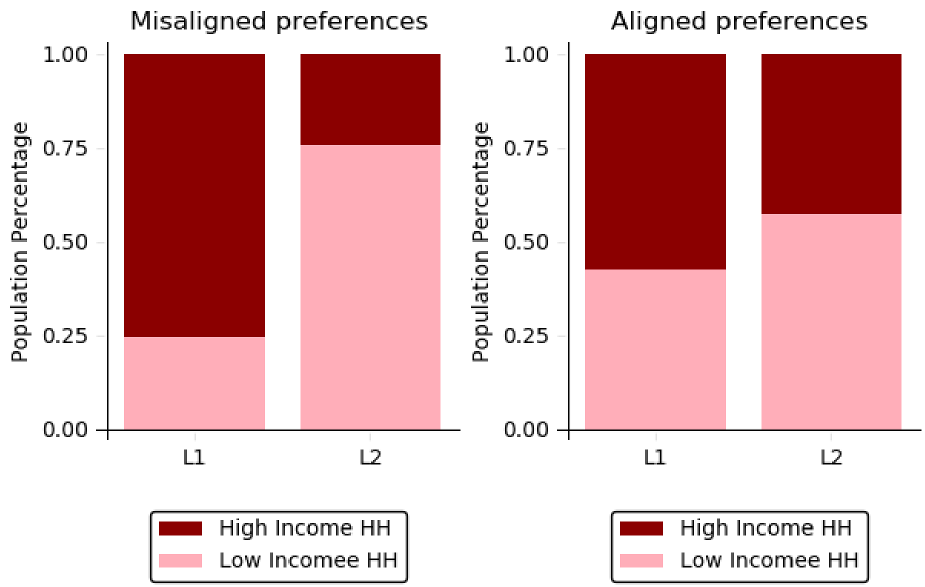


Figure 17: Population composition

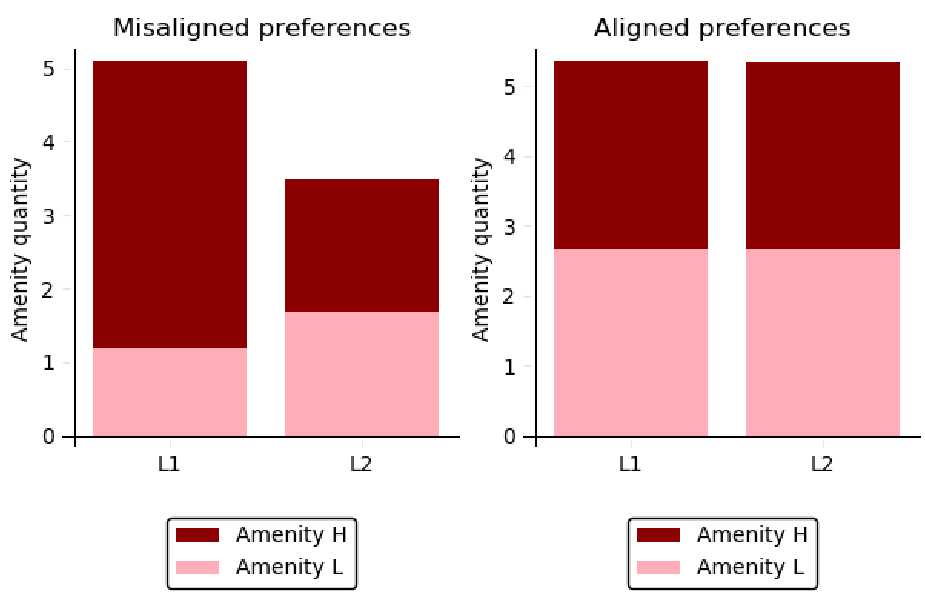


Figure 18: Amenities

We now proceed to calculate welfare. We do so in monetary units by dividing the average indirect utility of both type of agents by their valuation of money. The results of such calculations for both type of agents in both worlds is presented in Table 6. The main takeaway from this table is that when preferences are aligned, the welfare gap between high and low income agents increases by about 25% compared to the misaligned case. The reason is that when preferences are aligned, L types have to compete with H types to have access to the amenities that they value, and thus pay higher rental prices.

Table 6: Welfare

	Misaligned preferences	Aligned preferences
High Income	30.88k	32.27k
Low Income	25.01k	25.02k
Difference	5.87k	7.25k

This last result complements the existing literature on location sorting and endogenous amenities. For example, Diamond (2016) finds that when amenities are endogenous the welfare gap between low and high skill workers increases by 30% relative to a world where amenities are kept fixed. In her model, the one-dimensional endogenous amenity index is a function of the ratio of high over low skill households, and all households have increasing preferences over this index. While in her empirical results the endogeneity of amenities reinforces inequality, we have shown that in a world where preferences are sufficiently misaligned the endogeneity of amenities can decrease the welfare gap between different demographic groups by allowing them to sort along preferences and access the amenities that cater to their type.

7.2 Short-term rentals entry as a reduction in hosting costs

Our second exercise is to understand the welfare effects of the entry of short-term rental platforms, such as Airbnb, on households and landlords. We begin at a benchmark equilibrium where host-tourist matching costs are high, which we interpret as a world without Airbnb.

The tourist share (the short-term rental share) of the housing stock is near zero across the whole city because matching costs are high. Next, we model the entry of short-term rentals as a reduction in matching costs and we simulate the new equilibrium under two scenarios. In the first case, amenities are not allowed to adjust, remaining fixed to the benchmark level. In this case, we simply have a reduction in housing for locals, which leads rents and the tourist share of housing to rise across the city. Because of higher rents, all households are worse off.

In the second case, amenities are allowed to adjust, so that we have reduction in housing for locals due to the reduction in matching costs, but also a change in the locals' demand, because

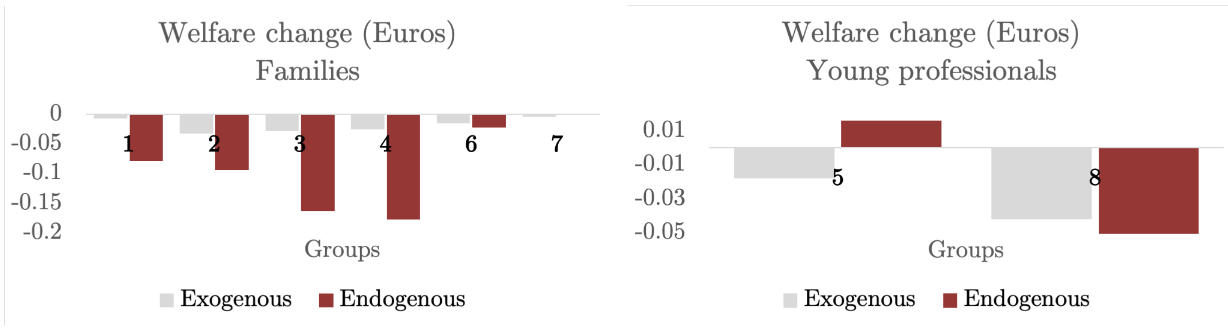


Figure 19: Welfare (Consumption Equivalent in Euros) changes of short-term rental entry

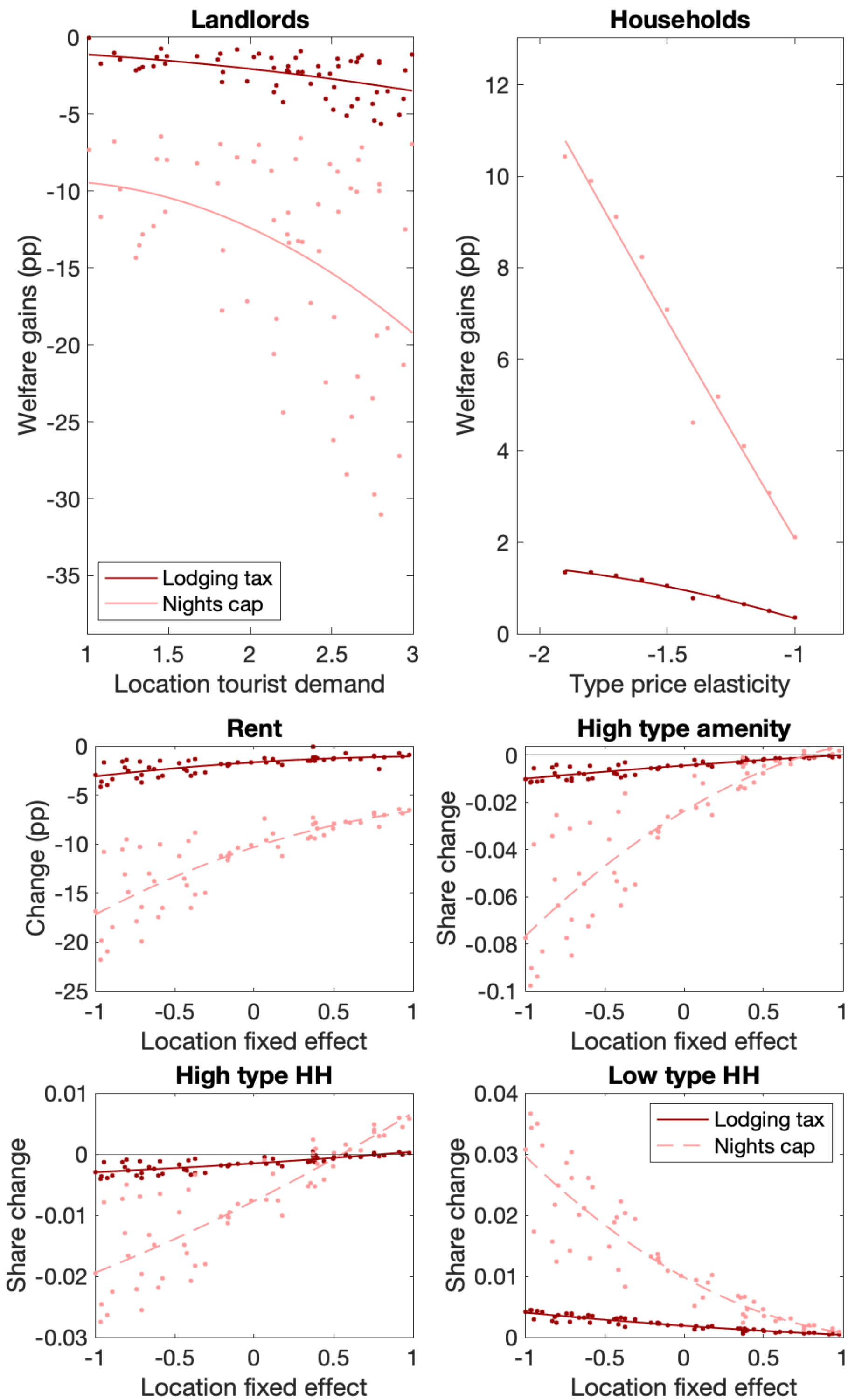
the neighborhoods are changing. In this parametrization, we have assumed tourists' preferences for amenities are the same as for young European ex-pats without children (group five). Welfare results are shown in Figure 19: all households are worse off with the entry of short-term rentals due to the rise in rents. However, young European ex-pats who enjoy bars, the type of amenities that tourists bring, are partially compensated because amenities tilt in their favor. In particular, group five is better off after the entry of short-term rentals since the positive effect from amenities is larger than the effect of higher rents. On the other hand, traditional families are hurt even more because they dislike these amenities.

