Location Sorting and Endogenous Amenities: Evidence from Amsterdam*

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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.

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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 modelled 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 et al. (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 et al., 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 methodology with Arellano-Bond

[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.

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 et al., 2004; Guerrieri et al., 2013; Ahlfeldt et al., 2015; Bayer et al., 2016; Diamond, 2016; Davis et al., 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 et al., 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 modelling 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 et al. (2017), Davis et al. (2018), and Diamond et al. (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 et al. (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 et al. (2016), Koster et al. (2018), Barron et al. (2018), and Garcia-López et al. (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

Our first source of data is restricted-access microdata from the Centraal Bureau voor de Statistiek (CBS), the statistics bureau of the Netherlands. A unique feature of our data is the residential cadaster, where we can track the housing unit in which every individual lives at every point in time. This type of data allows us to construct a panel of location choice at the household level for the universe of households in the Netherlands. Panel data covering the universe of individuals is rare, because often only censuses that take place every 10 years are available.[5] Moreover, these data allow us to link individuals to various socioeconomic variables using individual tax returns.[6] Tax returns allow us to observe the income and demographics of households such as age, household composition, and country of origin. We also have a yearly panel of the universe of individual housing units in the Netherlands, for which we observe tax appraisal, its geo-coordinates, and other features such as official measures of quality, and type of tenancy. With the information of tenancy status, we are able to distinguish between owner-occupied, rented, and social housing units. We also observe the universe of house sale transactions and their final sale prices. Rent data are available from a national survey, but do not cover the universe of tenants. To overcome this problem, we link the rent survey with the universal tax valuation data. We then use the matched subset to impute rents for housing units that do not appear in the rent survey. We impute rental prices using two different machine learning algorithms: random forest and gradient boosting machine. These two imputations greatly outperform a classic hedonic approach using linear regressions, with a substantially greater out-of-sample predictive power: while linear regression reaches an out-of-sample R^2 of 0.559, prediction using a random forest and a gradient boosting machine reach an out-of-sample R^2 of 0.702 and 0.801, respectively. Appendix A.2 describes the details of the imputation.

We obtain Airbnb listings data from InsideAirbnb.com, 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 coordi-

[5]Previous work has typically estimated static models (Diamond, 2016) from decadal census data. More recent papers estimating dynamic models only focus on a subset 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 or scrape public records.

[6]Unfortunately, at this stage we do not have data on workplace locations neither on occupations.

nates, host identifiers, prices per night, calendar availability, and reviews. We define commercial listings as entire-home listings with sufficient booking activity such that a household cannot plausibly be living there permanently (over 3 months booked per year). Appendix A.1 provides the details of how we implement the classification.

We combine the Airbnb data with publicly available zipcode-level aggregated data from the Amsterdam City Data (ACD).[7] The ACD consists of an annual panel of over 700 zipcode-level variables. These variables include sociodemographics (e.g., neighborhood-level 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 complement the ACD panel on amenities with tourism reports of the city of Amsterdam.[8]

4 Stylized facts

Before moving to our structural model, we show how tourism volume and Airbnb penetration correlate with our outcomes of interest: rents, house prices, touristic consumption amenities, and residential movements. We interpret these results as strong suggestive evidence of the overall effects of tourism and Airbnb. In what follows, we present five facts that we incorporate in our model.

Fact 1: Tourism flows have grown dramatically in Amsterdam

Amsterdam is a city with a remarkably high number of tourists relative to locals.[9] Figure 1 shows the number of visitors per resident doubled between 2008 and 2017. In absolute terms, overnight stays grew from 6 million to 16 million. During the same period, Amsterdam experienced a proliferation of short-term rentals and the development of a significant number of large and high-end hotels. Airbnb listings grew from zero in 2008 to 25,000 in 2017, while the number of hotels grew

[7] These data are publicly available at amsterdamsmartcity.com.

[8] All tourism reports are available at ois.amsterdam.nl/toerisme.

[9] Amsterdam ranked fourth among major cities with the largest number of hotel guests per capita (5.1), only below Venice (8.1), Lisbon (5.8), and Florence (5.7). Source: ois.amsterdam.nl/toerisme.

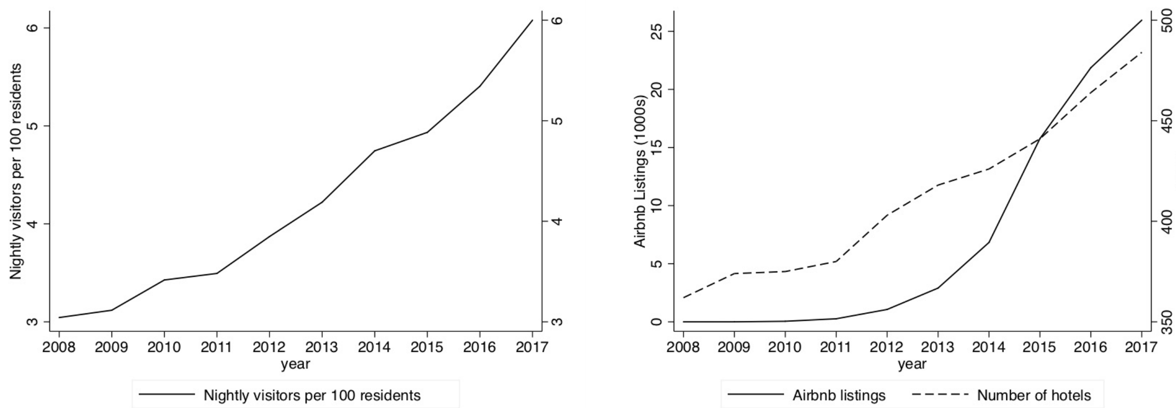


Figure 1: Volume of tourism per capita, number of hotels, and Airbnb listings.

from 374 to 484.[10] Airbnb dominates Amsterdam's short-term rental industry, with over 80% market share and accounting for 15% of the total overnight stays in 2017.[11]

Although both hotels and short-term rentals have experienced a surge in the last decade, their spatial distributions are significantly different. Whereas hotels tend to be concentrated in the city center due to zoning restrictions, Airbnb listings are spread out across the entire city. Figures 2 and 3 show how the number of hotel beds per capita and the share of commercial Airbnb listings evolved across space and time for 2011-2017.[12]

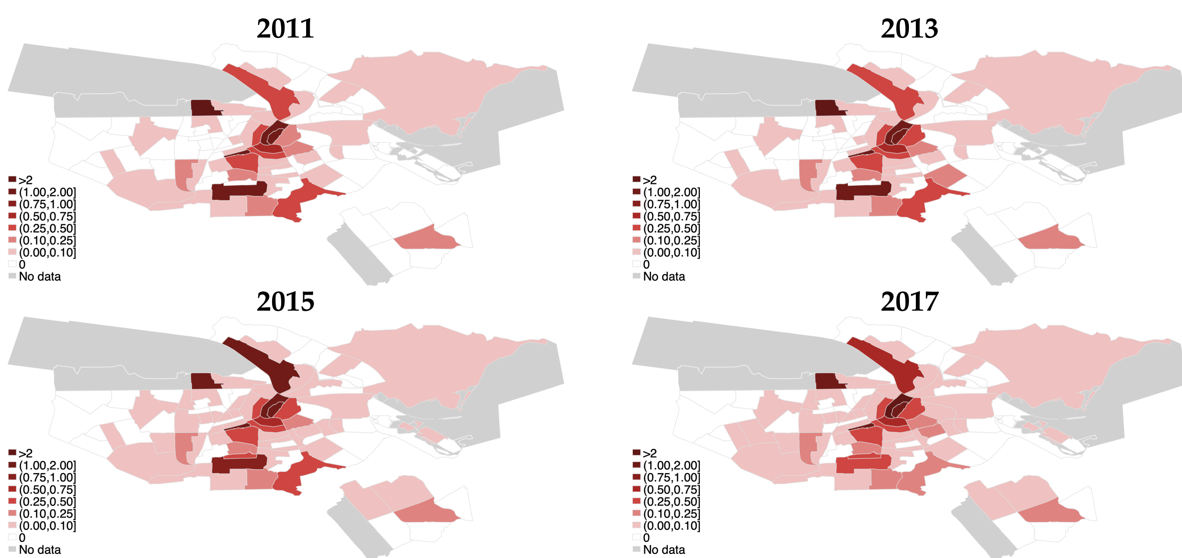


Figure 2: Number of hotel beds per capita: 2011-2017

[10]See Appendix C for more details about the hotel industry.
[11]Even though Airbnb entered in Amsterdam in 2008, we cannot detect any significant activity until 2011.
[12]We condition to neighborhoods with at least 500 inhabitants to remove industrial areas.

As expected, growth has been heterogeneous with central zipcodes reporting both more hotel beds per capita and higher Airbnb shares. Two main differences in the spatial distribution between hotels and Airbnb listings exist. First, whereas some neighborhoods have no hotels, all neighborhoods have a positive number of Airbnb listings. Second, hotels are more concentrated in the city center than Airbnb listings. Our takeaway from this analysis is that Airbnb provides more variation in the spatial distribution of tourists, especially outside central Amsterdam.

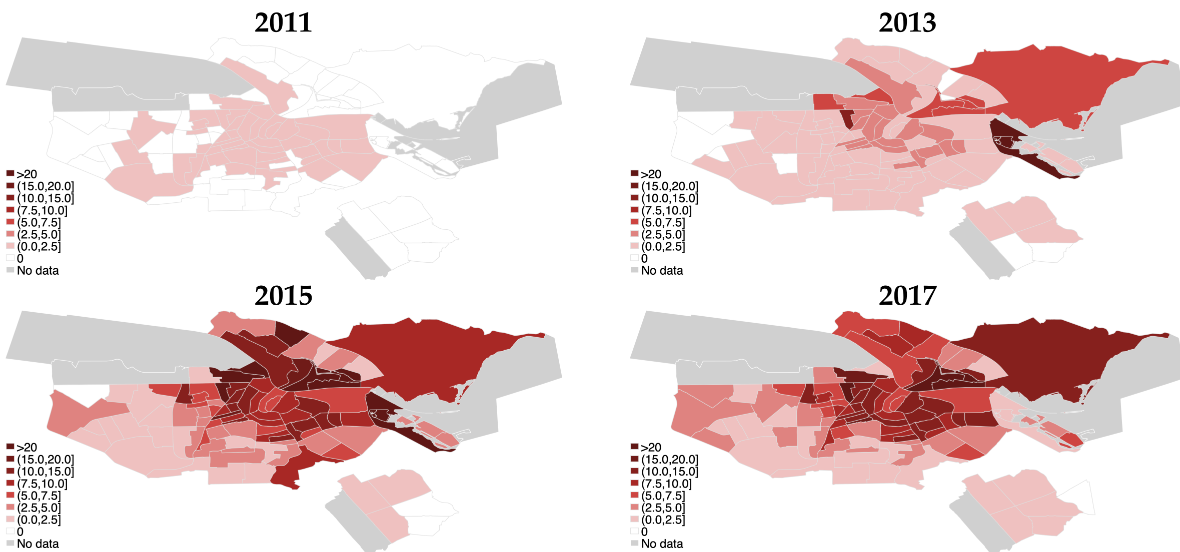


Figure 3: Commercial listings as a share of rental stock: 2011-2017

Fact 2: Amenities are tilting towards tourists

"Businesses related to tourism," as defined by ACD's classification, grew across all zipcodes during 2008-2017. Moreover, the number of touristic services and the share of the population that corresponds to tourists are positively correlated, as shown in the top-right panel of Figure 4. The opposite trend holds for nurseries, as shown in the bottom-left panel of Figure 4.[13] Moreover, as shown in the bottom-right panel, we see a negative relationship between the change in touristic businesses and the change in nurseries, suggesting the former are substituting the latter. Because touristic services cater relatively more toward tourists' needs and nurseries more locals, we interpret these changes as a shift of consumption amenities toward tourists.

[13] ACD defines touristic services as "accommodation and lodging, other restaurants, passenger reorganization and mediation, culture and recreation, marinas, sailing schools and recreational retail." We define total population as the sum of the number of residents and the number of tourists. Nurseries represent "Kinderdagverblijf," which is private child care.

