Two-Sided Sorting and Spatial Inequality in Cities

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Abstract

This paper studies how two-sided sorting of firms and households drives inequality within cities. I develop a quantitative model that features skill heterogeneity, non-homothetic demand for local consumption sectors and varying skill intensity in production. As a neighborhood become more skilled, firms catering to the rich and employing skilled workers enter, further reinforcing skill sorting. To validate the model's mechanisms, I replicate the estimated impact of Empowerment Zones on household and firm sorting in model counterfactuals. I apply the model to explore how alternative policies employing two-sided sorting as a tool reach targeted populations more effectively and direct neighborhood change.

KEYWORDS: cities, sorting, inequality, amenities, price index, non-homothetic preferences

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1 Introduction

Modern cities feature high degrees of segregation between households with different incomes and education levels. In part, this sorting of households reflects spatial inequality in access to jobs and consumption. At the same time, these employment and consumption opportunities are provided by firms who themselves sort across locations based on access to their customers and access to local factors such as skilled labor. Firm sorting can therefore reinforce spatial inequality and segregation.[1] Studying the location choices of households and firms in isolation from each other misses important interactions between them, in the way both sides shape local markets for consumption, labor and housing.

Better understanding of the forces underlying this two-sided sorting helps to improve the design of place-based policies addressing spatial inequality and segregation. For instance, many programs offer large incentives to firms for locating in disadvantaged neighborhoods, such as Empowerment, Opportunity or Enterprise Zones. Their success in improving living standards of low-income residents depends on which type of firms the program attracts – whether those firms employ high- or low-skilled labor, and whether they cater to rich or poor consumers. The entering firm's type then increases the value of the neighborhood more for certain household types, inducing their in-migration which further amplifies neighborhood change.[2] Hence, evaluating the policy's distributional impact requires a quantitative framework that accounts for heterogeneity and mobility of both households and firms.

In this paper, I develop a spatial model of the city to study how two-sided sorting of heterogeneous households and firms shapes the urban landscape. Then I use the model to assess the distributional welfare effects of place-based policies in general equilibrium. After estimating the key model elasticities with microdata from Los Angeles, I show that the model predicts gentrification of LA Empowerment Zones, aligning qualitatively and quantitatively with my empirical evaluation of the program. Going beyond validating the model using the existing Empowerment Zone policy, I study several alternative policy designs that leverage more effectively two-sided sorting as a mechanism to induce neighborhood change.

My model combines four features that are essential in fitting evidence from the policy experiment. First, households are endowed with *heterogeneous skills* which endogenizes differences in income. Second, demand across consumption sectors is *non-homothetic* such that variation in incomes translates to differences in how households value access to specific sectors.[3] Third,

[1]For example, Couture & Handbury (2020) identify the increased availability of restaurants and bars in downtown areas as a cause for the inflow of young, skilled residents into downtowns. Behrens *et al.* (2022) document that the presence of firms in specific "pioneer" sectors predicts gentrification of neighborhoods.

[2]Previous empirical work on the impact of Federal Empowerment Zones (Busso *et al.* (2013); Reynolds & Rohlin (2015)) provides evidence for the inflow of affluent, high-skilled households into targeted zones and large housing cost increases ("gentrification").

[3]Non-homothetic preferences have been used in the context of geography and trade, e.g., Borusyak & Jaravel (2018), Matsuyama (2019), Hottman & Monarch (2018). In particular, Handbury (2021) shows that when accounting for non-homothetic preferences across food items, income-specific price indices across cities are systemically correlated with local income. However, none have explored how non-homothetic demand affects sorting patterns.

firms face *localized demand* due to frictions in accessing consumption venues leading to spatial variation in consumption access.[4] Lastly, profit-maximizing firms choose locations based on access to consumers and local factor prices for skill and floor space. Combined with the previous model ingredients, this feature links back variation in consumption access across space and skill to the local skill composition and sorting of households. As a result, two-sided sorting leads to pecuniary externalities that create and amplify segregated neighborhoods. Household sorting is then further reinforced by amenity spillovers; utility of households depends directly on the local skill composition, a reduced-form way to capture many channels through which neighborhood composition feeds back into amenities such as policing, school quality, public parks.[5]

Firms have two distinct roles in the model: they provide employment opportunities, and they increase the consumption value of a neighborhood. However, their value to different households depends on the degree to which a firm demands skilled labor (skill intensity) and caters to rich customers (income elasticity). As firms enter a neighborhood, their skill intensity determines the impact on relative incomes, while their income elasticity governs the effect on relative cost-of-living. Therefore, the net effect on *relative real income* depends on whether the labor market access channel dominates the consumption access channel or vice versa. If demand effects are strong enough firm entry can trigger gentrification: influx of high-skilled households into the neighborhood, higher cost of housing and further feedback onto other firms responding to higher local income. Hence, the model allows for rich linkages between household and firm sorting along labor, consumption and housing markets.

The relative strength of labor market access and consumption access governing household sorting is ultimately an empirical question that I answer by estimating the key elasticities of the model using detailed microdata on households and firms from Los Angeles. Furthermore, I validate the model's predictions along empirical moments from a real-world policy experiment, i.e., Federal Empowerment Zones.

To do so, I begin by estimating the degree of sector heterogeneity. On the production side, I find significant variation in *skill intensity* across sectors, ranging from 14% in technical services to 65% in education.[6] Hence, the composition of local firms as employers imply potentially large differences in labor market access by skill. To discipline the strength of non-homotheticities in the model, I estimate *income elasticities* for 30 service and retail sectors with expenditure microdata from the Consumer Expenditure Survey (CEX).[7] I find that income elasticities of demand vary considerably, reflecting large differences in observed consumption bundles by income. Expenditure shares increase steeply with income in sectors such as recreation, apparel, and restau-

[4]As is common in urban models, markets for skilled labor are also localized due to commuting frictions.

[5]Amenity spillovers have been used extensively in the literature, e.g., Diamond (2016), Su (2022b), Tsivanidis (2021), Guerrieri *et al.* (2013), Brueckner *et al.* (1999), Fajgelbaum & Gaubert (2020)

[6]Skill intensity in production is calculated as the share in payroll accruing to employees with a bachelor degree or higher in Census microdata for the entire US.

[7]I manually categorize sectors as local if consumers physically go to an establishment to purchase a good or service. In my sector definitions, I try to account for quality differences as much as possible given the constraint that sectors need to match to industry codes in establishment microdata and expenditure categories in the expenditure data. For example, I differentiate fast food restaurants and full service restaurants.

rants whereas expenditure shares fall with income in liquor/tobacco or grocery stores. Thus, local availability of certain sectors can induce significant variation in consumption access between skill-types.

An important component of two-sided sorting is the degree to which firms sort in response to spatial variation in *localized demand*. Using geo-coded panel data on the near-universe of establishments in Los Angeles, I estimate a spatial supply elasticity of firms. I identify this parameter from the relationship of relative size of establishments belonging to the same chain and the total number of establishments in a location. To address endogeneity concerns, I exploit the differential exposure of sectors to arguably exogenous variation in local demand that is driven by households' preference for the steepness of a location, a natural amenity strongly related to the presence of affluent households. I find that firms are very sensitive to local demand, suggesting a tight link between firm and household sorting in the data.

Moving to the household side of two-sided sorting, I estimate a resident supply elasticity and the strength of amenity spillovers by relating sorting patterns across census tracts over time to changes in *relative real income* and a tract's surrounding skill-mix.[8] To jointly identify these key elasticities, I construct several shift-share instruments for consumption access and income that exploit plausibly exogenous shifts in the availability of local consumption venues and wage growth across sectors. This set of elasticities determines how strongly households respond to changes in real income as opposed to amenities, thereby, balancing the externalities linked to two-sided sorting and direct spillovers.

To introduce a benchmark for model validation, I empirically evaluate the impact of the Federal Empowerment Zone (EZ) program on the skill and firm composition of designated tracts. Among the largest place-based policies in the US to date, the EZ program awarded several cities, including Los Angeles, a set of place-based subsidies in order to upgrade disadvantaged neighborhoods.[9] For identification, I closely follow Busso *et al.* (2013) and Reynolds & Rohlin (2015) in comparing Round-1 EZs with "rejected" zones, reweighted with propensity scores to achieve further balance. However, I extend their analysis until the end of the program in 2011 and focus on somewhat different outcomes. My results suggest that EZ tracts saw an inflow of affluent, more educated households and large increases in income and rents. Moreover, the number of establishments increased significantly, in particular, in income-elastic sectors. Consistent with

[8]Since data on household expenditures and establishment-level prices are not available for most expenditure at the level of skill groups and tracts, I cannot directly construct price indices (consumption access) at this level of disaggregation. Instead, I rely on the demand structure of the model to find a sufficient statistic for changes in the price index of goods and, consequently, real consumption at the tract-skill level. Conditional on a common housing market and constant relative tastes for housing over time and space, available data on rents, income and housing expenditure shares captures all variation in cost-of-living and real consumption (with an estimate of the elasticity of substitution).

[9]Starting in 1994, EZs were awarded in three rounds with much smaller benefits given to rejected zones. Firms located in EZs received a tax benefit of up to \$3000 for every employee hired from the zone. In addition, cities received block grants amounting to \$100M for various business incentives and social spending in the zone. Los Angeles was "only" awarded a Supplemental Empowerment Zone (SEZ) in 1994 but received the full benefits by 2000. I restrict the treatment group to EZs and SEZs in 1994 and the control group to applicants which were not given an EZ designation in any of the rounds.

the earlier literature, EZs experienced changes tilted in favor of the high-skilled and, broadly speaking, underwent gentrification.

Having established a set of moments independent of the model estimation, I simulate the Los Angeles Empowerment Zone as a policy counterfactual in the model, and compare the model impacts to my empirical moments. While the policy benefits the low-skilled more than the high-skilled through larger income effects, consumption access changes in favor of more affluent households due to the inflow of firms and rent increases, thereby, outweighing the labor market access impacts. On net, the baseline model with two-sided sorting matches the empirical results on household and firm margin very well: the skill share in the EZ increases by 25%, and the firm composition shifts to sectors that cater to richer households and are less reliant on local demand. Further investigating the model's mechanisms, I show that model variants lacking my key model features are not able to fit the empirical results along important dimensions. For example, a model variant with homothetic preferences fails to predict the inflow of the high-skilled in response to the same policy, whilst a model without localized demand misses the changes in firm composition.

Next, I use the model to assess the welfare effects of the EZ program for Los Angeles. First, the welfare gains are larger for high-skilled households in absolute terms and relative to income, putting in question the policy's stated goal in improving outcomes for disadvantaged, low-skilled residents. Second, the policy created benefits worth $120 (in 1990) for the average LA resident at a cost of around $200. Importantly, due to various externalities present in the model the competitive equilibrium allocation is not necessarily efficient, in principle, allowing for policies to have a positive net welfare effect (Fajgelbaum & Gaubert, 2020). For instance, the model variant with homothetic preferences finds that the policy creates net welfare gains of around $100 for the average LA resident with larger benefits accruing to low-skilled households. Hence, accounting for non-hometheticity in preferences changes not only the policy's impact on sorting significantly but also the costs and benefits of the program.

I conclude the counterfactual analysis by exploring several alternative EZ policies, keeping the main policy tools intact but targeting specific sectors. In particular, if the policy is restricted to income-elastic or income-inelastic sectors, policymakers can steer neighborhood change and welfare impacts towards high- or low-skilled households. The policy is less selective in directing the policy impact if the policymaker picks treated sectors based on skill intensity, or the degree to which sectors depend on local demand. My results imply that policymakers are able to leverage sector heterogeneity in effectively targeting certain populations, and in doing so combining a people-based with a place-based policy approach. Thus, my model of two-sided sorting generates potentially important lessons for the evaluation and design of policies addressing spatial inequality and segregation.

Related Literature: In addition to the work discussed above, this paper relates to several strands of the literature. First, several recent contributions explore how heterogeneous preferences for consumption amenities and differential access to services lead to sorting of households within and across cities.[10] Closest to this paper are recent contributions by Couture *et al.* (2019) and Almagro & Dominguez-Iino (2022).[11] Key differences to these papers are that in my work (i) households have common non-homothetic preferences over many sectors; (ii) firms demand skilled labor locally with varying intensity; (iii) income differences across skill-types and space are endogenous; (iv) the model is set in a realistic geography with shopping and commuting linkages across space. The additional layers of heterogeneity in (i) and (ii) induce firm sorting, which is absent in other work in this area. Firm sorting allows me to study how the response of specific types of firms amplifies household sorting through consumption and labor market effects. Finally, these difference make my model amenable to evaluating real-world policies. Thus, I can validate my model using estimated effects of Empowerment Zones, and use the validated model to assess welfare impacts.

Hence, my paper contributes to a smaller literature that studies the spatial sorting of heterogeneous firms. For example, Behrens *et al.* (2014) and Gaubert (2018) find that firm sorting explains a sizable share of the productivity premium of large cities. Brinkman *et al.* (2015) and Ziv (2015) study how agglomeration forces and firm sorting interact within cities. Different from these contributions, my paper focuses on demand-side complementarities between local resident composition and the determinants of firm demand, such as income elasticities.

My paper adds new insights to recent work on place-based policies in cities, for example, Diamond & McQuade (2019), Diamond *et al.* (2018), and Davis *et al.* (2018). In particular, a sizable literature evaluates place-based tax incentives awarded to local firms, such as Empowerment Zones (Hanson (2009); Ham *et al.* (2011); Neumark & Young (2019); Gobillon *et al.* (2012); Mayer *et al.* (2017)). To my knowledge, my paper is the first to combine an empirical evaluation of Federal Empowerment Zones with a general equilibrium model.

Lastly, my model builds on the quantitative spatial economics literature that studies the rich structure of cities (Ahlfeldt *et al.* (2015); Allen *et al.* (2015); Redding & Rossi-Hansberg (2017)). The focus of this literature is primarily on the trade-off between job location and residence.[12]

[10]For example, Couture & Handbury (2020) and Baum-Snow & Hartley (2016) document that changing tastes for services over the last couple of decades are important drivers of the observed movement of college graduates into downtown neighborhoods. Gaigné *et al.* (2022) develop a theoretical extension of the linear city model, allowing for sorting based on commuting and amenity access with non-homothetic preferences. Diamond (2016) studies how endogenous amenities amplify sorting by skill. Another literature documents large spatial differences in the availability and variety of goods and services associated with the size and social composition of the local population. Waldfogel (2008), Schiff (2014), Couture (2016), and Davis *et al.* (2019) study variety and density of restaurants. Glaeser *et al.* (2018) and Behrens *et al.* (2022) look at several categories of local services. Handbury (2021) explores how price indices for food items vary systematically with household income and citywide income. My paper makes a similar argument. However, price indices and neighborhood composition are endogenous and analyzed within a general equilibrium framework in this paper.

[11]Couture *et al.* (2019) model endogenous differences in access to a single service sector that induce sorting of households in different income groups due non-homothetic demand for neighborhoods. The authors then use the model to relate the recent increase in income inequality to sorting across stylized neighborhoods, thereby quantifying the increase in welfare inequality. Almagro & Dominguez-Iino (2022) use a dynamic choice model to relate the availability of a bundle of services and sorting of heterogeneous households with homothetic preferences in Amsterdam.

[12]Miyauchi *et al.* (2021) develop a model allowing for rich travel itineraries beyond separate commuting and shop-

Moreover, it features homogeneous households with homothetic preferences.[13] I complement these papers by modeling spatial linkages within the city that are driven by both consumption and commuting patterns of heterogeneous households in a quantitative model amenable for policy analysis.

The rest of the paper is organized as follows. Section 2 introduces the model. Section 3 describes the data used in this paper. Section 4 takes the model to the data. Section 5 presents policy evaluation, model validation and alternative policy counterfactuals. Section 6 concludes.

2 Model

In this section, I develop a spatial general equilibrium model in the spirit of Ahlfeldt *et al.* (2015) and Tsivanidis (2021). It characterizes several forces leading to sorting of households across neighborhoods of a city, as well as the simultaneous sorting of firms in various sectors. Key features that distinguish the model are that preferences take the non-homothetic CES form over these sectors, and households are endowed with different skill levels. These novel features lead to sorting, since households with high or low skill (and consequently income) differently trade off access to jobs (local income), access to consumption venues and housing cost (local price index), and local amenities.

Similarly, heterogeneous firms make location decisions based on local input costs, local demand and productivity. Since firms operate in sectors that differ in the income elasticity of demand and skill intensity in production, the skill composition of potential locations determines local demand and labor supply. Hence, the model allows for rich interactions between households and firms. Moreover, the model features endogenous local amenities, spatial frictions in commuting and accessing consumption venues, and a construction sector that provides housing elastically. Despite the model's rich environment it provides a set of equations that I can estimate with widely available data in section 4 and can be used to simulate policy counterfactuals in general equilibrium in section 5.

2.1 Environment

The city consists of N neighborhoods, indexed by n, which can serve as residences and workplaces for households and production locations for firms. It is populated by K skill types of households, indexed k, each with fixed mass L_k. There are J sectors in the city whose products vary by income elasticity of demand in household preferences and skill intensity in production. Within each sector j there is endogenous mass of spatially mobile firms M_j that operate under monopolistic competition and choose where to produce differentiated varieties using commercial housing and a bundle of labor over skill types and commuter origins. A competitive con-

ping trips. They show that accounting for trip choice relates to local agglomeration forces and validate the model using rich smartphone movement data. However, their analysis abstracts from income or skill sorting.

[13] A notable exception is Tsivanidis (2021) who evaluates the distributional effects of infrastructure investment in Bogotá in a model of commuting by skill groups with Stone-Geary preferences.

struction sector supplies residential and commercial housing in each neighborhood using fixed land Z_n and capital Q_n provided from outside the city at fixed price P^Q.

2.2 Household Problem

Households face three related decisions: where to work? Where to reside? What and where to consume? For tractability, I impose a specific timing for these choices. First, upon observing expected income I_{kn} and prices in each neighborhood n, a household ι of type k decides on housing consumption $C_{knh}(\iota)$ and a bundle of goods $C_{kng}(\iota)$ resulting in a price index $P_{kn}(\iota)$ in each potential neighborhood of residence. Households consume housing in the neighborhood of residence n, while they consume varieties of goods in any neighborhood n' at ad-valorem shopping cost $\tau^S_{knn'}$.

In the second step, preference draws for neighborhoods $b_{kn}(\iota)$ are realized, distributed Fréchet with $b_{kn}(\iota) \sim \exp(-B_{kn} b^{-\kappa})$, where B_{kn} are type-specific, potentially endogenous amenities, and κ is the distribution's shape parameter. Taking expected income and price indices from the first step as given, the household chooses a neighborhood of residence n that yields the highest expected utility.

In the last step, conditional on residence n households draw a vector of efficiencies $e_{ki|n}(\iota)$ for each potential workplace i from a Fréchet distribution $e_{ki|n}(\iota) \sim \exp(-e^{-\rho})$ with scale parameter of 1 and shape parameter ρ. Taking wages w_{kni} as given, the household chooses a workplace i that provides the highest income net of ad-valorem commuting cost τ^W_{kni}. In the next paragraphs, I will detail each decision problem and proceed in reverse order, starting with the choice of where to work.[14]

Workplace Choice: Conditional on having chosen residence n, workers of type k pick the workplace i, which yields the highest income taking into account wages w_{kni}, efficiency draw $e_{ki|n}(\iota)$ and commuting cost τ^W_{kni}. Specifically,

$$I_{kn}(\iota) \equiv \max_i \left(\frac{e_{ki|n}(\iota) w_{kni}}{\tau^W_{kni}} \right).$$

[14] As discussed below, households are endowed with non-homothetic CES preferences. A feature of these preferences is that the price index of consumption varies with the household's "well-being". Steps 1 and 2 below insure that households of a given type k face the same price index for a given neighborhood n before the realization of idiosyncratic preference draws for neighborhoods. In other words, I define household "well-being" as their level of real consumption in a neighborhood not their idiosyncratic utility. Otherwise, the price index and expenditure shares for a given type k in a neighborhood would follow continuous distributions related to the realized distribution of utility making aggregation intractable. Despite making this assumption for tractability, it is ex-ante unclear whether systematic variation in tastes for different goods is due to real market consumption or overall "well-being" of a consumer. Residence and workplace choice are separated by steps 2 and 3 to insure that real consumption by type k in a neighborhood is a single value. Were those choices simultaneous the discrete distribution of wages across workplaces and the continuous distribution of efficiency draws would induce a non-degenerate distribution of nominal incomes for each type in each neighborhood. Again, real consumption would follow a non-degenerate distribution. Importantly, these considerations are irrelevant under homothetic preferences, since price indices of consumption are independent of "well-being" and aggregation is straightforward.

Under the assumption that $e_{ki|n}$ is distributed Fréchet with scale parameter of 1 and shape parameter ρ, the probability that a household of type k living in n commutes to i is:

$$\lambda^W_{ki|n} = \frac{w^{\rho}_{kni}\left(\tau^W_{kni}\right)^{-\rho}}{\sum_{i'} w^{\rho}_{kni'}\left(\tau^W_{kni'}\right)^{-\rho}} = \frac{w^{\rho}_{kni}\left(\tau^W_{kni}\right)^{-\rho}}{\Phi^W_{kn}}. \tag{1}$$

Labor supply in terms of workers of type k from n in i:

$$L^W_{kni} = \lambda^W_{ki|n} L^R_{kn},$$

where L^R_{kn} is the mass of residents of type k in n. Expected labor income in n for type k is given by

$$\tilde{I}_{kn} = \gamma^W \left(\Phi^W_{kn}\right)^{1/\rho}, \tag{2}$$

where $\gamma^W = \Gamma\left(1 - \frac{1}{\rho}\right)$ is the gamma function. I call the term $\tilde{I}_{kn}$ *Labor Market Access* for type k in n.[15] Additional to labor income, households receive a type-specific lump-sum transfer from the city government t_k such that total expected income is $I_{kn} = \tilde{I}_{kn} + t_k$.
Labor supply in efficiency units is $\tilde{L}^W_{kni} = \bar{e}_{kni} L^W_{kni}$, where

$$\bar{e}_{kni} = \frac{\tilde{L}^W_{kni}}{L^W_{kni}} = \gamma^W \left(\lambda^W_{ki|n}\right)^{\frac{-1}{\rho}} \left(\tau^W_{kni}\right)^{-1} \tag{3}$$

is the average efficiency of workers from n commuting to i.

Residence Choice: Conditional on observing vectors of expected income I_{kn} and local prices, households can infer a vector of price indices of consumption P_{kn} as described in the next step.[16] Real consumption can be expressed as $U_{kn} = I_{kn} P^{-1}_{kn}$. A household of type k chooses as residence the neighborhood n that provides the highest utility according to

$$\mathcal{U}_{kn}(\iota) \equiv \max_n U_{kn} b_{kn}(\iota),$$

where $b_{kn}(\iota)$ are preference draws for each neighborhood n, distributed Fréchet with scale parameter B_{kn} and shape parameter κ. Under this assumption, the probability of a type-k household choosing n is:

$$\lambda^R_{kn} = \frac{B_{kn} U^{\kappa}_{kn}}{\sum_{n'} B_{kn'} U^{\kappa}_{kn'}} = \frac{B_{kn}\left(I_{kn} P^{-1}_{kn}\right)^{\kappa}}{\Phi^R_k}, \tag{4}$$

while the mass of type-k residents in n follows $L^R_{kn} = \lambda^R_{kn} L_k$. I refer to the inverse of the price index of consumption as *Consumption Access*. Expected utility of type-k households in the city

[15] When setting $\tau^W_{knn'} = 1, \forall k, n, n'$, labor market access (and expected income) are identical across locations. This allows me to assess the importance of commuting frictions in counterfactuals (no commuting frictions) relative to the main specification.

[16] Under the aforementioned timing restrictions all households of the same type in a neighborhood behave identically. Hence, I can omit the ι-index on expected income and price indices.

is given by

$$\bar{\mathcal{U}}_k = \gamma^R \left(\Phi_k^R\right)^{\frac{1}{\kappa}}, \tag{5}$$

where $\gamma^R = \Gamma\left(1 - \frac{1}{\kappa}\right)$.

Consumption Choices: Next, I turn to the non-homotheticity in preferences, which are a key ingredient to household sorting based on endogenous price index differences. In the upper nest, real consumption U_{kn} follows a standard CES aggregator between housing C_{knh} and goods C_{kng} defined as

$$U_{kn} = \left(a_h^{\frac{1}{\eta}} C_{knh}^{\frac{\eta-1}{\eta}} + a_g^{\frac{1}{\eta}} C_{kng}^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}}, \tag{6}$$

where η is the elasticity of substitution between housing and goods. Parameters a_h and a_g are common demand shifters. The expenditure shares on housing and goods are:

$$s_{knh} = a_h \left(\frac{r_n^R}{P_{kn}}\right)^{1-\eta} \quad \text{and} \quad s_{kng} = a_g \left(\frac{P_{kng}}{P_{kn}}\right)^{1-\eta}, \tag{7}$$

where r_n^R are residential rents, P_{kng} is the price index of goods. The corresponding overall CES price index is given by $P_{kn}^{-1} = \left(a_h \left(r_n^R\right)^{1-\eta} + a_g \left(P_{kng}\right)^{1-\eta}\right)^{\frac{-1}{1-\eta}}$ or *Consumption Access*. Importantly, consumption over goods sectors J follows a *non-homothetic CES* aggregator with elasticity of substitution γ:

$$C_{kng} = \left(\sum_{j=1}^{J} \left(\alpha_j U_{kn}^{\nu_j}\right)^{\frac{1}{\gamma}} c_{knj}^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}. \tag{8}$$

The implied CES weights are functions of real consumption U_{kn}, income elasticity of demand ν_j and common demand shifters α_j.[17] Hence, the expenditure share on all varieties in sector j out of goods expenditure follows:[18]

$$\tilde{s}_{knj} = \alpha_j U_{kn}^{\nu_j} \left(\frac{p_{knj}}{P_{kng}}\right)^{1-\gamma}. \tag{9}$$

Taking sectoral prices p_{knj} as given, as a consumer's real consumption increases, she shifts expenditures to goods from sectors with higher income elasticity parameters ν_j.[19] To see this more formally:

$$\frac{\partial \log \frac{\tilde{s}_{knj}}{\tilde{s}_{knj^*}}}{\partial \log U_{kn}} = \nu_j - \nu_{j^*}.$$

[17] The aggregator collapses to a regular homothetic CES aggregator if $\nu_j = 0, \forall j$. It implies that consumption market access is independent of real income. For a comparison of the main model with a version without price index differences (homothetic) I can simulate counterfactuals with $\nu_j = 0, \forall j$.