Moreover, the welfare changes in a world where amenities are endogenous compared to a world where amenities are exogenous are 3.5 times larger, going from -2% to -7%. The main takeaway is that when a city or a neighborhood starts experiencing an increase in demand from a specific demographic group, policymakers should not only be concerned about rising rental prices but also about how the entry of this new type of residents affects the neighborhood by changing its characteristics.

7.3 Regulating prices vs. quantities

We test different regulatory polices for the full-fledged model with 60 neighborhoods and 12 agent types using our preliminary estimates. In the benchmark equilibrium hosting costs are relatively low, so there is a significant tourist share of housing across the city. We consider two regulatory counterfactuals motivated by real world examples: a lodging tax that is levied on the short-term rental nightly price, and a night cap that restricts landlords to a maximum number of nights hosted per year. Results are shown in Figure 20.

Figure 20: Effects of different regulations



The lodging tax shifts the housing share of each group in a predictable way and by a moderate magnitude: The tourist share falls and the low-type share rises. By contrast, the night cap has a much larger effect, with the tourist share falling nearly to zero. Landlords lose (households gain) under both regulations, and more so with night caps.

Furthermore, the top panel shows the slope of welfare gains with respect to tourist demand (for landlords) or rent elasticity (for households) is steeper under night caps. This finding is consistent with the night cap redistributing in favor of lower-willingness-to-pay households more than the lodging tax. Similarly, it penalizes landlords who were initially located in popular tourist locations more than those that were not. Thus, the night cap policy plays a larger re-distributive role, not only from landlords to residents, but also across different demographic groups of local residents.

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 that are provided by firms in a market for services. We leverage increasing tourism flows and the spatial variation in the entry of short-term rentals in Amsterdam as events that shift locations' demographic composition, and thus alter locations' 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 reduced-form findings, separate effects on supply from effects on demand, and conduct policy counterfactuals, we build a 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. In contrast to most studies that assume housing supply is exogenous or provided by a single representative construction firm, we endogenize and microfound supply through landlords' decisions to rent to locals on traditional leases or full time to tourists through the short-term rental market. Moreover, we also microfound how different consumption amenities arise in equilibrium for each neighborhood whose residents have heterogeneous preferences over a set a amenities.

We estimate three parts of our structural model using a set of different techniques that we borrow from the empirical industrial organization literature. On the housing supply side, we find significant heterogeneity of landlords in their operating costs across the long- and short-term rental markets. On the demand side, we estimate location preferences for eight groups of residents, finding substantial heterogeneity across households in their utility parameters. For example, among households who rent, the lowest-willingness-to-pay renters are five times more sensitive to prices than the highest-willingness-to-pay renters. Furthermore, the preference heterogeneity across groups correlate with sociodemographic status as expected. Finally, the structural parameters of amenity supply indicate large differences in barriers to entry as well as in how different services respond to changes in their location demographics.

Armed with our estimated parameters, we explore the role of endogenous amenities in defining within-city inequality. We find the reinforcement in sorting driven by the endogeneity of amenities can go either way in shaping welfare inequality across groups. We find that the sign of this effect depends on how correlated preferences are across groups, with the welfare gap increasing between households whose preferences are substantially aligned and decreasing for those whose preferences are misaligned. Moreover, in quantifying the welfare effects followed by Airbnb entry, we find that accounting for the endogeneity of amenities leads to welfare losses that are 3.5 times higher. This gap arises from amenities responding endogenously to the presence of tourists who consume services that locals do not value as much.

Finally, we present policy counterfactuals for lodging taxes and night caps, each of which have different distributional implications—not only do these policies redistribute differently *between* landlords and households, but also importantly *within* types of households.

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Appendix A. Tables

A.1 Shift-share IV results

Table 7: Relationship between rent and Airbnb listings

	Ln (rent/m2)					
	OLS	IV	OLS	IV	OLS	IV
Ln (commercial Airbnb listings)	**0.066*****	**0.090*****	**0.059*****	**0.113*****	**0.125*****	**0.194****
	(0.008)	(0.020)	(0.007)	(0.022)	(0.017)	(0.084)
Ln (housing stock)			-0.070**	-0.104***	-0.125***	-0.172***
			(0.029)	(0.029)	(0.028)	(0.058)
Ln (average income)			-0.482***	-0.465***	-0.316***	-0.273***
			(0.087)	(0.082)	(0.086)	(0.095)
Ln (high-skill population share)			0.291***	0.176***	-0.083	-0.210
			(0.058)	(0.066)	(0.114)	(0.193)
District-year FE					X	X
First stage F-stat		617.51		401.2		75.98
Observations	780	780	659	659	659	659
R2	0.154	0.133	0.423	0.361	0.578	0.550

Notes: Standard errors clustered at the wijk level in parenthesis.

Table 8: Relationship between home sale values and Airbnb listings

	Ln (house sale value)					
	OLS	IV	OLS	IV	OLS	IV
Ln (commercial Airbnb listings)	**0.108*****	**0.284*****	**0.053*****	**0.148*****	**0.054*****	**0.301*****
	(0.016)	(0.029)	(0.006)	(0.014)	(0.017)	(0.089)
Ln (housing stock)			-0.015	-0.073***	-0.038	-0.224***
			(0.024)	(0.024)	(0.029)	(0.078)
Ln (average income)			1.003***	1.050***	0.988***	1.157***
			(0.053)	(0.056)	(0.079)	(0.098)
Ln (high-skill population share)			0.281***	0.065	0.117	-0.377*
			(0.034)	(0.044)	(0.073)	(0.219)
District-year FE					X	X
First stage F-stat		594.62		375.27		69.49
Observations	746	746	634	634	634	634
R2	0.124	-0.208	0.768	0.705	0.898	0.796

Notes: Standard errors clustered at the wijk level in parenthesis.

The main endogeneity concern from regressing Airbnb listings on housing market outcomes is that any time-varying neighborhood-level unobservable variation that correlates with both variables will lead to biased OLS estimates (the bias could go in either way). For example, neighborhoods that are becoming unobservably more attractive to both locals and tourists will have higher housing prices and a higher number of Airbnb listings. To address this concern, we complement our analysis in the main text with a shift-share identification strategy, a frequently used research design in the literature measuring the causal effect of Airbnb on the housing market (Barron et al., 2021; Garcia-López et al., 2020).

The "shift" part of the instrument exploits time variation in worldwide demand for Airbnb as proxied by Google search volume, as in Barron et al. (2021). The "share" part constructs neighborhood-level exposure to tourism by using the spatial distribution of historic monuments. Our exclusion restriction requires both factors to be orthogonal to time-varying and neighborhood-level unobservables, conditional on the rest of the covariates. First, we do not expect worldwide Airbnb popularity to be informative of neighborhood specific unobservable trends. Second, we assume that the determinants of the spatial distribution of monuments from centuries ago are uninformative of current trends that may affect housing prices.

Our results for rent and house values are presented in tables 7 and 8. Note that OLS estimates are downward biased. This suggests that the unobservables correlating with Airbnb presence are negatively correlated with prices, i.e., they are disamenities for local residents.[36] The purpose of our structural model is precisely to quantify the welfare effects of Airbnb entry beyond housing price effects, in particular the heterogeneous welfare effects that arise due to changes in amenities.