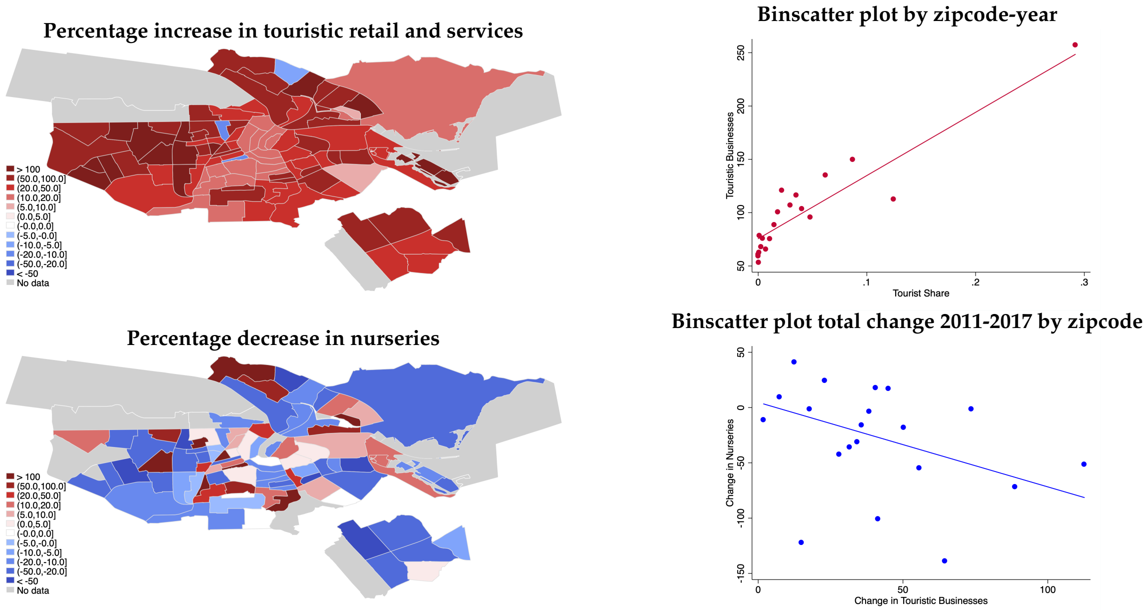


Figure 4: Growth between 2011-2017 for different consumption amenities

Fact 3: Demographic composition is changing heterogeneously across zipcodes

Figure 5 plots the change in population shares for different ethnic groups by zipcode, as defined by ACD. These demographic groups are Dutch, white non-Dutch, Moroccan, Antillean, Surinamese, Turkish, and other non-Westerns. Substantial changes occur in the composition of neighborhoods between 2011-2017. Moreover, different groups exhibit different trends. For example, groups with a Dutch or a Surinamese background are decreasing their shares, locals with a Moroccan or Turkish background are leaving the city center, while groups with white non-Dutch and other non-white background are increasing.

Fact 4: Short-term rentals have a significant effect on neighborhoods

Figure 3 showed that commercial Airbnb listings represented a large share of the rental stock, with some zipcodes above 20% as of 2017.[14] Consequently, theory would predict an increase in rents from a reduction in the rental stock available to locals. Because variation in rental prices may also reflect variation in size, we normalize our dependent variable to rental price by square

[14] In 2015, home-owners, renters, and social housing represented 30%, 25%, and 45% of the total housing stock respectively. Therefore, a 5% and a 20% share of the rental stock allocated to Airbnb translates to a 2.3% and a 9% share of the market housing stock respectively.

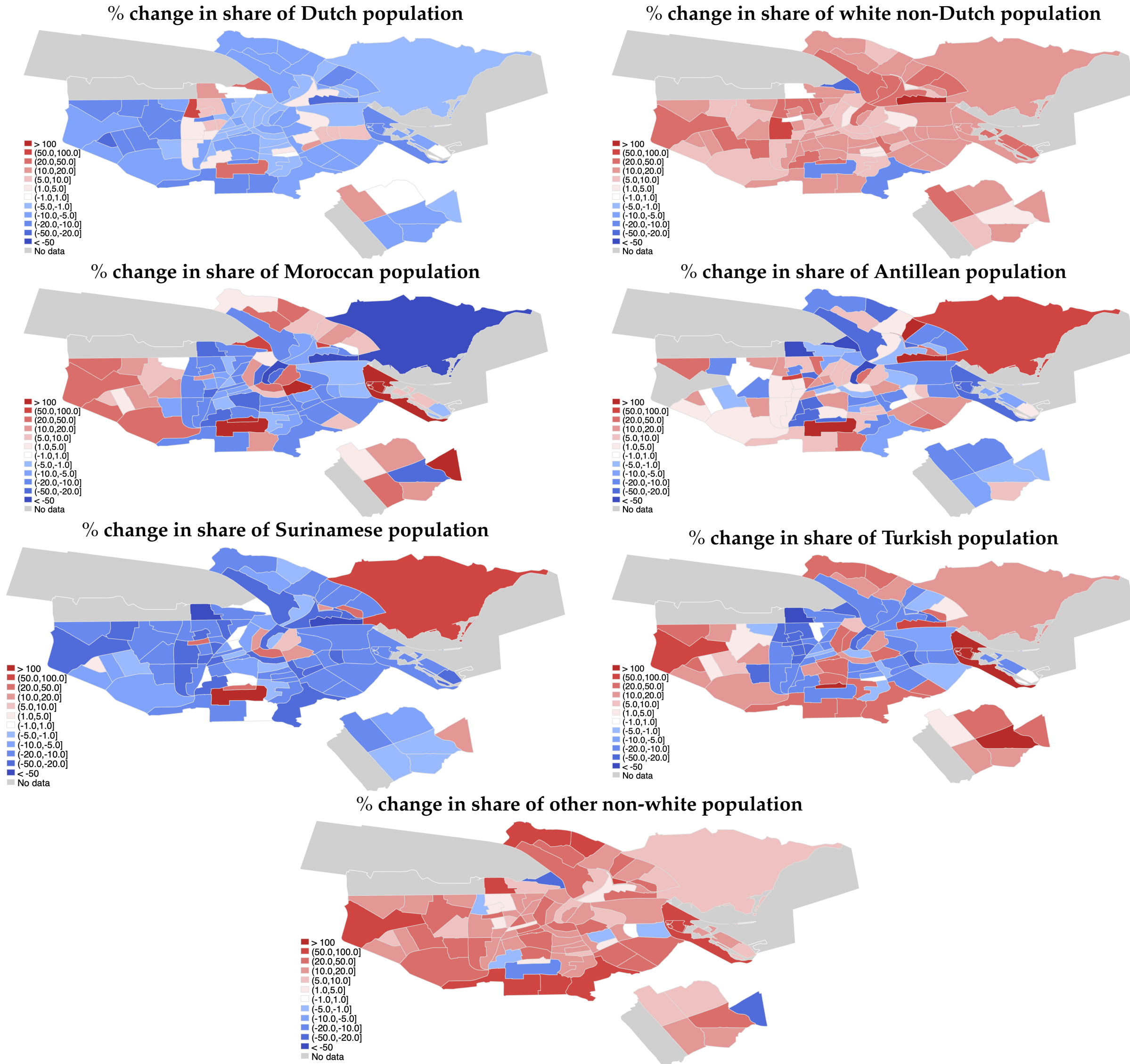


Figure 5: Percentage growth for shares of different demographic groups, 2011-2017

meter.[15] Using data at the housing unit level, we test this hypothesis by adopting the following specification:

$$Y_{it} = \beta \ln \text{listings}_{j(i)t} + \theta \ln \text{housing units}_{j(i)t} + \eta_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where Y_{it} is an outcome of interest for housing unit i in year t, $j(i)$ corresponds to the zip code of housing unit i, listings_{jt} is the number of commercial Airbnb listings in zip code j, η_i are housing unit fixed effects, λ_t are time effects, and $\text{housing units}_{j(i)t}$ is the housing stock, excluding social

[15] In Appendix A.4 we perform the same analysis using house sale prices at the unit level finding similar results.

housing units.[16] However, any time-varying unobservable variation included in ϵ_{it} that correlates with Airbnb listings and housing prices will lead to biased OLS estimates. For example, neighborhoods that are becoming "trendier" would have higher housing prices and a higher number of Airbnb listings, because such neighborhoods would be more attractive to certain locals as well as tourists. To overcome such endogeneity concerns, we instrument listings following a shift-share IV strategy as in Barron et al. (2018) and Garcia-López et al. (2020). The "shift" part of the IV exploits time variation in worldwide popularity of Airbnb as proxied by the Google search volume for Airbnb, which has grown significantly in the post-2008 period. The "share" part exploits spatial variation from the spatial distribution of historic monuments. A graphical representation of both parts of our instrument can be found in Figure 6.

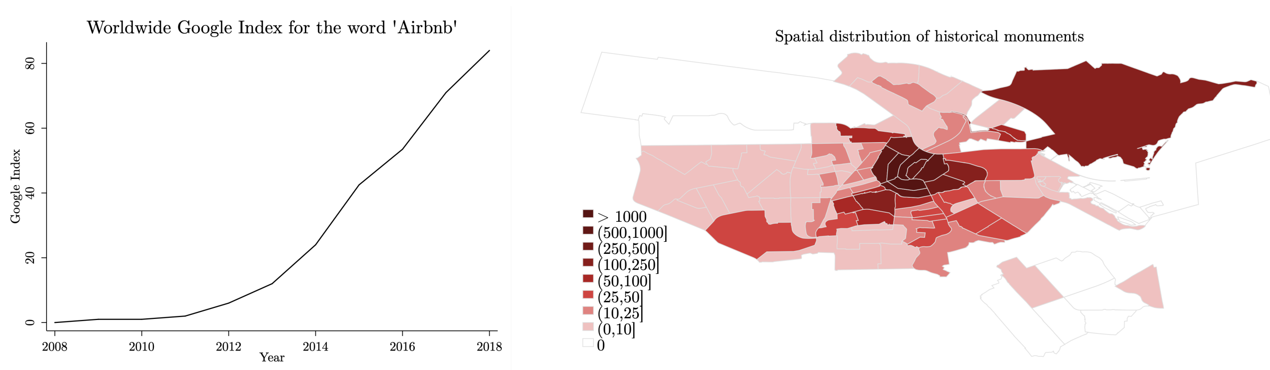


Figure 6: Visualization of the shift-share instrument (shift variation on left, share variation on right).

We construct our instrument as follows:

$$Z_{jt} = \text{Historic Monuments}_j \times \text{Worldwide Google Search Index for "Airbnb"}_t.$$

Our exclusion restriction is based on the fact that both factors are orthogonal to unobservable neighborhood temporal variation ϵ_{it}, conditional on the rest of the covariates. First, we do not expect worldwide Airbnb popularity to be informative of zip code specific unobservable trends. Second, making a similar argument as in Acemoglu et al. (2001), we assume that the determinants of the spatial distribution of monuments from hundreds of years ago are not informative of current trends that may affect housing prices. As for instrument relevance, in all our specifications we obtain a strong first stage relation. To summarize, our assumptions for the validity of the

[16] We exclude social housing from our analysis because these are not allocated to tenants through a traditional market. See Appendix B.1.2 for the institutional details on social housing.

instrument are as follows:

$$Cov(\text{listings}_{j(i)t}, Z_{j(i)t} | X_{j(i)t}, \eta_i, \lambda_t) \neq 0 \tag{2}$$

$$Cov(\epsilon_{it}, Z_{j(i)t} | X_{jt}, \eta_i, \lambda_t) = 0. \tag{3}$$

We show the results of total Airbnb listings as well as commercial listings for rental prices.