[18] For the remainder of the paper, I denote expenditure shares within a sector or within the goods bundle with tilde. Expenditure shares out of total consumption are denoted without tilde.

[19] A lengthier discussion of the properties of non-homothetic CES preferences can be found in Appendix C. Comin *et al.* (2018), Borusyak & Jaravel (2018), and Matsuyama (2019) provide detailed discussions of non-homothetic CES preferences.

Relative to a reference sector j^*, the consumer increases expenditure shares on sectors with $\nu_j > \nu_{j^*}$ when she gets richer, while she reduces the expenditure share on sectors with $\nu_j < \nu_{j^*}$. Moreover, as prices for goods in high-ν sectors fall, richer consumers weigh these sectors more leading to a larger reduction in the price index than for the poor.

Lastly, there is an endogenous set of differentiated varieties Ω_{nj} being offered in neighborhood n within each sector j. A variety is denoted by ω. Households aggregate varieties in sector j from all neighborhoods according to homothetic CES preferences with elasticity of substitution σ:

$$c_{knj} = \left(\sum_{n'=1}^{N} \left(\int_{\Omega_{n'j}} c_{knn'j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right) \right)^{\frac{\sigma}{\sigma-1}}.$$

To determine the endogenous set of varieties Ω_{nj}, I introduce the location choice problem of the firm next.

2.3 Firm Problem

There exists an infinite mass of potential entrepreneurs outside the city that each have access to a single variety ω in a given sector j. To enter the city entrepreneurs incur fixed costs f_j^e in terms of a numeraire good defined below. First, entrepreneurs observe expected profits from entering the city $E(\pi_{nj}(\omega))$, and they decide to enter if $E(\pi_{nj}(\omega)) \geq f_j^e$. Conditional on entry, an entrepreneur with variety ω in sector j receives productivity $z_{nj}(\omega)$ to produce in neighborhood n, drawn independently from a Fréchet distribution ($z_{nj}(\omega) \sim e^{-A_{nj}z^{-\theta}}$) with shape parameter θ and mean productivity A_{nj}.

Firm $\omega \in \Omega_{nj}$ produces output with a Cobb Douglas production function using commercial housing $h_{nj}(\omega)$ and labor inputs by skill in efficiency units $\tilde{l}_{knj}(\omega)$:

$$y_{nj}(\omega) = z_{nj}(\omega) \left(\frac{h_{nj}(\omega)}{\beta_j^h} \right)^{\beta_j^h} \prod_k \left(\frac{\tilde{l}_{knj}(\omega)}{\beta_j^k} \right)^{\beta_j^k}, \tag{10}$$

where $\beta_j^h + \sum_k \beta_j^k = 1$. Further, I assume that labor input of each skill-type follows a CES aggregator over commuter origins:[20]

$$\tilde{l}_{knj}(\omega) = \left(\sum_{i'} \left(\tilde{l}_{ki'nj}(\omega) \right)^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}}, \tag{11}$$

where ψ is the elasticity of substitution.

[20] I make this somewhat unusual assumption to be able to capture the nature of the Empowerment Zone program, which offers tax credits conditional on firm location and worker residence (both within zone). To be able to simulate such shifts in demand for workers from specific origins, I require a labor demand system with origin-destination specific wages w_{kin}. Note that, when ψ takes a large value workers from different residences become more substitutable. In the calibration below, I pick a large value for ψ, partly due to lack of empirical evidence on the magnitude of this elasticity.

Cost minimization implies the following unit cost:

$$\mathcal{C}_{nj}(\omega) = z_{nj}(\omega)^{-1} \left(r_n^C\right)^{\beta_j^h} \prod_k W_{kn}^{\beta_j^k} = z_{nj}(\omega)^{-1}\mathcal{C}_{nj},$$

where r_n^C is the rent for commercial housing. W_{kn} stands for the CES wage index for type-k efficiency units in n, corresponding to the aggregator in (11). The term $\mathcal{C}_{nj}$ captures location-sector-specific unit costs for floor space and labor. Since firms operate under monopolistic competition, the price of variety ω in sector j at the firm location n is $p_{nj}(\omega) = \sigma/(\sigma-1)\mathcal{C}_{nj}(\omega)$, while consumers shopping from n' buy ω at price $p_{kn'nj}(\omega) = \tau^S_{kn'n} p_{nj}(\omega)$.
Conditional on locating in n, variety ω's profits are:

$$\begin{aligned} \pi_{nj}(\omega) &= z_{nj}(\omega)^{\sigma-1}\frac{1}{\sigma-1} \underbrace{\mathcal{C}_{nj}^{1-\sigma}}_{\text{Factor Access } FA_{nj}} \underbrace{\sum_{n'}\sum_k \left(\frac{\tau^S_{kn'n}}{p_{kn'j}}\right)^{1-\sigma} \tilde{s}_{kn'j} s_{kn'g} I_{kn'} L^R_{kn'}}_{\text{Consumer Access } CA_{nj}} \qquad (12) \\ &\equiv z_{nj}(\omega)^{\sigma-1}\tilde{\pi}_{nj}. \end{aligned}$$

Profits of variety ω can be decomposed into idiosyncratic productivity $z_{nj}(\omega)$ and a profit term $\tilde{\pi}_{nj}$, independent of ω. This term consists of two location-sector-specific forces underlying profits and firm sorting: *Factor Access* FA_{nj} is decreasing in local input prices ($\sigma > 1$). *Consumer Access* CA_{nj} captures local demand for sector j: it combines accessibility of n by consumers from any neighborhood n' ($\tau^S_{kn'n}$), local competition in the sector price index $p_{kn'j}$ and economic size of the consumer base which is governed by local income ($I_{kn'}L^R_{kn'}$) and non-homothetic demand ($\tilde{s}_{kn'j}s_{kn'g}$).

Under the above assumption that $z_{nj}(\omega)$ is distributed Fréchet, the mass of varieties in sector j locating in n is:

$$M_{nj} = \frac{A_{nj}\tilde{\pi}_{nj}^{\frac{\theta}{\sigma-1}}}{\Pi_j} M_j, \qquad (13)$$

where M_j is the endogenous mass of active varieties in sector j, and $\Pi_j \equiv \sum_{n'}^N A_{n'j}\tilde{\pi}_{n'j}^{\frac{\theta}{\sigma-1}}$.

Expected profits per variety $E(\pi_j)$ in a given sector are equalized across locations,

$$\frac{1}{M_{nj}} \int_{\Omega_{n'j}} \pi_{nj}(\omega) d\omega = \gamma^F \Pi_j^{\frac{\sigma-1}{\theta}}. \qquad (14)$$

Lastly, using the free entry condition, I pin down the mass of active varieties in each sector M_j by equalizing expected profits $E(\pi_j)$ with fixed costs of entry f_j^e.

To allow for part of goods consumption independent of location (e.g. insurances, online purchases), I include a non-local sector (Jth sector) within the goods bundle. The only difference to local sectors is that consumers do not face shopping frictions for this sector such that $\tau_{knn'}(J) = 1, \forall k, n, n'$. In the absence of shopping frictions, firms' location choices are solely determined by factor access and productivities, and the price index of the Jth sector is the same anywhere in the city. Hence, I can set $p_{knJ} = 1, \forall k, n$ and use Jth-sector output as a numeraire good.[21]

2.4 Housing Market

Households demand housing in location n according to:

$$H_n^R = a_h \left(r_n^H\right)^{-\eta} \sum_k P_{kn}^{\eta-1} I_{kn} L_{kn}^R.$$

Housing demand by firms is:

$$H_n^C = \frac{1}{r_n^C} \left((\sigma-1)\gamma^F \sum_j \beta_j^C \Pi_j^{\frac{\sigma-1}{\theta}} M_{nj} \right).$$

Assuming a no-arbitrage condition, we can write $r_n^C = r_n^R = r_n$ The rent is determined by market clearing: $H_n = H_n^R + H_n^C$, where H_n is the total supply of floor space.[22]

Following Epple *et al.* (2010), housing is produced by a perfectly competitive construction sector with constant returns to scale using land Z_n (fixed and given) and capital Q_n (from outside city at price P_Q) according to:

$$H_n = A_{nH} Q_n^{\mu} Z_n^{1-\mu} \tag{15}$$

where A_{nH} is local productivity in the construction sector. Cost minimization and perfect competition imply a constant elasticity inverse housing supply function:

$$r_n = A_{nH}^{-\frac{1}{\mu}} P_Q \frac{1}{\mu} Z_n^{\frac{\mu-1}{\mu}} H_n^{\frac{1-\mu}{\mu}} \tag{16}$$

where $\frac{\mu}{1-\mu}$ is the housing supply elasticity.

The city government collects all housing expenditures in the city $\sum_n H_n r_n$ by fully taxing landlords and capital owners. I assume it redistributes revenues as type-specific lump-sum transfers t_k such that the citywide skill premium in labor earnings is equal to the citywide skill premium in household income.[23]

[21]Since this result holds for any sector without shopping frictions, I can remove relative price index differences in the goods bundle (no shopping frictions) by setting $\tau_{knn'}(j) = 1, \forall k, n, n', \forall j$ and compare counterfactual results to the main specification.

[22]I use the terms "floor space" and "housing" interchangeably.

[23]The magnitude of income differences between high- and low-skilled households is important for the strength of demand externalities. Lump-sum transfers are not directly observable in the data, while household income after taxes and transfers is available. Therefore, I test below whether the model can replicate the skill premium after taxes and transfers in household income data (not labor earnings).

2.5 Amenity Spillovers

To capture a wide range of other endogenous amenities affecting sorting not captured by the main mechanisms of the model (e.g. school quality, crime, homophily or other public goods), I allow for direct amenity spillovers within and across skill groups and locations. As is common in the literature, I model amenity spillovers for type-k households as returns to the number of residents of their own type k and any other types k'. Moreover, I allow spillovers to operate across neighborhoods, for example from n' to n, similar to Ahlfeldt *et al.* (2015). I assume:

$$B_{kn} = \bar{B}_{kn}\mathcal{L}_{kn} = \bar{B}_{kn}\prod_{n'}\prod_{k'}\left(L^R_{k'n'}\right)^{\delta_{k'n',kn}}, \tag{17}$$

where $\bar{B}_{kn}$ represents exogenous amenities, and $\mathcal{L}_{kn}$ denotes spillovers. Elasticities $\delta_{k'n',kn}$ govern how strongly amenities on households of type k in n respond to the number of residents of type k' in neighborhood n'.[24]

2.6 Competitive Equilibrium

The equilibrium of the economy is defined by a distribution of households by neighborhood and skill group $\{L^R_{kn}\}$ with $\sum_{n'\in\{1,2,\ldots,N\}} L^R_{kn'} = L_k, \forall k$; a distribution of commuting flows $\{L^W_{kni}\}$ with $\sum_{i\in\{1,2,\ldots,N\}} L^W_{kni} = L^R_{kn}, \forall n, k$; a distribution of firms by neighborhood and sector $\{M_{nj}\}$ with $\sum_{n'\in\{1,2,\ldots,N\}} M_{n'j} = M_j, \forall j$; mass of firms in sectors $\{M_j\}$; residential housing $\{H^R_n\}$; commercial housing $\{H^C_n\}$; prices in all sectors and neighborhoods $\{p_{knn'j}\}$; sector price indices $\{p_{knj}\}$; goods price indices $\{P_{kng}\}$; overall price indices $\{P_{kn}\}$; expected incomes $\{I_{kn}\}$; wages $\{w_{kni}\}$; wage indices $\{W_{kn}\}$; rents $\{r^R_n, r^C_n\}$ and transfers $\{t_k\}$ such that:

1. Households of type k in a neighborhood n maximize utility given $\{I_{kn}\}$, $\{r_n\}$, $\{p_{knn'j}\}$, $\{p_{knj}\}$, $\{P_{kng}\}$, $\{P_{kn}\}$ and amenities in (17). They choose residence n with probabilities in equation (4). They choose workplace i with probability in equation (1) taking wages $\{w_{kni}\}$ as given.

2. Firms in sector j in neighborhood n maximize profits in (12) taking $\{P_{kn}\}$, $\{P_{kng}\}$, $\{p_{knj}\}$, $\{w_{kni}\}$, $\{W_{kn}\}$, and the distribution of households as given. They choose production location with probabilities in (13). In each sector j, the mass of varieties is determined by the free entry condition.

3. Housing markets clear in each n with $r^C_n = r^R_n = r_n$. The labor market clears on each residence-workplace-type tuple. All goods markets clear.

A more formal definition can be found in Appendix C.

[24] This formulation nests spillovers from the local skill composition, as in Diamond (2016) or Su (2022b), by setting $\delta_{k'n',kn} = 0$ for all $n \neq n'$.

2.7 Two-Sided Sorting

Now, I discuss the model ingredients that lead to rich interactions between households and firms, in particular, how both sides of the market sort into neighborhoods. Households of skill-type k choose neighborhood n according to equation (4)

$$\lambda_{kn}^{R} = \frac{B_{kn}\left(I_{kn}P_{kn}^{-1}\right)^{\kappa}}{\Phi_{k}^{R}}.$$

Three source of variation determine this choice and vary by skill-type and neighborhood: amenities B_{kn} reflect not only that skill-types might have different tastes for fixed amenities but also how the skill composition of surrounding neighborhoods feeds back into utility due to spillovers. Expected income I_{kn} depends on demand for skill-type k of nearby employers (*Labor Market Access*). Hence, neighborhoods surrounded by firms with high skill intensity in production provide better labor market access for high-skilled households, which, in turn, attracts more skilled households.

The inverse of price index of consumption P_{kn}^{-1} captures how households with different incomes value local consumption options (*Consumption Access*). Note that two households in the same neighborhood but with different incomes (skill) face the same residential rents and sector price indices.[25] Variation in consumption access is driven by how agents weigh housing and consumption of different goods in their consumption bundle (non-homothetic preferences). For example, a more affluent, high-skilled household attaches more weight to income-elastic goods, reflected in higher expenditure shares. If housing is less elastic than goods consumption, high rents harm such a household less than a low-skilled household. Moreover, this household benefits more from lower prices and better availability of varieties in income-elastic sectors. However, price indices of local goods are determined by firms' willingness to enter a neighborhood.

When making location decisions, firms trade-off three forces, summarized in equation (13):

$$M_{nj} = \frac{A_{nj}\left(FA_{nj}CA_{nj}\right)^{\frac{\theta}{\sigma-1}}}{\Pi_{j}}M_{j},$$

First, a location n with higher productivity A_{nj} attracts more firms in sector j. Second, factor access FA_{nj} captures the local availability of inputs, in particular, the supply of skill. Hence, firms with high skill intensity prefer locations that are skill-abundant, i.e. surrounded by neighborhoods with a high skill share. Lastly, the local skill/income composition determines consumer access CA_{nj}: a firm producing an income-elastic good achieves larger demand in rich neighborhoods compared to a firm with an inelastic good because rich households spend a larger fraction of income on income-elastic goods although both firms are exposed to the same nominal income overall.

[25] I assume below that shopping frictions do not vary by type, i.e. $\tau_{knn'}^{S} = \tau_{nn'}^{S}, \forall k$

By allowing for household and firm mobility, local skill and firm composition become tightly linked. In Appendix C, I discuss more formally how the properties of non-homothetic CES preferences with firm mobility generate a pecuniary externality on residents that amplifies sorting pattern. Compared to amenity spillovers, pecuniary externalities arising from two-sided sorting are micro-founded and measurable in the data. In the following sections, I introduce the data and estimation used to discipline these externalities.

3 Data

In this section, I provide an overview of data sets I use to estimate and fit the model to Los Angeles for counterfactuals. In Appendix B, I provide further information on data sources and details on imputation steps.

I use 2010 Census tracts as the geographic definition of neighborhoods. The urban part of Los Angeles County, which I refer to as Los Angeles (LA) more generally, consists of 2235 tracts with a total population just under 10M in 2014. The National Historical Geographic Information System (NHGIS) provides data on tracts for the Census years 1980, 1990, 2000 and American Community Survey (ACS) 2007-2011 and 2012-2016[26]. All census tract data are interpolated to constant 2010 census tract boundaries using the Longitudinal Tract Data Base (LTDB).

Among other, more standard, demographic information, the primary information I extract from NHGIS are income distributions (by race and age) and distributions of housing expenditure shares by income (rent and owner-cost) at the tract-level. For each year, I combine this tract-level information with sample microdata from IPUMS at the level of Public Use Microdata Areas (Puma) to impute counts of households by skill, household income by skill and expenditure shares on housing by skill for each census tract.[27]

Throughout my analysis, I focus on outcomes for high-skilled (HS) and low-skilled households (LS). A high-skilled household is defined as having a household head with a bachelor's degree or higher. In 2014, Los Angeles is home to approximately 1.1 million high-skilled and 2 million low-skilled households. Figure 1 introduces the geography underlying the data, and it maps the share of high-skilled households in each census tract by deciles. For example, South and East Los Angeles are almost exclusively populated by low-skilled residents, while college-educated residents can be found along the coast (Santa Monica or Malibu) and in the hilly parts of Los Angeles.

To capture the location and size of firms, I use the National Establishment Time-Series Database (NETS) for California, collected by Duns and Bradstreet (D&B). This dataset provides annual information on exact geographic location, employment, sales, and industry codes for the universe of establishments in Los Angeles from 1990-2014.[28]

[26] I will refer to the 5-year ACS 2007-2011 as 2009 and 2012-2016 as 2014 for the remainder of the paper.

[27] Since IPUMS microdata reports only pre-tax income of households, I compute the tax liability for each household using NBER's TAXSIM software and adjust tract income and housing expenditure share by group accordingly.

[28] Throughout this paper I will use the terms establishment and firm interchangeably except when the distinction is crucial.

In order to map establishments into sectors, I first create 29 separate "local" sectors and one "non-local" sector. I define a sector as "local" if households physically go to an establishment to consume goods and services, while the "non-local" sector captures all other expenditure (other than housing). In defining these sectors, I account for quality differences as far as data on expenditures allows for a finer distinctions. For example, households can eat out at fast food establishments versus full-service restaurants, and buy food items at grocery or specialty stores. In both cases, I allow for two different sectors. Next, I create a crosswalk between NAICS six-digit codes in the NETS data and my 30 sectors, as well as a crosswalk between my sectors and items in household expenditure microdata. In all crosswalks, I assign establishments and expenditures to local sectors based on where a typical household buys a good as opposed to where it is produced.

To assess the degree to which demand for sectors varies by skill/income, I use the Consumer Expenditure Survey (CEX) interview data on household-level expenditures. For the years 1990 and 2010-2016, I map quarterly expenditures across roughly 700 unique expenditure categories in the CEX into quarterly expenditure on my 30 sectors and housing. Appendix Table 1 lists sectors as well as the 1990 expenditure shares of low- and high-skilled households US-wide in columns (1) and (2). The difference in expenditure shares on a sector between high- and low-skilled households represents a coarse measure of relative preferences by skill/income, which I will use several times in the estimation.

Geographic information such as area and various distances are calculated using shapefiles from the Census Bureau. Commuting flows for 2002-2016 are taken from the LEHD Origin-Destination Employment Statistics (LODES). Lastly, I use data from Lee & Lin (2017) to account for natural amenities such as average slope and distance to shore for each tract.

4 Bringing the Model to the Data

Next, I take the model to the data described in Section 3. First, I calibrate a set of parameters (σ, γ, η, ρ, ψ, β_j^k, β_j^C, μ, and spatial frictions) from the existing literature and reduced-form moments in the data. I proceed by estimating the key elasticities on the household side of the model (ν_j, κ, δ_k) and on the firm side, θ. Then, I discuss how to recover fundamentals $\{B_{kn}\}$, $\{A_{nj}\}$, $\{A_{nH}\}$, $\{f_j^e\}$. Lastly, I show how the simulated economy fits several non-targeted moments.

4.1 Calibrated Parameters

Elasticities of Substitution σ, γ and η: The existing literature provides several widely-varying estimates of the elasticity of substitution within service or retail sectors σ. On the higher end, Couture (2016) finds a value of 8.8 for restaurants, Dolfen *et al.* (2019) find 6.1 for offline stores, Miyauchi *et al.* (2021) estimate a value of 5, and Redding & Weinstein (2019) estimate a median σ to be 6.5 across disaggregated retail categories in Nielsen data. Atkin *et al.* (2018) find 2.28-4.36 for retailers in Mexico, Su (2022a) reports values between 3.69 and 16 for disaggregated sectors, similar to my sector definition. As my sectors are quite aggregated and about half are retail sectors, which tend to have lower levels of substitution compared to services, I calibrate $\sigma = 3$ towards the lower end of estimates.[29]

To my knowledge, there exist fewer estimates for the elasticity of substitution across service or retail sectors γ.[30] Hence, I rely on estimates from the trade literature and calibrate $\gamma = 1.6$. This elasticity is broadly in the middle of estimates from Redding & Weinstein (2017), who estimate the elasticity of substitution across 4-digit NAICS sectors using trade data to be 1.36 and Hottman & Monarch (2018), who find 2.78 for HS4 sectors.

For the elasticity of substitution between housing and goods η, I rely on a value from Albouy *et al.* (2016), who estimate very similar non-homothetic CES preferences as in this paper using variation in housing expenditure shares and returns to skill across MSAs. Taking their estimate for renters and owners, I calibrate $\eta = .493$. An elasticity of substitution of less than one implies that housing and goods are complements. It follows that housing expenditure shares increase with a decrease in the relative price of goods and vice versa.

Labor Demand & Supply Elasticities ρ and ψ: The efficiency heterogeneity parameter for workplaces ρ can be interpreted as the labor supply elasticity in equation (1). Existing estimates for a similar parameter roughly range between 2 and 7 (Ahlfeldt *et al.* (2015), Severen (2021), Tsivanidis (2021), Miyauchi *et al.* (2021)). Hence, I choose $\rho = 6$. One caveat, however, is that this literature estimates a preference heterogeneity parameter for the joint decision of workplace and residence. The exception is work by Miyauchi *et al.* (2021) who estimate this heterogeneity parameter for workplaces but taking into account consumption access as part of the commute. Since residence and workplace are two distinct decisions with independent Fréchet distributions in my model, I estimate a separate preference heterogeneity parameter for residences κ below.[31]

To the best of my knowledge, no estimate exists for the demand elasticity across commuter origins ψ. While work in this literature makes the implicit assumption that commuters for different origins are perfect substitutes, my model allows for any degree of substitution. Due to the lack of estimates and keeping in line with the existing literature, I assume $\psi = 20$, a very high elasticity of substitution across commuter origins.

Spatial Frictions: The model features three types of spatial frictions: commuting cost $\tau^W_{knn'}$, shopping cost $\tau^S_{knn'}$ and amenity spillover elasticities across neighborhoods $\delta_{kn,k'n'}$, which I assume to depend on distance. Combining commuter demand consistent with equation (11) and commuter supply in equation (4) with market clearing on each commuter pair, in equilibrium

[29] With a low value of σ agglomeration economies a la Krugman (1991) $(1/(\sigma-1))$ are quite large. However, in my economy these spillovers are mitigated by the firm supply elasticity θ, indicating a smaller value of σ to achieve a comparable level of agglomeration.

[30] See Borusyak & Jaravel (2018) for a short discussion.

[31] My estimate of κ of around 2.8 falls squarely into the more recent estimates such as Miyauchi *et al.* (2021), Severen (2021) and Tsivanidis (2021). However, absent any direct evidence it appears reasonable to assume that preferences for residences are more heterogeneous than efficiency draws for commuting locations. Hence, I choose $\rho > \kappa$.

the model yields a gravity equation for commuting:

$$\lambda^W_{kn'|n} = \left(\gamma^W\right)^{\frac{\rho}{1-\rho-\psi}} W_{kn'}^{\rho\frac{1-\psi}{1-\rho-\psi}} X_{kn'}^{\frac{-\rho}{1-\rho-\psi}} \left(\Phi^W_{kn}\right)^{\frac{\psi}{1-\rho-\psi}} \left(\tau^W_{knn'}\right)^{\rho\frac{\psi-1}{1-\rho-\psi}}, \tag{18}$$

where $X_{kn'}$ is total wage bill for type k in workplace n'. I further assume commuting costs are a log-linear function of the Euclidean distance between tract centroids $d_{nn'}$,[32] and they are independent of skill-type:

$$\tau^W_{knn'} = \tau^W_{nn'} = d_{nn'}^{\phi^W}, \forall k, \forall n, n'$$

Taking logs and replacing residence- and workplace-specific terms with respective fixed effects, I can regress conditional commuting shares in LODES data (all commuters) on $\log d_{nn'}$ using Pseudo-Poisson-Maximum-Likelihood (PPML).[33] The estimated semi-elasticity of commuting flows with respect to distance, $\frac{\phi^W\rho(\psi-1)}{1-\rho-\psi}$, is -1.199 $(.011)$, which implies $\hat{\phi}^W = .263$ under the assumptions on ρ and ψ above.