Appendix B. Data

B.1 Constructing Airbnb supply

A challenge in working with the web scraped Inside Airbnb data is that some of the listings may be inactive, and thus would overstate Airbnb supply. For example, a listing that was created for a single hosting experience in 2015 and left idle on the site would show up in our raw scrapes after 2015 even though it never had any further reservations. To deal with this we need to define what it means for a listing to be considered "active". Using calendar availability data, we say that a listing has "activity" at date t if it has been reviewed by a guest or its calendar has been updated by its host at t. We consider a listing to be active in month t if it has had activity in month t.

We define a listing as commercially operated if it is an entire home listing, it has received new reviews over the past year, and it satisfies any of the following three conditions:

1. In the past year it has had over 60 nights booked: this is equivalent to having over 10 new reviews if we assume a review rate of 67% and an average length of 3.9 nights per booking.

2. It shows intent to be booked for many nights over the upcoming year: the listing is available for more than 90 nights over the upcoming year and the "instant book" feature is turned on.

[36] See Garcia, Miller and Morehouse (2020) for a detailed discussion of how Airbnb externalities lead to heterogeneous effects of short-term rentals on rental prices.

3. It has had frequent updates, reflecting intent to be booked even though it may not have the "instant book" feature turned on: the listing has been actively available for more than 90 nights over the upcoming year, and this has happened at least twice within the past year.

Finally, a limitation of the listings data is that since our webscrapes begin in 2015 we need to construct Airbnb supply before 2015 using the calendar and review data, but we can only do this for listings that survived up to 2015. For example, a listing that was active in 2011 would only be detected by our methodology if it remained on the site in 2015. Thus, our measure of listings is biased downwards.

B.2 Rent imputation

We link microdata from the universe of housing units to a national rent survey which contains approximately 14,000 observations of units in the rental market between 2006 and 2019. The housing-unit level data contains tax-appraisal values (WOZ values) and physical characteristics such as floor area, number of rooms, latitude-longitude coordinates, and official quality indexes. The reason these data exist is because each year, the local government assesses every property and issues its resulting WOZ value.[37] According to the Amsterdam city government, WOZ values are mostly based on market values.[38]

We use the matched subset in the rental survey with their tax valuation information to predict rents for housing units that do not appear in the survey but do appear in the property value data as occupied by a renter. We predict total rental prices and rental prices by square meter. We use two methods to predict rental prices: linear regression and random forest. In the two methods, we use tax-appraisal values, official categories for measures of quality, total floor area, number of rooms, latitude and longitude coordinates, time and wijk-code fixed effects. We train our algorithms in 90% of the sample and test out-of-sample predictive power in 10% of the sample. For the hedonic linear regression, the in-sample R^2 for total rental prices is 0.649 while the out-of-sample R^2 is 0.617. Similarly the random forest delivers an in-sample R^2 of 0.814 and out-of-sample R^2 of 0.742.

Next, we show the performance of the model on the weighted average rental prices and average rental prices by square meter by wijk-code and year in Figure 21, where weights are given by the number of observations in the rental survey.[39] We observe that the average imputation values predict well the average true values, especially for rental price by square meter where imputed values predict nearly 70% of the variation of actual rental prices. We take these results as supporting evidence of the good performance of our rental price imputation.

[37] Any owner can object to the issued valuation and request a new one.
[38] amsterdam.nl/en/taxes/property-valuation/
[39] For confidentiality purposes we cannot show the performance of our random forest model on individual data.

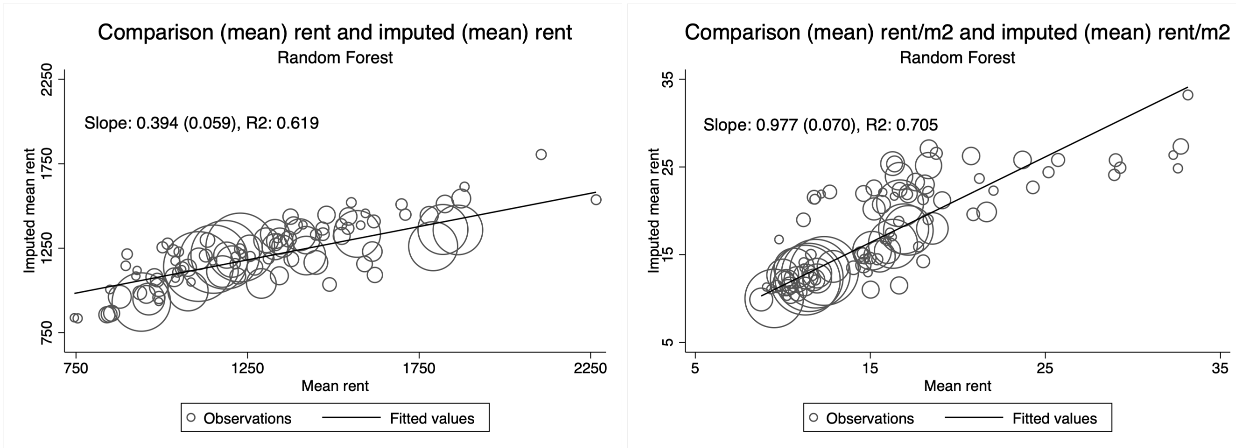

Figure 21: Rent (left) and rent/square meter (right)

B.3 Description of the micro data used for estimation

The time period covered by our data is 2008-2018. Our income data comes from the tax return files. Households are uniquely identified by the the id of the main breadwinner and year. Our residential data comes from the cadaster registry and contains the universe of all Dutch citizens. We only keep the cadaster data that is matched with the main breadwinner in the tax return data. We restrict to households that have lived at least once inside the city of Amsterdam between 2008 and 2018.

One of the limitations of our data is we do not observe all households for all periods of time. For example, a person who started reporting income in 2012 will appear in our sample only from that year onward. We also see some households leaving our sample, presumably because the household disappears for tax purposes. This can be driven by a change in the identity of the main breadwinner, death, or simply because the household leaves the country. To account for these movements in the tax return files, we only consider households from the first year they started reporting income until the last year they started reporting income. In some cases we also see households in the tax return files who leave and then come back again. We keep those missing years in between. Finally, we only keep households with tax return data available for at least two years.

We observe demographics of the main breadwinner, which are tenancy type (home-owner, renter, social housing), country of origin (all countries in the world), education level, gross and disposable income, income per-capita, source of income, age, households composition, and whether there are children in the household. We link this sociodemographic data with the income and cadaster data.

Given that we know the source of income for each household, we say that a household as a *working households* if its income source is not classified as social or unemployment benefits, pensions, student grants, etc. We only keep working households. Given a household, we keep all years between the first time until the last time it is classified as a working household.

We translate education level to a skill level. The Dutch system follows a non-standard system of education where children can access to several types of secondary education as well as several types of tertiary education.[40] We classify households as *low skill* if their maximum level of education is secondary education. We classify households as *medium skill* is if their maximum level of education is the equivalent of the American community college. Finally, we classify households as *high skill* if their maximum level of education is college or above.

For country of origin we reduce the subset of categories to four that seem to be the most important in Amsterdam: Dutch, Dutch colonies (includes Surinamese and Antillean households), Western (European, North American, and households from Oceania), and Non-western (includes Morocco, Turkish, Nigerian, etc).

Finally, even though we keep all households for the amenities estimation, we drop all years in which households are currently living in social housing for our demand estimation. We do so because we expect households living in social housing to have very different incentives from home-owners and traditional renters. See Appendix C.1 for more details about social housing in the Netherlands. Given a year with tenancy status different from social housing, we classify households as previously living in the outside option those who previously lived in social housing.

[40] For more details see https://en.wikipedia.org/wiki/Education_in_the_Netherlands

Appendix C. Institutional details

C.1 The housing market in Amsterdam

As of 2017, 70% of housing units in Amsterdam are rentals, which can be classified as either social or private housing.[41] Classification of a unit as social or private is determined by a points system based primarily on physical characteristics (size, number of bedrooms and bathrooms, among others). If a unit's total score is below an annually updated threshold it is classified as a social rental unit, making it subject to a rent ceiling that is proportional to its score. The maximum allowable rent for social units is commonly known as the "liberalization line", which stands at 710.68 euros for 2015-2018. In the private market, the initial rent a landlord charges is not regulated. According to van Dijk (2019), eligibility requirements for social housing are generous, as the income cutoff is set at household size-adjusted median income. For example, in 2018 the total maximum income per household to qualify for social housing was 36,798 euros. As a result, the pool of applicants is large and heterogeneous, consisting of households dependent on welfare receipt as well as households in the lower half of the income distribution. Eligible households apply through a centralized city-wide waiting list, with wait times in the range of 7-12 years. A small number of units are allocated by lottery, so that a few lucky households may avoid the long waiting times.