Table 1: Regression of Ln Rent/m^2 on Airbnb Listings

Dep. Var.:	Ln Rent/m^2			
	OLS	IV	OLS	IV
Ln Total Listings	0.007***	0.084***		
	(0.000)	(0.005)		
Ln Commercial Listings			0.001*	0.111***
			(0.000)	(0.007)
Ln Housing Units	−0.018***	−0.039***	−0.016***	−0.033***
	(0.001)	(0.002)	(0.001)	(0.002)
Year Effects	✓	✓	✓	✓
Individual Effects	✓	✓	✓	✓
Observations	1,072,753	1,072,753	1,072,753	1,072,753
Within R^2	0.183	0.158	0.183	0.102
F Statistic (1st stage)	-	-	12,001,778.293***	713,948.7017***
Note:	*p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.			

In theory, both an increase in the option value for tenants from renting part of their apartment and a reduction in the rental stock available can increase rental prices. To shed light on these two channels, we regress rental prices on two different measures of Airbnb listings: total listings and commercial listings. Total listings more closely capture the effect from a higher option value as it will include both casual Airbnb hosts as well as commercial hosts, while we expect commercial listings to more closely capture the effect from a reduction in the rental stock. Observe that our IV estimates present a larger effect from commercial listings than from total listings, which suggests that the effect on rental prices from a reduction in the rental stock is larger than the effect from the increase in option value. Concretely, column 3 and 4 of Table 1 show that for our IV specification a 1% increase in total listings and commercial listings lead to a 0.084% and a 0.111% increase in rental prices, respectively. In terms of economic significance, a 0.084% and a 0.111% increase in prices account for 9% and 12% of the annual growth in rent by square meter respectively (average annual growth from 2008 to 2019 is 0.94%).

Finally, note that in both specifications OLS estimates are downward biased. This finding suggests that unobservable trends that correlate with the presence of Airbnb and affect prices are perceived as disamenities. We interpret this finding as suggestive evidence that neighborhoods with more Airbnb listings, and therefore more touristic areas, experience trends that make them less attractive to residents. Some channels could be consumption amenities are tilting away from locals' needs, or congestion is being generated by tourists, a hypothesis that is further supported by the negative coefficient of touristic amenities.[17]

To conclude, we have presented four facts that hold for Amsterdam during our sample period. First, Amsterdam is experiencing increasing inflows of tourists, and Airbnb alters their spatial distribution by dispatching them to areas where hotels do not enter. Second, amenities appear to be catering increasingly to tourists overs locals. Third, the demographic composition of neighborhoods is changing, and these changes are heterogeneous across zipcodes. Finally, Airbnb has a significant effect on rents and housing prices.

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 modelling 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

[17] We obtain a similar downward bias when with a broad set of different instruments. For example, we can define the "share" part of the instrument as the number of marijuana coffee shops in 2015 by postcode. The exclusion restriction in this case is that coffee shops are a service that caters mostly to tourists and not to locals. We also obtain a similar result when the share part of the instrument is defined as the number of hotels in 2008 or as the number of touristic amenities.

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 7.[18]

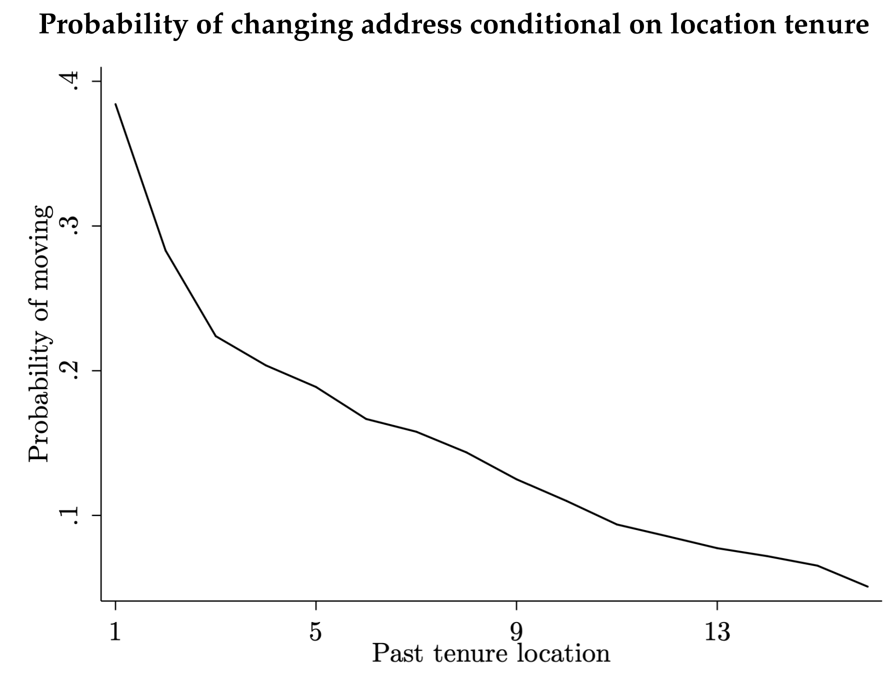


Figure 7: Decreasing hazard rate

Second, the literature commonly finds unreasonably large moving costs to rationalize the acute persistence of location decisions.[19] 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.

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

[19]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.

Last, absentee landlords supply units of housing to households. Assuming a fixed housing 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.[20] Within a service category, location, 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:[21]

$$\max_{\{q_{is}\}_{is}} \prod_s \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_s^k} \quad \text{s.t.} \quad \sum_{is} p_{is} q_{is} = b_j^k, \tag{4}$$

[20] 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 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.

[21] 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)

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:

$$q_i = \sum_k M_j^k \frac{\alpha_s^k b_j^k}{p_i} s(p_i, P) = \frac{\sum_k M_j^k \alpha_s^k b_j^k}{p_i} s(p_i, P). \tag{5}$$

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., $c_i = c_{sj}$.[22] Therefore, all firms have the same pricing

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

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,[23]

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

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.

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,

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

[23]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.

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,[24]

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

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

$$N_{sj} = \frac{\sum_k M_j^k \alpha_s^k b_j^k}{F_{sj}\sigma_s}. \tag{6}$$

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 6). 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.

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 $b_{jt}^k = w_t^k - r_{jt}$

[24] Given the competitive nature of our environment, we can treat firms' decisions as static given the absence of any future profits as in Desmet et al. (2018).

for consumption amenities.[25] 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.[26] 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

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

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

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.[27] Upon moving, the household incurs a moving cost that depends on the distance between two locations $\text{dist}(j, j')$:[28]

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

[25]This specification for the marginal utility of money has been widely used in the industrial organization literature, see for example Berry (1994), Berry et al. (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.

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

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

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

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,

$$u_t^k(d, x_{it}, \omega_t) = \delta_{j(d)}^k + \delta_\tau^k \tau_{it} + \delta_w^k \ln(w_t^k - r_{j(d)t}) + \delta_a^k \ln a_{j(d)t} - MC^k(d, j_{it-1}) + \xi_{jt}^k, \tag{7}$$

which can be micro-founded using utility function 4. See Appendix D.1 for more details.[29] In what follows, we denote with subscript t the functions that depend on the state variable ω_t. Household 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:

$$\mathbb{P}_t^k(j | x_{it}) = \frac{\exp\left(u_t^k(j, x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j, x_{it}, \epsilon_{it} \right] \right)}{\sum_{j'} \exp\left(u_t^k(j', x_{it}) + \beta \mathbb{E}_t \left[V_{t+1}^k(x_{it+1}, \epsilon_{it+1}) | j', x_{it}, \epsilon_{it} \right] \right)}. \tag{8}$$

[29] 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.

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,

$$\mathcal{D}_{jt}^{L} = \sum_{k} \sum_{x} \mathbb{P}_t^k(j|x) M_{xt}^k. \tag{9}$$

5.3 Housing supply

Every year, each location j has a fixed supply of housing units denoted by $\mathcal{H}_{jt}$.[30] Every period, absentee landlords choose to rent their unit in the traditional long-term market to locals, or in the short-term rental market to tourists.[31] 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 neigh-

[30] 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.

[31] 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.

borhood j is given respectively by

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

where $\mathcal{H}_{jt}^{L} + \mathcal{H}_{jt}^{S} = \mathcal{H}_{jt}\ \forall t$. 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,

$$s_{jt}^{L} = \frac{\mathcal{H}_{jt}^{L}}{\mathcal{H}_{jt}} = \frac{\exp(\alpha r_{jt})}{\exp(\alpha r_{jt}) + \exp(\alpha p_{jt} - c_{jt})},$$
$$s_{jt}^{S} = \frac{\mathcal{H}_{jt}^{S}}{\mathcal{H}_{jt}} = \frac{\exp(\alpha p_{jt} - \kappa_{jt})}{\exp(\alpha r_{jt}) + \exp(\alpha p_{jt} - \kappa_{jt})}.$$

We assume locals demand long-term rentals given the demand function derived in (9). 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.[32]

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,

[32]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' 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 for more details.

- 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,

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

- 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.6 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 8, 9, and 10, 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.[33] 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 11 we present evidence of a decreasing hazard rate of moving conditional on location tenure.