Shopping costs capture how demand for establishments in distant locations falls relative to close locations. As with commuting cost, I assume that shopping frictions between locations n and n' are an increasing function of distance, and I assume that this function is independent of local sector j and household type k:

$$\tau_{nn'}^{1-\sigma} = d_{nn'}^{\phi^S(1-\sigma)}, \forall j \in \{1, 2, ...J-1\}, \forall k \forall n, n'.$$

I calibrate this semi-elasticity $\phi^S(1-\sigma) = -1.8$ or three-halves of the estimated semi-elasticity for commuting. With $\sigma = 3$ this choice implies $\phi^S = .9$. The literature provides several pieces of evidence in support of this calibration, namely, that shopping trips decrease rapidly with distance/travel time, and more so than commuting-related trips: relying on smartphone movement data, Miyauchi *et al.* (2021) find that the semi-elasticity of shopping itineraries with respect to travel time is about 1.5 times the corresponding semi-elasticity for commuting. Davis *et al.* (2019) estimate spatial frictions in visiting restaurant from Yelp reviews and find strong spatial frictions (elasticity by car travel of -2). Using credit card transaction data, Agarwal *et al.* (2020) show that over 90% of consumption occurs within home location (incorporated place or census subdivision).

Lastly, I assume a parametric specification for amenity spillovers $\mathcal{L}_{kn}$ in equation (17):

$$\mathcal{L}_{kn} = \prod_{n'} \left(\frac{L^R_{HS,n'}}{L^R_{LS,n'}}\right)^{\delta_k \omega_{nn'}}, \tag{19}$$

where $\omega_{nn'}$ is a distance weight capturing the strength of decay in spillovers from the skill ratio

[32]For internal distances, I rely on Helliwell & Verdier (2001), who find that internal distances are well approximated by $d_{nn} = .52\sqrt{area_n}$ for a square city. I use this approximation, since census tracts are close to square.

[33]Although I report results for 2014, other years in the data yield very similar semi-elasticities. Moreover, I cannot observe the education level of commuters in the LODES data, hence, I assume commuting costs are identical, and I use data for all commuters in the estimation.

in other neighborhood n' onto neighborhood n residents (and onto themselves when $n = n'$). Specifically, I assume $\omega_{nn'} = d_{nn'}^{\phi^{\mathcal{L}}} / \sum_{n''} d_{nn''}^{\phi^{\mathcal{L}}}$ and set $\phi^{\mathcal{L}} = -3.5$. This choice of ω results in a similar (very rapid) decay in amenities as in Ahlfeldt *et al.* (2015).[34] In the main estimation below, I recover the strength of spillovers δ_k from the data.

Production parameters β_j^k, β_j^C, μ: Output elasticities β_j^k with respect to labor of type-k in sector j in firms' production function (10) are calibrated to the nation-wide payroll shares of high- and low-skilled workers in the Census 1990 or ACS 2014 microdata for the respective year.[35] Table 1 reports β_j^{LS} and β_j^{HS} for each sector in columns (6) and (7). The cost share on commercial housing by firms β_j^C is set to .2 for all sectors, based on evidence from the Census Bureau's 2012 Annual Retail Trade Survey ("Lease and rental payments for buildings, offices, stores" as share of total rent and labor payments for retail or hospitality sectors). The cost share of capital μ in the production of housing in (15) is calibrated to fit the housing supply elasticity $\mu/(1-\mu)$ for Los Angeles, which Severen (2021) estimates to be .43. Hence, $\mu = .3$.

4.2 A Model-based Statistic for the Price Index

Measuring the price index and changes thereof at fine geographic scale is challenging. In particular, since I do not have access to data on expenditures across sectors at skill-tract level and corresponding sector price indices, I am unable to construct skill-location-specific overall price indices in the data. Hence, I rely on the model to find a sufficient statistic for the price index. I can rearrange the model expression for the expenditure share on housing s_{knh} in equation (7) to solve for P_{kn} and, consequently, for the goods price index P_{kng}:

$$P_{kn} = a_h^{\frac{1}{1-\eta}} r_n^R s_{knh}^{\frac{1}{\eta-1}} \quad \text{and} \quad P_{kng} = \left(\frac{a_h}{a_g}\right)^{\frac{1}{1-\eta}} r_n^R \left(\frac{s_{knh}}{1-s_{knh}}\right)^{\frac{1}{\eta-1}} \tag{20}$$

Intuitively, conditional on a single rent for skill-types, as well as equal relative tastes for goods and housing across locations and skill-types, all variation in the relative price index of high- and low-skilled households across locations is captured by the relative expenditure share on housing (with elasticity of substitution η).[36] Hence, I can use variation in relative s_{knh} in the data as a sufficient statistic for variation in the relative price index. Importantly, under homothetic pref-

[34] Assuming a travel speed of 40km per hour, then a location 2km away (3mins) relative to the home tract (with weight 1) implies a relative weight of .09. In Ahlfeldt *et al.* (2015), a travel time of 3 mins implies 10% of spillovers from the population at the origin are still present. After 10 mins travel time or 6.6km distance only .1% of spillovers remain in both ways of specifying the decay. I choose this specification because distance weights add to 1 such that $\log \mathcal{L}_n$ captures the distance-weighted mean log skill ratio of surrounding tracts.

[35] I restrict the sample to workers aged 25-64, working at least 35 hours per week and residing in an MSA. Two sectors (other food away, toy stores) I cannot link to sectors in the Census industry classification. Instead, I use values from the closely related sectors (restaurants, specialty stores).

[36] Atkin *et al.* (2023) make a similar argument: If, and only if, preferences are quasi-separable (non-homothetic CES preferences satisfy quasi-separability) price index changes can be read off horizontal shifts in "relative" Engel curves, even when price changes of all goods are not observable as long as the price changes of some goods are. In my case, prices for housing are observable but not the goods price index.

erences (i.e., $\nu_j = 0, \forall j$) price indices for low- and high-skilled households in a neighborhood are equal as housing expenditure shares do not vary by type (but can vary across neighborhoods).

The key advantage of expression (20) lies in variables entering the sufficient statistics on the right-hand side being observable in the data, while price indices are generally not available. However, to show that variation in this statistic is meaningful in terms of observable outcomes, I plot the relative goods price index statistic $\frac{P_{HS,ng}}{P_{LS,ng}}$ according to (20) against the share of high-skilled in a tract on the left side of Figure 2. Indeed, tracts with low relative prices for goods are associated with a high skill share, either as product of spatial sorting or its cause. Note that under homothetic preferences there would not be such a correlation (given same rents and tastes). Moreover, relative goods prices vary significantly across neighborhoods, ranging from .5 to 2.5. On the right side of Figure 2, I show that the relative goods price index is negatively correlated with the share of establishments operating in sectors preferred by the high-skilled, i.e. sectors on which the difference in expenditure share between high- and low-skilled is above the median in the CEX for 1990. Tracts relatively more affordable for the high-skilled are associated with the presence of firms that cater to the rich. The overall relative price index statistic $\frac{P_{HS,n}}{P_{LS,n}}$ shows very similar patterns.

Furthermore, I can express real consumption as:

$$U_{kn} = \frac{I_{kn}}{a_h^{\frac{1}{1-\eta}} r_n^R s_{knh}^{\frac{1}{\eta-1}}}. \tag{21}$$

Equation (21) turns out to be very useful for the estimation below, since data on incomes/expenditures, rent and expenditure shares on housing are available at skill-tract-level, while real consumption at such fine scale is generally unobservable.

4.3 Estimation of Income Elasticities ν_j

Income elasticity parameters ν_j govern the degree to which households reallocate expenditures across goods sectors as total consumption increases (slope of Engel curve). In particular, I write equation (9) as the expenditure on sector j relative to the expenditure on a reference sector j^* for household i in location n at time t and taking logs:

$$\log\left(\frac{p_{nj,t}c_{i,nj,t}}{p_{nj^*,t}c_{i,nj^*,t}}\right) = \log\left(\frac{\alpha_{i,j,t}}{\alpha_{i,j^*,t}}\right) + (1-\gamma)\log\left(\frac{p_{nj,t}}{p_{nj^*,t}}\right) + (\nu_j - \nu_{j^*})\log U_{i,n,t},$$

where demand shifters $\alpha_{i,j,t}$ may be household- and time-dependent. I estimate the elasticity of relative expenditures with respect to real consumption $\nu_j - \nu_{j^*}$ using household-level expenditure data and real consumption $U_{i,n,t}$. Since I cannot directly observe real consumption in the data, I rely on the sufficient statistic for $U_{i,n,t}$ in equation (21) above. I express the final regression specification as:

$$\log\left(\frac{p_{n,t}(j)c_{i,n,t}(j)}{p_{n,t}(j^*)c_{i,n,t}(j^*)}\right) = \iota_{nj,t} + (\nu_j - \nu_{j^*})\log\left(\frac{I_{i,n,t}}{r^R_{i,n,t}s^{\frac{1}{\eta-1}}_{i,n,t}}\right) + u_{i,nj,t}, \tag{22}$$

where $u_{i,nj,t} = \log\left(\frac{\alpha_{i,j,t}}{\alpha_{i,j^*,t}}\right) + \frac{\nu_j-\nu_{j^*}}{\eta-1}\log a_{i,h,t}$ is the error term and $\iota_{n,j,t}$ is a location-sector-time fixed effect capturing relative prices between j and j^* in a given location n and time t.

Data: I estimate equation (22) using quarterly household-level expenditure data from the CEX interview survey for 2010-2016.[37] I choose grocery stores as the reference sector (j^*), since expenditure on groceries is consistently reported across households, and I restrict the sample to households living in an MSA and with a household head aged between 25 and 64. I construct the independent variable (real consumption proxy) for each i using total quarterly expenditures ($I_{i,n,t}$), reported rent payments per room ($r_{i,n,t}$) and the fraction of quarterly housing expenditure out of total quarterly expenditure ($s_{i,n,t}$).

Identifcation: Similar Aguiar & Bils (2015) and Comin *et al.* (2018), I include dummies for household size (≤ 2, 3-4, ≥ 5), age of household head (25-37, 38-50, 51-64), home-ownership and number of earners (1, $\geq$2) interacted with sector dummies to account for heterogeneity in preferences for sectors and housing across cells defined by household characteristics. I also control for sector-MSA-time fixed effects to capture differences in relative prices and aggregate preference shocks across regions, sectors, and time. Lastly, to deal with measurement error in the constructed independent variable and endogeneity concerns, I instrument the real consumption proxy with log reported after-tax income in the previous year.

Results: Figure 3 shows the estimated income elasticities by sector relative to grocery expenditure with 95% confidence intervals. In addition, Table 1 reports these results in columns (3) and (4). The ordering of the estimates is quite intuitive: Liquor stores, grocery stores, hardware stores have the lowest income elasticities; amusement, family services (daycares,...) jewelry stores, and clothing exhibit the highest elasticities. Aguiar & Bils (2015) and Hubmer (2018) reassuringly find similar orderings using somewhat different sector definitions. To interpret the magnitude of the estimates, consider the expenditure on restaurants relative to grocery stores; a doubling of real consumption increases relative expenditure by around 140%.

Scaling of ν_j: Since the estimated income elasticities from equation (22) are relative to a reference sector (grocery stores), I need an appropriate re-scaling to recover ν_j for all j. More detail on scaling of income elasticities ν_j is discussed in Appendix C. Moreover, when consumers get

[37] One concern could be that income elasticities are not stable over time. Aguiar & Bils (2015) discuss this issue and find that income elasticities are quite stable over time.

richer, they reallocate expenditures within the goods bundle due non-homothetic preferences affecting the price index of goods relative to housing, resulting in changing relative expenditures on goods and housing. In other words, the non-homotheticity in the goods bundle is inherited by the upper utility nest through relative prices. Hence, the scaling of ν_j determines the overall degree of non-homotheticity between housing and goods. Formally, the elasticity of relative expenditure on housing and goods with respect to real consumption follows:

$$\frac{\partial \log \frac{s_{knh}}{s_{kng}}}{\partial \log U_{kn}} = (\eta - 1)\frac{\bar{\nu}_{kn}}{1-\gamma},$$

where $\bar{\nu}_{kn} = \sum_j \tilde{s}_{knj}\nu_j$. Along with η, calibrated at $.493$ above, Albouy *et al.* (2016) estimate this elasticity to be around $.76$ on average. I apply the average expenditure weights in the estimation sample and calibrated γ to recover the income elasticity for grocery stores and scale all other ν_j accordingly. The calibration implies that housing and goods are complements ($\eta < 1$) and that housing is a necessity relative to goods as $(\eta - 1)\frac{\bar{\nu}}{1-\gamma} < 0$.[38] Table 1 lists re-scaled elasticites ν_j in column (5).

In Appendix Table 2, I show that the expenditure share on housing indeed falls with income (or skill) in the data. I regress the expenditure share on housing out of after-tax income in Census/ACS microdata for Los Angeles County in columns (1) and (2) on a dummy for skilled household, a set of location fixed effects (PUMAs), and dummies for sex, race, age, household size, and home-ownership. In columns (3) and (4), I regress tract-level expenditure shares by skill on a dummy for skill and a tract fixed effect. Consistent with housing being a necessity, I find in both specifications that high-skilled households spend around 3ppt in 1990 and 6ppt in 2014 less on housing than low-skilled households.

4.4 Estimation of Resident Supply Elasticity κ and Spillovers Elasticities δ_j

The preference heterogeneity parameter κ governs how strongly households respond to variation in real consumption across neighborhoods, summarized in equation (4). Thus, I will refer to κ as the resident supply elasticity. Moreover, the strength of amenity spillovers from the skill composition surrounding a tract, captured by δ_k in equations (17) and (19), determine the degree to which changes in relative real consumption between the high- and low-skilled translate into changes in neighborhood composition itself. Hence, I estimate both elasticities jointly. Plugging the expressions for amenities B_{kn} in equations (17) and (19) into the residence choice probability (4) and taking logs, yields the number of residents as a function of real consumption and

[38] Furthermore, within the range of expenditure shares in the data, real consumption is increasing in total expenditure but concave as $s_{kng}\frac{\bar{\nu}_{kn}}{1-\gamma}$ increases with expenditure (income). To see this, I can write the elasticity of real consumption with respect to nominal income as

$$\frac{\partial \log U_{kn}}{\partial \log I_{kn}} = \frac{1}{1 + s_{kng}\frac{\bar{\nu}_{kn}}{1-\gamma}}.$$

In other words, the model calibration implies that the consumption value of an additional dollar falls with income.

spillovers:

$$\log L_{kn}^R = \kappa \log U_{kn} + \delta_k \log \left(\prod_{n'} \left(\frac{L_{HS,n'}^R}{L_{LS,n'}^R} \right)^{\omega_{nn'}} \right) - \log \Phi_k^R + \log L_k + \log \bar{B}_{kn}. \tag{23}$$

As before, I can replace U_{kn} with the sufficient statistic in expression (21). Taking first differences with respect to time t (denoted by hats), equation (23) can be estimated according to:

$$\log \hat{L}_{kn,t}^R = \kappa \log \left(\widehat{\frac{I_{kn,t}}{r_{n,t}^R s_{knh,t}^{\frac{1}{\eta-1}}}} \right) + \delta_k \log \left(\prod_{n'} \left(\widehat{\frac{L_{HS,n',t}^R}{L_{LS,n',t}^R}} \right)^{\omega_{nn'}} \right) + \hat{X}_{kn,t}\beta + \iota_{kn,t} + u_{kn,t}, \tag{24}$$

where I collect skill-specific terms in a skill-time fixed effect $\iota_{kn,t}$, $\hat{X}_{kn,t}$ are controls, and $u_{kn,t} = \frac{\kappa}{\eta-1} \log \hat{a}_{h,t} + \log \hat{\bar{B}}_{kn,t}$ captures changes in fixed amenities and relative tastes for housing in the error term.

Data: To estimate regression (24), I pool changes in the number of households by skill in LA Census tracts between 1990-2000 and 2000-2014. I exclude tracts with a population of less than 1000 to restrict to neighborhoods existing in 1990. The key independent variable is the change in real consumption (net of taste shocks), which I construct from census tract data on after-tax income, housing expenditure shares out of after-tax income, and housing cost by room as a measure of rents. The distance-weighted log changes in the skill ratio are constructed with household counts by skill and weights based on the distance between tract centroids, detailed in equation (19). To account for skill differences in tastes for fixed amenities, I control for natural amenities such as log distance to the city center (City of Los Angeles City Hall), average slope in a tract, log distance to shoreline and log density of residential square footage in 1990, all interacted with skill-type dummies. Regressions are weighted using 1990 household counts.

Identification: To identify the resident supply elasticity κ and skill-specific spillover elasticities δ_k in equation 24, I need three sources of exogenous variation, i.e. uncorrelated with unobserved exogenous amenity shocks and taste shocks in error term. For example, a neighborhood that experiences reductions in local crime rates might attract more residents due to better amenities. However, firms also locate in this neighborhood, since they also benefit from better safety, in turn, affecting consumption access. Moreover, spillovers might also be affected because changes in local amenities might change the skill composition in close-by neighborhoods which feeds back to utility of residents in the treated neighborhood. Hence, I outline three separate shift-share type instruments used to estimate equation (24).

Average Price Index Instrument: I use plausibly exogenous variation in a tract's access to consumption venues over time as an instrument for real income changes. In particular, I construct a shift-share instrument based on cross-sectional variation in the share of establishments by sector in a location, which I interact with sector growth rates in establishments from the other two large urban areas in California, San Francisco Bay Area and San Diego. The initial sector shares in the number of establishments contain information about supply-side characteristics of a location, such as access to suppliers, specific worker pools, or natural advantages. The idea is that a sector's growth in urban areas due to changing tastes or technological improvements will lead to a larger increase in the number of establishments in locations that provide such supply-side advantages. For example, many establishments in the recreation sector concentrate along the beach, since many recreation activities are related to water. We would expect that overall growth in the number of recreation establishments bring more businesses to locations by the water than inland tracts.

Formally, I construct the following average price index instrument,

$$P_{n,t}^{IV} = \sum_j \left(\sum_{n'} \frac{M_{n'j,t_0} \mathbf{1}(d_{nn'} < b)}{M_{j,t_0}} \right) \log \hat{M}_{j,t}^O$$

where b is a distance buffer, t_0 refers to a base period 1990 and superscript O stands for urban areas other than LA. Motivated by Agarwal *et al.* (2020), who report that consumers travel only short distances to consumption venues, I choose $b = 10km$ in the main specification but I also report additional results for a smaller buffer of $5km$. Since this shift-share instrument captures the growth in available establishments in a location, we expect the instrument to improve market access, i.e. real consumption should increase.

The identifying assumption goes as follows: conditional on controls, sector growth rates in San Francisco and San Diego are orthogonal to tract-level changes in amenities and tastes in Los Angeles, for example, changes in crime rates. In other words, I argue that growth rates are as good as randomly assigned to sectors even though exposure of a location to sectors is endogenous, see Borusyak *et al.* (2022). First, since the sector shares do not add to one, locations with initially more service establishments on average, such as downtown tracts, are more exposed to overall growth in services. They might also experience faster population growth due to changing preferences for such locations, specifically, by skilled households (Couture & Handbury, 2020). Thus, I control for the sum of establishment shares in each location interacted with time-skill-type dummies to isolate the effect of the local composition of sectors. As proposed by Borusyak *et al.* (2022), I perform pre-trend tests investigating whether changes in residents by skill between 1980 and 1990 can be predicted with the instruments.

Relative Price Index Instrument: To identify spillover elasticities δ_k, I require a source of exogenous variation that causes movements in the skill-mix surrounding a location. Intuitively, many shocks to exogenous amenities or tastes might lead to spatially correlated movements in the skill composition surrounding a tract. Suppose improvements in local school quality attract more high-skilled residents into a cluster of neighborhoods. This amenity shock leads to correlation between changes in the skill-mix surrounding a tract in the cluster and changes in populations by skill in the tract itself. Hence, I interact the establishment shares in the average price shift-share instrument with the difference in sector expenditure shares by high- and low-skilled households derived from nation-wide difference in expenditure shares on sectors in the CEX, $\tilde{s}^{CEX}_{kj,t_0}$ (see Table 1) according to

$$\Delta P^{IV}_{n,t} = \sum_j \left(\tilde{s}^{CEX}_{HS,j,t_0} - \tilde{s}^{CEX}_{LS,j,t_0}\right) \left(\sum_{n'} \frac{M_{n'j,t_0}\mathbf{1}(d_{nn'} < b)}{M_{j,t_0}}\right) \log \hat{M}^O_{j,t}.$$

The relative price instrument exploits differences in expenditure shares by skill-type due to non-homothetic demand, resulting in differential exposure of skill groups to growth in varieties across sectors. This leads to differential impacts on the consumption access, which changes the skill composition surrounding a tract. Since the instrument varies only by location but not by skill-type, I can interact the relative price instrument with a skill dummy to recover type-specific spillover elasticities.

Bartik Wage Instrument: In principle, average and relative price instrument (interacted with skill dummy) provide enough variation to identify κ and δ_k. However, to stay in line with the existing literature (Diamond (2016), Severen (2021), Couture *et al.* (2019)), I augment the analysis with a more standard wage Bartik instrument. This additional instruments allows me to better benchmark my results to other estimates and perform over-identification tests. For each industry (IND90) i in Census 1990/2000 and ACS 2014 microdata, I calculate the average growth rates in wages by skill $\log \hat{W}^O_{ki,t}$ and the share of workers in each skill-type using all workers outside Los Angeles (with the same sample restrictions described in Section 3). Then, I compute total employment by tract using NETS establishment data. I assign the share of workers by skill in an industry from the 1990 Census to arrive at a measure of employment shares by skill and industry in a tract at t_0, $L^W_{kn'i,t_0}/L^W_{kn',t_0}$. By interacting these industry shares and leave-out growth rates, I predict the wage growth by skill-type in each workplace tract n'. However, income by residents in a tract is different from wages paid in a tract due to commuting. Hence, I further interact growth rates in wages by skill at workplace with a predicted commuting matrix, using only commuting costs $\tau^W_{nn'}$, to arrive at a measure of income growth in residence tract n. Formally,

$$I^{IV}_{kn,t} = \sum_{n'} \frac{\left(\tau^W_{nn'}\right)^{\frac{\rho(\psi-1)}{1-\rho-\psi}}}{\sum_{n''}\left(\tau^W_{nn''}\right)^{\frac{\rho(\psi-1)}{1-\rho-\psi}}} \sum_i \frac{L^W_{kn'i,t_0}}{L^W_{kn,t_0}} \log \hat{W}^O_{ki,t}.$$

The identifying assumption is similar to the average price shift-share, namely, that growth rates across industries are as good as randomly assigned, i.e. uncorrelated with taste and amenity shocks at the residence tract. While industry shares in workplaces are predetermined but likely not exogenous, one could argue that predicted income growth in a residence tract is less prone to endogeneity concerns due to the exogenous commuting cost.

In Table 3, I investigate whether the instruments can jointly predict changes in residents between 1980 and 1990, prior to the baseline period t_0. I perform this pre-trend test for instruments between 1990-2000 and 2000-2014 as well as using the instruments between 2000 and 2014 to predict the dependent variable between 1990 and 2000. The wage and relative price instruments are insignificant in all specifications, while the average price instrument has a some predictive power. However, I show below that results are robust to removing the average price instrument. Moreover, over-identification tests are broadly successful plausibly indicating exogeneity of the shift-share instruments.

Results: Table 4 reports the main regression results. I estimate equation (24) with OLS in column (1). The estimated κ is very small, likely due to considerable measurement error in the constructed real consumption variable. In column (2), I use all instruments but I assume homothetic housing demand by applying the weighted average housing expenditure share across skill-types when constructing real consumption. The estimate of κ increases, however, the over-identification test fails indicating that residual variation in expenditure shares (or price indices) in the error term are correlated with the instruments. Column (3) reports the full model with all 4 instruments. The first stage F-statistic is sufficiently strong with 24, in particular, given multiple instruments. I cannot reject the null that instruments are jointly uncorrelated with the error term with a p-value of .269. The estimate of $\hat{\kappa} = 2.734$ falls squarely into the range of values found in the literature such Severen (2021), Tsivanidis (2021), Miyauchi *et al.* (2021) and others. In columns (4)-(6), I remove each shift-share instrument individually. Except for removing the relative price instrument in column (6), F-stats remain high, and estimates of κ and spillover elasticities δ_k are stable. Table A.1 reports first stages for columns (2) to (6): as expected, average price and wage instrument shift up real consumption, while the relative price instrument lowers spillovers for the low-skilled and raises it for the high-skilled.

