

Income Growth and the Distributional Effects of Urban Spatial Sorting*

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Abstract

We explore the impact of rising incomes at the top of the distribution on changes in spatial sorting patterns within large US cities. We develop and quantify a spatial model of a city with heterogeneous agents, heterogeneous neighborhoods of endogenous quality, and non-homothetic preferences for locations with different amenities. As the rich get richer, their increased demand for luxury amenities available downtown drives housing prices up in downtown areas. The poor are made worse off, either being displaced or paying higher rents for amenities that they do not value as much. Endogenous provision of private amenities amplifies the mechanism, while public provision of other amenities in part curbs it. We quantify the corresponding impact on well-being inequality. Through the lens of the quantified model, the change in income distribution between 1990 and 2014 lead to neighborhood change and spatial resorting within urban areas that increased the welfare of richer households relative to that of poorer households by an additional two percentage points on top of their differential income growth.

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1 Introduction

Over the last three decades income inequality in the United States has grown sharply, with income growth disproportionately concentrated at the top of the earnings distribution. During this same time period, the urban cores of American cities have attracted more college educated and higher income individuals.¹ This latter trend has accompanied a renewed discussion of neighborhood change within many U.S. cities.²

In this paper, we explore the link between rising incomes of the rich and the net in-migration of richer households to the downtown areas of American cities, since 1990. We set out to trace the effects of this change in spatial sorting on well-being inequality. Our analysis of within-city spatial sorting is guided by two empirical regularities. First, demand system estimates suggest that local urban amenities, like restaurants or entertainment options, tend to be relative luxury goods.³ Second, downtown areas of major cities have a higher density of such amenities.

We build a model of residential sorting within a city, which embeds these two empirical regularities. The model features heterogeneous agents and heterogeneous neighborhoods. As the incomes of the rich increase, their demand for urban amenities rises, and they choose to reside in downtown urban areas to be closer to these amenities. In turn, as the income composition of downtown urban areas changes, the supply of high quality urban amenities responds endogenously. This fuels the in-migration of the rich further. It also drives up downtown rents which imposes a pecuniary externality on low income residents of downtown urban areas. Given the empirical fact that most poor residents in downtown urban areas are renters, they do not reap the capital gains of increasing house prices. Poorer residents have the choice between paying higher rents for a bundle of amenities that they do not value as much, and moving out of the downtown urban area.

We quantify the model and find that increased incomes of the rich are, in part, causing a phenomenon that looks like urban gentrification. In areas initially populated by poorer residents, the in-migration of higher income residents causes the amenity mix of neighborhoods to endogenously change.⁴ We use the model to estimate the economic impact of the increased incomes of the higher income households, mediated by these spatial sorting responses, on well-being inequality. We find that, because of changes in neighborhood quality and prices imposed by the in-migration of the rich, welfare estimates of increased income inequality are *understated* when spatial sorting responses are

¹See e.g. Couture and Handbury (2017) and Baum-Snow and Hartley (2017).

²For instance, in response to the influx of higher income residents into downtown areas, some municipalities, like New York City, have implemented policies to slow down neighborhood gentrification. See “New York Passes Rent Rules to Blunt Gentrification”, New York Times, March 22, 2016.

³For example, Aguiar and Bills (2015) estimate that restaurant meals and non-durable entertainment are among the goods with the highest income elasticities.

⁴Throughout the paper, we often use “neighborhood change” for low income neighborhoods and “gentrification” interchangeably. We realize that gentrification is a complex process with many potential definitions and drivers. Our interpretation is closest to the definition in the Merriam-Webster dictionary that defines gentrification as “the process of renewal and rebuilding accompanying the influx of middle-class or affluent people into deteriorating areas that often displaces poorer residents.” Our paper is not intended to explore all potential underlying causes of neighborhood gentrification. Rather, we wish to focus on the dimension of gentrification that follows the rise in top incomes. Specifically, we focus on the interaction of rising top incomes, non-homothetic preferences for urban amenities, and endogenous spatial responses.

ignored. Our estimates suggest that welfare differences between those in the top decile of the income distribution and those at the bottom decile of the income distribution increased by an additional 2.0 percentage points between 1990 to 2014, once accounting for spatial responses, compared to a baseline income gap increase of 22 percentage points during this time period. Furthermore, we find that the resulting neighborhood change within downtown areas in response to the rising incomes of the rich *reduced* the well-being of those renters in the bottom decile of the income distribution on net by 0.50 percent in consumption equivalent terms.