[33] 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

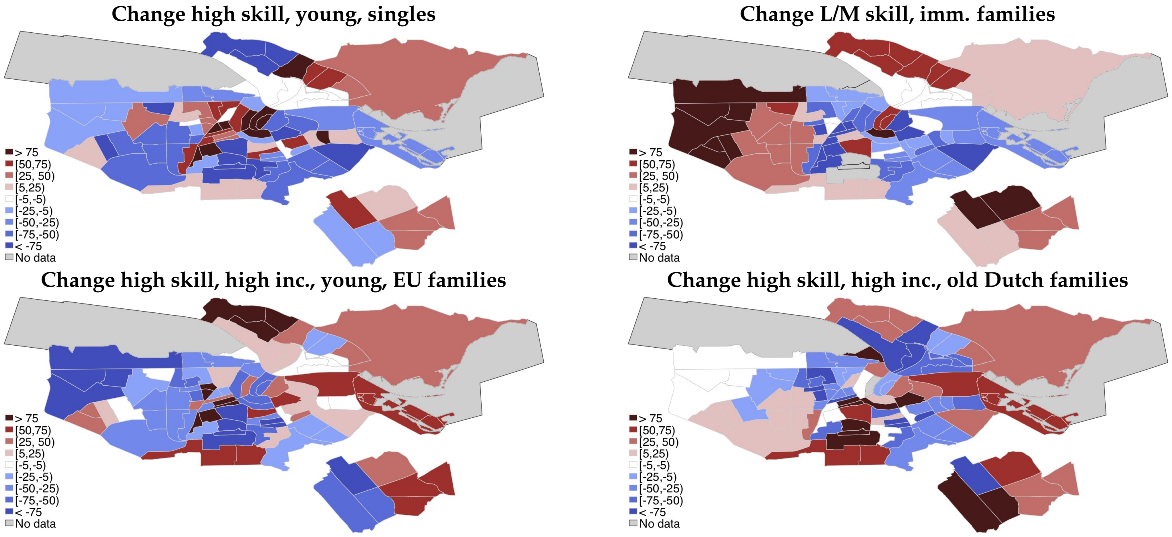


Figure 8: Percentage growth for shares of clusters of homeowners, 2011-2017

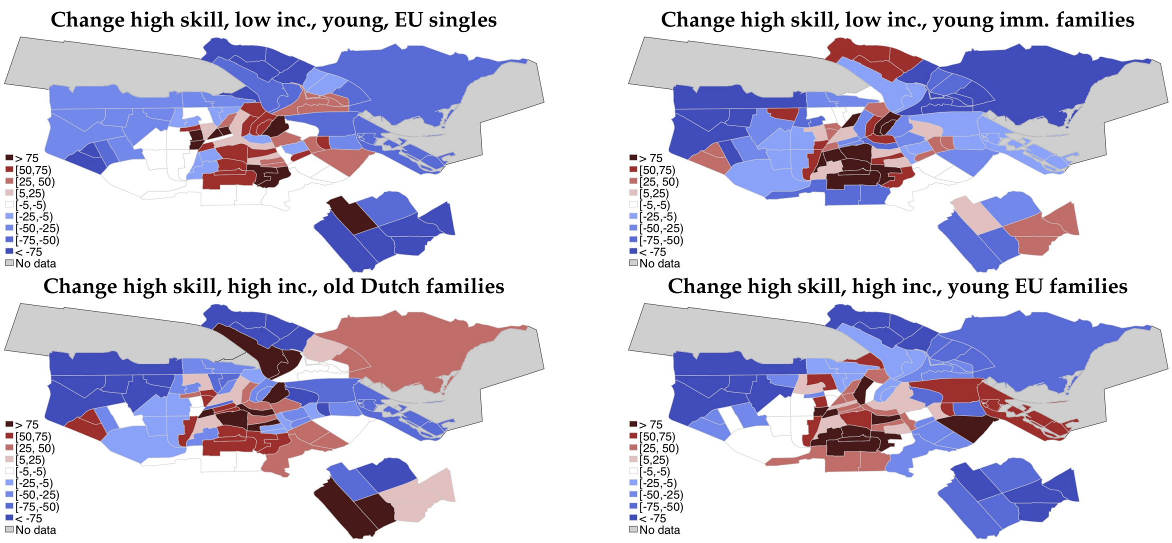


Figure 9: Percentage growth for shares of clusters of renters, 2011-2017

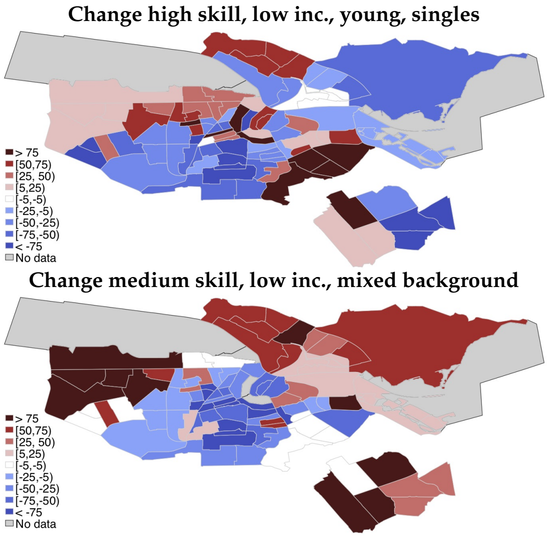


Figure 10: Percentage growth for shares of clusters for social housing, 2011-2017

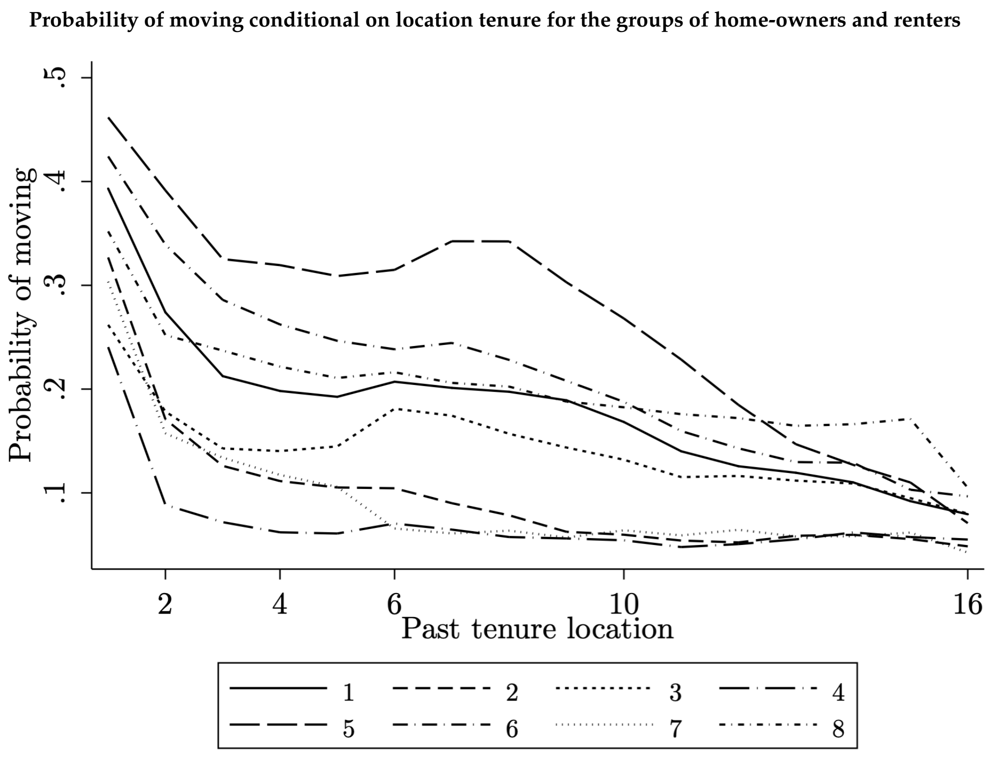


Figure 11: Decreasing hazard rate

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

$$\begin{aligned} \log N_{sjt} &= -\log \sigma_s - \log F_{sjt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) \\ &= \lambda_s + \lambda_{jt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) + \psi_{sjt}, \end{aligned} \tag{10}$$

where $\psi_{sjt} \equiv -\log \Psi_{sjt}$, $\lambda_s \equiv -\log \sigma_s - \log \Lambda_s$, and $\lambda_{jt} \equiv -\log \Lambda_{jt}$.[34]

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).[35] 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

[34] Observe that parameters $(\lambda_s, \alpha_s^1, ..., \alpha_s^K)$ are not separately identified. Therefore, to estimate equation 10 we make the normalization $\sum_k \alpha_s^k = 1$.

[35] Bayer et al. (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.[36] 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.[37] 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.[38]

[36]See Appendix B.1.2 for more details of the rental point system.
[37]The average number of beds in a commercial listing is four and the average occupancy rate is about 50%.
[38]The full definition of these services can be found in Appendix C.7.

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	$\checkmark$							
IV	$\checkmark$							

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	$\checkmark$							
IV	$\checkmark$							

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 12.

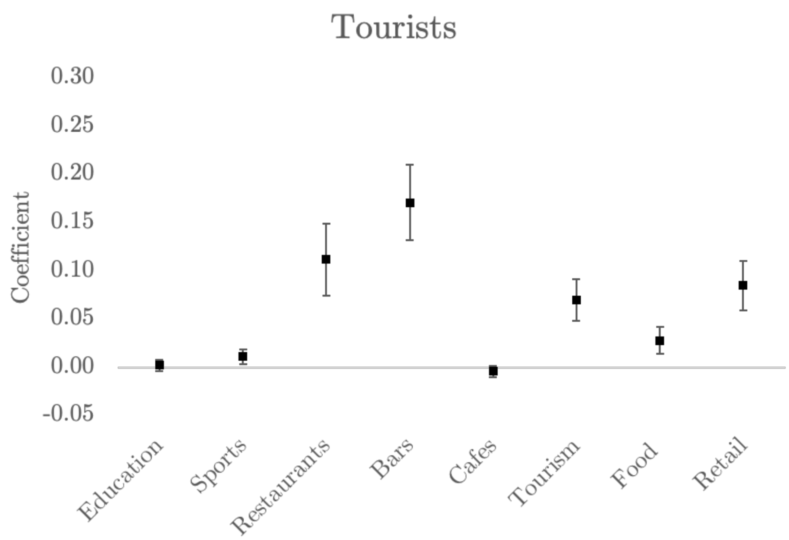


Figure 12: Amenities supply in response to tourists

Moreover, Figure 13 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.

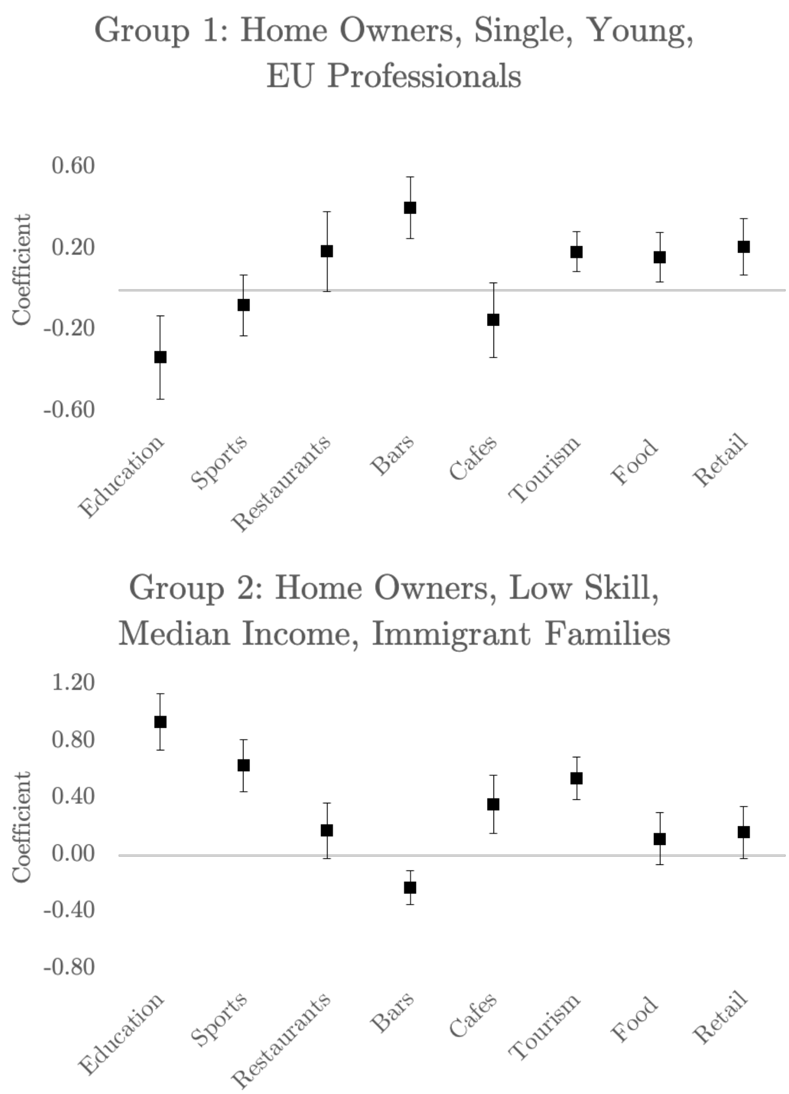


Figure 13: Amenity supply parameters of young professionals and immigrant families

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 $\tilde{j}$,

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

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,

$$Y^k_{t,d,d',\tilde{d},x_{it}} = u^k_t(j(d), x_{it}) - u^k_t(j(d'), x_{it}) + \beta\big(u^k_t(j(\tilde{d}), x_{it+1}) - u^k_t(j(\tilde{d}), x'_{it+1})\big) + \tilde{\varepsilon}_{t,d,d',x_{it}}, \tag{11}$$

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,

$$\begin{aligned}
Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta_j^k - \delta_{j'}^k + \delta_\tau^k \Big(\tau(d, x_{it}) - \tau(d', x_{it})\Big) \\
&+ \delta_a^k \Big(\ln a_{jt} - \ln a_{j't}\Big) - \delta_r^k \Big(\log\left(w_t^k - r_{jt}\right) - \log\left(w_t^k - r_{j't}\right)\Big) \\
&- \Big(MC^k(j, j_{it-1}) - MC^k(j', j_{it-1})\Big) - \beta\Big(MC^k(\tilde{j}, j) - MC^k(\tilde{j}, j')\Big) \\
&+ \tilde{\varepsilon}_{t,d,d',x_{it}}. \qquad (12)
\end{aligned}$$

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 (12) 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

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

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.[39] Following a similar argument as in Scott (2013) and Kalouptsidi et al. (2018), we proceed to estimate equation 12 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

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

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

$$\nabla Y^k_{t,d,d',\tilde{d},x} = \delta^k_a \nabla\Big(\ln a_{jt} - \ln a_{j't}\Big) + \delta^k_w \nabla\Big(\log\left(w_t^k - r_{jt}\right) - \log\left(w_t^k - r_{j't}\right)\Big) + \nabla\tilde{\varepsilon}_{t,d,d',x}. \tag{13}$$

Inspection of equation 13 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 $\ln(w_t^k - r_{jt})$. 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

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

up rents as well as the probability of certain sociodemographic groups to live in specific locations. 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 13 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 (12) using the parameters obtained by the first-difference regression of equation (13). 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.[40] 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.1, 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

[40] 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 14 for more details.