Estimates of spillover elasticities δ_k indicate strong homophily in preferences: an increase in the distance weighted skill ratio surrounding a tract by 1% raises the amenity value of a neighborhood by around .7% for the high-skilled and reduces it by about .9% for the low-skilled, leading to an additional 1.6% higher skill ratio in the tract, ceteris paribus. However, the literature finds similarly high values: despite using a different definition of amenity spillovers and working with MSAs instead of census tracts Diamond (2016) finds 1.9 for the difference between high-skilled and low-skilled, while Su (2022b) estimates spillover elasticities for this difference to be 1.3 using census tracts.[39]

Table A.2 reports several robustness checks in estimating equation (24): removing controls, using wages instead of household income, computing spillovers with population by skill instead of households, using only renters to compute housing shares, using a 5km buffer when constructing the price instruments, imputing expenditure weights in relative price instrument using

[39]Only relative spillovers $\delta_{HS} - \delta_{LS}$ matter for differences in sorting between low- and high-skilled households. Consider the case when elasticities are identical for high- and low-skilled. Then, taking the difference of equation (24) between high- and low-skilled cancels spillovers. However, the level of δ_k matters for spatial sorting within skill-type.

average citywide incomes and income elasticities from previous section, lowering the distance decay in spillovers and dropping weights from the regression. In all specifications, estimates of κ remain within a reasonable range around the preferred value of 2.8, while the estimates of δ_k vary more. However, $\delta_{HS} - \delta_{LS}$ shows less variation across specifications.

For the calibration of the model, I use $\kappa = 2.8$ as the preference heterogeneity parameter in line with Table 4. However, the estimates of δ_k in columns (2)-(5) fall into a parameter range for which the baseline equilibrium is not necessarily unique. Specifically, if $\delta_{HS} - \delta_{LS}$ exceeds 1 (given all other parameters), the simulated baseline equilibrium does not necessarily align with the equilibrium observed in the data.[40] To ensure the model has a unique solution, I choose $\delta_{HS} = .5$ and $\delta_{LS} = -.5$, just below this cutoff.

4.5 Estimation of Firm Supply Elasticity θ

In equation (13), the productivity heterogeneity parameter θ can be interpreted as the elasticity subject to which firms substitute between neighborhoods in response to differences in profits. To derive the relationship underlying the estimation of θ, I begin by noting that profits of firm ω in n at time t, $\pi_{nj,t}(\omega)$ in equation (12), is related to its number of workers $l_{nj,t}(\omega)$ according to:

$$l_{nj,t}(\omega) = \sum_k l_{knj,t}(\omega) = \left(\sum_k \sum_i \frac{\beta_j^k}{\bar{e}_{kin,t}} \frac{w_{kin,t}^{-\psi}}{W_{kn,t}^{1-\psi}} \right) (\sigma - 1) \tilde{\pi}_{nj,t}(\omega) z_{nj,t}(\omega)^{\sigma-1}. \tag{25}$$

Integrating (25) over the set of active varieties $\Omega_{nj,t}$ gives total employment $L^W_{nj,t}$ in neighborhood n, sector j and time t. Dividing equation (25) by $L^W_{nj,t}$ and replacing $\tilde{\pi}_{nj,t}(\omega)$ with rearranged equation (13) yields the share of employment of firm ω as function of the number of varieties in n, sector j at t in logs:

$$\log \frac{l_{nj,t}(\omega)}{L^W_{nj,t}} = \alpha + \left(\frac{\sigma - 1}{\theta} - 1 \right) \log M_{nj,t} + \iota_{j,t} + \upsilon_{nj,t}(\omega), \tag{26}$$

where $\iota_{j,t}$ is a sector-time fixed effect replacing sector-wide profits and the total number of varieties in j, and $\upsilon_{nj,t}(\omega) = \frac{1-\sigma}{\theta} \log A_{nj,t} + (\sigma - 1) \log z_{nj,t}(\omega)$ is an error term capturing sector-location productivity and idiosyncratic firm productivity. Identification of θ follows from the curvature in the relationship between employment share of a given variety with productivity $z_{nj,t}$ and the number of all varieties in a location. If firms are homogeneous ($\theta = \infty$) then the employment share falls one-to-one with the number of firms (with identical productivity), while any finite, positive θ the curvature must be larger than -1. If many firms in sector j are observed

[40] When I slightly perturb the observed household and firm distributions as starting values in the computation of the equilibrium, the model can fail to converge to the observed equilibrium in the data although the initial distributions are consistent with the equilibrium conditions. In other words, without the perturbation the algorithm finds the initial equilibrium. Instead, with perturbed starting values the algorithm finds alternative configurations of the city, consistent with the model's fundamentals. When I simulate policy counterfactuals in the model, such multiplicity makes it difficult to separate the effects of a policy from an alternative equilibrium. I want to emphasize that the multiplicity of equilibria in an urban context is an interesting area of research, see for example Monte *et al.* (2023); however, it is beyond the scope of this paper.

in location n, then it must offer high profits, conditional on average productivity A_{nj} and idiosyncratic productivity $z_{nj,t}(\omega)$. Specifically, location n has high demand for varieties in j. Now, suppose a firm that operates in a location with few firms must have a relatively high productivity draw otherwise it would not be able to compete. However, suppose that same firm was present in another location with many firms then it must be in the right tail of the size distribution since it is also successful in a location with low demand. In other words, its relative size (employment share) must fall less than one-to-one with the number of varieties.

Data: To estimate equation (26) in the data, I use the census tract and employment for private, for-profit establishments in Los Angeles in 29 local sectors over the period 1990-2014 from NETS. To construct the dependent variable, I restrict to establishments with directly reported employment numbers. However, I construct total employment in the denominator using all reported employment. I count all establishments in a sector and location to construct the independent variable. I restrict to sector-tract observations with at least two establishments.[41]

Identification: Equation (13) directly states that $M_{nj,t}$ is positively correlated with $A_{nj,t}$ in the error term. To address this concern, I instrument the log number of establishments $\log M_{nj,t}$ with the average slope in a location and distance to the shoreline, both interacted with the difference in expenditure shares on sector j between high- and low-skilled households in the CEX 1990, already employed as a measure of demand differences above. The slope of a location is a very strong predictor of the skill composition in Los Angeles because households prefer living in steeper locations, such as locations with a better view.[42] Similarly, distance to shoreline predicts household income very well. Furthermore, I include a tract-time fixed effect that captures location supply shocks such as regulation or availability of retail space as well as levels of slope and distance to shore. Conditional on tract-time and sector-time fixed effects the instruments pick up differential exposure of sectors to higher household income due to higher slope or proximity to shore, natural amenities highly valued by households.

I address selection bias by comparing employment shares of very similar establishments across locations. In particular, I assume that all establishments of multi-establishment firm m ("chain") have a common productivity component independent of location,

$$z^m_{nj,t}(\omega^m) = z^m_{j,t}(\omega^m).$$

Consistent with this assumption, the literature provides evidence that retail chains follow uniform pricing across stores, see DellaVigna & Gentzkow (2019).[43] By restricting the sample to

[41]Although NETS has been shown to capture the spatial firm distribution well in the cross-section (Barnatchez *et al.* (2017), Neumark *et al.* (2005)) the data cannot capture employment dynamics well. For this reason, I estimate equation (26) with cross-sectional data.

[42]Regressing log average household income or log skill ratio in a location on the slope yields an R^2 of over 20% and highly significant positive coefficients.

[43]Chains are defined as having the same headquarter in the NETS data. I restrict each chain to the sector with

chain establishments, I can include a chain-time fixed effect standing in for idiosyncratic productivity. Hence, I identify $\frac{\sigma-1}{\theta}-1$ only with variation across locations serviced by the same chain. Conditional on assuming common productivity within chains, variation in employment shares is then either due to local demand or average sector productivity differences. By instrumenting the number of establishments with the slope and distance instruments, I isolate how demand differences affect employment shares of establishments within the same chain.

Results: Table 5 reports the estimates of $\frac{\sigma-1}{\theta}-1$ and implied θ (given $\sigma = 3$). Across specifications, the employment share of chain establishments decreases less than one-to-one with the number of establishments in a location implying some heterogeneity in productivity across firms. However, IV estimates are around $-.87$ and $\theta \approx 16$, which suggests firms are fairly homogeneous nonetheless. Moreover, my estimate of θ implies that firms are very sensitive to local demand – small changes in consumer access lead to large changes in the number of firms. The specification in column (2) uses all sectors and the slope instrument: as predicted, the slope instrument raises the number of establishments in sectors that cater to higher income households in the first stage. In columns (3) and (4), I cut the sample into two time periods with roughly equal numbers of observations. Again, estimates are almost identical. In columns (5) and (6), I drop two sectors (Amusement and Recreation) since productivities in these are potentially correlated with slope and distance to shore. However, results remain stable. Lastly, I employ both instruments jointly on the sample of column (5) and find similar estimates. Proximity to shore has a positive effect on the number of establishments in income-elastic sectors. Reassuringly, I cannot reject the null that slope and distance to shore are uncorrelated with the error term with a p-value of .339. For the model calibration, I use $\theta = 16$. Table 6 provides a summary of all model parameters.

4.6 Model Solution

My model falls into the set of quantitative urban economics models (e.g. Tsivanidis (2021), Monte *et al.* (2018), and Ahlfeldt *et al.* (2015)) that are fully saturated with structural residuals or "fundamentals", which cover all variation in the data unexplained by the inherent model structure. Equipped with the full set of model parameters, I invert the model using observable moments in the data and equilibrium conditions to recover fundamentals of the economy, which are then used to solve for counterfactual equilibria.[44] In particular, I require location-specific exogenous amenities by skill $\bar{B}_{kn}$, sector-location productivities A_{nj}, housing production shifter A_{nH} as well as fixed cost of entry by sector f^e_j and demand shifters.

most establishments in each year when chains operate in several sectors. Moreover, I add employment numbers over establishments if a chain has more than one establishment in a given location. As a result, a chain-time fixed effect subsumes the sector-time fixed effect.

[44]In principle, counterfactuals in this model can be solved using exact-hat algebra as in Dekle *et al.* (2007). However, this solution method requires prior knowledge of several equilibrium outcomes such as shopping flows or wages by skill-residence-workplace which are not available in my context.

Proposition 1. *Given data on the observed equilibrium: residents by skill and location, L^R_{kn}, number of firms by sector and location, M_{nj}, citywide revenue shares by sector, rs_{cj}, citywide and tract-level expenditure share on housing, s_{ch} and s_{nh}, land endowment by tract Z_n and citywide income Y, there exist unique vectors of model fundamentals: exogenous amenities $\bar{B}_{kn}$, composite demand and productivity shifters $\bar{A}_{nj} = A_{nj} a_g^{\frac{\theta}{\eta-1}} \alpha_j^{\frac{\theta}{\gamma-1}}$, housing supply productivities $\bar{A}_{nH} = A_{nH}^{-\frac{1}{\mu}} P_Q$, fixed entry costs by sector f^e_j and transfers t_k such that the observed equilibrium in the data is replicated by the model.*

In Appendix C, I describe the algorithm used to invert the model in detail. I should note that the model needs to be inverted for every model variant and year separately to replicate the observed equilibrium under various model assumptions, e.g. model without shopping frictions or homothetic model. Counterfactuals are then solved using a fixed point algorithm, summarized in Appendix C. The model supports multiple equilibria if the skill-specific agglomeration externalities (love of variety, entry and spillovers) dominate the various dispersion forces present in the model (residential and commercial rents, continuous and unbounded support of preference, efficiency and productivity draws, local competition). I calibrate the parameters of the model to ensure that household and firm distributions are uniquely reproduced when simulating the baseline economy. I perform a number of numerical simulations to test whether the baseline model calibration supports a unique equilibrium.[45] These tests suggest that the pecuniary externality from two-sided sorting and spillovers are weaker than the dispersion forces if preference and productivity draws are sufficiently dispersed (κ and θ), spillover elasticities δ_k are not too large, the elasticity of substitution between housing and goods η is less than one, and real consumption is concave in expenditure.

4.7 Model Fit

After estimating key parameters and recovering the fundamentals of the economy, I compare moments produced by the simulated baseline economy to non-targeted data moments. First, the model calibration does not explicitly target the degree of non-homotheticity in housing demand. In Table 2, I compare differences in expenditure shares on housing by skill implied by the model (Columns (5) and (6)) with Census/ACS microdata ((1) and (2)) and tract-level data ((3) and (4)) for 1990 and 2014. Reassuringly, the model hits those differences in the data very closely. Turning to the non-homotheticity across local sectors, in Figure 4, I compare the model-implied citywide skill differences in expenditure shares by local sector with the corresponding nationwide differences in the CEX for 1990 and 2014. The model fits the data reasonably well as the log expenditure differences differences cluster around the 45 degree line, in particular, for important sectors (large circles).

[45]In the first step, the model is inverted using the proposition above. Next, I simulate the baseline economy to recover moments in the model that are not observed in the data directly such as price indices, rents, wages, commuting and shopping flows etc. Varying the starting values in the latter step allows me to assess whether the model reproduces the observed equilibrium in the data. In the absence of potential multiplicity the algorithm consistently finds the same initial equilibrium.

Similarly, my calibration does not target the skill premium in household income. It is an equilibrium outcome of sectoral skill intensities, location of firms and workers, and relative sizes of sectors. Nonetheless, the model hits the skill premium in the data quite closely as can be seen in Table 7. In columns (1) and (2), I regress log household income on a dummy for skilled household head controlling for various demographics (consistent with demographics used in imputing tract-level household income by skill). I find the skill premium to be around 48% in 1990 and 62% in 2014. The following two columns show similar coefficients but using tract-level average incomes by skill and tract fixed effects. Columns (5) and (6) show the corresponding skill premia in the baseline model. In particular, the numbers for 1990 line up almost perfectly, while the model slightly overstates the skill premium in 2014.

So far, I considered aggregate targets, however, it is important to assess whether the model hits spatial distributions as well. In Figure 5, I compare the relative price of goods P_{HSng}/P_{LSng} implied by the model with the relative goods price index statistic in the data for every tract, see equation (20).[46] For both years the model does well in capturing the spatial differences in relative prices although the model understates the spatial variation as seen by the steep best fit line. The other local prices are rents in each tract. In Figure 6, I show binscatters comparing model-implied rents at baseline with three rent measures in the data. For 1990 and 2014 (left and middle), log rents in model and rents per room in the data are strongly positively correlated, however, rents in the model are more dispersed. For 2014, I can compare rents from the Zillow Rent Index with model-implied rents. Similarly, rents in the model are more dispersed, however, both measures are strongly correlated.

Moreover, the model calibration does not explicitly target the floorspace supplied by developers in each tract as well as the split between residential and commercial housing. In Figure 7, I plot log floorspace in the model on the horizontal axis against the log square footage in each tract from parcel-level shapefiles provided by the Los Angeles County Tax Assessor (left). On the right, I plot the share of commercial floorspace out of total floorspace in the model and the parcel-level data. Both measures line up very tightly, in particular, the model gets the split between commercial and residential housing correctly despite not being targeted and assuming full arbitrage between both housing types in the model.

Lastly, turning to labor market outcomes, the model predicts the number of commuters (summed over skill-types) between any two tracts. In Table 8, I regress model-implied commuter flows on commuter flows in the LODES data, residence and workplace fixed effects using PPML to account for zero flows in the data[47]. The model fits commuting flows almost perfectly on average. Going from column (2) to (4), I remove residence and workplace fixed effects - capturing population and employment, respectively - one by one. Even unconditional on fixed effects the coefficient is precisely estimated at one. Further, the model calibration targets the number of establishments in each tract and sector, however, it does not specifically fit employment. In Figure

[46] Note that the ratio of goods prices is proportional to the ratio of housing expenditure shares in equation (20). Hence, a good fit between model and data in the relative prices also implies a good fit in expenditure shares.

[47] All flows are positive in the model due to unbounded and continuous support of efficiency draws.

8, I show that employment by skill and the share of high-skilled in the baseline model economy lines up very tightly with employment numbers from the workplace files in LODES which separately report employment by education. To summarize, the model performs very well along relevant dimensions such as consumption patterns, prices, housing and labor allocations across space. In the next section, I further validate the model by comparing estimated effects of the Federal Empowerment Zone Program with counterfactual predictions in the model.

5 Place-based Policy Counterfactuals and Model Validation

In this section, I use the calibrated model to study the effects of a prominent place-based policy aimed at improving conditions in disadvantaged neighborhoods. The policy incentivizes firms to operate in such neighborhoods by providing tax or wage subsidies. Through the lens of the model, subsidies lead to the inflow of firms into targeted tracts, thereby, improving labor market access as well as consumption access. First, I empirically evaluate the effect of Federal Empowerment Zone (EZ) program between 1990 and 2009 on the skill composition and other gentrification-related outcomes in targeted locations, replicating and extending empirical results on EZs found in Busso *et al.* (2013) and Reynolds & Rohlin (2015). Then, I compare the reduced-form outcomes with counterfactual predictions of the baseline model with two-sided sorting and other model variants common in the literature (homothetic preferences, no shopping frictions, no commuting frictions). This exercise gives credibility to my model as the baseline variant is able to replicate several gentrification-related changes in EZs found in the empirical analysis, while the other model variants fail along important dimensions. Second, I show that alternative policies aimed at specific sectors (by income elasticity, skill intensity and tradability) can be used more effectively in directly targeting low- or high-skilled households, thereby, combining a place-based and people-based policy approach.

5.1 Effect of Empowerment Zones on Gentrification

The Federal Empowerment Zone (EZ) program, enacted in 1993, provides several spatially-targeted tax incentives and block grants to designated zones, comprised of 1990 census tracts. EZs were awarded by the Department for Housing and Urban Development (HUD) through a competitive process based on applications submitted by municipalities and subject to certain restrictions on poverty rate, unemployment rate and population.[48] In the first round, 6 urban EZs were awarded in 1994, however, Los Angeles received only a "supplemental" EZ (SEZ).[49] By 2000, Los Angeles was awarded the full set of EZ subsidies. Figure 9 shows the location of the LA Empowerment Zone. EZs had two main elements: first, firms operating in an EZ receive a $3,000 tax credit (or

[48]See Busso *et al.* (2013) or Reynolds & Rohlin (2015) for a more detailed description of the EZ program. Several other papers have contributed to evaluating EZs (and state Enterprise Zones) with widely varying effects: Hanson (2009), Reynolds & Rohlin (2015) and Neumark & Young (2019) find limited average effects on poverty and employment while Ham *et al.* (2011) and Busso *et al.* (2013) find large positive effects on employment, earnings and establishments.

[49]Like EZs, Supplemental Empowerment Zones were rewarded block grants but not the tax credit until 1999.

up to 20% of the first $15,000 of income) for every employee who lives and works in the EZ. The tax credit is heavily tilted towards low-skilled households, since as a percentage of their income the tax credit is much higher for low-income than for high income earners (or high-skilled). Second, each EZ received $100M in block grants for business support (access to capital, business assistance) and social spending in the zone.

Despite being tilted towards and targeting low-income workers, the literature finds that EZs experience an increase in the share of high-income and skilled workers: Busso *et al.* (2013) compare Round-1 EZs (excluding LA) with rejected and future zones and find that the share of college graduates increases by 2 percentage points from a base of 6.7 percent (or roughly 30%) between 1990 and 2000. Moreover, they report increases in the number of jobs, weekly earnings and the number of establishments operating in EZs. Employing a similar identification strategy, Reynolds & Rohlin (2015) show a decrease in the share of residents with less than high school by around 3.3 percentage points and an increase in the share of more educated residents by around 1-2 points in the same time period. They argue that the EZ designation fails to improve outcomes for existing low-income residents but leads to in-migration of high-income, high-skilled residents (gentrification).

In keeping with this literature, I apply a similar empirical strategy as in Busso *et al.* (2013) and Reynolds & Rohlin (2015):[50] I compare Round-1 EZs and SEZs (incl LA) with "rejected" tracts, i.e., tracts in zones which applied to the program in some of the three rounds but whose application for an EZ was denied.[51] Using "rejected" tracts as control group has several advantages: First, tracts were selected by local governments and satisfy the program's selection criteria. Second, rejected zones represent similar clusters of tracts, and they are located in different cities which limits geographic spillovers. The data used is broadly the same as for the estimation in Section 4 but extended for 1980 to 2009 (5-year ACS 2007-11) to be able to study pre-trends before the program's inception and broaden the policy window until the end of the program in 2011. The data on firm-level outcomes from NETS is limited to 1990-2011, and I have access to this data for California only.

Although "rejected" and treated tracts qualified for inclusion in the program, the literature nonetheless has found losing zones to be different from winning zones (Neumark & Young, 2019). To correct for such imbalances, I follow Reynolds & Rohlin (2015). I reweight "rejected" tracts using a propensity score, defined as the probability of being included in the program based on observable characteristics prior to the program.[52] Specifically, I predict the probability of being selected $\hat{P}$ with a logit regression on all Round-1 EZs and all "rejected" zones. Then, I regress

[50] I use the census block file covering all 1990 blocks that applied to an EZ in any round, provided by Busso *et al.* (2013). Then, I apply a crosswalk from 1990 to 2010 blocks from NHGIS and aggregate to 2010 census tracts. I include 2010 tracts that are contained in a control or treatment zones with at least 90% of their area.

[51] "Rejected" zones received a so-called Enterprise Community which entailed a small block grant ($3M) and eligibility for tax-exempt bond financing.

[52] Characteristics include: 1990 levels and 1980-90 changes of unemployment rate, poverty rate, employment-to-population ratio, minority share, skill share in population, vacancy share, homeowner share, housing share, citywide skill share; log size of EZ; 1980-90 log changes in average HH income, home value, rent per room.

changes in an outcome on a dummy for EZ using $\hat{P}/\left(1-\hat{P}\right)$ (normalized to add to one) as regression weights for control tracts and $1/N(treated)$ for treated tracts. The identification assumption of this difference-in-difference estimator with reweighting is as follows: in the absence of the program the average EZ tract would have had similar changes in outcomes as the counterfactual reweighted control tract. When studying the effects of the LA EZ compared to "rejected" zones in California (Fresno, Sacramento and San Diego) I predict propensity scores using the full sample of EZs and control tracts. Standard errors are computed using a block-bootstrap with 1000 repetitions.[53]

In Table 9, I report pre-treatment means in reweighted control tracts and differences to EZ tracts. The first four columns compare all Round-1 EZs and SEZs tracts with all ever "rejected" tracts while the last 4 columns compare only the LA EZ with 3 "rejected" Californian zones. The full sample is broadly balanced in 1990 levels as well as 1980-90 changes. The LA EZ sample is much less balanced, likely due to using the full sample in predicting propensity scores and small sample size. Hence, I will focus on the larger sample for the model validation exercise. Lastly, the LA EZ has significantly less establishments and lower employment in 1990 but the sector mix by income elasticity is balanced. Despite these imbalances in the LA EZ sample, impacts of the EZ program turn out to be broadly similar in both samples.

Table 10 reports the main gentrification-related outcomes, which I compare to model counterfactuals below. More outcomes and the impacts on the LA EZ are presented in Table A.3. In column (1), I show short-run results between 1990 and 2000 consistent with Busso *et al.* (2013): The skill share in EZ tracts increases by 27%, household income increases by 8.6% for low- and insignificant 14.5% for high-skilled households, rents do not change. In column (3), I extend the short-run results commonly found in the literature until the end of the EZ program in 2011. Effects are comparable to column (1), except rents increase significantly by around 15%. Despite both types experiencing increases in income of around 10% (insignificant for the high-skilled), the high-skilled raise expenditure shares on housing (only renters) more than the low-skilled, consistent with the relative price of goods decreasing more for the high-skilled.

Since it seems unlikely that the EZ program improves the skills of existing residents, the effect on the skill composition must come through migration, where the high-skilled move into EZs and the low-skilled migrate out. In Table A.3, one can see that the number of households does not change significantly. Moreover, the poverty rate falls significantly, while employment ratio and unemployment rate improve but insignificantly so. This is counteracted by significantly higher rents and home values. In column (5) of Table A.3, I show the results for the LA EZ sample. Point estimates are broadly consistent with the full sample, however, standard errors are larger. On the bottom of Table 10, I show the impact on firms for the California sample. The number of establishments increases by 50% (from a low level) and the share of establishments in income-elastic sector increases by 11%, consistent with firms responding to higher local in-

[53] I sample separately from within the treatment and control groups to ensure the proportion of control and treatment tracts in each sample is the same.

comes. Interestingly, firms in the non-local sector enter EZs more than local firms due to not being constrained by local demand but benefiting from subsidies. To summarize, my results suggest that the EZ program led to improvements in income and business environment, consistent with some of the earlier literature. However, treated neighborhoods show strong patterns of gentrification (increase in skill share, rent hikes) which puts in question whether EZs led to higher living standards of incumbent residents. Next, I compare these empirical findings with model counterfactuals in order to validate the main mechanism in the model and, moreover, assess the welfare consequences of the EZ program through the lens of the model.