The role of housing associations

A "housing association" is an organization that focuses on the building and management of social housing units. Roughly half of the total housing stock in Amsterdam is owned by these independent not-for-profit associations (van der Veer and Schuiling, 2005). These organizations originated in the mid-1800s as charitable institutions, founded by workers' associations as well as employers, with the goal of providing housing as well as other social services for urban workers. After the Housing Act of 1901, the associations were assigned the sole objective of promoting public housing, in return for favorable loans and subsidies for construction and management from the government. The associations became especially prominent after WWII due to a housing shortage induced by the baby boom, which led the Dutch state to provide the associations with further construction subsidies to increase housing supply (Musterd, 2014). In the mid 1990s the housing associations were privatized as part of a nationwide strategy to encourage home ownership over renting and reducing the fiscal burden of social housing. This meant that financial support from the state ended but housing associations still remained subject to the statutory obligation of providing good and affordable houses for lower income groups (Regout, 2016). The government wrote off all outstanding loans to the associations, while simultaneously cancelling its subsidies. Government policy has been to actively encourage housing associations to sell off units to owner

[41] The Netherlands is well known for having the largest social housing program in Europe, and Amsterdam is no exception to this national trend: 42% of the city's housing stock is social housing as of 2017.

occupants. For example, the requirement for housing associations to obtain government permission before selling their rental properties has been removed. In Amsterdam, the home ownership share of the housing stock increased from 11 to 30% between 1995 and 2015, while the social housing share declined from 58 to 44% (van Duijne and Ronald, 2018). As of recently, two thirds of social housing is owned by housing associations, while one third is owned by private individuals or real estate management companies (recall that the "social housing" label is based on the physical features of the house, not who owns it).

The points system and the determination of rents in social housing units

The national points system determines if a housing unit is considered social housing, and if so, how much its rent should be and at what rate it may be increased within a tenancy (Fitzsimons, 2013). Both private owners and housing corporations have to follow this system.

The number of points a unit receives is predominantly based on physical characteristics such as room sizes, heating type, number of bathrooms, and neighborhood amenities, such as public parks and access to public transport. Therefore, two houses with identical physical features and neighborhoods, one in Amsterdam and one in a small rural town, would have the same number of points and thus the same maximum allowable rent. This failure to account for regional discrepancies has been one reason why the system has been criticized, as well as why it has recently been adjusted. Since October 2011, a market-based element has been added to the system: units in areas with housing shortage are allocated more points so that higher rents may be allowed. However, the units may only receive up to a maximum of 25 points based on this criterion (as of 2013, total points for a unit range between 40 and 250). Units with less than 143 points are classified as social housing and always have a rent ceiling. Those units over 143 points are classified as private market and have no rent ceiling. These units also don't have a rent floor, so the actual agreed upon rent could be below the "liberalization line", in which case they are classified as social housing. This typically happens with housing units owned by housing associations in low demand neighborhoods. The unit may have enough points to be in the private sector but if demand is low it is rented below the liberalization line and any within-tenancy rent increases are restricted in the same way as a social unit. Thus, by possibly subjecting houses with high quality physical characteristics to social housing status and rent increase restrictions, the system has crowded out investors from the market for dwellings with points in the 142-200 bracket.

Rent increases and contract termination

Social housing is subject to controls on initial rent levels as well as maximum within-tenancy rent increases that are set annually by the Ministry of Public Housing, often tracking the inflation rate. Private housing does not face restrictions on the size of within-tenancy rent increases, but such increases cannot take place more than once a year (Fitzsimons, 2013). Landlords may terminate contracts with their tenants on the following grounds: i) the tenant not behaving in a responsible manner, ii) in the case of temporary tenancy, the landlord can officially end the contract, iii) urgent use by the landlord himself, with the landlord's interest in living in the house being greater than that of the tenant, iv) the tenant turning down a reasonable offer to enter into a new tenancy agreement referring to the same apartment, or v) realization of a zoning plan. In the case of disputes, the parties must submit their case for deliberation to the Rent Commission, which charges a fee for analyzing each case (Fitzsimons, 2013).

Rent subsidies

Rent subsidies are only available for tenants of social housing units. First, the total income in 2018 of the household should be below 30,400 euros (22,400 for a single household) as compared to the 36,798 maximum income for social housing. Second, rent has to be between 225,08 and 710,68 euros for 2018 with different cut-offs depending on the household composition.

C.2 The tourism industry in Amsterdam

Between 2008 and 2017, the number of overnight stays in Amsterdam grew from 8.3 to 15.9 million. This rapid growth in tourist volume has been accompanied by an expansion of the hotel industry, with more high-end hotels being constructed on average. The number of hotels, rooms, and beds have increased by 34%, 65%, and 66% respectively.

The explosion of tourism in Amsterdam has also led to an increase in the number of jobs and businesses dedicated to this sector, increasing by 41% and 50% respectively. As of 2017, half of the jobs in the tourism sector correspond to food-catering (bars, restaurants), 18% to hotels, 15% to culture and recreation, and 7% to transportation.

The average room price has followed an increasing trend, going from EUR 105 in 2009 to EUR 138 in 2017, with average annual price growth of 3.3% and a peak of 8.8% in 2015. Furthermore, occupancy rates have been steadily increasing from 71% to 84% across hotels of all quality ranges. Overall, average annual hotel revenue has had a total growth of 57% from 2008-2017.[42]

Airbnb

First, Airbnb hosts can rent their property in three ways: as an entire home rental, a private room rental, or a shared room rental. Entire home rentals for extended periods of time are typically associated with commercial operators, while live-in hosts are more likely to offer short, private or shared rentals. This distinction between rental types is key to understanding the degree to which the platform is being used by commercial operators and thus removing housing stock from locals, rather than simply allowing locals to make use of their idle capacity.

Second, guests and hosts have incentives to review each other after a stay has been completed due to the reputational nature of the platform. These reviews allow us to infer actual reservations, which cannot be directly observed in the InsideAirbnb data.

[42] All statistics are from tourism reports commissioned by Onderzoek, Informatie en Statistiek (Research, Information, and Statistics) of the Amsterdam City Data project. Source: ois.amsterdam.nl/toerisme

Third, hosts keep an availability calendar which potential guests can see and make reservations on. We argue that these calendars reflect true availability since hosts have incentives to keep them up to date. Calendars have a default "instant booking" feature, which means that a potential guest can make a reservation on an available calendar date without host approval. At the moment the reservation is made, the guest is charged for his entire stay. If a host decides to cancel because her calendar availability was incorrectly set, she is fined, receives an automated negative review, and in some cases may have her listing removed. This provides incentives for hosts to keep their calendars updated. There is an option to disable the "instant booking" feature, so that any reservation has to be approved by the host before the guest is charged. However, over 60% of bookings are instantly booked since hosts can set "Instant Book" to apply only to guests with positive reviews. Furthermore, Airbnb strongly encourages hosts to use the "Instant Book" since these listings tend to appear first in search results and they streamline the reservation process for guests (some of which may only search among listings with "Instant Book").[43] The reason why we stress this is that we will use calendars to measure Airbnb supply, so we want to argue that they reflect true availability.

Finally, the global average review rate by guests is 67% (Fradkin, Grewal and Holtz, 2018), and the average booking in Amsterdam is for 3.9 nights.[44]

Airbnb regulations

In order to rent an Amsterdam apartment on Airbnb the host must be the apartment's main occupant or owner. Hosts who live in social housing owned by a housing association may not rent their apartments on Airbnb at all.

In December 2016 Airbnb agreed to enforce short-term rental regulations on behalf of the Amsterdam city council, making Amsterdam one of only two cities in the world in which Airbnb has agreed to police its hosts.[45] Specifically, Airbnb has agreed to put caps on the number of nights hosts are allowed to rent out their entire homes: no more than 60 nights per year per entire home listing. Exceptions to the cap are handled on a case-by-case basis and must be approved by the Amsterdam municipality (private rooms and shared rooms listings remain uncapped). Preliminary research from Airbnbcitizen.com suggests the regulation seems to have had a significant impact since its implementation on March 1, 2017: the number of entire homes being shared has been reduced by two thirds between May 2016 and May 2017.[46] Furthermore, the company has agreed to reduce the cap further to 30 nights per year beginning on January 1, 2019.[47] In addition to the caps being directly enforced by the site, users are required to report to the Amsterdam municipality each time the home is rented out. Failure to do so results in fines between 6,000-20,500

[43] press.airbnb.com/instant-book-updates/

[44] Data for 2012-203. Source: press.airbnb.com/instant-book-updates/

[45] The Guardian (December 3, 2016)

[46] airbnbcitizen.com/new-data-on-responsible-home-sharing-in-amsterdam/

[47] Techcrunch (January 10, 2018)

euros.[48]

Airbnb competitors

Airbnb's main competitors are other short-term rental platforms and traditional hotels. As of 2016, Airbnb's share of total overnight stays in Amsterdam was 15%, with the rest of the market being dominated by traditional hotels. Airbnb prices lie slightly below the average price for 3-star hotels.[49] It is precisely low-end hotels that report having suffered the most from short-term rentals, while 4- and 5-star hotels report little competition from this new form of accommodation.[50] Therefore, it seems that Airbnb competes with the hotel industry but only at mid- and low-scale hotels, as pointed also by Farronato and Fradkin (2018). Within Amsterdam's short-term rental market, Airbnb accounted for 80% market share in 2017.[51] The main competitor is Wimdu, with 13% market share in 2017. Other platforms such as Booking, Homeaway, Flipkey, and 9flats accounted for 4000 listings in 2016.

[48] amsterdam.nl/veelgevraagd
[49] Source: 2019 Tourism Report in ois.amsterdam.nl/toerisme
[50] ois.amsterdam.nl/toerisme
[51] ois.amsterdam.nl/toerisme

C.3 Technical details for k-means clustering

In this section we describe the technical details of the k-means classification performed on the set of observations described in B.3.