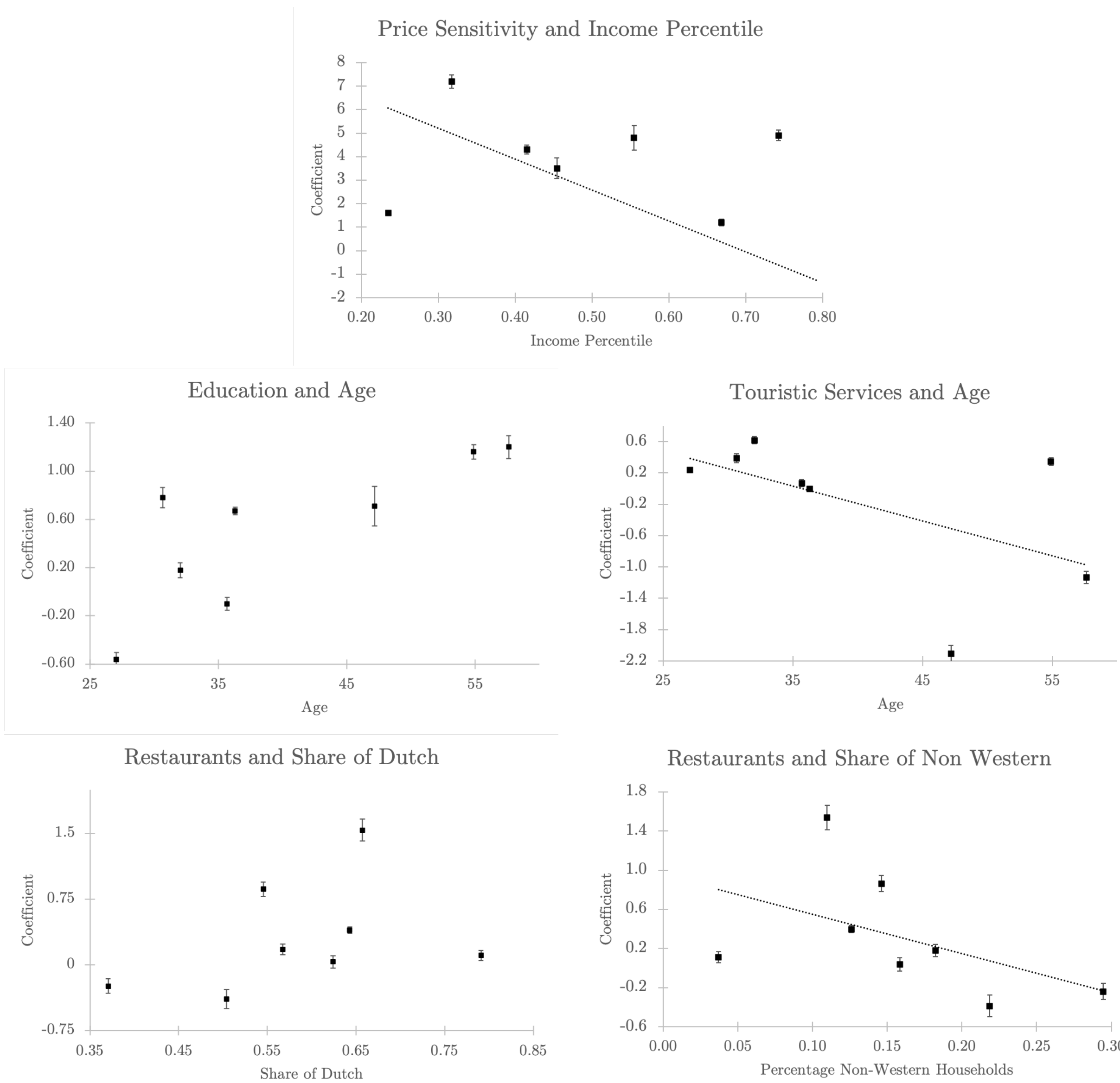


Figure 14: Relationship between demand estimation coefficients and demographics

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 15 and 16 plot the equilibrium outcomes for each location (population composition and amenities) under both worlds.

From Figure 15 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 16). 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.

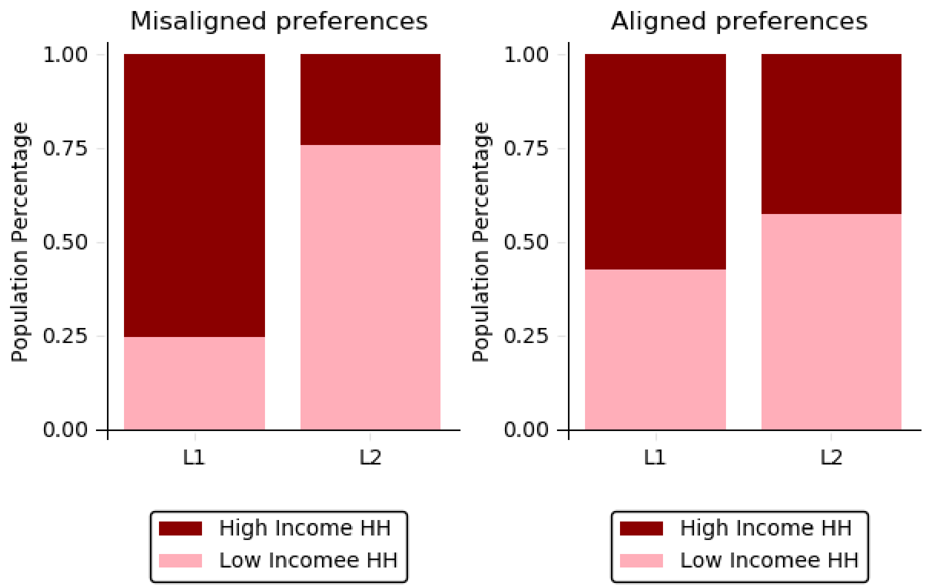


Figure 15: Population composition

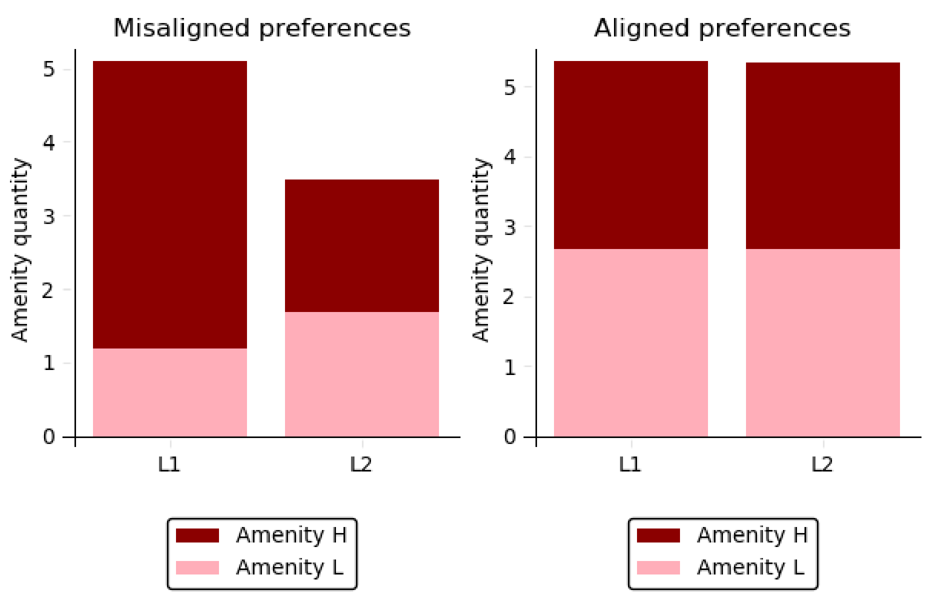


Figure 16: Amenities

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

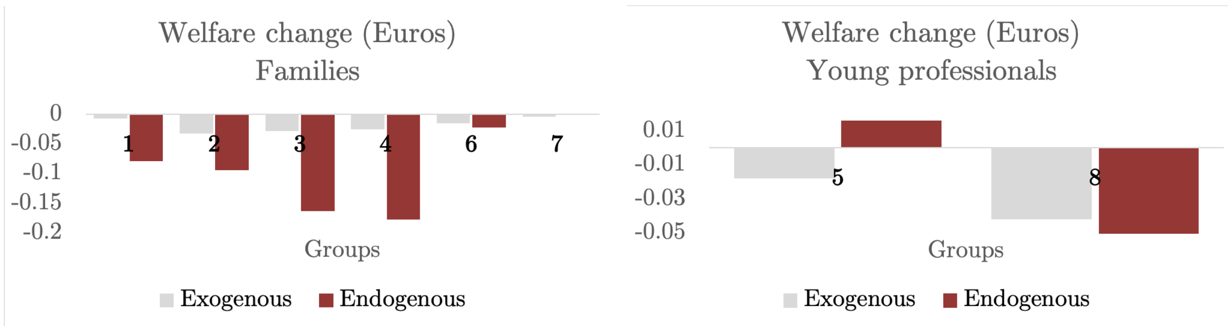


Figure 17: Welfare (Consumption Equivalent in Euros) changes of short-term rental entry

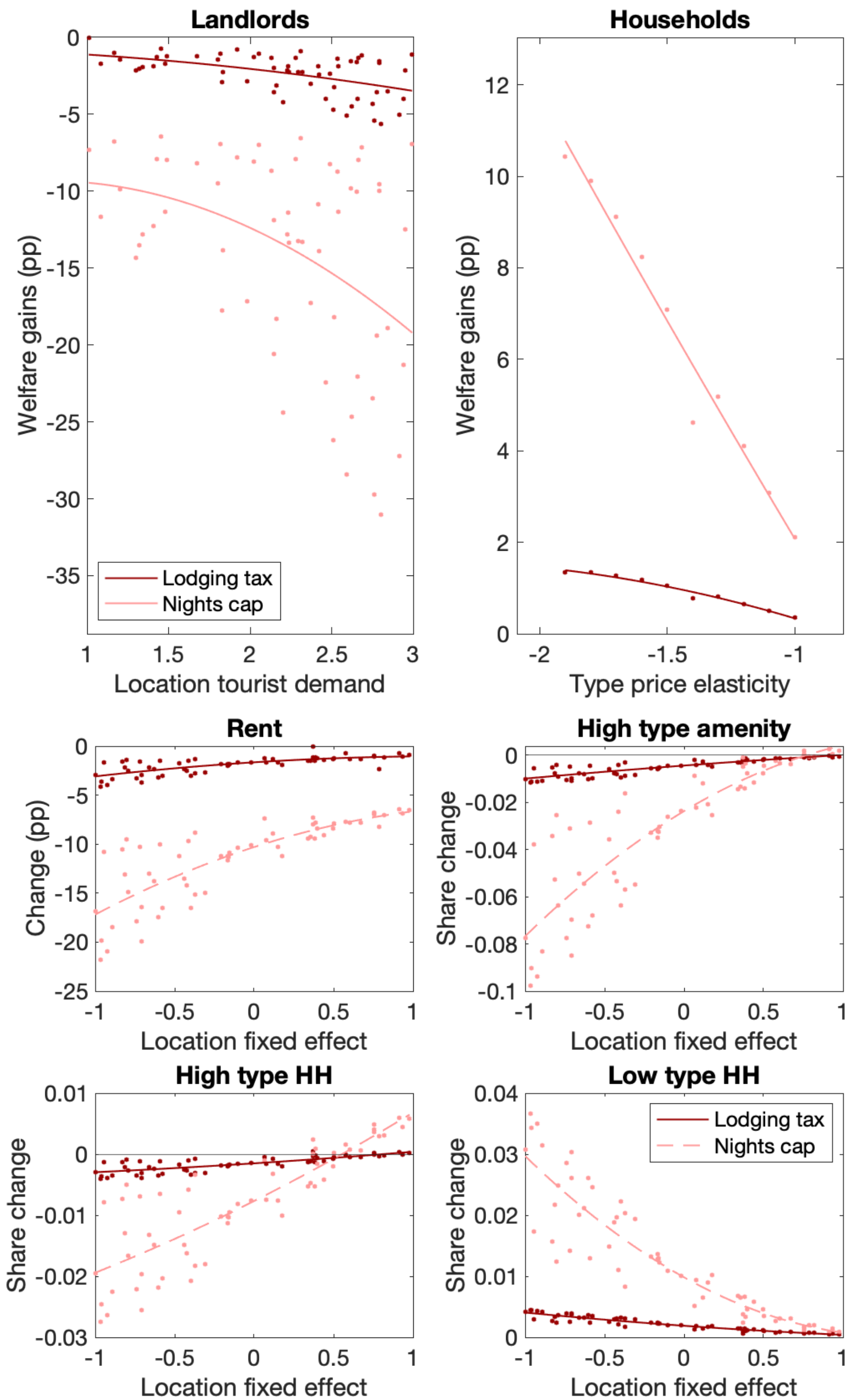
the neighborhoods are changing. In this parametrization, we have assumed tourists' preferences for amenities are the same as for young European ex-pats without children (group five). Welfare results are shown in Figure 17: all households are worse off with the entry of short-term rentals due to the rise 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 18.