Our paper proceeds in four parts. We first document a set of stylized facts on the residential choices, within large US cities, of households with different incomes, which our model aims to match. Focusing on the 100 largest CBSA's, we show that the propensity to live in downtown areas (as opposed to the suburbs) is U-shaped in resident income. On the one hand, poorer residents are more likely to live downtown than middle-income residents. On the other hand, as resident family income increases above \$100,000 (in 1999 dollars), the propensity to live downtown becomes monotonically increasing in income. This fact persists across different survey years of the U.S. Census, for a variety of definitions of downtown urban areas and income measures, as well as conditioning on household type, race, and age. While stable in prior years, the relationship between income and the share of households living downtown has become steeper for the richest households between 1990 and 2014. This suggests an increasing propensity for the rich to live in downtown urban in recent years, even conditional on income. Across cities, we find that this urbanization of the rich was more pronounced in CBSAs that saw greater income growth.

Second, we then propose a new model of within city residential choice and its variation with household income. The model is rich enough to match the stylized facts presented above, and aims to formalize the link between income inequality growth and neighborhood change. It features heterogeneous households who differ in their level of income and in their idiosyncratic tastes for residential location. They choose where to live among neighborhoods that vary in how attractive they are. A key mechanism in the model is that desirable neighborhoods are luxury goods: in equilibrium, richer households disproportionately choose to live in high quality-high cost neighborhoods. The desirability of a neighborhood is determined by two main elements. First, it is shaped by public amenities, like parks or schools. We assume that these depend on the location of the neighborhood (downtown or suburbs) and are non-rival within each location. Public amenities are financed, within each location, by a local government that collects property taxes. Second, the desirability of a neighborhood is shaped by the quality of private amenities such as restaurants and entertainment options, as well as the quality of the housing stock. Households value the quality of the private amenities of their own neighborhood, as well as access to a variety of private amenities offered in other places. Therefore, the *density* of urban amenities in a location increases the desirability of this choice.⁵ Private amenities of each quality level are provided endogenously by developers, who build differentiated neighborhoods featuring housing units and private amenities.

⁵In the model, neighborhoods are also more attractive if there is a higher variety of neighborhoods to choose from - guaranteeing a better match with one's own idiosyncratic tastes.

Households make their residential choice trading off higher desirability of a neighborhood with higher cost of living there. In the model, this cost depends on housing prices, taxes and commuting costs to work.

The model accommodates the equilibrium that we observe in the data where downtown areas are disproportionately populated by both very low and very high earners. Low income households minimize commuting costs to jobs by residing downtown mostly in low-quality neighborhoods. At the same time, higher income households are attracted downtown by the density of high-quality neighborhoods offered there. Finally, middle income individuals are over-represented in the mid-range options offered by suburbs, with good quality public amenities and reasonable costs. Starting from this baseline equilibrium, we study the impact of a change in the income distribution.

With an influx of high-income households, the relative demand for high-quality neighborhoods downtown increases, putting upwards pressure on housing prices. Poorer incumbent households either remain in low quality neighborhoods downtown and see their rents increase or choose to migrate out. On average, even accounting for the fraction of households that own their own home, they are made worse off relative to the rich. This mechanism is further amplified by the endogenous provision of high quality downtown neighborhoods by developers, in response to higher demand which in turn makes downtown even more attractive to high earners. This type of amplification mechanism is not as pronounced in the suburbs, which grow through sprawl rather than density as they have a higher housing supply elasticity than urban areas. As a result, as the city grows, downtown increases its comparative advantage compared to the suburbs in providing access to a dense variety of residential amenities. Finally, *public* amenities also react to, and feed back into, these changes in spatial sorting. As downtown gets richer, more tax is collected leading to an increase in public amenities for all downtown residents. Incumbent households in low quality neighborhoods downtown benefit from this spillover. At the same time though, as low quality downtown neighborhoods are made more attractive by this channel, rents tend to increase. Ultimately, low quality neighborhood downtown become relatively more of a luxury choice compared to their suburban alternatives.