First, the subset of demographics that we use to cluster households are: percentile of disposable income, percentile of per person income, ethnic background (Dutch, Dutch colonies, Western, and Non-western), skill (high, medium, and low), tenancy type (home-owners, renters, and social housing), children, proportion of time with children, and age. Choosing the optimal number of clusters is a statistically complicated task. Moreover, standard statistical criteria do not apply here. In our case, the optimal number of clusters is the one that minimizes variance and bias, but also takes into account the measurement error in the CCP estimation. To the best of our knowledge there is no statistical criterion that incorporates all of those features. Our practical solution was to start with a large number of clusters, and decrease this number sequentially until we hit a small number of cluster but still with clearly defined differences across clusters.

We use a two-step clustering algorithm, clustering first on housing tenancy using three groups. We do so, because we expect households with different tenancy status (home-owners vs. renters vs. social housing) to have significantly different preference parameters in their utility estimation. For example, we can expect home-owners to have larger moving costs than renters. Second, we use the rest of the demographics, by choosing the number of subgroups inside each tenancy-status category. Unfortunately, classifications with more than 15 clusters (5 sub-clusters) lead to groups with a low number of households. This is problematic, because the smaller the initial groups, the higher the measurement errors in CCP frequencies.[52] The classification with 15 clusters lead to groups without any stark differences. For example, for two groups the only difference was the skill level, where one group was low skill and the other one medium skill. Given that our goal is to have as few groups as possible, as we do not expect these groups to have extremely different preferences, we decided to cluster households using 4 sub-groups inside each tenancy status group. With this classification we see clear differences across groups. Results can be seen in Table 2.

[52]Monte Carlo simulations indicate that a reasonable minimum number of households per group needs to be around 18000. The reason is that the demand estimation problem has around 180 states. Observe than with 18000 initial households and 180 states, there is an average of 100 agents per state.

C.4 Description of consumption amenities

Table 9: Description of consumption amenities in ACD

Variable	Dutch name	English translation
Touristic amenities	**Vestigingen toerisme** Vestingen met de activiteitencodes: logies en overnachtingen, overige horeca, personenvervoer, reisorganisatie- en bemiddeling, cultuur en recreatie, jachthavens, zeilscholen en recreatieve detailhandel.	**Tourism branches** Fortresses with activity codes: accommodation and accommodation, other catering, passenger transport, travel organization and mediation, culture and recreation, marinas, sailing schools and recreational retail.
Sport amenities	**Voorzieningen: vestigingen sport en recreatie** De deelfunctie 'sport en recreatie' wordt aan een vestiging toegekend op basis van de activiteitencode (SBI) waarmee deze vestiging is geregistreerd bij de Kamer van Koophandel.	**Facilities: sports and recreation locations** The sub function 'sports and leisure' is awarded to a settlement based on the activity code (SIC) that this office is registered at the Chamber of Commerce.
Education amenities	**Voorzieningen: vestigingen onderwijs** De deelfunctie 'onderwijs' wordt aan een vestiging toegekend op basis van de activiteitencode (SBI) waarmee deze vestiging is geregistreerd bij de Kamer van Koophandel.	**Services: education establishments** The sub-function 'education' is assigned to an establishment on the basis of the activity code (SBI) with which this establishment is registered with the Chamber of Commerce.
Catering[53]	**Horecavestigingen per 1.000 inwoners** Aantal vestigingen horeca per 1.000 inwoners.	**Catering establishments per 1,000 inhabitants** Number of branches in the hospitality industry per 1,000 inhabitants.
Restaurants	**Horeca: vestigingen restaurant** De deelfunctie 'restaurant' wordt aan een vestiging toegekend op basis van de activiteitencode (SBI) waarmee deze vestiging is geregistreerd bij de Kamer van Koophandel.	**Catering: restaurant locations** The sub function 'restaurant' is awarded to a settlement based on the activity code (SIC) that this office is registered at the Chamber of Commerce.
Restaurants	**Horeca: vestigingen cafe** De deelfunctie 'cafe' wordt aan een vestiging toegekend op basis van de activiteitencode (SBI) waarmee deze vestiging is geregistreerd bij de Kamer van Koophandel.	**Catering: cafe locations** The sub function 'cafe' is awarded to a settlement based on the activity code (SIC) that this office is registered at the Chamber of Commerce.
Food Stores	**Winkelruimtes food** Aantal winkelruimtes voor food (dagelijkse goederen).	**Number of food stores** Number of retail space for food (daily goods).
Non-Food Stores	**Winkelruimtes non-food** Aantal winkelruimtes voor non-food (niet-dagelijkse goederen)..	**Number of non-food stores** Number of retail space for non-food (non-daily goods).

[53]We convert the variables "Catering" to total number of catering establishments by location per year. It includes pubs, bars, restaurants, canteens, and others.

Appendix D. Technical appendix

D.1 Micro-foundation of the utility function

In this section we micro-found household utility for the location demand model presented in section 5.2. We also outline the connection to the demand for endogeneous amenities found in section 5.1.

We follow a similar specification for the marginal utility of money in our indirect utility as in Couture et al. (2019), where households pay r_j for a unit of housing leaving them with total budget $b_j^k = w^k - r_j$ for consumption amenities.[54] We also assume that there are non-market amenities in location j that also enter utility, denoted by A_j, such as access to public transport, nuisance and congestion of public spaces generated by tourists. Finally, households derive utility from their location tenure τ. Conditional on living in j, a household of type k solves the following nested problem to maximize its utility over services:[55]

$$\max_{\{q_{is}\}_{is}} A_j \tau^{\nu^k} \prod_s \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_s^k} \quad \text{s.t.} \quad \sum_{is} p_{is} q_{is} = (w^k - r_j), \tag{11}$$

with $\sum_s \alpha_s^k = 1$.

Next, we show that the demand system in section 5.1 can be derived from the nested preferences in 1. First order conditions with respect to q_{is} gives

$$A_j \tau^{\nu^k} \alpha_s^k \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_s^k - 1} \left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{1}{\sigma_s - 1}} q_{is}^{-\frac{1}{\sigma_s}} \prod_{s' \neq s} \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_{s'}^k} = \lambda^k p_{is}.$$

Trivially, all firms within a service s face the same demand curve. Because we have assumed that firms within a service have the same marginal cost, in equilibrium $q_{is} = q_s$ and $p_{is} = p_s$ for all i in sector s. Hence, in equilibrium, a type k consumer demands the same quantity q_s^k from the N_s establishments offering service s. With a bit of algebra, we can show

$$\frac{p_s}{\alpha_s^k} N_s q_s^k = \frac{p_s'}{\alpha_{s'}^k} N_s' q_{s'}^k,$$

for all s, s'. Substituting inside the budget constraint, we obtain

$$N_s q_s^k = \frac{\alpha_s^k}{p_s} (w^k - r_j),$$

which gives the desired result.

Under the symmetric equilibrium presented in section 5.1.3, the indirect utility that a type k

[54] This specification has been widely used in the industrial organization literature. See for example Berry (1994), Berry et al. (1995), or Nevo (2000). We can also allow for $b_s^k = \lambda^k \alpha_s^k (w^k - r_j)$ and qualitatively results do not change.

[55] We can allow households to buy a good available at all locations with normalized price equal to 1 as in Couture et al. (2019).

household living in j at time t receives is

$$A_{jt}\tau^{\nu^k}\prod_s\left(\frac{\alpha_s^k}{p_{sjt}}(w_t^k-r_{jt})N_{sjt}^{\frac{1}{\sigma_s-1}}\right)^{\alpha_s^k}.$$

We also know that in equilibrium prices are given by

$$p_{sjt}=\frac{c_{sjt}}{1-\frac{1}{\sigma_s}},$$

so substituting inside the indirect utility yields,

$$A_{jt}\tau^{\nu^k}(w_t^k-r_{jt})\prod_s\left(\frac{\alpha_s^k(1-\frac{1}{\sigma_s})}{c_{sjt}}N_{sjt}^{\frac{1}{\sigma_s-1}}\right)^{\alpha_s^k}, \tag{12}$$

We assume that the utility obtained from non market amenities is given by

$$A_{jt}=\prod_d a_{jt}^{\beta_a^k},$$

where a_{jt} denotes a specific non-market good in location j at time t.

Substituting in 12, taking logs, and rearranging:

$$\mu_j^k+\nu^k\log\tau_t+\sum_a\beta_a^k\log a_{jt}+\log(w_t^k-r_{jt})+\sum_s\frac{\alpha_s^k}{\sigma_s}\log N_{sjt}+\psi_{jt}^k,$$

where $\mu_j^k=\sum_s\alpha_s^k\big(\log\alpha_s^k+\log(1-\frac{1}{\sigma_s})\big)$, and $\psi_{jt}^k=-\sum_s\alpha_s^k\log c_{sjt}$.

Finally, the utility flow for living in location j is given by

$$\mu_j^k+\nu^k\log\tau_t+\log(w_t^k-r_{jt})+\sum_a\beta_a^k\log a_{jt}+\sum_s\frac{\alpha_s^k}{\sigma_s}\log N_{sjt}+\psi_{jt}^k+\epsilon_{ijt},$$

where ϵ_{ijt} is a type I EV error. We divide the previous equation by the variance of the shock ϵ_{ijt} to normalize it to 1. As in section After such normalization, the final expression for the indirect utility is

$$\begin{aligned}&u_{jt}^k+\varepsilon_{ijt}=\\&\delta_{d(j)}^k+\delta_\tau^k\tau_t+\delta_w^k\log(w_t^k-r_{jt})+\sum_a\delta_a^k\log a_{jt}+\sum_s\delta_s^k\log N_{sjt}+\xi_{jt}^k+\varepsilon_{ijt}.\end{aligned}$$

Observe that ξ_{jt}^k will be part of the unobservable component in our regression equation.