Figure 18: 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. Data appendix

A.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". To do this we use calendar availability data, which as we argued in the institutional details appendix, reflects true availability.

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. A listing is considered to be operated commercially 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. Intent to be booked for many days over the next year: the "Instant Book" feature is turned on and the listing is available for more than 90 days over the next year.

2. Frequent updates, reflecting intent to be booked even though it may not have the "Instant Book" feature turned on: the listing has shown availability for more than 90 days over the next year at least twice in the year.

3. Over 60 nights a year booked, as inferred from reviews: the listing has had over 10 new reviews, which at a review rate of 67% and an average stay of 4 nights translates into 60 nights a 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.

A.2 Rent imputation

We link microdata from the universe of housing units to a national rent survey which contains about 12500 observations between 2006 and 209. The data that we have at the housing-unit level contains tax-appraisal values (WOZ value), physical characteristics, such as official measures of quality and size, and exact location of the unit given by its latitude and longitude. The reason these data exist is because each year, the local government assesses every property and issues its resulting WOZ value.[41] According to the Amsterdam city government, WOZ values are mostly based on market values.[42]

[41] Any owner can object to the issued valuation and request a new one.
[42] amsterdam.nl/en/taxes/property-valuation/

We use the matched subset in the rental survey with their information on tax valuations to predict rents for housing units that do not appear in the survey but appear the property value data as being occupied by a renter. We predict total rental prices, rental prices by square meter, as well as total floor space. We use three methods to predict rental prices: linear regression, random forest, and gradient boosting machine. In all methods, we use WOZ values, official categories for measures of quality and size, 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 0.572 while the out-of-sample R^2 is 0.559. Similarly the random forest delivers an in-sample R^2 of 0.777 and out-of-sample R^2 of 0.702. Finally the gradient boosting machine, our most preferred method and the one that we will use in the text throughout, gives an in-sample R^2 of 0.888 and out-of-sample R^2 of 0.801. For further results see Table 7.

Table 7: Imputation results

	Random Forest			Gradient Boosting Machine		
	Rental Prices	Price/m^2	Total m^2	Rental Prices	Price/m^2	Total m^2
In-sample R^2	0.777	0.839	0.840	0.888	0.927	0.956
Out-of-sample R^2	0.702	0.827	0.655	0.801	0.934	0.908
Reg. Coeff.	0.844	0.912	0.834	0.765	0.94	0.847
Standard Error	0.003	0.004	0.06	0.005	0.005	0.059
R^2	0.918	0.965	0.885	0.808	0.956	0.882

Next we show the performance of the model on the weighted average rental prices, average rental prices by square meter, and average total floor space by wijk-code and year as shown in Figure 19.[43] We observe that the average imputation values and the average true values are fairly aligned along the 45-degree line, especially for rental price by square meter. We take these results along with those in Table 7 as supporting evidence of the good performance of our rental price imputation.

[43]For confidentiality purposes we cannot show the performance of our random forest model on individual data.

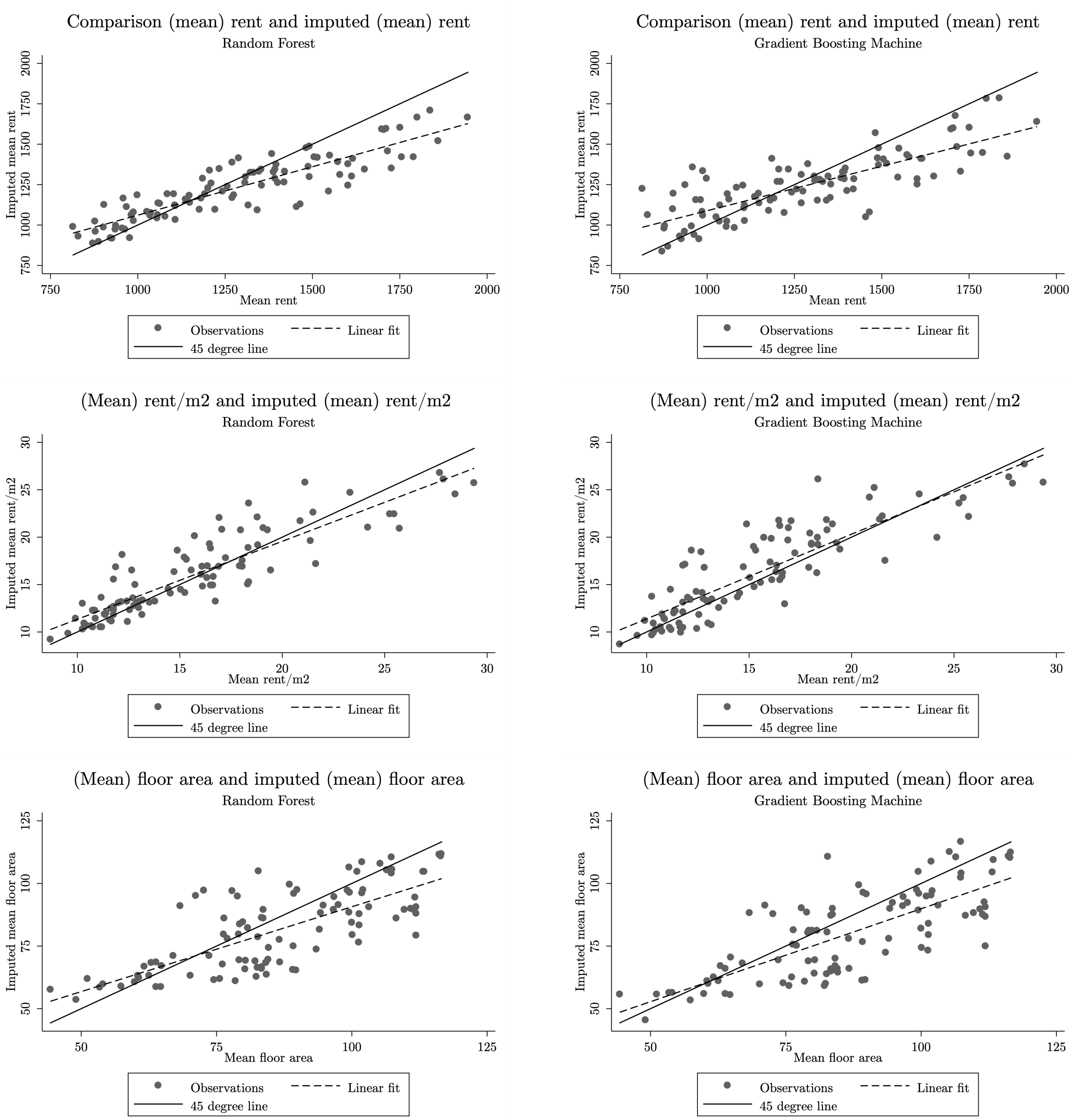

Figure 19: Comparison true rental values and rental imputation values

A.3 Evolution of rental and house sale prices

In this section we show how the average rent, average rent by square meter, and house prices have evolved over time, weighted by the number of observations in each year (Figure 20). The average annual growth rate of rental prices and price per square meter is 1.77% and 0.94% respectively from 2008 to 2019. For house prices, the average annual growth rate is 4.8% from 2008 to 2019.

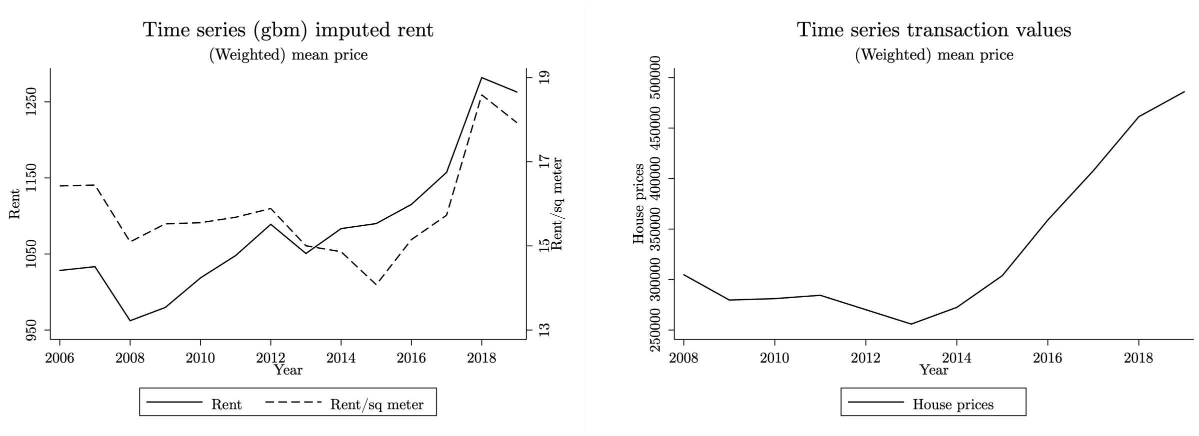

Figure 20: Time series of rent and sale prices.

A.4 Effect of short-term rentals on house sale prices

We now turn to study the impact of Airbnb listings on house sale prices. Our administrative data covers the entire universe of transactions from 1995 to 2019, however for comparability we look at individual transaction after 2008. Following similar arguments as for rental prices we also expect house prices to increase. As discussed by Barron et al. (2018) house prices should not only increase from the (discounted) capitalization of higher rental prices, but also from the additional option value that short-term rental platforms imply for homeowners. Therefore, in this case, the combination of both effects should imply higher effects of short-term rentals on house prices than on rental prices. Unfortunately, we do not have information of price by square meter, so our dependent variable in this case is the total transaction value by housing unit. Table 8 presents our reduced form results.

Table 8: Regression of Ln House Sale Prices on Airbnb Listings

Dep. Var.:	Ln House Sale Prices			
	OLS	IV	OLS	IV
Ln Total Listings	−0.002	0.4053*		
	(0.039)	(0.2104)		
Ln Commercial Listings			0.497	0.393*
			(0.308)	(0.204)
Ln Housing Units	−0.197	−0.243	−0.197	−0.194
	(0.146)	(0.195)	(0.148)	(0.1748)
Year Effects	✓	✓	✓	✓
Individual Effects	✓	✓	✓	✓
Observations	1,617	1,617	1,617	1,617
Within R^2	0.194	0.125	0.196	0.118
F Statistic (1st stage)	-	-	1,014.443***	338.1757***

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

We again observe that OLS estimates are downward bias as in rental prices. Our explanation is that unobservables that correlate positively with short-term rentals are disamenities for locals, leading to lower housing prices. Furthermore, we also observe a larger effect from commercial listings than from total listings, which can be explained following a similar argument as in section 4. The interpretation of the results are as follows. Taking the our IV specification, we observe that a 1% increase in commercial listings leads to an increase of 0.393% in house sale prices, which accounts for 8.2% of the average growth in house prices.

A.5 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.[44] 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

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

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 B.1.2 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.