In the third part of the paper, we take the model to the data. To that end, we first bring novel data to bear to estimate the key elasticities of the model. In particular, to estimate the elasticity of substitution between different residential choices, we exploit how the spatial sorting response of individuals at differing levels of income respond differentially to a CBSA-wide income shock. To measure neighborhood quality and estimate our amenity demand system, we use a rich database of smartphone location data, that allows us to trace the extent to which individuals of differing income levels travel to different venues that provide urban amenities (restaurants, bars, theaters, gyms, etc.). By estimating an amenity gravity equation, we can discipline the magnitude of gains from density in amenity consumption. We also use existing micro data sources to pin down other key parameters of the model. In a second stage, armed with these parameters, we then calibrate the full model by a method of moments procedure. The procedure targets the whole U-shaped distribution of the propensity to reside downtown as a function of income, as well as the relative

housing prices between different neighborhoods types and location, both in 1990. We show that the model can replicate these salient cross-sectional features of the data.

We finally use the quantified model for welfare and counterfactual analysis. In order to isolate how much the rising incomes of the rich can explain of the change in spatial sorting patterns observed in the data between 1990 and 2014, we feed into the model a single (but complex) shock: the observed change in income distribution over that time period, which we refer to below as the “income inequality shock”. We then compute the corresponding new spatial equilibrium. We find that increases in the incomes of high income individuals largely contributed to the changing within-city spatial sorting patterns by income levels in the U.S. during the last three decades. Using the structure of the model, we compute the corresponding welfare effects of the income inequality shock, mediated by spatial responses (prices, neighborhood quality, and spatial sorting changes), at all levels of income. As reported at the beginning of the introduction, we find that the income inequality shock triggered an even larger increase in well-being inequality, once spatial sorting responses are taken into account.

These large neighborhood changes in US cities have sparked a debate and a renewed interest in policy circles for policies aiming at curbing gentrification and keeping city centers socially diverse. Our model can be used to assess the potential effect of implementing such policies. For instance, we simulate a policy in which a specific tax on high-quality neighborhoods downtown is levied, and the tax collected is used to directly subsidize housing downtown for the poor, keeping housing more affordable there. We find that if such policies can be effective in shaping the income mix of urban residents, their well-being effects are quantitatively limited. They are far from overturning the increase in well-being inequality that we found for 1990-2014 in our quantification exercise.

2 Related Literature

Our paper is related to several lines of research. A growing literature studies the determinants and consequences of neighborhood change. Empirical studies have argued that neighborhood change in the U.S. has followed a change in hours worked by high skill workers (Edlund et al., 2016; Su, 2017), a decline in urban crime (Ellen et al., 2017), and a rising value of local amenities (Baum-Snow and Hartley, 2017; Couture and Handbury, 2017). Our paper isolates quantitatively the role played by an increase in top income inequality, combined with a change in urban amenities, without excluding these other channels which can be nested in our model. In that sense, the paper is related to Guerrieri et al. (2013) who exploit cross-city variation to document that neighborhoods within a city endogenously gentrify in response to a city wide income shock. Regarding the consequences of neighborhood change, the literature has found little evidence of *short-run* displacement of poorer households out of gentrifying neighborhood⁶ and has found that gentrifying neighborhoods experience job gains away from manufacturing, (Lester and Hartley, 2014), rising commute times (Meltzer

⁶See, for example, Vigdor et al. (2002); Lance Freeman (2005); McKinnish et al. (2010); Ellen and ORegan (2010); Ding et al. (2016); Brummet and Reed (2018). Waights (2014), however, finds evidence the poor renters in the UK are more likely to exit neighborhoods with rapidly rising educational achievement.

and Ghorbani, 2017), and decline in crime (Autor et al., 2017). Compared to this literature, we use a structural approach to study the *long-run* consequences of neighborhood change on spatial sorting and well-being inequality.

We connect with an extensive literature that studies the rise in income inequality (see e.g., Piketty et al. 2018) by exploring how much the shift in the top of the income distribution can explain neighborhood change. In an early contribution to this line of research, Gyourko et al. (2013) show that the rising number of rich households nationally explains some of the rapid rise in house prices and income in "superstar" cities. Contemporaneous to our paper is Fogli and Guerrieri (2017). Like us, they connect income inequality with changes in spatial sorting patterns, but their analysis is focused on the consequences of increase in segregation on educational outcomes. Also contemporaneous to our work is Su (2017), who studies the impact of rising value of time for high-skilled worker on location choices and land prices, and Berkes and Gaetani (2018) who study the impact of patent intensity on neighborhood income segregation. Our work focuses on a different channel by proposing and estimating a theory of the endogenous provision of luxury urban amenities. Our focus on urban amenities follows the insight of Glaeser et al. (2001): the comparative advantage of cities is not only in productivity, but is also to offer a variety of consumption opportunities. Diamond (2016) shows that across cities, amenities respond endogenously to the composition of residents. As workers of different skills value these urban amenities differently, well-being inequality is impacted. We follow her insight and study sorting patterns and well-being inequality *within* a city and show how this leads to neighborhood change akin to gentrification.⁷