At time t, a household i of type k with past location j_{t-1} and tenure τ_{t-1} chooses the location that maximizes its value function given the indirect utility values for each location $u_{j(d)t}^k$

$$V_t^k(j_{t-1},\tau_{t-1})=\max_d u_{j(d)t}^k-MC^k(j(d),j_{it-1})+\varepsilon_{ijt}+\beta EV_{t+1}^k(d,j_{t-1},\tau_{t-1}),$$

D.1.1 Extra household income from short-term rentals

Conditional on living in location j, assume household i has some idle capacity of their housing unit. If household i rents the apartment, it earns profits p_j while incurring cost c_{ij}. If it does not rent its idle capacity, it makes no income and does not incur any cost. Assume that $c_{ij} \sim F(c)$. Hence, household i rents in the short-term rental market with probability,

$$\mathbb{P}(c_{ij} \leq p_j) = F(p_j)$$

Hence, if household i rents its idle capacity, it will earn total income equal to,

$$w_i + p_j$$

and therefore, expected household total income is given by

$$w_i + F(p_j)p_j = w_i + h(p_j).$$

D.2 Technical details of the demand estimation

In this section we sometimes drop the type superscript k to simplify notation.

D.2.1 Expected Value Function

Using Assumption 2, we can integrate over future ϵ to reduce the dimensionality of the problem, defining the ex-ante value function as follows:

$$\begin{aligned}
\mathbb{E}_t\left[V_{t+1}(x', \epsilon')|d, x, \epsilon\right] &= \int V_{t+1}(x', \epsilon') dF_t(x', \omega_{t+1}, \epsilon'|d, x, \epsilon') \\
&= \int \Big(\int V_{t+1}(x', \epsilon') dF_t(s', \omega_{t+1}|d, x) \Big) dF(\epsilon') \\
&= \int \Big(\int V_{t+1}(x', \epsilon') dF(\epsilon') \Big) dF_t(x', \omega_{t+1}|d, x) \\
&= \int \bar{V}_{t+1}(x') F_t(x', \omega_{t+1}|d, x) = \mathbb{E}_t\left[\bar{V}_{t+1}(x')|d, x\right]
\end{aligned}$$

We can also define the conditional value function

$$v_t(d, x) = u_t(d, x) + \beta \mathbb{E}_t\left[\bar{V}_{t+1}(x')|d, x\right] = u_t(d, x) + \beta EV_t(d, x),$$

where $\bar{u}_t(d, x) = u(d, x, \omega_t, 0)$. By assumption 3 and the properties of the logit errors we obtain

$$P_t(j, x) = \frac{\exp(v_t(j, x))}{\sum_d \exp(v_t(d, x))}, \tag{13}$$

and

$$\bar{V}_t(x) = \log\left(\sum_d \exp v_t(d, x)\right) + \gamma,$$

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

$$\bar{V}_t(x) = v_t(d, x) - \ln(P_t(d, x)) + \gamma. \tag{14}$$

Observe that the previous equation holds for any state s, and, more importantly, for any action j. This will be key to exploit renewal actions.

D.2.2 Toward a demand regression equation

Our demand regression equation's starting point follows Hotz and Miller (1993), by taking differences on equation 13:

$$\ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = v_t(d,x_{it}) - v_t(d',x_{it}). \tag{15}$$

Observe that $v_t(d,x_{it}) - v_t(d',x_{it})$ is equal to a threshold value $\Delta\epsilon_t^*$ in the error differences $\epsilon_{idt} - \epsilon_{id't}$ which make the agent indifferent between location d and location d'. That is if $\epsilon_{idt} - \epsilon_{id't} > \Delta\epsilon_t^*$ agent prefers location d over location d'.

Substituting for the choice specific value function,

$$\bar{u}_t(d,x_{it}) - \bar{u}_t(d',x_{it}) - \ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = \beta\mathbb{E}_t\left[\bar{V}_{t+1}(x'_{it+1})|d',x_{it}\right] - \beta\mathbb{E}_t\left[\bar{V}_{t+1}(x_{it+1})|d,x_{it}\right] \tag{16}$$

The previous equation has an easy interpretation: at the indifference threshold, the surplus in utility today is equal to the loss in tomorrow's expected utility of location d compared to d'. This is the discrete version of the Euler conditions for continuous choice variables.

The expected value at time $t+1$ can be decomposed between its expectation at time t and its expectational error

$$V_{t+1}(x'_{it+1}) = \mathbb{E}_t\left[\bar{V}_{t+1}(x'_{it+1})|d,x_{it}\right] + \nu_t(d,x_{it})$$

Now, recall state variables j_{it} and τ_{it} evolve deterministically, and

$$F(w_{it+1}|j_{it},\tau_{it},w_{it}) = F(w_{it+1}|w_{it})$$

Plugging in everything in equation 16 gives us

$$\begin{aligned}\bar{u}_t(d,&x_{it}) - \bar{u}_t(d',x_{it}) - \ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = \\ \beta\Bigg[&\sum_{w_{it+1}\in\mathcal{W}} F(w_{it+1}|w_{it})\left(V_{t+1}(x'_{it+1}) - V_{t+1}(x_{it+1})\right) \\ &- \nu_t(d,x_{it}) + \nu_t(d',x_{it})\Bigg].\end{aligned}$$

Using equation 14 to replace the continuation values $\bar{V}_{t+1}$ for choice $\tilde{d}$ gives us

$$\begin{aligned}\bar{u}_t(d,&x_{it}) - \bar{u}_t(d',x_{it}) - \ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = \\ \beta\Bigg[&\sum_{w_{it+1}\in\mathcal{W}} F(w_{it+1}|w_{it})\left(v_{t+1}(\tilde{d},x'_{it+1}) - v_{t+1}(\tilde{d},x_{it+1}) - \ln\left(\frac{P_{t+1}(\tilde{d},x'_{it+1})}{P_{t+1}(\tilde{d},x_{it+1})}\right)\right) \\ &- \nu_t(d,x_{it}) + \nu_t(d',x_{it})\Bigg]\end{aligned} \tag{17}$$

Now assume that $\tilde{d}$ is a renewal action at time $t+1$, i.e, moving to the same neighborhood makes the future from period $t+2$ forward looks the same to the household, and hence it cancels out. The following holds

$$v_{t+1}(\tilde{d}, x'_{it+1}) - v_{t+1}(\tilde{d}, x_{it+1}) = \bar{u}_{t+1}(\tilde{d}, x'_{it+1}) - \bar{u}_{t+1}(\tilde{d}, x_{it+1}) = MC(j(\tilde{d}), j) - MC(j(\tilde{d}), \tilde{d})$$

so that plugging 17 inside gives us

$$\begin{aligned}\bar{u}_t(d, x_{it}) - \bar{u}_t(d', x_{it}) - \ln\left(\frac{P_t(d, x_{it})}{P_t(d', x_{it})}\right) =& \beta\Bigg[MC(j(\tilde{d}), j) - MC(j(\tilde{d}), \tilde{d}) \\ & - \sum_{w_{it+1}\in\mathcal{W}} F(w_{it+1}|w_{it}) \ln\left(\frac{P_{t+1}(\tilde{d}, x'_{it+1})}{P_{t+1}(\tilde{d}, x_{it+1})}\right) \\ & - \nu_t(d, x_{it}) + \nu_t(d', x_{it})\Bigg]\end{aligned}$$

Rearranging terms, the previous equation leads to the following regression equation

$$\begin{aligned}\ln\left(\frac{P_t(d, x_{it})}{P_t(d', x_{it})}\right) + \beta \ln\left(\frac{P_{t+1}(\tilde{d}, x_{it+1})}{P_{t+1}(\tilde{d}, x'_{it+1})}\right) =& \bar{u}_t(d, x_{it}) - \bar{u}_t(d', x_{it}) \\ & + \beta\Big(MC(\tilde{d}, j(d)) - MC(\tilde{d}, j(d')) + \nu_t(d, x_{it}) - \nu_t(d', x_{it})\Big)\end{aligned}$$

Now if we define the following,

- The operator

$$\Delta_{d,d'} x = x_d - x_{d'}$$

- The dependent variable

$$Y_{t,d,d',\tilde{d},x_{it}} \equiv \ln\left(\frac{P_t(d, x_{it})}{P_t(d', x_{it})}\right) + \beta \ln\left(\frac{P_{t+1}(\tilde{d}, x_{it+1})}{P_{t+1}(\tilde{d}, x'_{it+1})}\right)$$

- Error term

$$\tilde{\varepsilon}_{t,d,d',x_{it}} = \beta\big(\nu_t(d, x_{it}) - \nu_t(d', x_{it})\big)$$

then the final regression equation we obtain is

$$Y_{t,d,d',\tilde{d},x_{it}} = \Delta_{d,d'}\Big(\delta_{j(.)} + \delta_\tau \tau_{x_{it}} - \delta_r \ln r_t + \delta_a \ln a_t + \xi_t + \beta MC(j(.), \tilde{d})\Big) + \tilde{\varepsilon}_{t,d,d',x_{it}}. \qquad (18)$$

Observe the previous expression is a linear regression equation.