A.6 Event study and diff-in-diff results with public access data

To understand the impact of tourism we first check that the most exposed zipcodes (in the sense of being historically attractive to tourists) were not already experiencing changes in outcomes of interest prior to the touristic. To do so we construct a "tourism index" using a zipcode's number of "businesses related to tourism" in 2009. This would include establishments such as souvenir shops, bike day-rentals, museums, etc. We then split zipcodes into "touristic" and "non-touristic" according to a threshold value of this index. Figure 21 plots our results, which suggest that both touristic and non-touristic zipcodes had similar trends before 2009, but not after. Touristic zipcode rents grow faster post-2009, and this result is robust to how one may pick the threshold to split the groups. Furthermore, the touristic premium post-2009 is both statistically and economically significant: if one runs a difference-in-difference regression with time varying controls and two-way fixed effects the resulting estimates is roughly 40 euro (nearly 10% of the average monthly rent during this period).

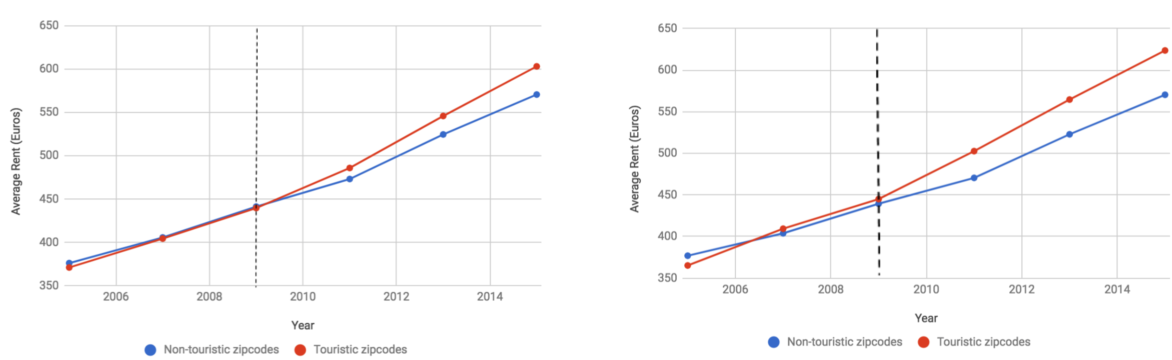

Figure 21: Average Monthly Rent, 2005-2015. In the top figure, touristic zipcodes are defined as those above the median tourism index value, and non-touristic as those below. The bottom figure uses the top quartile and the bottom quartile of the index as the cutoff value.

In what follows we generalize the above to exploit the continuity of our "treatment" variable (the tourism index) rather than splitting zipcodes into two groups at an arbitrary threshold. We conduct an event study, so that our regression of interest is as follows,

$$Y_{it} = \beta_t \text{Touristic Businesses}_i + \phi X_{it} + \eta_i + \lambda_t + \varepsilon_{it},$$

where Y_{it} is an outcome of interest such as rent, X_{it} is a vector of zipcode and time-varying controls, and η_i and λ_t are zipcode and time fixed effects, respectively. Figure 22 plots estimates for β_t from 2005 to 2015 along with 95% confidence intervals, with 2009 as the omitted year. The estimates for β_t increase significantly above zero only after 2009. We repeat the analysis taking the share of non-Dutch residents per zipcode as our outcome variable and plot the results in Figure 22.[45] The results indicate that the share of immigrants is declining post-2009 in more touristic zipcodes.

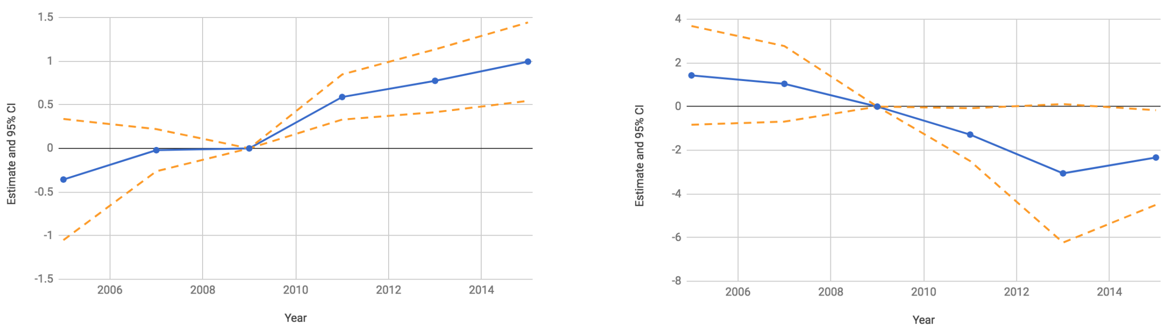

Figure 22: Event study coefficients for average monthly rent (top) and share of non-Dutch residents (bottom).

Summing up, outcomes of interest are changing in touristic relative to non-touristic zipcodes after 2009, and not before. Thus, any candidate explanation driving these outcomes must fit this time pattern. For instance, a story of urban revival and young, high-skill workers returning to cities would be ruled out by the event study unless it is happening precisely after 2009, and not before. While there could be many explanations that fit this timing, our stylized facts from previous sections suggest we propose the recent boom of tourism and Airbnb entry as a hypothesis since it fits the timing of the event study and it is sufficiently large to have a meaningful impact on the housing market.

[45] Amsterdam City Data defines a person to be "Dutch" if both of the person's parents were born in the Netherlands, regardless of where the person is actually born. Thus, this is a measure of cultural or ethnic background, rather than citizenship status. We use this definition because we think the former is a better predictor of socioeconomic status than the latter.

Appendix B. Institutional details

B.1 The housing market in Amsterdam

In Amsterdam, 70% of housing units are rentals, and they can be classified as either social or private housing. The Netherlands is well known for having the largest social housing program in Europe, and Amsterdam is no exception to this national trend: nearly half of the city's housing stock is social housing. Classification of a unit as social or private is determined by a points system based primarily on physical characteristics (size, amenities, number of bedrooms and bathrooms, among others). If the total score of a unit is below an annually updated threshold it is by definition a social rental unit. The maximum amount of rent that can be charged for a social unit is regulated and is proportional to its total points. This implies a maximum rent for social units, and this threshold is commonly known as the "liberalization line", which stands at 710.68 euros for 2015-2018 and 720.42 euros as of 2019. 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 may 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 though, so that some lucky households may avoid the long waiting times.

B.1.1 The role of housing associations

A "housing association" is an organization that focuses on the building, management and letting 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 with the aim of providing housing for urban workers, and were typically founded by workers' associations or by employers as a means to avoid social unrest among their employees. A major policy shift was the Housing Act of 1901, which assigned the associations the sole objective of promoting public housing, in return for favorable loans and subsidies for construction and management from the government. According to Musterd (2014) the associations became especially prominent after WWII due to a housing shortage induced by the baby boom. This led the Dutch state to provide the associations with further construction subsidies to increase housing supply. 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 to provide 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 occupants. For example, the requirement for housing associations to obtain government permission before selling their rental properties has been removed. In Amsterdam the share of home ownership increased from 11 to 30% between 1995 and 2015, while the ratio of social rental housing 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).

B.1.2 The points system and the determination of rents

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. This correction allows rents to adjust to the market on a regional basis: 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: however, they also have no rent floor. Therefore, their actual agreed upon rent may be very low, and in the case it is below the "liberalization line" (an annually determined threshold, 681 euros in 2013) they are classified instead 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 unregulated sector but if demand is low it is rented below the liberalization line: thus any rent increases within tenancy are restricted in the same way as a social unit (where typically increases are tied to inflation). 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 to 200 points bracket.

B.1.3 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 (typically tied to the inflation rate). Private housing is not subject to within-tenancy rent increases (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).

B.1.4 Rental subsidies

Another housing affordability policy in the Netherlands are rental subsidies (huurtoeslag). Requirements to qualify a rental subsidy are more strict than for social housing and several criteria that must be met. First, the total income in 2018 of the household should not be above 30,400 euros (22,400 if it is a single household) as compared to 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. In any case, total rent has to be below the maximum rent allowance for housing associations.

Appendix C. Hotels and Airbnb in Amsterdam

In this section we point out key features of the hospitality sector that we use in our analysis.

C.1 The hotel industry in Amsterdam

The number of overnight stays in Amsterdam has almost doubled, with 6 million of overnight visitors in 2008 and 16 million in 2017. More interestingly, Amsterdam is a city with a high number of tourists by resident. According to Mastercard Visitor Index Report of 2017, Amsterdam ranked first in number of overnight visitors per capita among the top 20 most visited cities in the world as shown in Figure 23. This rapid growth in tourist volume has been accompanied by an expansion

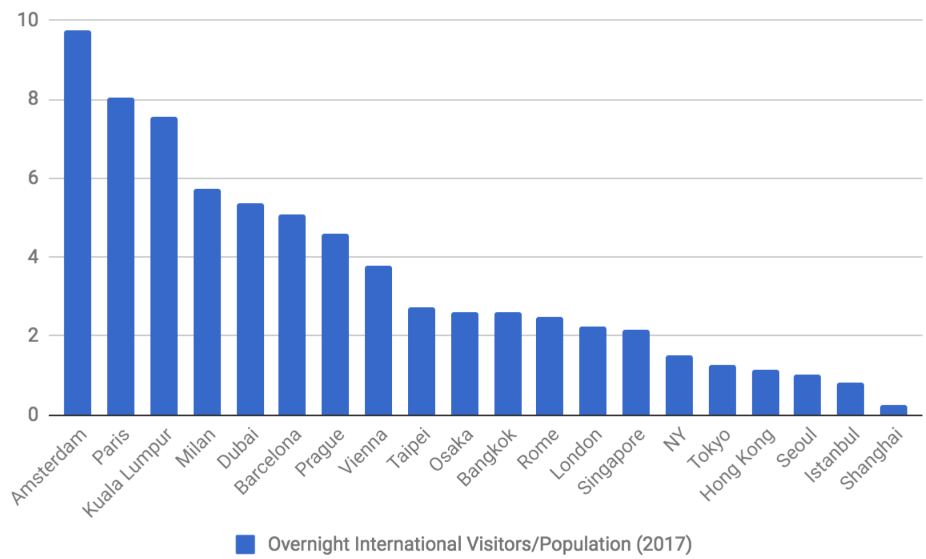

Figure 23: Tourists per resident for major global cities (2017)

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 between 2008 and 2017. The difference in growth rates is due to the opening of large-scale hotels in the last decade.

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 50% and 63% respectively in the same time period. Half of the jobs in the tourism sector correspond to catering services. Culture and recreation related jobs account for 16%, the same amount as jobs in the hotel sector, while transportation represent 8% of the total number of jobs dedicated to tourism.

Finally, hotel performance has also improved for the same time period. First, the average room price has followed an increasing trend, going from EUR 105 in 2009 to EUR 138 in 2017. The average annual price growth has been of 3.3% with a peak in 2015 of 8.8%.[46] We can see a slight drop in 2009 in both occupancy rate and average hotel rates, due to the financial crisis, followed

[46] Average inflation for the same time period and year are 1.4% and 0.22% respectively. Source: IMF inflation reports.

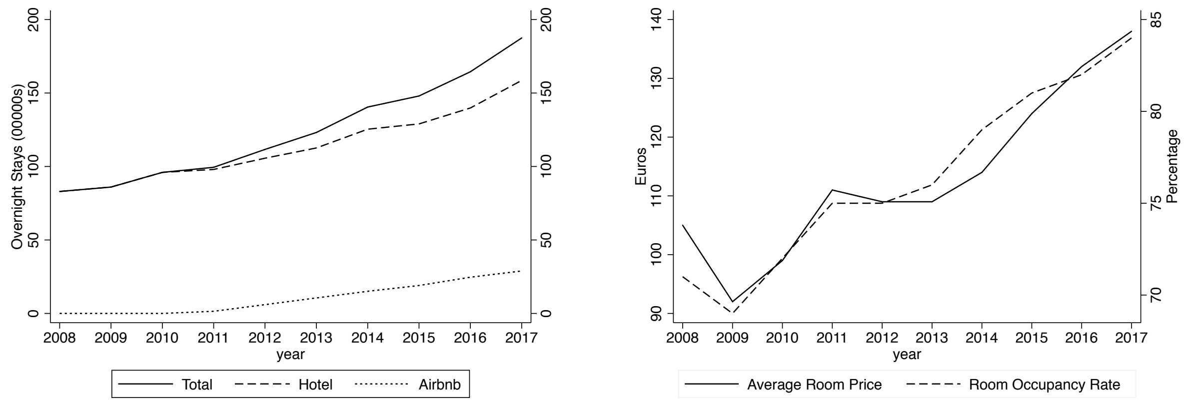

Figure 24: Hotel and Airbnb listings volume, occupancy rates, and prices.

by a fast recovery in 2010. Second, occupancy rates have been steadily increasing from around 70% to 84%, a pattern that similarly holds for hotels of all quality ranges. Overall, average annual hotel revenue has had a total growth of 57% from 2008-2017.