5.2 Empowerment Zone Counterfactual

The first challenge in implementing the LA Empowerment Zone counterfactual lies in how to introduce the "policy bundle" in the model. First, to capture the wage subsidy, I assume that wages of workers hired from the relevant tracts i enter into the wage index of a firm in n (in the zone) with $w_{kin} - subsidy_j/e_{kin}$, where $subsidy_j$ is the model equivalent of $3000, and dividing by e_{kin} insures that the subsidy applies to income (as opposed to wages per efficiency unit). Moreover, I assume that firms operating in an EZ receive a 30% profit subsidy (or subsidy on fixed costs of entry), broadly capturing additional business incentives in block grants. Busso *et al.* (2013) report that a large share (around 35%) of block grants were devoted to business incentives.[54]

To account for the social spending component, I assume that the program improved fixed amenities. In Table 11, I report results from regressing the log change in model-implied $\bar{B}_{kn}$ between 1990 and 2014, recovered from inverting the model for each period, on a dummy for EZ tracts. Comparing EZ tracts with other tracts within 1 km of the EZ suggests that fixed amenities improved by 8% for the low-skilled and 11% for the high-skilled. Including more distant tracts increases the effects on amenities and statistical significance, however, the gap between the skill groups remains at around 3%. Based on evidence that central locations such as EZ tracts have experience a revival since the 1990s (Couture & Handbury, 2020), I simulate an improvement in $\bar{B}_{kn}$ along the estimated effects of comparing EZs with close-by tracts. Busso *et al.* (2013) report that roughly 65% of the block grant are spent on amenity improvements (workforce development, social improvements, public safety, physical development, housing, capacity improvement), hence I calculate that the government spends an additional $65M out of $100M on improving amenities in the EZ.[55]

[54]In addition to the block grant, Los Angeles received funding for the LA Community Development Bank in 1994, which was designed to provide loans to high-risk ventures inside the SEZ. The bank was capitalized with $435M in public funds and gave loans worth $130M between 1996-2003 (Krol & Svorny (2004)). However, the bank ultimately failed due to bad performance of its loan portfolio.

[55]These changes in amenities are consistent with estimates on the elasticity of amenities with respect to public spending: in the baseline model, the citywide value of annual housing costs is $41.6B. Assuming an annual return on housing of 6% and with California's property tax rate of 1%, the tax revenue per household is $3160. Multiplied by the number of households in the EZ, government spending in the EZ before the policy sums to $100M. Using estimates from Fajgelbaum *et al.* (2019) for the elasticity of amenities with respect to government spending of .16, gives $\left(\frac{165}{100}\right)^{.16} = 1.08$.

Second, I assume that the subsidies are financed by the federal government, i.e., subsidies arrive from outside the city. Although this assumption is stark given that current and future LA residents and firms pay federal taxes, any assumption on how the policy is financed locally, even as lump-sum transfer, has implications for distributional welfare effects. The reason is that households vary in marginal utility from income across types and locations. Hence, I refrain from taking a stand on how the policy is financed. Instead, I report the costs and benefits (compensating variation) of the policy across specifications. Lastly, since there is no appropriate control group outside LA in the model, I compare outcomes in EZ tracts with other LA tracts at least 15km from the zone to minimize spillovers from the policy affecting results. I simulate the LA EZ program in the model economy calibrated to 1990.

Table 12 compares the estimated impact of the EZ program in column (1) with a model counterfactual based on all three policy instruments (wage, profit and amenity) in column (2). The baseline model predicts an increase of the skill share of 25%, similar to the 27% found in the data. Furthermore, the model replicates the hike in rents, income changes biased towards the low-skilled and the larger increase in housing expenditure share of the high-skilled. However, it misses the magnitude of income changes and housing shares somewhat. Turning to firms, the baseline model finds an inflow of firms into EZs of around 56%, compared to 50% in the data. It correctly predicts that local firms respond less to subsidies than non-local firms such as manufacturing or services less bound by local demand. Lastly, firms in income-elastic sectors respond more to the policy as found in the data.

Columns (3) through (6) report counterfactual impacts for each policy instrument separately. The amenity shock, shown in column (6), causes the largest change in the skill share of EZs (85% of the total effect). However, it has very little effect on incomes, prices and firms. The wage subsidy alone (column (4)) leads to an inflow of firms improving labor market access for the low-skilled more than for the high-skilled, while price effects go in the opposite direction. In this case, labor market access changes dominate consumption access changes, leading to a fall in the skill share. The profit subsidy (column (5)) also creates local job opportunities for low-skilled workers by massively attracting firms into EZs, but relative prices (or housing share) change in favor of high-skilled consumers, thereby creating gentrification. Here, the consumption access channel dominates the labor market access channel. Combining wage and profit subsidies, these "firm-level" subsidies in column (3) are responsible for the remaining 15% of the overall effect on the skill share in column (2) and lead to large impacts on other outcomes such as incomes, rents and firm entry. To sum up, the baseline model with two-sided sorting replicates the empirical results qualitatively and quantitatively. Next, I investigate more closely the mechanisms underlying the policy impact in the model.

To isolate the contribution of the novel model ingredients (non-homothetic preferences + local consumption), I benchmark the baseline model against three alternative variants of the model: In the "homothetic" model, I turn off price index differences between skill-types by setting $\nu_j = 0, \forall j$. In this case, preferences are homothetic, i.e., skill types weigh sectors (and housing) in the same proportions in the consumption bundle. In the "no shopping frictions" variant, I set $\phi^S = 0$. Now, sectoral price indices are equal across neighborhoods. Hence, any changes in local consumption varieties have no bearing on the goods price index. This assumption effectively turns off the pecuniary externality arising from firm mobility and localized demand.[56] In the third model variant, I remove commuting frictions by setting $\phi^W = 0$. Now, the entry of firms into a location does not lead to changes in local labor demand. However, EZ tracts experience increases in labor demand nonetheless, since the wage subsidies are conditional on hiring workers from the zone.[57]

Table 13 compares estimated impacts of the EZ program in column (1), baseline model in column (2) and the three model variants in columns (3)-(5). The amenity shock leads to an inflow of high-skilled households into EZs in all variants. Similar to the empirical results, the number of firms in the zone increases by around 55% across model variants. Residents are impacted by the inflow of firms through three channels: First, as intended by the policy, the inflow of firms triggers higher local labor demand, particularly for low-skilled workers, as seen by the larger increase in household income for low-skilled residents. This channel is solely active when preferences are homothetic in column (3). Since real consumption increases more for the low-skilled than for the high-skilled, I predict a significantly smaller net increase in the skill share by about 9%, inconsistent with the estimated impact in the data.

Second, as in the data, rents increase by about 10-14%, primarily because firms demand more floor space. Since housing demand is less elastic relative to goods demand, the high-skilled are less hurt by higher rents resulting in a higher skill share. The model variant without shopping frictions, shown in column (4), captures the first and second channel. In this setting, the skill share increases by 23% in response to the policy. However, the model variant fails to predict the increase in the share of varieties in income-elastic sectors and differences between local and non-local firms' responses.

Third, the price of local goods falls relative to rents due to more local varieties. Such relative price movements benefits high-skilled households more due to non-homotheticity in preferences, and are illustrated by the larger increase in housing expenditure shares for the high-skilled (as in the data). Price effects are further amplified by endogenous, larger increases in varieties in income-elastic sectors, tilting consumption access more in favor of the high-skilled. Despite larger relative income gains for the low-skilled, the EZ program leads to an inflow of high-skilled households (or gentrification), even in the absence of the amenity shock. The model without commuting frictions does well in replicating the main data targets, however, it predicts a very small increase in incomes, since very few local residents commute into EZs and benefit from wage subsidies. Compared to model assumptions, commonly used in the literature such as ho-

[56] Goods price and overall price index still vary by location and skill-type due to the non-homotheticity and income differences. However, firms face uniform demand across the city.

[57] In each model variant, I separately invert the model under these parameter restrictions and recover fundamental such that each model variant replicates the distributions of households and firms in the initial economy. Then, I use the recovered fundamentals to simulate counterfactuals in each variant.

mothetic preferences and frictionless shopping across the city, the baseline model with non-homothetic preferences and local demand externalities fits the empirical results on EZs along several dimensions: as in the data, EZ tracts are gentrifying due to higher rents and relative local prices favoring the high-skilled.

5.3 Welfare Impact of EZ Program and Spillovers

Having established that the baseline model captures the estimated impacts of the EZ program reasonably well, I can now move to evaluating the welfare impacts of the policy, summarized in Table 14. In the baseline model, citywide expected welfare increases by around .3% with a slightly larger increase for the high-skilled.[58] This result is striking given the stated policy goal of improving living conditions for poor residents in disadvantaged neighborhoods. Translated into monetary values, using compensating variation, the intervention is worth \$175 to the average high-skilled household in LA and \$99 to the low-skilled at pre-intervention prices and amenities. The costs of the policy amount to \$204 per LA household, \$84 higher than the population weighted compensating variation of \$120. In conclusion, the baseline model with non-homothetic preferences and localized demand predicts that the EZs are an inefficient policy.

In contrast, the model with homothetic preferences concludes that the policy is quite beneficial at the same cost per household. Not only are welfare gains higher for the low-skilled, under homothetic preferences the policy creates net welfare gains valued at \$97 for the average LA household. While marginal utility from nominal income is one under homothetic preferences, my targets underlying the calibration of the baseline model suggest marginal utility is considerably below one. Hence, gains in nominal income due to the policy are valued less in the baseline model. This mechanism shifts down the level of welfare gains and tilts the benefits of the policy towards the high-skilled in the baseline model.[59]

The impact of the policy intervention are not limited to the EZ itself due to various spatial forces in the model such as amenity spillovers, shopping and commuting. Table 16 shows the impact onto tracts at various distances from the EZ relative to tracts more than 15km away. The skill share increases in tracts beyond 5km from the EZ. However, income and price index effects dissipate much faster with distance which implies that amenity spillovers are responsible for gentrification of nearby tracts. Due to the inflow of the high-skilled into the EZ, amenities change in favor of high-skilled residents in nearby tracts, amplifying gentrification of the EZ itself and nearby tracts. The reason for the muted price index effects on such tracts can be seen in Figure 10: firms entering EZs are predominantly drawn for surrounding tracts (right map) leading to increases in the goods price index around the EZ (left map). These price movements offset income gains, making those areas relatively more attractive for low-skilled residents.

[58] Welfare changes of individuals or specific neighborhoods are not well-defined in the model once we allow for mobility and individual preference draws. Expected utility is defined city-wide, thereby accounting for welfare changes of migrants.

[59] The other two model variants are similar to the baseline model in the level of welfare gains. However, when removing shopping frictions (demand is no longer local) rent effects tilt welfare towards the high-skilled but less than at baseline.

5.4 Alternative EZ Policies

So far, I have taken the design of the EZ Program as given and validate the baseline model along empirically estimated impacts of the policy. Now, I use the model to assess alternative policy designs. In particular, I study how treating specific sectors with the same formal policy as the EZs (wage and profits subsidy to firms) can be used to target specific populations and outcomes. I abstract from the amenity shock in this exercise to tease out the reaction of households to changes in the local firm distribution more clearly. As reported in column (2) of Table 15, restricting the policy to firms in sectors with high income elasticity amplifies the gentrification effect of the policy - the skill share increases by 10% - and shifts the benefits even more towards the high-skilled. First, consumption access tilts in favor of higher income earners, lowering the price index more for the rich than the poor. Second, income elasticities and skill share in production (β_j^{HS}) across sectors are positively correlated (1990 correlation $.55$, SE $.002$) which implies the high-skilled also experience a larger labor demand shock when firms in income-elastic sectors enter the neighborhood. In column (2), I show the impacts when treating sectors with low income elasticity. Now, EZ tracts experience an outflow of high-skilled households and welfare gains are concentrated among the low-skilled. Notably, the latter policy is about half as expensive as the former but also creates less benefits relative to costs (low benefit-cost ratio).

Next, I evaluate policies which subsidize sectors based on skill-intensity in labor demand. In column (4), I show the results from treating sectors with high skill intensity in production. The share of skilled households in EZ tracts increases more than in column (1) but not as much as when treating income-elastic sectors in column (2). Consequently, welfare gains are highly regressive. In the next column, I treat sectors with low skill intensity. The skill share falls and welfare gains are now progressive. Comparing both sets of results, one could argue that a policy treating sectors based on income elasticity as opposed to skill intensity is more targeted and at higher efficiency (higher benefit-cost ratio). Hence, this result further highlights how important it is to account for demand effects when evaluating policies targeting firms' location.

Lastly, I treat only local sectors, shown in column (6), and the single non-local sector in column (7). Both policies lead to an increase in the skill share but for different reasons. When treating local firms, price indices fall more for high-income households leading to an inflow of the high-skilled. However, when subsidizing the non-local sector, firms in local sectors are crowded out due to competition on factor markets (housing and labor) which increases local prices. This counteracted by larger wage gains for the high-skilled, since the non-local sector exhibits a high skill share in production. Hence, attracting firms in the non-local sector generates larger welfare gains for the high-skilled, while targeting local sectors benefits the low-skilled due to more demand for low-skilled labor. Notably, treating the non-local sector has the highest benefit relative to costs (.94) although the policy remains inefficient.

My reduced-form and model-based results suggest that offering place-based subsidies to firms in disadvantaged neighborhoods can have several, potentially unintended, consequences. Although such policies lead to higher labor demand for local, low-income residents, these benefits might be outweighed by less desirable consumption options, higher rents and displacement of incumbent residents. As found in the empirical analysis, place-based subsidies to firms lead to the inflow of affluent, more educated residents. My model is rich enough to account for such gentrification trends, since it allows firms to be not just employers but also improve local consumption access which is valued highly by richer, more educated households. Even if gentrification of low-income neighborhoods is the policy goal, welfare results indicate that these policies are costly in general, and benefits accrue to high-skilled more than to low-skilled households. Interestingly, abstracting from non-homotheticity in preferences potentially leads to misleading conclusions about the predicted degree of gentrification and efficiency of the policy. While the policy draws sharp boundaries which neighborhoods to treat, the design of the policy itself is not specifically targeted at the needs and resources of incumbent populations in the zone. More targeted policy alternatives, such as subsidizing sectors with less elastic demand or sectors with lower skill intensity, can avoid gentrification and raise welfare for incumbent residents, albeit with potentially large efficiency losses.

6 Conclusion

Spatial inequality and segregation in cities has sparked interest by the public and policy makers. To inform urban policies, it is important to understand their sources, in particular, how the composition of local residents endogenously shapes the attractiveness of a neighborhood, and the role firms play therein as employers, as well as points of consumption. This paper studies how two-sided sorting of heterogeneous households and firms generates pecuniary externalities that amplify inequality and segregation in cities. First, I develop a quantitative general equilibrium model of the city that features two-sided sorting of skill-types and firms in various local consumption sectors. Second, I quantify the model with rich administrative microdata from Los Angeles. Third, I assess the distributional impacts of Federal Empowerment Zones in the data and through the lens of the model, whereby I not only validate the model but also study the policy's welfare effects in general equilibrium.

I find that the location choices of firms and households are tightly connected through demand and labor market linkages. This interdependence has important implications for urban policies: attracting firms into a neighborhoods creates employment opportunities for low-income residents which can be outweighed by changes in consumption access that favor the rich. Mine and existing empirical findings on existing policies support the notion that certain types of firms can trigger gentrification. My model-based welfare analysis implies that such place-based policies, designed to support low-income neighborhoods, can lead to welfare costs that fall disproportional on low-income households.

The model developed in this paper lends itself naturally to the study of other important topics in urban economics. For example, the large reallocation of specific industries, such as skill-intensive office-based sectors, from central cities towards the suburbs in the wake of Covid-19 and remote work interacts in potentially meaningful ways with the sorting of households. Moreover, exploring quality differences within sectors and income-dependent tastes for quality as a potential drivers of neighborhood sorting present another promising research avenue.

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Figures and Tables

Figures

Figure 1: Skill Share, ACS 2014

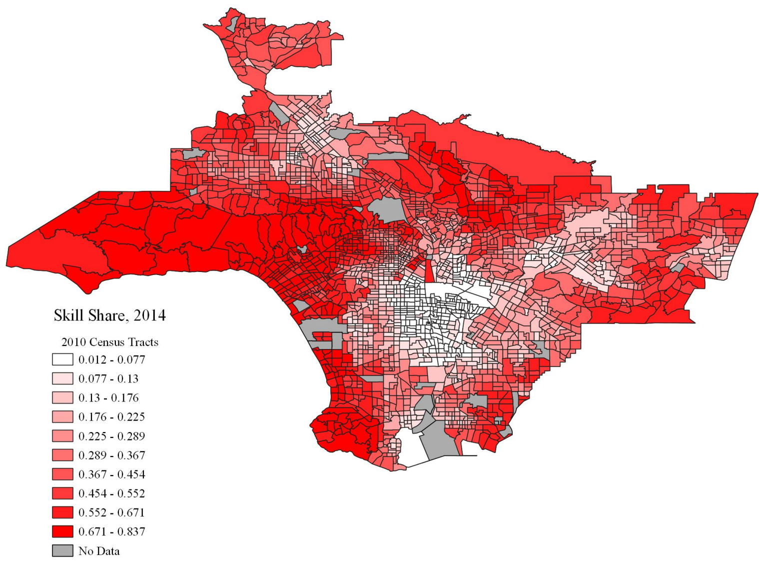
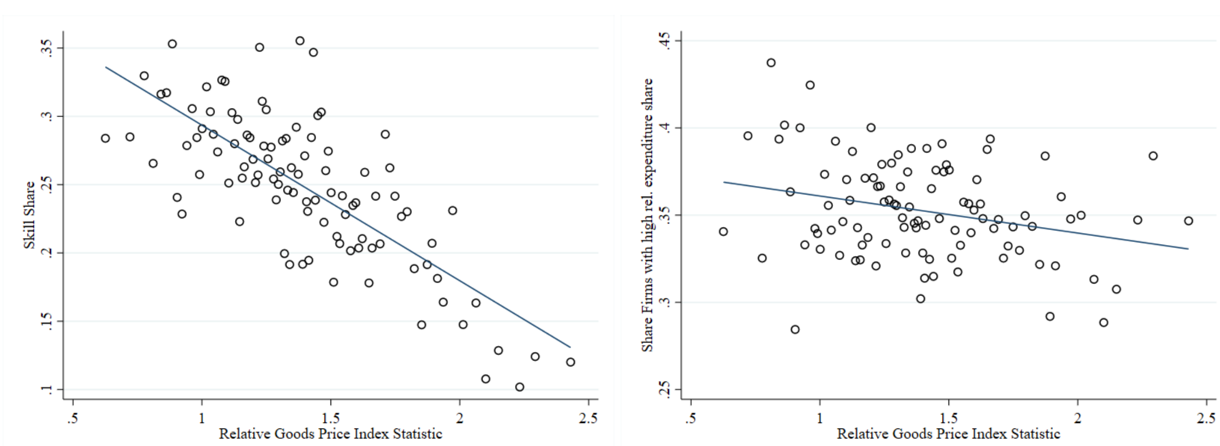
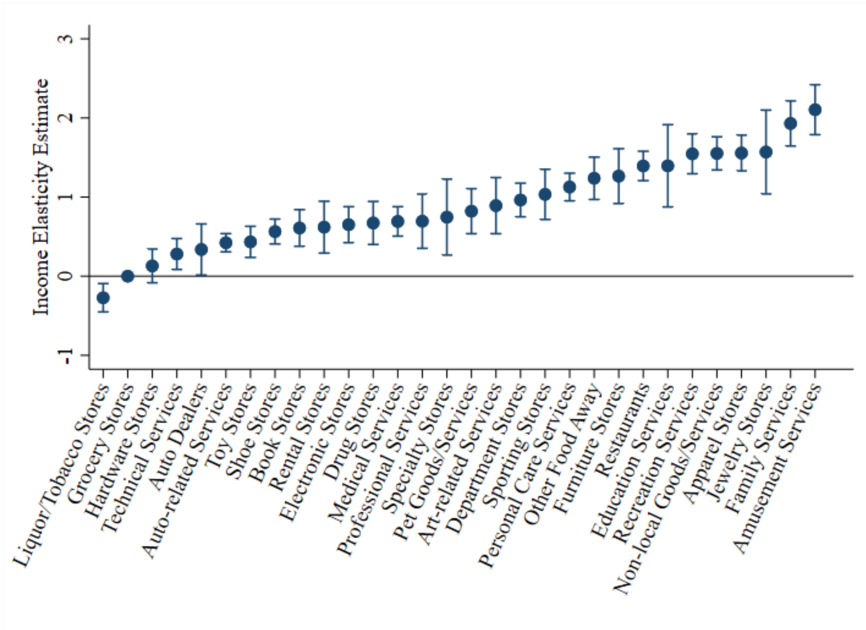


Figure 2: Correlation of Relative Goods Price Index Statistic and Skill Share (left); Share of Establishments in sectors with high relative expenditure by the high-skilled (right)



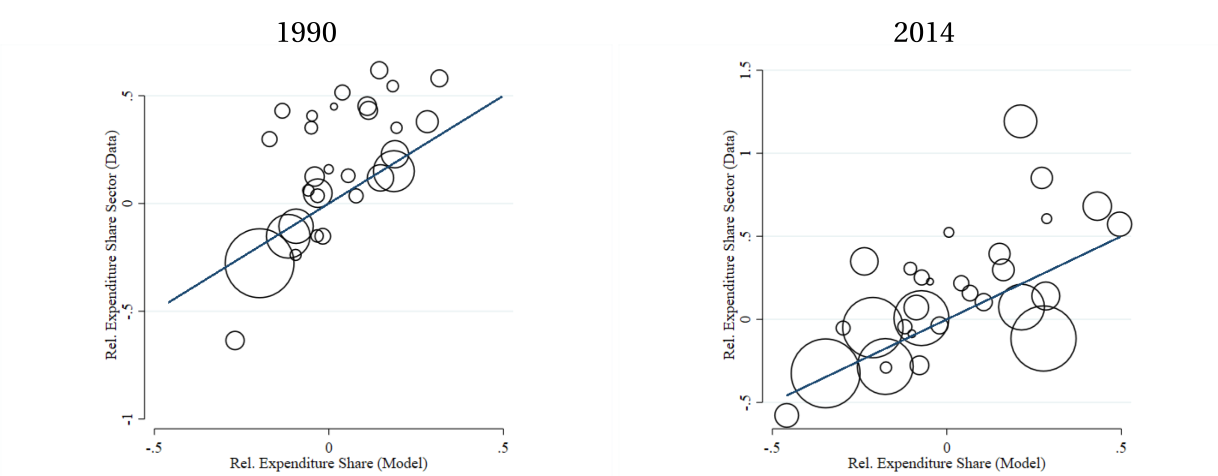
Notes: The left figure plots the ratio of goods price index statistics (HS/LS) with $\eta = .493$ against the share of high-skilled residents in a tract using the census tract data for 1990 with housing expenditure shares, see Section 3 (Slope: -0.114 $(.010)$). The right figure plots the same ratio against the share of establishments for which the difference in expenditure shares between high- and low-skilled households in the CEX 1990 is above the median difference (Slope: $-.021$ $(.008)$). Both figures are binscatters with 100 bins.

Figure 3: Estimates of $\nu_j - \nu_{j^*}$



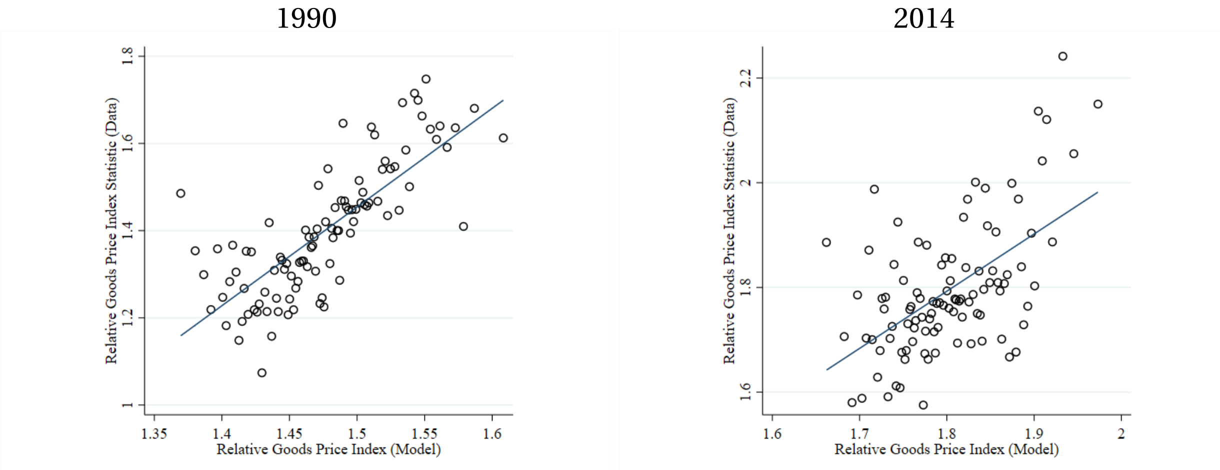
Notes: The figure plots point estimates of income elasticities by sector relative to Grocery Stores and 95% confidence intervals. Estimates ordered by size of coefficient.