D.2.3 Computational details of the estimation

The regression equation that we want to run is

$$\begin{aligned} Y_{t,d,d',\tilde{d},x_{it}} &= \ln\Big(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\Big) + \beta \ln\Big(\frac{P_{t+1}(\tilde{d},x_{it+1})}{P_{t+1}(\tilde{d},x'_{it+1})}\Big) \\ &= \Delta_{d,d'}\Big(\delta_{j(.)} + \delta_\tau \tau_{x_{it}} - \delta_r \ln r_t + \delta_a a_t + \xi_t + \beta MC(j(.),\tilde{d})\Big) + \tilde{\varepsilon}_{t,d,d',x_{it}}. \end{aligned}$$

Observe that the previous equation is valid for any two different actions d, d', any $\tilde{d}$ such that $\tilde{d}$ is a renewal action for d and d', any state variable x_{it} and any time period $t = 1, .., T-1$. The number of actions is equal to the number of locations plus 2 ($d =$ outside option or $d =$ stay). We collapse 100 zipcodes to 60 locations because many zipcodes contain very few households. The collapsing criterion requires that there are at least 30 households for every state x_{it}. In our practical application, the maximal tenure composition $\bar{\tau}$ is set equal to three:

$$\bar{\tau} = 3.$$

Given that $\bar{\tau}$, the number of state variables is 168. Considering that we have 10 time periods (from 2008 until 2017) and 62 choices, the total number of possible combination of the previous equation is equal to

$$\binom{62}{2} \times 59 \times 178 \times 9 \approx 179 \times 10^6$$

Running a regression with 179×10^6 millions of observations may be computationally problematic if we use standard techniques.[56] In order to reduce the number of path combinations, we construct $(d, d', \tilde{d})$ tuples using *empirical probabilities* for each household i as follows:

- For any individual i, take d as the realized decision

$$d = d_{it}$$

- For the counterfactual action d', use moving to the outside option which never has zero probability in the data.

- Set $\tilde{d}$ using the joint empirical cdf

$$\begin{aligned} \tilde{d} &\sim \hat{F}(d_{t+1} = d | x_{it+1}, x'_{it+1}, d \neq d_{it}, 0) \\ &= \hat{F}(d_{t+1} = d | x_{t+1}, d \neq d_{it}, 0)\hat{F}(d'_{t+1} = d | x'_{it+1}, d \neq d_{it}, 0), \end{aligned}$$

  where independence follows from the Markovian nature of the dynamic problem. Finally, we set

$$\tilde{d} = \arg\max_d \hat{F}(d_{t+1} = d | x_{it+1}, x'_{it+1}, d \neq d_{it}, 0).$$

[56] There are big data techniques that partition the data into blocks, runs separate regression, and appropriately combines the estimated parameters in a Map-Reduce type of algorithm. We leave this method as a future alternative venue to estimate the parameters.

After constructing the $(d, d', \tilde{d})$ tuple for each of the (i, t) sampled observations, we estimate parameters using a standard regression procedure.

We also keep states (j_{t-1}, τ_{t-1}, k) with at least 150 households in them. The reason for it is to make sure that empirical CCPs probabilities, $\hat{\mathbb{P}}^k(d|j_{t-1}, \tau_{t-1})$, are constructed with enough observations. However, according to Monte Carlo simulations, directly using empirical frequencies as the estimated CCPs can lead biased second stage estimates with an average bias of up to 30%. In the next section, we explain where this bias is coming and construct a new smoothing technique for the first-stage non-parametric CCPs that reduces the bias by more than 50%.

D.2.4 Bayesian smoothing with data-driven priors

Assume $\hat{p}$ is the frequency estimate of p_0 after N realizations:

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N} y_i,$$

where $y_i = 1$ with probability p_0, and $y_i = 0$ with probability $1 - p_0$, that is, each y_i is i.i.d. distributed following a Bernoulli with parameter p_0. The Taylor expansion of order 3 of $\log(\hat{p})$ around p_0 is given by:

$$\log(\hat{p}) = \log(p_0) + \frac{1}{p_0}(\hat{p} - p_0) - \frac{1}{p_0^2}(\hat{p} - p_0)^2 + \mathcal{O}(\hat{p} - p_0)^3 \tag{19}$$

Taking expectations with respect to realizations $\{p_i\}_i$ we obtain[57]

$$\mathbb{E}[\log(\hat{p})] = \log(p_0) - \frac{1}{2N}\frac{1 - p_0}{p_0} + \mathcal{O}_p(N^{-2}).$$

Observe the bias may be substantial when p_0 is close to 0 and N is small. Unfortunately, this is commonly the case in our residential leave choice setting, with a large amount of choices with almost all the probability concentrated in one choice (staying in the same house).[58] Therefore, the remaining 61 choices have in general very small probability to be chosen. This is not a particular feature of our framework, but it arises in any problem with a large number of decisions in which there is large persistence in choices, such as, residential choice (Bayer et al., 2016; Davis et al., 2017; Diamond et al., 2018; Davis et al., 2018), occupational choice (Traiberman, 2018), etc.

Our approach to circumvent this difficulty is smooth the empirical frequencies in a way that is informed by the data. The intuition is that the probability of action a conditional on state s correlated with the probability of action a in state s' for a particular time period. We leverage this correlation by constructing a prior distribution of CCPs. To be more precise, for a given action a

[57] We can also derive the exact analytical expression of the bias by using the full Taylor expansion for the case $\frac{1}{(N+1)p_0} < 1$, which will always be true as N grows large. After some algebra the final expression is given by

$$\mathbb{E}[\log(\hat{p})] = \log(p_0) + N\log\left(1 + \frac{1}{N}\right) + Np_0\log\left(1 - \frac{1}{(N+1)p_0}\right)$$

[58] The average probability of staying in the same house hovers around 80%

and a given state x, we collect all $\hat{p}(a|x')$ across all states $x' = (j_{t-1}, \tau_{t-1}) \in \mathcal{X}$, where $\hat{p}_t(a|x')$ is the empirical CCP given by frequencies. Next, we use the set of probabilities

$$\{\hat{p}_t(a|x')\}_{x'}$$

to construct a prior distribution for $p(a|x)$. We assume that this prior distribution follows a Beta($\hat{\alpha}, \hat{\beta}$), where we recover $\hat{\alpha}, \hat{\beta}$ solving the following equations:

$$\mathbb{E}\hat{p} = \frac{1}{|\mathcal{X}|}\sum_{x'} \hat{p}_t(a|x') = \frac{\hat{\alpha}}{\hat{\alpha}+\hat{\beta}} \tag{20}$$

$$\mathrm{Var}[\hat{p}] = \frac{1}{|\mathcal{X}|}\sum_{x'} (\hat{p}_t(a|x') - \mathbb{E}\hat{p})^2 = \frac{\hat{\alpha}\hat{\beta}}{(\hat{\alpha}+\hat{\beta})^2(\hat{\alpha}+\hat{\beta}+1)}. \tag{21}$$

Then, we treat our observed decisions as Bernoulli draws from the true distribution, Bernoulli(p_0), and update our prior probability with them. The resulting posterior is again a Beta distribution with parameters:

$$\hat{\alpha}_P = \hat{\alpha} + \sum_i \{d_i = a\} \tag{22}$$

$$\hat{\beta}_P = \hat{\beta} + N - \sum_i \{d_i = a\}, \tag{23}$$

where N is the number of individuals in state x. We take the mean of this posterior distribution as our first-stage CCP. The final expression for our smoothed CCP is given by:

$$\hat{p}^{Smooth} = \frac{N}{N+\hat{\alpha}+\hat{\beta}}\hat{p} + \frac{\hat{\alpha}+\hat{\beta}}{N+\hat{\alpha}+\hat{\beta}}\mathbb{E}\hat{p}.$$

It is easy to see

$$\hat{p}^{Smooth} \overset{N\to\infty}{\to} p_0,$$

so it is still a consistent estimator. Moreover, this method allows us to deal with the "many-zero" problem that is ubiquitous is this literature, because the prior distribution puts mass on the non-zero probability range. Therefore, both the mean of prior as well as the mean of the posterior will always be strictly positive.

Finally, Monte Carlo simulations show that this smoothing can reduce the bias by more that 50%. Figure 22 contains the results of 100 Monte Carlo model simulations and estimations, where we show the percentile of the distribution of parameters and the mean. We compare the mean of each Monte Carlo exercise to the true parameters. For the model without any smoothing, we obtain a bias of 30.22%. When we apply the Bayesian smoothing and the 2nd order bias correction derived in the previous section, we obtain a bias of 13.56% and 13.22% respectively, a reduction of more than 50% of the original bias.