All these figures were obtained from tourism reports commissioned by Onderzoek, Informatie en Statistiek (Research, Information, and Statistics in English), which collects data for the Amsterdam City Data project.[47]

C.2 Airbnb details

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.

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 turn off "instant booking", so that any reservation has

[47] ois.amsterdam.nl/toerisme

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").[48] 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.

C.3 Host statistics

According to Airbnb the average booking in Amsterdam is for 3.9 nights in 2012-2013.[49] This number has decreased to 3.3, 3.2, and 3.4 nights in 2015, 2016, and 2017, respectively.[50] Fradkin et al. (2018) report an average review rate by guests of 67% for Airbnb worldwide.

C.4 Policies regulating Airbnb

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.[51] 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. While regulations such as the nights cap exist in many Airbnb markets, enforcement by city regulators is weak due to the decentralized nature of the platform's listings. Unless enforcement is carried out directly by the platform, regulations cannot be expected to have much bite. 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.[52] Furthermore, the company has agreed to reduce the cap further to 30 nights per year beginning on January 1, 2019.[53] 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 euros.[54]

[48] press.airbnb.com/instant-book-updates/
[49] press.airbnb.com/instant-book-updates/
[50] ois.amsterdam.nl/toerisme
[51] The Guardian (December 3, 2016)
[52] airbnbcitizen.com/new-data-on-responsible-home-sharing-in-amsterdam/
[53] Techcrunch (January 10, 2018)
[54] amsterdam.nl/veelgevraagd

C.5 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. Prices of Airbnb listing lie slightly below than the average price for 3-star hotels, see Figure 25 below.[55] It is precisely low-end hotels that report having suffered the most from short-term rentals, while 4- and 5-star hotels report to have very little competition from this new form of accommodation.[56] 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 the short-term rental market in Amsterdam, Airbnb accounted for 80% of total short-term rentals in 2016 and in 2017 Amsterdam.[57] Its main competitor is Wimdu, with 13% of the market in 2017, but there are other platforms like Booking, Homeaway, Flipkey, and 9flats. All of those accounted for 4000 listings in 2016.

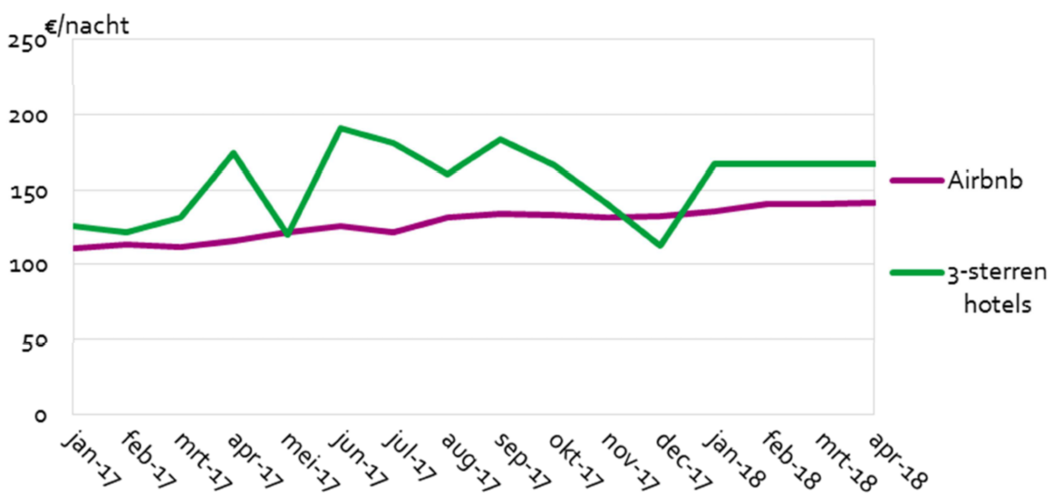

Figure 25: Airbnb and 3-star hotel prices in Amsterdam

Farronato and Fradkin (2018) also find that Airbnb utility from short-term rentals is below the mean of budget hotels. Their results suggest that Airbnb lowers hotel profits but not the number of occupied rooms. The reason is that hotels are inelastic in the short run, so during peak demand dates Airbnb overflows the market with supply and prevents hotels from spiking up their prices. However, during off-peak period they find that Airbnb has no negative effect on hotel prices.

Given that in our analysis we use average prices and quantities at the year-zipcode level, based on the evidence previously exposed, our assumption is that Airbnb hosts take the 3-star hotel prices as given, and set their prices below those. In other words, Airbnb does not have an effect in the average yearly prices of the hotel industry.

[55]Source: 2019 Tourism Report in ois.amsterdam.nl/toerisme
[56]ois.amsterdam.nl/toerisme
[57]ois.amsterdam.nl/toerisme

C.6 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 A.5.

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.[58] 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.

[58] 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.7 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[59]	**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).

[59] 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.[60] 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:[61]

$$\max_{\{q_{is}\}_{is}} A_j \tau^{\nu^k} \prod_s \left(\left(\sum_{i=1}^{N_s} q_{is}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right)^{\alpha_s^k} \quad \text{s.t.} \quad \sum_{is} p_{is} q_{is} = (w^k - r_j), \tag{14}$$

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 4. 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

[60] 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.

[61] 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,

$$A_{jt}\tau^{\nu^k}(w_t^k-r_{jt})\prod_s\left(\frac{\alpha_s^k(1-\frac{1}{\sigma_s})}{c_{sjt}}N_{sjt}^{\frac{1}{\sigma_s-1}}\right)^{\alpha_s^k}, \tag{15}$$

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 15, 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

$$P_t(j,x) = \frac{\exp(v_t(j,x))}{\sum_d \exp(v_t(d,x))}, \tag{16}$$

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,

$$\bar{V}_t(x) = v_t(d,x) - \ln(P_t(d,x)) + \gamma. \tag{17}$$

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 16:

$$\ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = v_t(d,x_{it}) - v_t(d',x_{it}). \tag{18}$$

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,

$$\bar{u}_t(d,x_{it}) - \bar{u}_t(d',x_{it}) - \ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = \beta\mathbb{E}_t\left[\bar{V}_{t+1}(x'_{it+1})|d',x_{it}\right] - \beta\mathbb{E}_t\left[\bar{V}_{t+1}(x_{it+1})|d,x_{it}\right] \tag{19}$$

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 19 gives us

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

Using equation 17 to replace the continuation values $\bar{V}_{t+1}$ for choice $\tilde{d}$ gives us

$$\begin{aligned}\bar{u}_t(d,x_{it}) - \bar{u}_t(d',x_{it}) - \ln\left(\frac{P_t(d,x_{it})}{P_t(d',x_{it})}\right) = \\ \beta\Bigg[\sum_{w_{it+1}\in\mathcal{W}} F(w_{it+1}|w_{it})\left(v_{t+1}(\tilde{d},x'_{it+1}) - v_{t+1}(\tilde{d},x_{it+1}) - \ln\left(\frac{P_{t+1}(\tilde{d},x'_{it+1})}{P_{t+1}(\tilde{d},x_{it+1})}\right)\right) \\ - \nu_t(d,x_{it}) + \nu_t(d',x_{it})\Bigg]\end{aligned} \tag{20}$$

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 20 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

$$Y_{t,d,d',\tilde{d},x_{it}} = \Delta_{d,d'}\Big(\delta_{j(.)} + \delta_\tau \tau_{x_{it}} - \delta_r \ln r_t + \delta_a \ln a_t + \xi_t + \beta MC(j(.), \tilde{d})\Big) + \tilde{\varepsilon}_{t,d,d',x_{it}}. \tag{21}$$

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.[62] 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

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

[62] 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:

$$\log(\hat{p}) = \log(p_0) + \frac{1}{p_0}(\hat{p} - p_0) - \frac{1}{p_0^2}(\hat{p} - p_0)^2 + \mathcal{O}(\hat{p} - p_0)^3 \tag{22}$$

Taking expectations with respect to realizations $\{p_i\}_i$ we obtain[63]

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

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).[64] 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

[63] 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

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

[64] 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:

$$\mathbb{E}\hat{p} = \frac{1}{|\mathcal{X}|}\sum_{x'} \hat{p}_t(a|x') = \frac{\hat{\alpha}}{\hat{\alpha} + \hat{\beta}} \tag{23}$$

$$\text{Var}[\hat{p}] = \frac{1}{|\mathcal{X}|}\sum_{x'} (\hat{p}_t(a|x') - \mathbb{E}\hat{p})^2 = \frac{\hat{\alpha}\hat{\beta}}{(\hat{\alpha} + \hat{\beta})^2(\hat{\alpha} + \hat{\beta} + 1)}. \tag{24}$$

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:

$$\hat{\alpha}_P = \hat{\alpha} + \sum_i \{d_i = a\} \tag{25}$$

$$\hat{\beta}_P = \hat{\beta} + N - \sum_i \{d_i = a\}, \tag{26}$$

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 26 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 26: Monte Carlo simulation results

D.2.5 Exclusion Restrictions

To be able to identify the parameters with regression 13 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 12 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:

$$
\begin{aligned}
Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta^k_{j(d)} - \delta^k_{j(d')} + \delta^k_\tau\Big(\tau(d,x_{it}) - \tau(d',x_{it})\Big) \\
&+ \delta^k_a\Big(\ln a_{j(d)t} - \ln a_{j(d')t}\Big) - \delta^k_r\Big(\log r_{j(d)t} - \log r_{j(d')t}\Big) \\
&+ MC^k(j(d), j_{it-1}) - MC^k(j(d'), j_{it-1}) \\
&+ \beta\Big(MC^k(j(\tilde{d}), j(d)) - MC^k(j(\tilde{d}), j(d'))\Big) \\
&+ \xi_{jt} - \xi_{j't} + \tilde{\varepsilon}_{t,d,d',x_{it}} \\
&= \Theta' X_{d,d',\tilde{d},s_{it},t} + \Delta\xi_{t,d,d'} + \tilde{\varepsilon}_{t-1,d,d'}, \qquad (27)
\end{aligned}
$$

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 27

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

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 $X_{d,d',\tilde{d},x_{it},t}$.[65]

[65] 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:

$$\log N_{sjt} = -\log \sigma_s - \log F_{sjt} + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) \tag{28}$$

$$= \lambda_s + \lambda_j + \lambda_t + \log \Big(\sum_k M_{jt}^k \alpha_s^k (w_t^k - r_{jt}) \Big) + \xi_{sjt}, \tag{29}$$

and the location demand equation:

$$\begin{aligned} Y^k_{t,d,d',\tilde{d},x_{it}} &= \delta^k_{j(d)} - \delta^k_{j(d')} + \delta^k_\tau \Big(\tau(d, x_{it}) - \tau(d', x_{it}) \Big) \\ &+ \delta^k_a \Big(\ln a_{j(d)t} - \ln a_{j(d')t} \Big) + \delta^k_r \Big(\log(w_t^k - r_{j(d)t}) - \log \big(w_t^k - r_{j(d')t} \big) \Big) \\ &- \Big(MC^k(j(d), j_{it-1}) - MC^k(j(d'), j_{it-1}) \Big) \\ &- \beta \Big(MC^k(j(\tilde{d}), j(d)) - MC^k(j(\tilde{d}), j(d')) \Big) \\ &+ \tilde{\varepsilon}_{t,d,d',x_{it}}. \end{aligned} \tag{30}$$

It is easy to see from 29 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 30 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:

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