Figure 4: Expenditure share differences by skill across sectors implied by model and data for 1990 and 2014



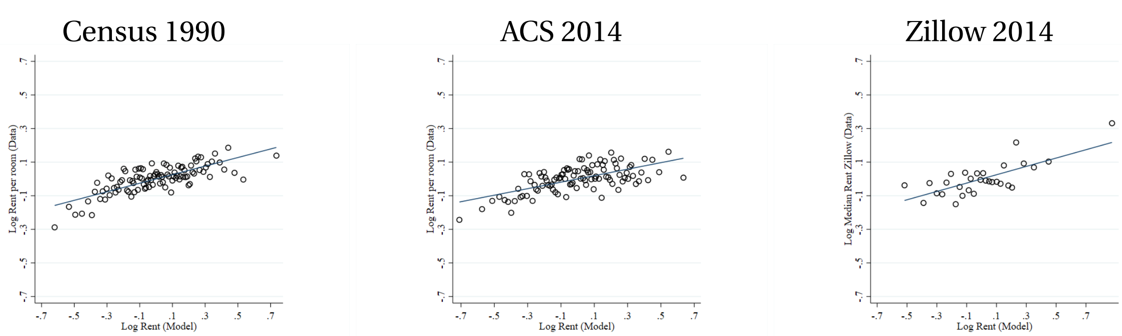
Notes: Figures plot the difference in log expenditures shares by sector in the baseline model (horizontal axis) and in nationwide CEX microdata (vertical axis). 45 degree line in blue. Size of circle correspond to overall expenditure share on the sector in CEX data.

Figure 5: Relative Goods Price Index Statistic and Model-implied Relative Goods Prices for 1990 and 2014



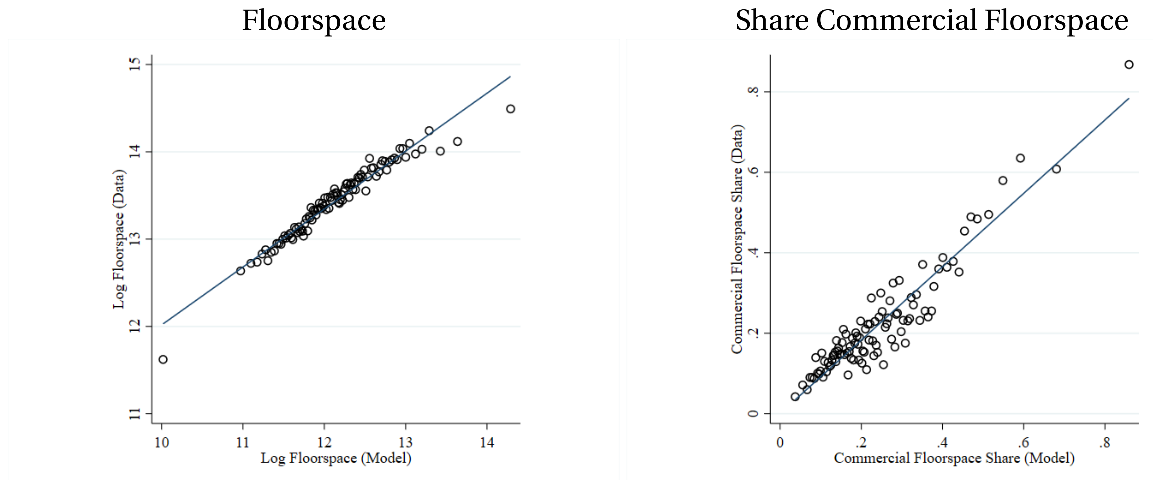
Notes: Figures plot goods price index statistics (HS/LS) with $\eta = .493$ in the data against the relative goods prices implied by the baseline model for 1990 (left) and 2014 (right). Slope of best fit line in blue for 1990: 2.263 $(.195)$. Slope for 2014: 1.093 $(.171)$. Both figures are binscatters with 100 bins.

Figure 6: Model-implied rents and data from Census 1990, ACS 2014 and Zillow 2014



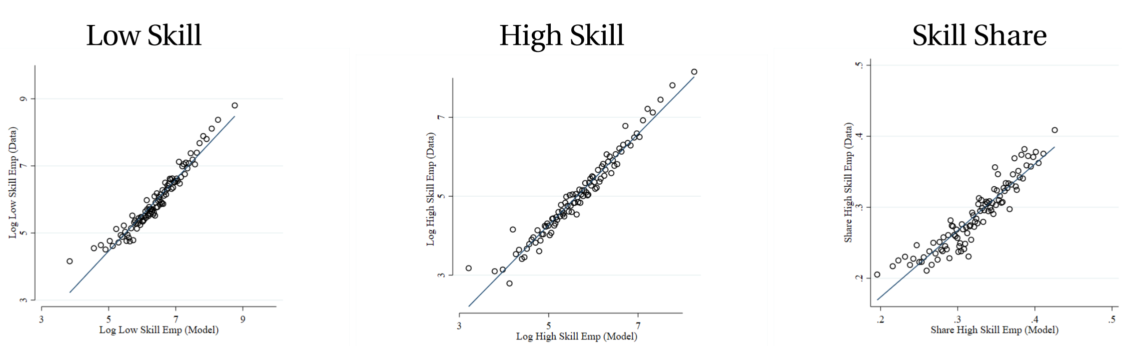
Notes: Figures plot rents in the baseline model (horizontal axis) against the rent per room in the Census 1990 (left), in the ACS 2014 (middle) and Zillow Rent Index for 2014 (right). Slope of best fit line in blue for rent per room: $.255$ $(.021)$ (left), $.194$ $(.019)$ (middle). Slope for Zillow Rent Index: $.248$ $(.052)$. Both figures are binscatters with 100 bins (left & middle) and 30 bins (right). Zillow Rent index only available at the zipcode level and not available for 1990.

Figure 7: Floorspace and share of commercial space in model and data from Los Angeles County Tax Assessor, 2014



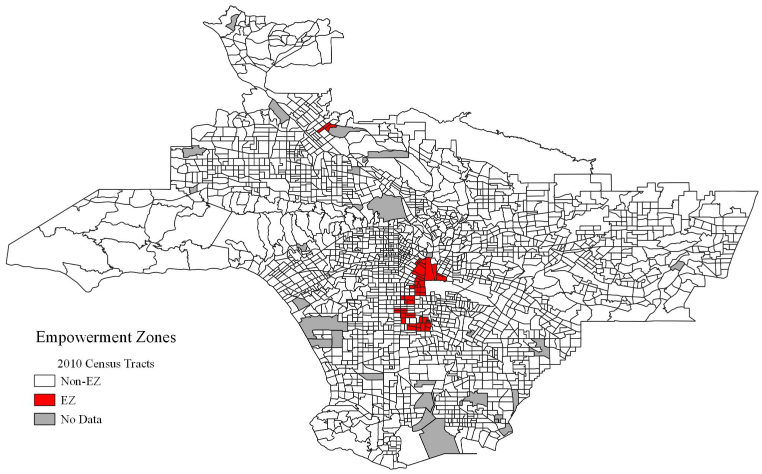
Notes: Figures plot log floorspace H_n and the share of commercial floorspace $H_n^C / \left(H_n^C + H_n^R\right)$ (right) in model against log total square footage and share of commercial square footage in each tract from the Los Angeles County Tax Assessor (left). Slope of best fit line in blue (left): $.664$ $(.018)$. Slope (right): 0.912 $(.031)$. Both figures are binscatters with 100 bins.

Figure 8: Employment by tract & skill in model and LODES data, 2014



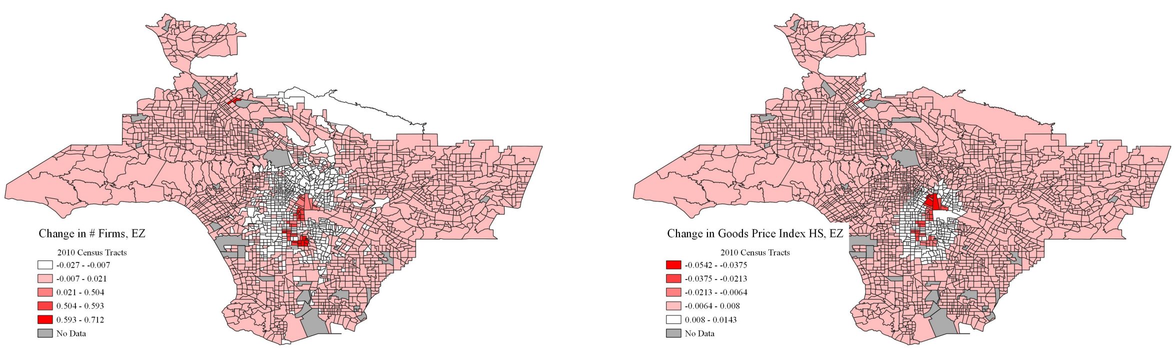
Notes: Figures plot log tract employment by skill and the skill share in employment in the model and employment data from LODES workplace files for 2014. Slope of best fit line in blue (left): 1.070 $(.024)$. Slope (middle): 1.154 $(.024)$. Slope (right): $.938$ $(.032)$. Both figures are binscatters with 100 bins.

Figure 9: Location of LA Empowerment Zone



Notes: Maps show the location of designated LA Empowerment Zone census tracts on 2010 Census geography.

Figure 10: Impact of EZ beyond EZ tracts



Notes: Maps show the % change the number of firms (left) and in the goods price index of the high-skilled (right) due to EZ policy.

Tables

Table 1: Sector-level Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sector	Expenditure Share HS, CEX 1990	Expenditure Share LS, CEX 1990	$\widehat{\nu_j - \nu_{j^*}}$	SE($\widehat{\nu_j - \nu_{j^*}}$)	Rescaled ν_j	β^{HS}	β^{LS}
Liquor/Tobacco Stores	0.012	0.023	-0.273	(0.091)	-2.012	0.225	0.575
Grocery Stores	0.244	0.322			-1.740	0.139	0.661
Hardware Stores	0.015	0.011	0.130	(0.109)	-1.610	0.170	0.630
Technical Services	0.016	0.010	0.280	(0.100)	-1.460	0.120	0.680
Auto Dealers	0.106	0.123	0.337	(0.165)	-1.403	0.131	0.669
Auto-related Services	0.067	0.074	0.423	(0.059)	-1.317	0.088	0.712
Toy Stores	0.006	0.007	0.433	(0.100)	-1.306	0.255	0.545
Shoe Stores	0.007	0.007	0.564	(0.080)	-1.175	0.211	0.589
Book Stores	0.011	0.008	0.609	(0.118)	-1.130	0.397	0.403
Rental Stores	0.008	0.005	0.619	(0.167)	-1.121	0.226	0.574
Electronic Stores	0.023	0.021	0.651	(0.116)	-1.089	0.364	0.436
Drug Stores	0.008	0.009	0.672	(0.139)	-1.067	0.488	0.312
Medical Services	0.050	0.048	0.692	(0.095)	-1.048	0.464	0.336
Professional Services	0.011	0.010	0.694	(0.175)	-1.045	0.471	0.329
Specialty Stores	0.013	0.015	0.746	(0.245)	-0.993	0.255	0.545
Pet Goods/Services	0.005	0.004	0.821	(0.145)	-0.918	0.590	0.210
Art-related Services	0.003	0.002	0.892	(0.181)	-0.848	0.411	0.389
Department Stores	0.017	0.010	0.963	(0.108)	-0.777	0.230	0.570
Sporting Stores	0.011	0.010	1.033	(0.162)	-0.706	0.253	0.547
Personal Care Services	0.011	0.011	1.127	(0.089)	-0.613	0.054	0.746
Other Food Away	0.026	0.016	1.237	(0.137)	-0.503	0.157	0.643
Furniture Stores	0.024	0.016	1.264	(0.177)	-0.475	0.199	0.601
Restaurants	0.045	0.040	1.393	(0.095)	-0.346	0.157	0.643
Education Services	0.023	0.013	1.395	(0.265)	-0.345	0.540	0.260
Recreation Services	0.010	0.006	1.546	(0.129)	-0.193	0.232	0.568
Non-local Goods/Services	0.112	0.096	1.552	(0.107)	-0.188	0.323	0.477
Apparel Stores	0.051	0.040	1.556	(0.115)	-0.183	0.264	0.536
Jewelry Stores	0.008	0.006	1.569	(0.270)	-0.171	0.247	0.553
Family Services	0.035	0.024	1.930	(0.145)	0.190	0.312	0.488
Amusement Services	0.023	0.013	2.104	(0.161)	0.364	0.406	0.394

Notes: Columns (1) and (2) show expenditure shares out of goods consumption by sector in CEX 1990. Columns (3)-(5) show the estimates for income elasticity of demand ν_j. Columns (6) and (7) show share of payroll accruing to high- and low-skilled workers in 1990 US-wide Census microdata.

Table 2: Expenditure Share on Housing and Skill

	(1) Census 1990	(2) ACS 2014	(3) Census 1990	(4) ACS 2014	(5) Model 1990	(6) Model 2014
Skill	-0.024***	-0.057***	-0.031***	-0.064***	-0.040***	-0.067***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	133,433	122,837	4,412	4,412	4,412	4,412
R-squared	0.148	0.129	0.927	0.955	0.998	0.997
Individual controls	X	X				
Location FE	Puma	Puma	Tract	Tract	Tract	Tract
Sample	LA HH	LA HH	LA Tracts	LA Tracts	LA Tracts	LA Tracts

Notes: Individual controls include dummies for sex, race, age (24-44, 45-64), household size and home-ownership. Observations weighed with survey weights in (1) and (2). Tracts weighted with population in (3)-(6). Robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Pre-Trend Test for Shift-Share Instruments

	(1) Instruments 1990-2000	(2) Instruments 2000-2014	(3) Instruments 2000-2014
Avg Price IV	-0.096**	-0.088***	-0.044***
	(0.048)	(0.026)	(0.012)
Wage IV	3.680	-2.227	1.956
	(2.701)	(3.927)	(3.163)
Rel Price IV	0.125	0.118	-0.113
	(0.315)	(0.211)	(0.119)
Observations	4,324	4,322	4,349
Dependent Variable:	1980-1990	1980-1990	1990-2000

Notes: Controls include log distance to the city center, average slope, log distance to shoreline and log density of residential square footage in 1990, all interacted with skill-type dummies. Regressions are weighted using 1990 household counts. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Estimation Results for κ and δ_k

	(1) Non-Homothetic	(2) Homothetic	(3) Non-Homothetic	(4) Non-Homothetic	(5) Non-Homothetic	(6) Non-Homothetic
$\hat{\kappa}$	0.038**	1.472***	2.734***	2.833***	2.629***	3.419**
	(0.019)	(0.106)	(0.318)	(0.337)	(0.326)	(1.369)
$\hat{\delta}^{LS}$	-0.154***	-0.305***	-0.879***	-0.964***	-0.970***	-0.525
	(0.017)	(0.118)	(0.184)	(0.199)	(0.191)	(0.324)
$\hat{\delta}^{HS}$	1.046***	0.930***	0.712***	0.760***	0.700***	-0.012
	(0.020)	(0.118)	(0.201)	(0.205)	(0.197)	(0.531)
Observations	8,343	8,343	8,343	8,343	8,343	8,343
Instruments	None	All	All	No Wage IV	No Avg Price IV	No Rel Price IV
R^2	0.567					
K-P F-Stat		50.56	24.05	31.14	27.58	2.288
Hansen J p-val		7.09e-05	0.269			

Notes: Controls include sum of establishment shares interacted with time-skill dummy; log distance to the city center, average slope, log distance to shoreline and log density of residential square footage in 1990, all interacted with skill-type dummies. Regressions are weighted using 1990 household counts. Standard errors clustered at tract level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Estimation Results for θ

	(1) OLS	(2) IV Slope	(3) IV Slope	(4) IV Slope	(5) IV Slope	(6) IV Slope & Distance
2SLS						
log $M_{nj,t}$	-0.903***	-0.867***	-0.886***	-0.846***	-0.876***	-0.857***
	(0.005)	(0.078)	(0.111)	(0.109)	(0.082)	(0.082)
Implied $\hat{\theta}$ ($\sigma = 3$)	20.574***	15.083*	17.533	12.990	16.111	14.001*
	(1.001)	(8.876)	(17.106)	(9.221)	(10.695)	(8.000)
1st Stage						
Avg Slope X rel Exp Share		0.259***	0.252***	0.268***	0.249***	0.254***
		(0.020)	(0.027)	(0.031)	(0.020)	(0.021)
Dist to Shore X rel Exp Share						-0.025***
						(0.008)
Observations	178,809	178,809	93,841	84,968	174,191	174,191
Sample	all	all	2004-2014	1990-2003	excl Amusement & Recreation	excl Amusement & Recreation
K-P F-Stat		164.5	89.18	74.61	147.4	76.57
Hansen J p-val						0.339

Notes: All regressions include tract-time and chain-time fixed effects. Standard errors clustered at zipcode-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Summary of Model Parameters

Parameter	Description	Value	Source
κ	Resident supply elasticity	2.8	Estimated
ν_j	Income elasticities by sector	see Table 1	Estimated
η	EoS housing vs goods	.493	Albouy et al (2016)
γ	EoS across sectors	1.6	Literature
σ	EoS across varities	3	Literature
ρ	Commuter supply elasticity	6	Literature
θ	Firm supply elasticity	16	Estimated
ψ	Commuter demand elasticity	20	Assumed
$\mu/(1-\mu)$	Housing supply elasticity	.43	Severen (2021)
β^C	Housing share in production	.2	Retail Survey 2012
β_j^k	Labor share of k in sector j	see Table 1	Census/ACS
δ^{HS}	Spillover elasticity LS	-.5	Estimated
δ^{LS}	Spillover elasticity HS	.5	Estimated
$\phi^{\mathcal{L}}$	Distance decay spillover	-3.5	Ahlfeldt et al (2015)
ϕ^S	Distance elasticity shopping	.9	Redding et al (2021)
ϕ^W	Distance elasticity commuting	.263	Estimated

Table 7: Skill Premium in Household Income

	(1) Census 1990	(2) ACS 2014	(3) Census 1990	(4) ACS 2014	(5) Model 1990	(6) Model 2014
Skill	0.484***	0.616***	0.489***	0.587***	0.495***	0.781***
	(0.005)	(0.006)	(0.011)	(0.011)	(0.002)	(0.001)
Observations	140,887	133,982	4,412	4,412	4,412	4,412
R-squared	0.240	0.256	0.339	0.443	0.972	0.993
Individual controls	X	X				
Sample	LA HH	LA HH	LA Tracts	LA Tracts	LA Tracts	LA Tracts

Notes: Individual controls include dummies for sex, race, age (24-44, 45-64) and household size. Observations weighed with survey weights in (1) and (2). Tracts weighted with population in (3)-(6). Robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Commuter Flows in Baseline Model and LODES data, 2014

	(1)	(2)	(3)	(4)
Log Commuters, Model	1.006***	0.960***	1.018***	1.002***
	(0.009)	(0.017)	(0.020)	(0.018)
Observations	4,864,230	4,864,230	4,864,230	4,864,230
Residence FE	X		X	
Workplace FE	X	X		

Notes: Regression compares the number of workers commuting between two tracts in the model with data from LODES for 2014 (including zero flows). Regressions use Pseudo Poisson Maximum Likelihood (PPML). Standard errors clustered at residence and workplace. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Pre-Treatment Balance for EZs and Reweighted Control Tracts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Difference	Control Mean	p-value	Obs	Difference	Control Mean	p-value	Obs
Levels, 1990	*All EZs*				*LA EZ*			
UE Rate	-0.012	0.234	0.617	849	-0.233	0.426	0.037	71
Poverty Rate	-0.005	0.458	0.901	849	-0.052	0.458	0.733	71
Emp-Pop Ratio	0.030	0.415	0.277	849	0.175	0.286	0.044	71
Minority Share	0.042	0.813	0.260	849	0.257	0.566	0.001	71
Housing Share	0.010	0.212	0.123	849	0.073	0.185	0.001	71
Vacant Share	0.032	0.111	0.006	849	-0.024	0.083	0.463	71
Homeowner Share	-0.002	0.237	0.960	849	0.083	0.202	0.608	71
Skill Share	0.009	0.053	0.203	849	-0.059	0.096	0.046	71
Changes, 1980-90								
UE Rate	-0.011	0.054	0.616	849	-0.182	0.218	0.317	71
Poverty Rate	0.002	0.035	0.915	849	-0.014	0.028	0.821	71
Emp-Pop Ratio	0.009	0.006	0.675	849	0.137	-0.116	0.360	71
Minority Share	-0.012	0.035	0.183	849	-0.023	-0.009	0.464	71
Housing Share	0.003	0.029	0.595	849	0.056	0.007	0.091	71
Vacant Share	0.018	0.006	0.173	849	-0.009	0.013	0.872	71
Homeowner Share	-0.005	0.009	0.374	849	-0.005	-0.005	0.845	71
Skill Share	0.002	0.021	0.697	849	-0.067	0.072	0.036	71
Log HH Income	-0.001	0.542	0.986	849	0.065	0.635	0.536	71
Log Home Value	-0.037	0.816	0.693	849	-0.152	1.148	0.349	71
Log Rent	0.032	0.814	0.465	849	0.366	0.817	0.000	71
Firms, 1990								
Log Firms					-1.318	5.359	0.003	71
Log Firms Local					-0.964	4.242	0.054	71
Log Firms Non-Local					-1.604	4.894	0.004	71
Log Employment					-2.006	8.395	0.006	71
Share Income-elastic					-0.006	0.382	0.882	71

Notes: Columns (1) and (5) show differences between EZ tracts and reweighted control tracts; Columns (2) and (6) show means in the control group; Columns (3) and (7) show block-bootstrapped p-values of difference based on 1000 repetitions; Columns (4) and (8) show the number of tracts. The first 4 columns report results from comparing all EZs and SEZs with all ever "rejected" tracts (256 treated and 608 control tracts). Columns (5) through (8) report results for the LA EZ compared to 3 "rejected" Californian zones (47 treated and 24 control tracts).

Table 10: Impact of EZ Program on Gentrification Outcomes

	(1)	(2)	(3)	(4)
	All EZ	Obs	All EZ	Obs
Tract-Level Changes	*1990-2000*		*1990-2009*	
Log Skill Share	0.270	847	0.269	843
	(0.153)*		(0.128)**	
Log HH Income HS	0.145	847	0.103	843
	(0.126)		(0.093)	
Log HH Income LS	0.086	848	0.109	843
	(0.043)*		(0.050)**	
Log Rent	0.006	848	0.147	690
	(0.050)		(0.041)***	
Log Housing Share HS	0.039	847	0.072	840
	(0.031)		(0.035)**	
Log Housing Share LS	-0.037	848	0.009	840
	(0.024)		(0.023)	
Log Firms			0.499	71
			(0.265)**	
Log Firms Local			0.365	71
			(0.388)	
Log Firms Non-Local			0.624	71
			(0.204)***	
Share Income-elastic			0.115	71
			(0.038)***	

Notes: Columns (1) and (2) show the impact between 1990 and 2000, consistent with Busso *et al.* (2013); Columns (3) and (4) extend the time period to the end of the program. Firm-level outcomes only available for California tracts. Standard errors and *p*-values block-bootstrapped with 1000 repetitions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Impact of EZ program on model-based Fixed Amenities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Less 1km from EZ	Obs	Less 5km from EZ	Obs	Less 15km from EZ	Obs	All tracts	Obs
$\Delta \log \bar{B}_{HS}$	0.106	152	0.282	564	0.539	1559	0.624	2206
	(0.114)		(0.102)***		(0.101)***		(0.101)***	
$\Delta \log \bar{B}_{LS}$	0.083	152	0.250	564	0.502	1559	0.588	2206
	(0.088)		(0.079)***		(0.078)***		(0.078)***	
Difference	0.023	152	0.032	564	0.037	1559	0.035	2206
	(0.054)		(0.050)		(0.050)		(0.050)	

Notes: Regressions of model-based fixed amenities by skill and difference on indicator for EZ tract. Dependent variable is the log difference in $\bar{B}_{kn}$ form inverted models for 2014 and 1990. Going from left to right, I increases the size of the control group by including tracts further and further from the EZ. Robust standard errors *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Impact of EZ Program in Data and Individual Policy Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Data	Policy Instrument				
Policy Version		Subsidies & Amenity Shock	Subsidies	Wage Subsidy	Profit Subsidy	Amenity Shock
Log Skill Share	0.269	0.248	0.037	-0.030	0.084	0.213
	(0.128)**	(0.005)	(0.002)	(0.003)	(0.004)	(0.006)
Log HH Income HS	0.103	0.013	0.019	0.008	0.008	-0.006
	(0.093)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Log HH Income LS	0.109	0.026	0.025	0.012	0.009	0.001
	(0.050)**	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Log Rent	0.147	0.122	0.129	0.024	0.100	-0.007
	(0.041)***	(0.009)	(0.008)	(0.001)	(0.008)	(0.001)
Log Housing Share HS	0.072	0.052	0.054	0.009	0.043	-0.002
	(0.035)**	(0.004)	(0.003)	(0.000)	(0.004)	(0.000)
Log Housing Share LS	0.009	0.047	0.050	0.008	0.041	-0.003
	(0.023)	(0.003)	(0.003)	(0.000)	(0.003)	(0.001)
Log Firms	0.499	0.565	0.563	0.039	0.537	0.002
	(0.265)**	(0.010)	(0.009)	(0.002)	(0.008)	(0.001)
Log Firms Local	0.365	0.482	0.496	0.058	0.442	-0.014
	(0.388)	(0.009)	(0.009)	(0.002)	(0.009)	(0.001)
Log Firms Non-Local	0.624	0.657	0.639	0.020	0.637	0.021
	(0.204)***	(0.015)	(0.013)	(0.002)	(0.013)	(0.002)
Share Income-elastic	0.115	0.027	0.021	-0.005	0.028	0.006
	(0.038)***	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)

Notes: Columns (1) replicates empirical results for the LA EZ (column (5) of Table 10). Column (2) reports counterfactual changes for the baseline model with all 3 shocks (wage subsidy, profit subsidy and amenity shock). Column (3) reports results for only the "firm-level" subsidies. Column (4) shows results for only the wage subsidy. Column (5) shows results the profit subsidy and column (6) reports counterfactual results for the amenity shock only.