	True Coefficients							
	2.5	-3	-2	0.5	-0.1	-0.5	0.35	-0.3
	Raw Model							
	(Intercept)	MC1	MC2	MC tau	MC dist	r	a1	a2
Pctl 0.5%	-1.08	-3.83	-2.18	0.63	-0.13	-0.64	0.10	-0.34
Pctl 2.5%	-0.86	-3.70	-2.15	0.66	-0.12	-0.57	0.16	-0.33
Pctl 5%	-0.68	-3.65	-2.14	0.71	-0.12	-0.54	0.17	-0.32
Mean MC Coeff	0.88	-3.39	-2.01	0.85	-0.09	-0.35	0.26	-0.23
Pctl 95%	2.33	-3.10	-1.87	0.99	-0.06	-0.15	0.34	-0.14
Pctl 97.5%	2.38	-3.05	-1.83	1.00	-0.06	-0.12	0.36	-0.12
Pctl 99.5%	3.13	-2.98	-1.81	1.06	-0.05	-0.07	0.37	-0.08
Approx. Bias	0.65	0.13	0.00	0.70	0.12	0.30	0.26	0.25
	Bayesian smoothing							
	(Intercept)	MC1	MC2	MC tau	MC dist	r	a1	a2
Pctl 0.5%	1.41	-3.26	-2.27	0.52	-0.08	-0.61	0.24	-0.34
Pctl 2.5%	1.57	-3.20	-2.26	0.54	-0.07	-0.56	0.27	-0.33
Pctl 5%	1.62	-3.17	-2.24	0.56	-0.07	-0.55	0.27	-0.33
Mean MC Coeff	2.44	-2.98	-2.17	0.62	-0.05	-0.45	0.32	-0.28
Pctl 95%	3.19	-2.81	-2.09	0.69	-0.04	-0.34	0.36	-0.23
Pctl 97.5%	3.41	-2.76	-2.08	0.70	-0.03	-0.34	0.37	-0.23
Pctl 99.5%	3.86	-2.69	-2.05	0.72	-0.03	-0.32	0.39	-0.21
Approx. Bias	0.02	0.01	0.09	0.25	0.46	0.10	0.09	0.07
	Bayesian smoothing + 2nd order analytical bias correction							
	(Intercept)	MC1	MC2	MC tau	MC dist	r	a1	a2
Pctl 0.5%	1.54	-3.29	-2.41	0.30	-0.08	-0.60	0.23	-0.33
Pctl 2.5%	1.71	-3.23	-2.37	0.33	-0.07	-0.56	0.26	-0.32
Pctl 5%	1.75	-3.20	-2.36	0.37	-0.07	-0.54	0.26	-0.32
Mean MC Coeff	2.47	-3.03	-2.28	0.45	-0.05	-0.44	0.31	-0.27
Pctl 95%	3.21	-2.86	-2.19	0.51	-0.04	-0.36	0.35	-0.23
Pctl 97.5%	3.37	-2.82	-2.18	0.51	-0.04	-0.35	0.36	-0.22
Pctl 99.5%	3.82	-2.73	-2.16	0.52	-0.03	-0.34	0.39	-0.20
Approx. Bias	0.01	0.01	0.14	0.10	0.45	0.12	0.13	0.10

Figure 22: Monte Carlo simulation results

D.2.5 Exclusion Restrictions

To be able to identify the parameters with regression 10 we need extra structure on the time-varying unobservables which. We introduce a new approach combining Arellano-Bond estimators (Arellano and Bond, 1991) with the ECCP methodology. In the following discussion we present an example in which we impose that the unobservable component in equation 9 follows an AR(1) process. For simplicity we present the example on the levels equation, but similar arguments carry through the equation in differences. That is:

$$
\begin{aligned}
Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta^k_{j(d)} - \delta^k_{j(d')} + \delta^k_{\tau}\Big(\tau(d,x_{it}) - \tau(d',x_{it})\Big) \\
&+ \delta^k_a\Big(\ln a_{j(d)t} - \ln a_{j(d')t}\Big) - \delta^k_r\Big(\log r_{j(d)t} - \log r_{j(d')t}\Big) \\
&+ MC^k(j(d), j_{it-1}) - MC^k(j(d'), j_{it-1}) \\
&+ \beta\Big(MC^k(j(\tilde{d}), j(d)) - MC^k(j(\tilde{d}), j(d'))\Big) \\
&+ \xi_{jt} - \xi_{j't} + \tilde{\varepsilon}_{t,d,d',x_{it}} \\
&= \Theta' X_{d,d',\tilde{d},s_{it},t} + \Delta\xi_{t,d,d'} + \tilde{\varepsilon}_{t-1,d,d'},
\end{aligned} \tag{24}
$$

with

$$
\xi_{jt} = \rho\xi_{jt-1} + \nu_{jt} \quad \text{and} \quad \text{where } \nu_{jt} \overset{i.i.d.}{\sim} (0,1),
$$

where ν_{jt} is orthogonal to the vector of observable covariates. In this way, we introduce time persistence in the unobservable component of utility in a parsimonious and tractable way. It follows that differences across locations

$$
\Delta\xi_{t,d,d'} = \xi_{dt} - \xi_{d't} = \rho(\xi_{jt-1} - \xi_{j't-1}) + \nu_{jt} - \nu_{j't},
$$

also follow $AR(1)$ process. Observe that

$$
\Delta\xi_{t,d,d'} = Y_{t,d,d',\tilde{d},x_{it}} - \Bigg(\Theta X_{d,d',\tilde{d},x_{it},t} + \tilde{\varepsilon}_{t,d,d'}\Bigg).
$$

Substituting inside the regression equation 24

$$
\begin{aligned}
Y_{t,d,d',\tilde{d},s_{it}} &= \Theta' X_{d,d',\tilde{d},x_{it},t} + \Delta\xi_{t,d,d'} + \tilde{\varepsilon}_{t,d,d'} \\
&= \Theta' X_{d,d',\tilde{d},s_{it},t} + \rho\Bigg(Y_{t-1,d,d',x_{it-1}} - \Big(\Theta X_{d,d',\tilde{d}',x_{it-1},t-1} + \tilde{\varepsilon}_{t-1,d,d'}\Big)\Bigg) + \Delta\nu_{t,d,d'} + \tilde{\varepsilon}_{t,d,d'} \\
&= \Theta' X_{d,d',\tilde{d},s_{it},t} + \rho Y_{t-1,d,d',x_{it-1}} - \rho\Theta X_{d,d',\tilde{d},x_{it-1},t-1} + \rho\tilde{\varepsilon}_{t-1,d,d'} + \tilde{\varepsilon}_{t,d,d'} + \Delta\nu_{t,d,d'}.
\end{aligned}
$$

By assumption $\Delta\nu_{t,d,d'}$ is uncorrelated with the covariates. Also, by the rational expectations assumption

$$
\mathbb{E}\big[\tilde{\varepsilon}_{t,d,d'} | X_{d,d',\tilde{d},x_{it-1},t-1}, X_{d,d',\tilde{d},x_{it},t}\big] = 0 \quad \text{and} \quad \mathbb{E}\big[\tilde{\varepsilon}_{t-1,d,d'} | X_{d,d',\tilde{d},x_{it-1},t-1}\big] = 0.
$$

so we only need to find instruments for $X_{d,d',\tilde{d},x_{it},t}$ as this is correlated with $\tilde{\epsilon}_{t-1,d,d'}$. Similar to Arellano and Bond (1991), the rational expectations assumption yields the following orthogonality conditions

$$
\mathbb{E}\big[\tilde{\epsilon}_{s,d,d'} X_{d,d',\tilde{d},x_{it},t}\big] = 0 \forall s \leq t,
$$

so any $X_{d,d',\tilde{d},x_{is},s}$ for all $s \leq t-2$ is a valid instrument for $X_{d,d',\tilde{d},x_{it},t}$.[59]

[59]Observe that neither $X_{d,d',\tilde{d},x_{it},t}$ or $X_{d,d',\tilde{d},x_{it-1},t-1}$ can be used as instruments as they are part of the regression equation.

The final set of assumptions for ξ_{jt} is still under discussion. For robustness, in the final draft the structural estimation will be carried under different sets of assumptions, and we will also test their statistical validity.

D.2.6 Recovering structural parameters

Recall the amenities regression equation:

$$\log N_{sjt} = -\log \sigma_s - \log F_{sjt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) \tag{25}$$

$$= \lambda_s + \lambda_j + \lambda_t + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) + \xi_{sjt}, \tag{26}$$

and the location demand equation:

$$\begin{aligned} Y_{t,d,d',\tilde{d},x_{it}}^k &= \delta_{j(d)}^k - \delta_{j(d')}^k + \delta_\tau^k \Big(\tau(d, x_{it}) - \tau(d', x_{it}) \Big) \\ &+ \delta_a^k \Big(\ln a_{j(d)t} - \ln a_{j(d')t} \Big) + \delta_r^k \Big(\log(w_t^k - r_{j(d)t}) - \log \big(w_t^k - r_{j(d')t} \big) \Big) \\ &- \Big(MC^k(j(d), j_{it-1}) - MC^k(j(d'), j_{it-1}) \Big) \\ &- \beta \Big(MC^k(j(\tilde{d}), j(d)) - MC^k(j(\tilde{d}), j(d')) \Big) \\ &+ \tilde{\varepsilon}_{t,d,d',x_{it}}. \end{aligned} \tag{27}$$

It is easy to see from 26 that the recovered parameters are the estimates of the Cobb-Douglas preferences for consumption services. Moreover, following the microfoundations of these two equations in Section D.1, the parameter δ_r^k is the inverse of the variance of the logit shocks:

$$\delta_r^k = \frac{1}{\sigma_\epsilon^k}.$$

Finally, observe that the rest of the δ parameters in 27 are estimates of the following function of structural parameters:

$$\delta_a^k = \frac{\alpha_s^k}{\sigma_s \sigma_\epsilon^k},$$

therefore we can recover the elasticity of substitution σ_s using the previous estimates:

$$\hat{\sigma}_s = \frac{\hat{\alpha}_s^k}{\hat{\delta}_a^k \hat{\sigma}_\epsilon^k}.$$