Table 13: Impact of EZ Program in Data and Model Counterfactuals

	(1)	(2)	(3)	(4)	(5)
	Data	Counterfactual			
Model Version	Data	Baseline	Homothetic Preferences	No Shopping Frictions	No Commuting Frictions
Log Skill Share	0.269	0.248	0.088	0.232	0.253
	(0.128)**	(0.005)	(0.005)	(0.005)	(0.007)
Log HH Income HS	0.103	0.013	0.016	0.014	-0.004
	(0.093)	(0.001)	(0.001)	(0.001)	(0.000)
Log HH Income LS	0.109	0.026	0.024	0.027	0.007
	(0.050)**	(0.002)	(0.002)	(0.002)	(0.000)
Log Rent	0.147	0.122	0.142	0.125	0.104
	(0.041)***	(0.009)	(0.008)	(0.009)	(0.009)
Log Housing Share HS	0.072	0.052	0.053	0.050	0.048
	(0.035)**	(0.004)	(0.003)	(0.004)	(0.004)
Log Housing Share LS	0.009	0.047	0.053	0.045	0.044
	(0.023)	(0.003)	(0.003)	(0.003)	(0.004)
Log Firms	0.499	0.565	0.556	0.580	0.551
	(0.265)**	(0.010)	(0.009)	(0.011)	(0.008)
Log Firms Local	0.365	0.482	0.505	0.586	0.441
	(0.388)	(0.009)	(0.008)	(0.011)	(0.009)
Log Firms Non-Local	0.624	0.657	0.615	0.572	0.667
	(0.204)***	(0.015)	(0.012)	(0.010)	(0.014)
Share Income-elastic	0.115	0.027	0.016	-0.002	0.034
	(0.038)***	(0.002)	(0.001)	(0.000)	(0.002)

Notes: Columns (1) replicates empirical results for the LA EZ (column (5) of Table 10). Column (2) reports counterfactual changes for the baseline model. Column (3) reports results for the "homothetic" model variant ($\nu_j = 0, \forall j$). The variant in column (4) does not feature shopping frictions i.e., demand is not local for all sectors. Column (5) shows results for the model variant without commuting frictions i.e., labor demand is not local.

Table 14: Welfare Effect of EZ program

	(1)	(2)	(3)	(4)
Model Version	Baseline	Homothetic Preferences	No Shopping Frictions	No Commuting Frictions
Welfare HS (x100)	0.298	0.702	0.309	0.280
Welfare LS (x100)	0.275	0.730	0.290	0.281
CV HS ($)	175	410	181	164
CV LS ($)	99	260	104	101
CV weighted ($)	120	302	125	118
Cost per HH ($)	204	205	207	195

Notes: See Table 13. Compensating variation (CV) calculated as the additional income to achieve the same counterfactual citywide expected welfare at baseline prices. CV weighted refers to CV of each skill-type weighted by citywide household shares.

Table 15: Alternative Firm Subsidies in EZ program

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Sectors Treated	Income-elastic Sectors	Income-inelastic Sectors	High-skill Sectors	Low-skill Sectors	Local Sectors	Non-local Sector
Log Skill Share	0.037	0.097	-0.105	0.068	-0.069	0.013	0.011
Welfare HS (x100)	0.333	0.329	0.045	0.366	0.020	0.050	0.366
Welfare LS (x100)	0.316	0.243	0.150	0.226	0.182	0.126	0.271
CV HS ($)	195	193	26	215	12	29	215
CV LS ($)	113	87	53	81	65	45	97
CV weighted ($)	136	116	46	118	50	41	130
Cost per HH ($)	175	157	80	148	103	120	138
Benefit-Cost Ratio	0.776	0.739	0.576	0.799	0.488	0.339	0.937

Notes: Columns (1) replicates the effect on skill share and welfare for the baseline model. Column (2) through (7) evaluate alternative policies with sectors eligible for firm subsidies: (2) sectors with high income elasticity, (3) low income elasticity, (4) high skill intensity, (5) low skill intensity. Each subset account for roughly 50% of citywide consumption. (6) 29 local sectors, (7) 1 non-local sector. Benefit-Cost Ratio is the ratio of CV weighted and Cost per HH. It measures the return for each dollar spent.

Table 16: Spillovers of the EZ Program onto Nearby Tracts

	(1)	(2)	(3)	(4)	(5)
Treatment	EZ	less 1km from EZ	1-2.5km from EZ	2.5-5km from EZ	Log Distance from EZ
Log Skill Share	0.248	0.096	0.037	0.014	-0.019
	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)
Log HH Income HS	0.013	0.003	0.002	0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Log HH Income LS	0.026	0.005	0.003	0.002	-0.001
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Log Price Index HS	0.020	-0.002	0.000	0.001	0.000
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Log Price Index LS	0.030	-0.002	0.001	0.001	0.000
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Log Firms	0.565	-0.005	-0.007	-0.005	0.002
	(0.010)	(0.001)	(0.000)	(0.000)	(0.000)
Log Firms Local	0.482	-0.049	-0.021	-0.008	0.010
	(0.009)	(0.003)	(0.001)	(0.000)	(0.000)
Log Firms Non-Local	0.657	0.052	0.011	-0.003	-0.008
	(0.015)	(0.004)	(0.001)	(0.001)	(0.001)
Share Income-elastic	0.027	0.017	0.005	0.001	-0.003
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)

Notes: Columns (1) replicates counterfactual results for baseline model. Column (2) through (4) report the effect on tracts with 1km (2), 1-2.5km (3) and 2.5-5km (4) of the EZ. Column (5) shows the effect outside EZ as a function log distance to the EZ boundary. Results based on all subsidies.

ONLINE APPENDIX
NOT FOR PUBLICATION

Appendix A Additional Figures and Tables

Figure A.1: Graphical Example of Sorting Patterns in the Model

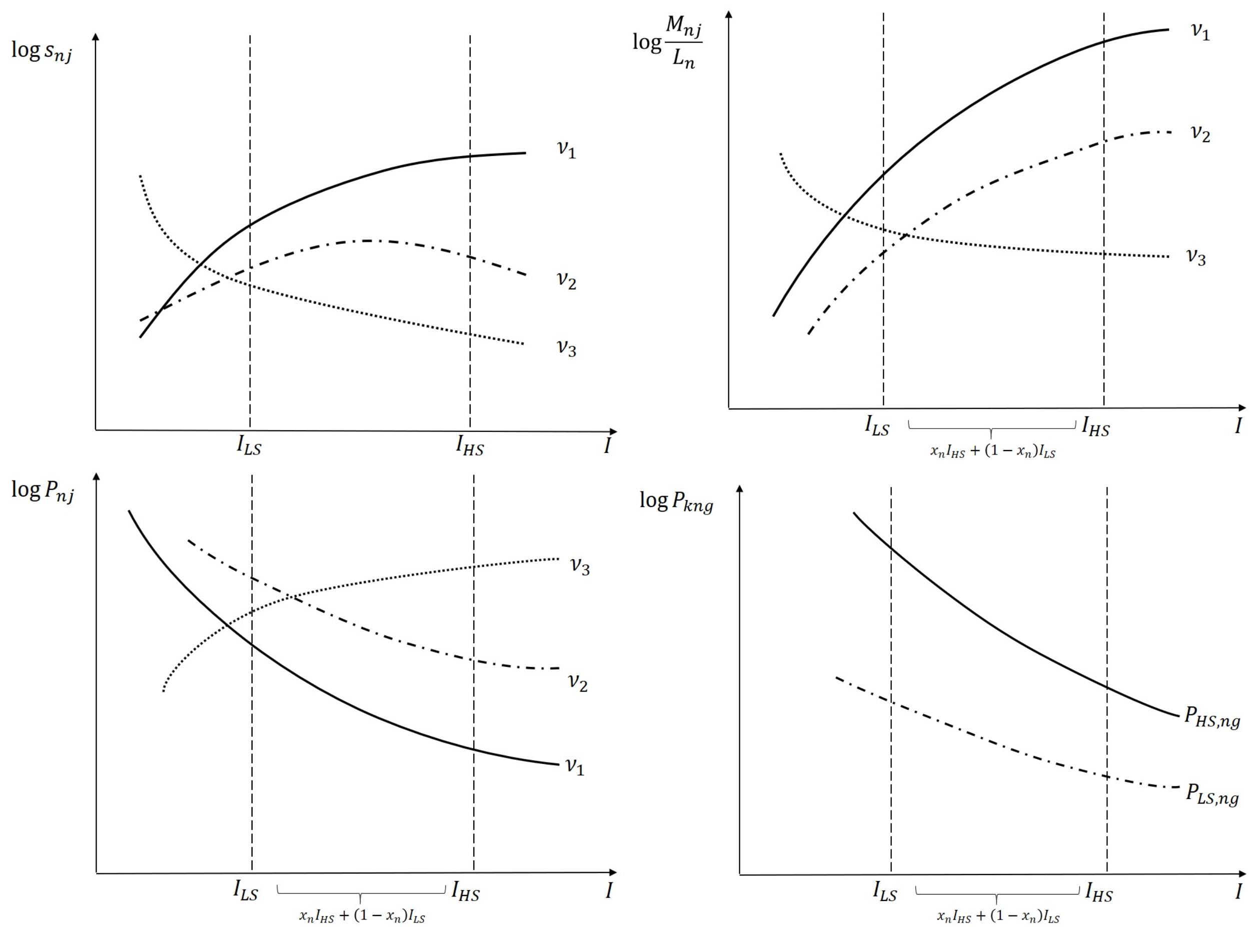


Table A.1: First Stages for Estimation of κ and δ_k

Column in Table 4	(2)	(3)	(4)	(5)	(6)
Real Consumption					
Avg Price IV	0.596***	0.321***	0.404***		0.071***
	(0.044)	(0.037)	(0.038)		(0.023)
Wage IV	-1.094	4.883***		10.265***	4.450***
	(1.225)	(1.098)		(1.147)	(1.100)
Rel Price IV	-1.594***	-0.639***	-0.705***	-0.193***	
	(0.090)	(0.073)	(0.075)	(0.046)	
Rel Price IV X HS	0.016	-0.239***	-0.134*	-0.355***	
	(0.085)	(0.078)	(0.074)	(0.081)	
Avg Price IV X HS					0.034
					(0.042)
R^2	0.430	0.223	0.221	0.215	0.210
Spillover for LS					
Avg Price IV	0.368***	0.368***	0.372***		0.667***
	(0.032)	(0.032)	(0.029)		(0.032)
Wage IV	0.240	0.240		6.414***	3.591***
	(0.705)	(0.705)		(0.697)	(0.770)
Rel Price IV	0.478***	0.478***	0.475***	0.990***	
	(0.076)	(0.076)	(0.075)	(0.058)	
Rel Price IV X HS	-1.087***	-1.087***	-1.081***	-1.219***	
	(0.061)	(0.061)	(0.059)	(0.061)	
Avg Price IV X HS					-0.748***
					(0.036)
R^2	0.459	0.459	0.459	0.448	0.475
Spillover for HS					
Avg Price IV	0.276***	0.276***	0.373***		-0.027***
	(0.030)	(0.030)	(0.029)		(0.010)
Wage IV	5.724***	5.724***		10.350***	2.769***
	(1.005)	(1.005)		(0.978)	(1.015)
Rel Price IV	-0.531***	-0.531***	-0.608***	-0.147***	
	(0.047)	(0.047)	(0.049)	(0.015)	
Rel Price IV X HS	0.953***	0.953***	1.076***	0.854***	
	(0.061)	(0.061)	(0.059)	(0.061)	
Avg Price IV X HS					0.667***
					(0.034)
R^2	0.461	0.461	0.459	0.455	0.474
Observations	8,360	8,360	8,360	8,360	8,360
Instruments	All	All	No Wage IV	No Avg Price IV	No Rel Price IV

Notes: See Table 4

Table A.2: Robustness Checks for Estimation of κ and δ_k

	(1) Baseline	(2) No controls	(3) Wages	(4) Pop-based	(5) Rent Share	(6) 5km Buffer	(7) Imputed Exp-Weights	(8) $\phi^{\mathcal{L}} = -1.5$	(9) Unweighted
$\hat{\kappa}$	2.734***	4.470***	3.595***	2.651***	2.153***	2.991***	2.325***	2.684***	2.731***
	(0.318)	(0.695)	(0.560)	(0.293)	(0.272)	(0.577)	(0.629)	(0.333)	(0.324)
$\hat{\delta}^{LS}$	-0.879***	-0.445	-1.384***	-0.976***	-0.288	0.190	-0.298**	-1.851***	-0.888***
	(0.184)	(1.007)	(0.270)	(0.229)	(0.177)	(0.775)	(0.147)	(0.394)	(0.186)
$\hat{\delta}^{HS}$	0.712***	-1.370	0.346	0.737***	0.830***	-0.642	0.467**	1.642***	0.761***
	(0.201)	(0.994)	(0.302)	(0.254)	(0.202)	(0.859)	(0.219)	(0.448)	(0.208)
Observations	8,343	8,343	8,343	8,343	8,343	8,343	8,343	8,343	8,343
Instruments	All	All	All	All	All	All	All	All	All
K-P F-Stat	24.05	4.502	12.07	31.83	17.78	3.508	4.104	20.80	23.60
Hansen J p-val	0.269	0.0390	0.836	0.183	0.001	0.000	0.148	0.178	0.479

Notes: Column (1) reports the baseline estimate in column (3) of Table 4. Controls are dropped in column (2). In column (3), I use labor earnings of the household head when computing real consumption. Column (4) reports the same specification as column (1) but computes spillovers using skill ratios in population instead of households. Column (5) uses the share of income renters pay when constructing price index proxy. Columns (5) through (8) change the way the price instruments are constructed: smaller distance buffer of 5km, relative expenditure weights are constructed using average citywide income by type and income elasticity estimates, smaller distance decay parameter $\phi^{\mathcal{L}} = -1.5$ instead of -3.5. Column (9) drops weights in the regression. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Impact of EZ Program, Additional Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	All EZ	Obs	All EZ	Obs	LA EZ	Obs
Tract-Level Changes	*1990-2000*		*1990-2009*		*1990-2009*	
UE Rate	0.009	848	-0.025	843	0.039	71
	(0.026)		(0.024)		(0.056)	
Poverty Rate	-0.029	848	-0.079	843	-0.020	71
	(0.022)		(0.036)**		(0.020)	
Emp-Pop Ratio	0.004	849	0.049	844	-0.004	71
	(0.020)		(0.037)		(0.023)	
Log Households	-0.055	849	-0.036	843	0.011	71
	(0.051)		(0.073)		(0.106)	
Log Skill Share	0.270	847	0.269	843	0.238	71
	(0.153)*		(0.128)**		(0.339)	
Log HH Income	0.155	848	0.157	842	0.154	71
	(0.057)**		(0.073)**		(0.144)	
Log HH Income HS	0.145	847	0.103	843	0.222	71
	(0.126)		(0.093)		(0.202)	
Log HH Income LS	0.086	848	0.109	843	-0.069	71
	(0.043)*		(0.050)**		(0.047)	
Log Home Value	0.352	820	0.693	709	0.246	56
	(0.100)***		(0.157)***		(0.117)**	
Log Rent	0.006	848	0.147	690	0.107	55
	(0.050)		(0.041)***		(0.050)**	
Log Housing Share HS	0.039	847	0.072	840	0.132	71
	(0.031)		(0.035)**		(0.044)***	
Log Housing Share LS	-0.037	848	0.009	840	-0.029	71
	(0.024)		(0.023)		(0.065)	
Share Commute u10min	0.013	848	0.024	843	0.181	71
	(0.020)		(0.025)		(0.055)***	
Log Firms					0.499	71
					(0.265)**	
Log Firms Local					0.365	71
					(0.388)	
Log Firms Non-Local					0.624	71
					(0.204)***	
Log Employment					0.298	71
					(0.245)	
Share Income-elastic					0.115	71
					(0.038)***	

Notes: Columns (1) and (2) show the impact between 1990 and 2000, consistent with Busso *et al.* (2013); Columns (3) and (4) extend the time period to the end of the program; Columns (5) and (6) show the impacts for the LA EZ sample. Standard errors and p-values block-bootstrapped with 1000 repetitions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix B Details on Data Processing

In this Appendix, I discuss imputation steps underlying the empirical analysis in the paper. Further information is available upon request.

B.1 Geography of Los Angeles

For my analysis, I rely on constant 2010 geography definitions of Census Tracts as neighborhoods. The Longitudinal Tract Database (LTDB) provides interpolation weights for tracts that changed geography in earlier years. I apply those weights to all data from the Census 1990 and 2000 as well as the 5-year American Community Surveys, 2007-2011 and 2012-2016. I define Los Angeles as the urban part of Los Angeles County, as defined by the Census. The Los Angeles metropolitan area includes parts of adjacent counties such as Orange County which I do not cover currently. This omission might matter for some areas close to county borders, in particular, for my counterfactuals. However, some of the variables used in my analysis such as the assessor data on tract level housing stock are not publicly available in these counties. Moreover, due to the large geographic area and the large number of census tracts (2235 in total) I cover, I am quite confident that the overall results of my counterfactual analysis should hold when omitting adjacent counties.

B.2 Census and ACS Data, Imputation Steps

The key variables I extract from the tract-level information in the Census 1990, 2000 and ACS 2007-2011 and 2012-2016 are the income distributions by age and race, distributions of housing expenditure shares by income (rents and owner costs) and total housing expenditure. Since the tract-level data does not report the number of households by skill or housing expenditure by skill, I use the above income distributions to impute those variables. To do so I first geographically merge tracts to Public Use Microdata Areas (Puma) for which microdata by skilled household head are available. I then apply NBER's TAXSIM software to compute each households tax liability to construct after-tax income and housing expenditure share out of after-tax income. To impute the counts of households by skill and income by skill in a tract I construct the same income distribution by age and race in the microdata as in the aggregate tract-level data (based on gross income). Then, I compute the skill share in each income-age-race bin and average after-tax income by skill-age-race. I then assign the high (low) skilled share to each income-race-age bin in all tracts in the same Puma. I compute the number of high (low) skilled households in each tract by summing over the household counts in bins at the tract level multiplied with the high (low) skilled share. The imputed share of high skilled households in a tract line up very closely with the share of high skilled individuals directly reported in the Census and ACS data. Household income by skill is constructed as the average after-tax income in each bin by skill-age-race weighted by the share of each group in a tract. The computation of expenditure share on housing follows a similar procedure; to my knowledge this is the first paper to utilize the tract-level household distributions on expenditure share on housing at the tract level in the Census and ACS. Both datasets provide counts within given expenditure share bins, e.g. 20-24% share of gross rent in income, for each household income bins e.g. $35,000-$49,999. The household distributions are reported for gross rent shares and owner costs for owner-occupied housing from which I also construct a single distribution for housing costs shares.[1] For each category, I assign the Puma-level means of after-tax expenditure shares and household shares by skill in each expenditure share-income bin. I then weight each bin by the tract-level counts to construct average expenditure shares on housing, rent and owner costs by skill in each tract. Table 2 shows that the gap in expenditure share between high and low skilled household in the ACS microdata for Los Angeles line up very closely with the imputed tract-level data.

Residential rents by tract are constructed by dividing total housing expenditure (as the sum of gross rent and owner costs) by the total number of rooms in a tract.

[1] Selected Monthly Owner Costs are defined as the sum of mortgage payments, taxes, insurance, utilities and other fees.

Appendix C Additional Model Details & Proofs

C.1 Properties of Household Preferences

The following analysis is under the assumptions of given prices and from the view of an individual household of any type. To save on notation I omit location and type subscripts. Furthermore, I assume for completeness that the upper utility nest in equation (6) in the main text is represented by a non-homothetic CES aggregator between housing and goods consumption according to

$$(a_h U^{\epsilon_h})^{\frac{1}{\eta}} C_h^{\frac{\eta-1}{\eta}} + (a_g U^{\epsilon_g})^{\frac{1}{\eta}} C_g^{\frac{\eta-1}{\eta}} = 1.$$

Depending on the relative size of ϵ_h and ϵ_g consumers shift expenditure between housing and goods when real consumption changes. For example, if housing is a necessity ($\epsilon_h < \epsilon_g$) then consumers with a higher level of real consumption spend a larger fraction of income on goods at given relative prices. When $\epsilon_h = \epsilon_g = 1 - \eta$, as in the main text, the expression reduces to the regular CES consumption aggregator.

First, let us look at the elasticity of the price index of goods with respect to real consumption

$$\frac{U \partial P_g}{P_g \partial U} = \frac{1}{1-\gamma} \sum_{j=1}^{J} \tilde{s}_j \nu_j = \frac{\bar{\nu}}{1-\gamma}$$

where $\bar{\nu} = \sum_{j=1}^{J} \tilde{s}_j \nu_j$ is the expenditure weighted sum of income elasticities of demand across sectors inside the goods sector. Second, I can compute the elasticity of real consumption with respect to income

$$\frac{E \partial U}{U \partial E} = \left(\frac{1}{1-\eta} \left(s_h \epsilon_h + s_g \left(\epsilon_g + \frac{1-\eta}{1-\gamma} \bar{\nu} \right) \right) \right)^{-1} = \frac{1-\eta}{\bar{\epsilon}}$$

where $\bar{\epsilon} = s_h \epsilon_h + s_g \left(\epsilon_g + \frac{1-\eta}{1-\gamma} \bar{\nu} \right)$ is the expenditure weighted average income elasticity of demand across housing and goods.

With the above result, I can compute the expenditure elasticity of demand for housing

$$\frac{\partial \log C_h}{\partial \log E} = \eta + \epsilon_h \frac{\partial \log U}{\partial \log E} = \eta + (1-\eta) \frac{\epsilon_h}{\bar{\epsilon}}$$

and goods,

$$\frac{\partial \log C_g}{\partial \log E} = \eta + (1-\eta) \left(\frac{\epsilon_h - \frac{\eta}{1-\gamma} \bar{\nu}}{\bar{\epsilon}} \right).$$

For the expenditure elasticity of demand for a particular sector j, it holds that

$$\frac{\partial \log C_j}{\partial \log E} = (\gamma - \eta) \frac{\log P_j}{\log E} + \eta + (\nu_j + \epsilon_g) \frac{\partial \log U}{\partial \log E} = \eta + (1-\eta) \frac{\epsilon_g + \nu_j}{\bar{\epsilon}} + (1-\eta) \frac{(\gamma - \eta)}{(1-\gamma)} \frac{\bar{\nu}}{\bar{\epsilon}}$$

Next, we can compute the mobility elasticity with respect to income. Recall

$$\lambda_n = \frac{B_n U_n^\kappa}{\sum_{n'} B_{n'} U_{n'}^\kappa}$$

So,

$$\frac{E\partial\lambda_n}{\lambda\partial E} = \kappa \frac{E\partial U}{U\partial E}\Big|_n - \frac{E\partial\Phi}{\Phi\partial E} = \kappa(1-\eta)\left(\frac{1}{\bar{\epsilon}_n} - \sum_{n'} \lambda_{n'} \frac{1}{\bar{\epsilon}_{n'}}\right)$$

These elasticities imply the following:

- Engel aggregation: $s_h \frac{\partial \log C_h}{\partial \log E} + s_g \sum_j \tilde{s}_j \frac{\partial \log C_j}{\partial \log E} = 1$
- Conditional on prices income elasticities of demand parameters ϵ_g, ν_j are defined up to scale. Consumption choices are not affected by scaling the parameters by a constant factor. Furthermore, if κ is scaled by the same factor agents mobility choices are unaffected.
- As a result of the above I can normalize one income elasticity parameter and one taste shifter without affecting the economic choices of agents.
- Sufficient: If $0 < \eta < 1$ and $\gamma > 1$ then $\epsilon_i > 0, \forall i \in \{h, g\}$ and $\bar{\nu} < 0$ such that utility is increasing in expenditure and the goods price index is increasing in expenditure.
- 1. $\epsilon_i = 1 - \eta, \forall i$ and $\nu_j = 0, \forall j$: preferences are homothetic nested CES, many trade models
  2. $\epsilon_i = 1-\eta, \forall i$ and $\exists \nu_j \neq 0$: upper nest is homothetic and within sectors non-homothetic, Borusyak & Jaravel (2018)
  3. $\epsilon_i \neq 1-\eta, \forall i$ and $\nu_j = 0, \forall j$, upper nest is non-homothetic and lower nest homothetic, Comin et al. (2018), Matsuyama (2018)
- In the case of homothetic upper nest ($\epsilon_g = 1-\eta$): $\frac{E\partial U}{U\partial E} = \frac{1}{1+s_g \frac{\bar{\nu}}{1-\gamma}}$

C.2 Non-homotethic CES and Sorting Patterns

Now, I discuss the theoretical underpinnings for the model's main contribution, namely, that firms in sectors with high income elasticity collocate with high-skilled households based on demand patterns arising from non-homothetic preferences. In particular, with such preferences the relative price index of the high-skilled (HS) and low-skilled (LS) decreases with a larger skill share in a neighborhood summarized the the proposition below. To keep the exposition and notation simple, I assume for now that shopping frictions outside the location of residence are infinite, $\tau_{knn'}(j) = \infty, \forall n' \neq n$, meaning households can only access varieties in their residence. If shopping frictions do not vary by skill type $\tau_{knn'}(j) = \tau_{nn'} \forall k, j$ which I assume for the calibration of the model, results of this section are unaffected since spatial consumption patterns are independent of skill type. However, defining local demand faced by firms in a location and the price index faced by households become complex functions of geography when shopping frictions are finite outside the residence, which makes the exposition less tractable without conveying more intuition. I also assume that incomes of both types are exogenous.

Due to the preferences in expression (8) and implied firm mobility the price index of goods is a function of the local high skilled share x_n and real consumption U_{kn}. P_{kng} has the following property:

Proposition 2. *Taking M_n, $M_{n'}$ and x_n as given and $\sigma, \gamma > 1$, households' price index of goods consumption, $P_{kng}^{1-\gamma}$, is log-supermodular in real consumption U_{kn} and high-skilled share x_n or*

$$\frac{P_{HS,ng}}{P_{LS,ng}} < \frac{P_{HS,n'g}}{P_{LS,n'g}}$$

if $x_n > x'_n$.

Richer households have higher expenditure shares on income-elastic sectors and locations with a larger share of high skilled households attract disproportionately more varieties in such sectors. Hence, the relative price index of goods must be lower in more skilled neighborhoods compared to locations with more low skilled households. In equilibrium, the high-skilled share and real consumption are related through the location choice of households. Locations with lower relative goods prices attract more high skilled households. This, then, increases the high skilled share in the population and further reduces the relative price due to more local varieties in income-elastic sectors. Due to the interaction of location choice of households and firms, the model endogenously produces relative price differences that generates a pecuniary externality on residents.

For the proof of proposition 2 I first prove a two auxiliary results. The key variable summarizing underlying sorting patterns is the local expenditure share by skill group k in location n on goods from a sector j, $s_{knj} = s_{kng}\tilde{s}_{knj}$ and is described in the following proposition:

Proposition 3. *Given prices, the expenditure share of households of skill k in location n on goods of sector j, s_{knj}, is log-supermodular in real consumption U_{kn} and sector income elasticity parameter ν_j.*

Proof. The proof is straightforward and can be found in a similar form in Matsuyama (2019). Recall the expression for the expenditure share on goods from sector j in location n' by household k in n and taking logs

$$\log s_{knn'j} = \log a_g + \log \alpha_j + (\gamma - \eta) \log p_{knj} + (\eta - 1) \log I_k + (\epsilon_g + \nu_j) \log U_{kn} + (1 - \gamma) \log p_{nj}$$

Taking prices and nominal income as given, I take the derivative with respect to U_{kn}

$$\frac{\partial \log s_{knn'j}}{\partial U_{kn}} = \frac{1}{U_{kn}} \left(\epsilon_g + \nu_j + \frac{\gamma - \eta}{1 - \gamma} \bar{\nu}_{kn} \right)$$

Note that $s_{knn'j}$ is increasing in real consumption if $\epsilon_g + \nu_j > \frac{\gamma-\eta}{1-\gamma}\bar{\nu}_{kn}$ which captures the property that as household get richer they allocate more spending to sector with higher income elasticity. For any $\nu_1 > \nu_2$,

$$\frac{\partial \log s_{knn'1}}{\partial U_{kn}} - \frac{\partial \log s_{knn'2}}{\partial U_{kn}} = \frac{1}{U_{kn}}(\nu_1 - \nu_2) > 0.$$

This establishes log-supermodularity of $s_{knn'j}$ in U_{kn} and ν_j. The result holds by the same logic for $\tilde{s}_{knj}$. ∎

Proposition 3 states that as households get richer[1] they value goods from sectors with higher income elasticity relatively more and that the difference is increasing with real consumption (see Matsuyama (2019) for a similar argument). As a consequence, high-skilled households' expenditure is tilted towards income-elastic sectors relative to low-skilled households. The top-left graph of Figure A.1 shows a stylized graphical representation of this finding: I plot the log of expenditure shares for three sectors with decreasing income elasticity ($\nu_1 > \nu_2 > \nu_3$) on the vertical axis and household income on the horizontal axis. High-skilled households with income I_{HS} spend a larger fraction of income on the first sector and less on the other sectors in comparison to low-skilled households with I_{LS}.

To relate proposition 3 to firm profits in n, I can rearrange profits of all varieties in sector j and location n in equation (12) as a function of the share of high skilled residents x_n in local population L_n,

$$\frac{\Pi_{nj}}{L_n} = \frac{1}{\sigma}\left(s_{HS,nj} I_{HS} x_n + s_{LS,nj} I_{LS}(1 - x_n)\right).$$

Now, I can relate proposition 3 to average profits by resident of sector j according to the following corollary:

Proposition 4. *Given prices, total profits by resident of firms in sector j in location n is log-supermodular in high-skilled share x_n and sector income elasticity parameter ν_j.*

Proof. Given $U_{HS,n} > U_{LS,n}$ Proposition 3 implies for any $\nu_1 > \nu_2$

$$\frac{s_{HS,n1}}{s_{HS,n2}} > \frac{s_{LS,n1}}{s_{LS,n2}}.$$

With $I_k > 0, \forall k$

$$\frac{\pi_{HS,n1}}{\pi_{HS,n2}} > \frac{\pi_{LS,n1}}{\pi_{LS,n2}}$$

where $\pi_{k,nj} = s_{k,nj} I_k$. Hence, $\pi_{k,nj}$ is log-supermodular in x_n and ν_j. We want to show for any $x_n > x_n'$ and $\nu_1 > \nu_2$

$$\frac{\pi_{HS,n1}x_n + \pi_{LS,n1}(1 - x_n)}{\pi_{HS,n1}x_n' + \pi_{LS,n1}(1 - x_n')} > \frac{\pi_{HS,n2}x_n + \pi_{LS,n2}(1 - x_n)}{\pi_{HS,n2}x_n' + \pi_{LS,n2}(1 - x_n')}.$$

Note that the left-hand side is increasing in $\pi_{HS,n1}$ since $x_n > x_n'$. Applying the log-supermodularity

[1] I assume that real consumption is increasing in nominal income I_k.

of $\pi_{k,nj}$ we can write the left-hand side as

$$\frac{\pi_{HS,n1}x_n + \pi_{LS,n1}(1-x_n)}{\pi_{HS,n1}x'_n + \pi_{LS,n1}(1-x'_n)} > \frac{\frac{\pi_{HS,n2}}{\pi_{LS,n2}}x_n + (1-x_n)}{\frac{\pi_{HS,n2}}{\pi_{LS,n2}}x'_n + (1-x'_n)} = \frac{\pi_{HS,n2}x_n + \pi_{LS,n2}(1-x_n)}{\pi_{HS,n2}x'_n + \pi_{LS,n2}(1-x'_n)}.$$

This completes the proof. ■

Intuitively, since high-skilled households spend more on income-elastic sectors, locations with a larger share of high skilled residents offer larger profits to firms in income-elastic sectors relative to income-inelastic sectors. Applying equation (14) and Proposition 4 it follows immediately that the number of varieties M_{nj} in income-elastic relative to income-inelastic sectors in locations with more high skilled residents must be larger than in locations with a lower share whereby keeping prices and total residents equal.[2] We can conclude that M_{nj} is also log-supermodular in the high-skilled share x_n and sector income elasticity parameter ν_j. This implies: $\frac{M_{nj}}{M_{n'j}}$ is non-decreasing in ν_j if $x_n > x_{n'}$. This result establishes that firms offering varieties in income-elastic sectors collocate with high income residents. Top-right graph of Figure A.1 summarizes how the number of varieties M_{nj} increase faster in sector 1 (the highly elastic sector) than for the two less elastic sectors as the average income per resident in n on the horizontal axis increases.[3]

Next, I can combine Proposition 3 and Proposition 4 to characterize how residents respond to the distribution of varieties in a location and prove Proposition 2.

Proof. The proof uses results from Athey (2002) on monotone comparative statistics of sums of log-spm functions. I can write the goods price index as

$$P(U_{kn}, x_n)^{1-\gamma} = \sum_j \underbrace{\alpha_j U_{kn}^{\nu_j}}_{=f(U_{kn},\nu_j)} \underbrace{P_{nj}(x_n)^{1-\gamma}}_{=u(\nu_j,x_n)}$$

Theorem 1 in Athey (2002) states that iff $f(U_{kn}, \nu_j)$ is log-spm in U_{kn} and ν_j a.e. and $u(x_n, \nu_j)$ is log-spm in x_n and ν_j a.e. then $P(U_{kn}, x_n)^{1-\gamma}$ is log-spm in U_{kn} and x_n a.e. To show log-spm of $u(x_n, \nu_j)$ I start with equation (14) implies

$$\frac{M_{nj}}{L_n} = \frac{\pi_{nj}}{L_n f_j^e}.$$

By Proposition 4 $\frac{\pi_{nj}}{L_n f_j^e}$ is log-spm in x_n and ν_j, hence $\frac{M_{nj}}{L_n}$ is log-spm in x_n and ν_j.[4] Specifically for $x_n > x'_n$ and $\nu_1 > \nu_2$,

$$\frac{M_{n1}(x_n)}{M_{n1}(x'_n)} > \frac{M_{n2}(x_n)}{M_{n2}(x'_n)}.$$

[2] Profits are also increasing with total number of residents but at given expenditure shares and prices, in equal proportions for all sectors, such that only the composition of residents is relevant for relative sorting of varieties by sector.

[3] Note that with fixed income by type, the average income per resident is a sufficient statistic for x_n.

[4] Dividing by a positive constant f_j^e does not affect log-supermodularity.

Applying equation the price index corresponding to equation (8) under the assumption that shopping frictions are infinite outside n we can directly see that

$$\frac{P_{n1}(x_n)^{1-\gamma}}{P_{n1}(x_n')^{1-\gamma}} > \frac{P_{n2}(x_n)^{1-\gamma}}{P_{n2}(x_n')^{1-\gamma}}$$

and conclude that $P_{nj}(x_n)^{1-\gamma}$ is log-spm in x_n and ν_j.
Lastly, log-supermodularity of $f(U_{kn}, \nu_j)$ is given by Proposition 3. Hence, I can apply therorem 1 in Athey (2002) and conclude that $P(U_{kn}, x_n)^{1-\gamma}$ is log-spm in x_n and U_{kn}. ■

Proposition 2 combines the intuition of both earlier findings and is graphically depicted in the bottom graphs of Figure A.1.

C.3 Details on Model Inversion

The process to show Proposition 1 follows several steps.

1. With citywide sectoral revenue shares rs_{cj} and citywide income Y we can compute fixed cost of entry f_j^e

$$f_j^e = \frac{1}{\sigma} \frac{rs_{cj} Y}{M_j} \tag{C.1}$$

Note that the revenue shares already include fixed costs for Jth sector (as observed in the data).

2. Next, I solve for the matrix of wages per efficiency unit w_{kni}. Labor supply on a commuting link between n and i is $e_{kni} \lambda^W_{ki|n} L^R_{kn}$. Equalizing with labor demand by all sectors in i gives

$$w_{kni} \bar{e}_{kni} \lambda^W_{ki|n} L^R_{kn} = (\sigma - 1) \left(\frac{w_{kni}}{W_{ki}} \right)^{1-\psi} \sum_j \beta_j^k f_j^e M_{nj}$$

where I can replace $\bar{e}_{kni} = \gamma^W \left(\lambda^W_{ki|n} \right)^{\frac{-1}{\rho}} \left(\tau^W_{kni} \right)^{-1}$ and $W_{ki} = \left(\sum_n w_{kni}^{1-\psi} \right)^{\frac{1}{1-\psi}}$. Commuting probabilities are given by equation (1). Hence, I need to solve a system of $N \times N$ equations with $N \times N$ unknown wages. This type of system allows for a unique solution and can be solved via a fixed point algorithm, see Allen & Arkolakis (2014). Labor earnings are computed according to equation 2.

3. Once we have labor earnings from the previous step I can compute the citywide skill premium and transfers t_k. Total transfers are $Y - \sum_n \sum_k \tilde{I}_{kn} L^R_{kn}$ and citywide skill premium in labor earnings is $\frac{\sum_n \tilde{I}_{HSn} \lambda_{HSn}}{\sum_n \tilde{I}_{LSn} \lambda_{LSn}}$. Then, I compute t_k by keeping skill premium in income equal to skill premium in earnings. Income is then $I_{kn} = \tilde{I}_{kn} + t_k$.

4. With the results of the previous steps I jointly recover A_{nj} (as composites of As and demand shifters), $\bar{B}_{kn}$ and housing productivity $\bar{A}_{nH} = A_{nH}^{-\frac{1}{\mu}} P_Q$ using an iteration based on

a contraction mapping. I need to use firm counts M_{nj} (informs As) and populations L^R_{kn} (informs $\bar{B}_{kn}$). I normalize $a_h = 1$ w.l.o.g. First, we rewrite the price indices in terms of composite of A_{nj}, a_g and α_j with

$$\bar{A}_{nj} = A_{nj} a_g^{\frac{\theta}{\eta-1}} \alpha_j^{\frac{\theta}{\gamma-1}}$$

Rewrite sector price index as

$$p_{knj} =$$
$$a_g^{\frac{1}{\eta-1}} \alpha_j^{\frac{1}{\gamma-1}} \frac{\sigma}{\sigma-1} \left(\gamma^F\right)^{\frac{1}{1-\sigma}} M_j^{-\frac{1}{\theta}} \left(\sum_{n'} \left(\tau^S_{knn'}\right)^{1-\sigma} \left(r^C_{n'}\right)^{\beta^C_j(1-\sigma)} \left(\prod_k \left(w_{kn'}\right)^{\beta^k_j(1-\sigma)} \right) \bar{A}_{n'j}^{\frac{\sigma-1}{\theta}} M_{n'j}^{1-\frac{\sigma-1}{\theta}} \right)^{\frac{1}{1-\sigma}}.$$

Rearranging gives

$$\alpha_j p_{knj}^{1-\gamma} =$$
$$a_g^{\frac{1-\gamma}{\eta-1}} \underbrace{\left(\frac{\sigma}{\sigma-1} \left(\gamma^F\right)^{\frac{1}{1-\sigma}} M_j^{-\frac{1}{\theta}} \left(\sum_{n'} \left(\tau^S_{knn'}\right)^{1-\sigma} \left(r^C_{n'}\right)^{\beta^C_j(1-\sigma)} \left(\prod_k \left(w_{kn'}\right)^{\beta^k_j(1-\sigma)} \right) \bar{A}_{n'j}^{\frac{\sigma-1}{\theta}} M_{n'j}^{1-\frac{\sigma-1}{\theta}} \right)^{\frac{1}{1-\sigma}} \right)^{1-\gamma}}_{\tilde{p}_{knj}^{1-\gamma}}. \tag{C.2}$$

We get

$$\tilde{p}_{knj}^{1-\gamma} = a_g^{\frac{1-\gamma}{1-\eta}} \alpha_j p_{knj}^{1-\gamma}.$$

Next, we rewrite the goods price index in the same way

$$P_{kng} = \left(\sum_j \left(U^{\nu_j}_{kn}\right) \alpha_j p_{knj}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} = \left(\sum_j \left(U^{\nu_j}_{kn}\right) a_g^{\frac{1-\gamma}{\eta-1}} \tilde{p}_{knj}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} = a_g^{\frac{1}{\eta-1}} \left(\sum_j \left(U^{\nu_j}_{kn}\right) \tilde{p}_{knj}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}.$$

We can write

$$a_g P_{kng}^{1-\eta} = \underbrace{\left(\sum_j \left(U^{\nu_j}_{kn}\right) \tilde{p}_{knj}^{1-\gamma} \right)^{\frac{1-\eta}{1-\gamma}}}_{\tilde{P}_{kng}^{1-\eta}}. \tag{C.3}$$

Lastly, rewrite the overall price index

$$P_{kn} = \left(\left(r^R_n\right)^{1-\eta} + a_g P_{kng}^{1-\eta} \right)^{\frac{1}{1-\eta}} = \left(\left(r^R_n\right)^{1-\eta} + \tilde{P}_{kng}^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{C.4}$$

The number of varieties in each sector/location informs $\bar{A}_{nj}$ so

$$\frac{M_{nj}}{M_j}\Pi_j = \left(\frac{\sigma}{\sigma-1}\left(r_n^C\right)^{\beta_j^C}\prod_k \left(w_{kn}\right)^{\beta_j^k}\right)^{-\theta} \underbrace{A_{nj}\left(\sum_{n'}\sum_k \left(\tau_{kn'n}^S\right)^{1-\sigma} p_{kn'j}^{\sigma-1}\tilde{s}_{kn'j}s_{kn'g}I_{kn'}L_{kn'}^R\right)^{\frac{\theta}{\sigma-1}}}_{\breve{\pi}_{nj}} \tag{C.5}$$

where we can write the left-hand side as

$$\frac{M_{nj}}{M_j}\left(\frac{f_j^e}{\gamma^F}\right)^{\frac{\theta}{\sigma-1}}$$

which is observable in the data and previous steps. The term $\breve{\pi}_{nj}$ is dependent on A_{nj} so we need to rewrite it using the above expressions

$$\begin{aligned}\breve{\pi}_{nj} &= A_{nj}\left(\sum_{n'}\sum_k \left(\tau_{kn'n}^S\right)^{1-\sigma} p_{kn'j}^{\sigma-\gamma}\alpha_j P_{kn'g}^{\gamma-\eta}a_g P_{kn'}^{\eta-1-\nu_j}I_{kn'}^{1+\nu_j}L_{kn'}^R\right)^{\frac{\theta}{\sigma-1}} \\ &= \underbrace{A_{nj}a_g^{\frac{\theta}{\eta-1}}\alpha_j^{\frac{\theta}{\gamma-1}}}_{\bar{A}_{nj}}\left(\sum_{n'}\sum_k \left(\tau_{kn'n}^S\right)^{1-\sigma} \tilde{p}_{kn'j}^{\sigma-\gamma}\tilde{P}_{kn'g}^{\gamma-\eta}P_{kn'}^{\eta-1-\nu_j}I_{kn'}^{1+\nu_j}L_{kn'}^R\right)^{\frac{\theta}{\sigma-1}}\end{aligned}$$

The system is recast in terms of $\bar{A}_{nj}$. Within the same step I compute real consumption which enters P_{kng} with $U_{kn} = I_{kn}/P_{kn}$.
With real consumption U_{kn} I can solve for B_{kn} using equation (4). Once I have B_{kn}, I can invert the spillover function (19) to arrive at $\bar{B}_{kn}$. I can normalize $\bar{B}_{kn^*} = 1, \forall k$ in some neighborhood n^*. Lastly, I calculate rents r_n in each iteration step using the fact that I observe tract-level expenditure shares on housing in the data and incomes for the previous steps. Once I have P_{kn} I can calculate floorspace demand. Due to arbitrage in the housing market computing residential rents is sufficient for tract-level rents.

5. In the last step I can compute $\bar{A}_{nH}$, H_n^R, H_n^C, commuting and shopping flows using tracts' land endowments and recovered rents.

In models with non-homothetic preferences economic choices of agents are not invariant to normalizing nominal income, since relative consumption does not respond proportionally to income changes - the key mechanism of non-homothetic preferences. I overcome this issue by normalizing the economy to citywide expenditure share on goods and citywide expenditure shares by sector, which pins down average real consumption. Model-implied variation in expenditure shares across space and skill groups reflect deviations from this average due to price differences and skill premium that inform location choices of households through the lens of the model. However, the model calibration ensures that the spatial distribution of expenditure shares is invariant to the level of nominal income, which implies that consumption elasticities as defined in C.1 are also invariant. Hence, model counterfactuals are independent of initial level of nominal income. In principle, it is possible to target higher order moments like the spatial distribution of expenditure shares on goods or housing or average shares by skill group. However, I chose to keep the model inversion as parsimonious as possible and instead apply the limited available information on higher order moments to assess the model fit.

C.4 Solution to Counterfactuals

I solve for counterfactuals using an iterative algorithm. First, I define the equilibrium more formally:

The equilibrium of the economy is defined by a distribution of households by neighborhood and skill group $\{L^R_{kn}\}$ with $\sum_{n'\in\{1,2,\dots,N\}} L^R_{kn'} = L_k, \forall k$; a distribution of commuting flows $\{L^W_{kni}\}$ with $\sum_{i\in\{1,2,\dots,N\}} L^W_{kni} = L^R_{kn}, \forall n,k$; a distribution of firms by neighborhood and sector $\{M_{nj}\}$ with $\sum_{n'\in\{1,2,\dots,N\}} M_{n'j} = M_j, \forall j$; mass of firms in sectors $\{M_j\}$; residential housing $\{H^R_n\}$; commercial housing $\{H^C_n\}$; prices in all sectors and neighborhoods $\{p_{knn'j}\}$; sector price indices $\{p_{knj}\}$; goods price indices $\{P_{kng}\}$; overall price indices $\{P_{kn}\}$; expected incomes $\{I_{kn}\}$; wages $\{w_{kni}\}$; wage indices $\{W_{kn}\}$; rents $\{r^R_n, r^C_n\}$ and transfers $\{t_k\}$ such that:

1. $$L^R_{kn} = \frac{B_{kn}U^{\kappa}_{kn}}{\sum_{n'} B_{kn'}U^{\kappa}_{kn'}} L_k,$$

   where

   - $U_{kn} = I_{kn}P^{-1}_{kn}$
   - $P_{kn} = \left(\left(r^R_n\right)^{1-\eta} + \tilde{P}_{kng}\right)^{\frac{1}{1-\eta}}$ as defined in (C.4),
   - $\tilde{P}_{kng} = \left(\sum_j \left(U^{\nu_j}_{kn}\right) \tilde{p}^{1-\gamma}_{knj}\right)^{\frac{1-\eta}{1-\gamma}}$ as defined in (C.3),
   - $\tilde{p}^{1-\gamma}_{knj}$ as defined in (C.2),
   - $I_{kn} = \gamma^W \left(\sum_{i'} w^{\rho}_{kni'} \left(\tau^W_{kni'}\right)^{-\rho}\right)^{1/\rho} + t_k,$
   - And B_{kn} is defined according to (19): $B_{kn} = \bar{B}_{kn}\prod_{n'}\left(\frac{L^R_{HS,n'}}{L^R_{LS,n'}}\right)^{\delta_k\omega_{nn'}}$.

2. Equation (C.5) implies

   $$M_{nj} = \left(\frac{\sigma}{\sigma-1}\left(r^C_n\right)^{\beta^C_j}\prod_k \left(w_{kn}\right)^{\beta^k_j}\right)^{-\theta} \bar{A}_{nj}\left(\sum_{n'}\sum_k \left(\tau^S_{kn'n}\right)^{1-\sigma} \tilde{p}^{\sigma-\gamma}_{kn'j}\tilde{P}^{\gamma-\eta}_{kn'g}P^{\eta-1-\nu_j}_{kn'} I^{1+\nu_j}_{kn'} L^R_{kn'}\right)^{\frac{\theta}{\sigma-1}}\left(\frac{\gamma^F M_j}{f^e_j}\right)^{\frac{\theta}{\sigma-1}}$$

   where

   - $M_j = \sum_n M_{nj}$

3. Wages w_{kni} satisfy

$$\gamma^W \frac{w_{kni}^{\rho}\left(\tau_{kni}^W\right)^{-\rho}}{\left(\sum_{i'} w_{kni'}^{\rho}\left(\tau_{kni'}^W\right)^{-\rho}\right)^{1-\frac{1}{\rho}}} L_{kn}^R = (\sigma-1)\frac{w_{kni}^{1-\psi}}{\sum_n w_{kni}^{1-\psi}} \sum_j \beta_j^k f_j^e M_{nj}$$

4. Rents r_n satisfy $r_n^R = r_n^C = r_n$ and

$$r_n^{\frac{1}{1-\mu}} \bar{A}_{nH}^{\frac{\mu}{\mu-1}} Z_n \mu^{\frac{\mu}{1-\mu}} = \left(r_n^H\right)^{1-\eta} \sum_k P_{kn}^{\eta-1} I_{kn} L_{kn}^R + (\sigma-1)\gamma^F \sum_j \beta_j^C \Pi_j^{\frac{\sigma-1}{\theta}} M_{nj}$$

The equilibrium system of equations is defined in terms of equilibrium prices $\{w_{kni}\}$, $\{r_n\}$ and allocations $\{L_{kn}^R\}$ and $\{M_{nj}\}$. This system is just-identified as there is one equation per unknown variable.

To solve the system for counterfactual changes I follow a simple iterative algorithm:

1. Make initial guesses for $\{w_{kni}^0\}$, $\{r_n^0\}$, $\{L_{kn}^{R\ 0}\}$ and $\{M_{nj}^0\}$. For example, observed allocations in the data and prices as recovered from the inversion step make good initial guesses.

2. Plug into equations 1.-4. above (rearranged in an arbitrary way such that eq. variables appear on the LHS, but also potentially on the RHS) and solve for new values $\{w_{kni}'\}$, $\{r_n'\}$, $\{L_{kn}^{R\ \prime}\}$ and $\{M_{nj}'\}$.

3. Calculate absolute percent deviation between variables x^0 and x' if below some tolerance STOP. If above continue.

4. Update variable x according to $x^1 = \chi x^0 + (1-\chi)x'$ with $\chi \in (0,1)$

5. Repeat steps 2. through 4. until variables have converged.

References for Online Appendix

Allen, Treb, & Arkolakis, Costas. 2014. Trade and the Topography of the Spatial Economy. *The Quarterly Journal of Economics*, **129**(3), 1085–1140.