Finally, in terms of methodology, we propose a new model of the internal structure of a city, which features non-homothetic location decisions over the full distribution of incomes within a representative city. Our model builds on recent developments in quantitative spatial economics, reviewed in Redding and Rossi-Hansberg (2017), more specifically on papers studying the internal structure of cities. Ahlfeldt et al. (2015), Redding and Sturm (2016), and Allen et al. (2015) have proposed such quantitative models with an application to Berlin, London and Chicago, respectively. We take a more stylized approach aimed at modeling a representative city rather than a specific city. This approach allows us to endogenize the quantity and sprawl of neighborhoods of a city, when neighborhood boundaries are typically fixed and exogenous in these models. The framework retains the tractability and quantifiability of spatial models, which allows us to take it to the data.⁸ Our model builds on Fajgelbaum et al. (2011)'s international trade model with non-homothetic preferences which we extend and adapt to an urban context, when spatial models traditionally feature homogeneous workers with homothetic preferences. A notable recent exception is Tsivanidis (2018) who uses a spatial sorting model with heterogeneous residents to analyze the distributional effects of a new urban transit infrastructure investment in Bogota.⁹

⁷See also Couture (2016), Murphy (2017) and Su (2018) for evidence that cities provide valuable access to non-tradable service variety.

⁸Gaigne et al. (2017) extend a classic linear polycentric city model, with jobs and amenities exogenously given at different locations on the line. Non-homothetic preferences generates heterogeneous spatial sorting.

⁹Turning to spatial equilibrium models of a country, rather than a city, Peters et al. (2018) include non-homothetic preferences in a country-wide spatial equilibrium model to study the heterogenous impact of structural change across

3 Motivating Facts

In this section, we document that location choices, within a city, systematically vary with income: there is strong *spatial sorting* within U.S. cities. Specifically, we document that these spatial sorting patterns display an interesting non-monotonic relationship with income. These stylized facts motivate our development of a residential choice model with non-homothetic preferences, in the next section.

3.1 Data

The stylized facts we report below are based on Census data from the 1970, 1990, and 2000 U.S. Censuses, as well as from the 2012-2016 American Community Surveys (ACS), taken from the Integrated Public Use Micro-data Series (Ruggles et al., 2018). Specifically, we aggregate microdata from the 1% IPUMS sample in 1970 and from the 5% IPUMS sample in 1990, 2000, and 2012-2016. We refer to the 2012-2016 pooled ACS data as the 2014 ACS. We also use census tract level data published by the National Historical Geographic Information System (NHGIS). All data are interpolated to constant 2014-boundary CBSAs using the Longitudinal Tract Data Base (LTBD). In what follows, all income measures are CPI-adjusted to 1999 dollars. With this data, we measure the location choice of households with differing levels of income.

Central to our analysis is the notion of the dense urban center of a CBSA, which we refer to as “downtowns”, “urban areas”, or “urban centers” interchangeably in the paper. Our baseline definition of an urban center is as follows. In each CBSA, we focus on the CBSA’s main city, and within this main city on its city center.¹⁰ We then classify as downtown the set of tracts closest to the city center that accounted for 10 percent of the CBSA’s population in 2000. This defines a spatial boundary of downtown, which we keep constant across all years. For each CBSA, we refer to all remaining non-downtown tracts as being *suburban* tracts: tracts are either classified as downtown (D) or suburban (S). Note that our notion of the downtown area of a city is measured in population units, as opposed to distance, given that CBSAs differ in size and density. Our key motivating facts are robust, however, to alternative definitions of downtown areas, including defining downtown as census tracts with centroids within a three mile radius of the city center as in Baum-Snow and Hartley (2017). Appendix E features maps of New York, Chicago, Philadelphia, San Francisco, Boston, and Las Vegas where tracts are classified as downtown and suburban based on our definition.

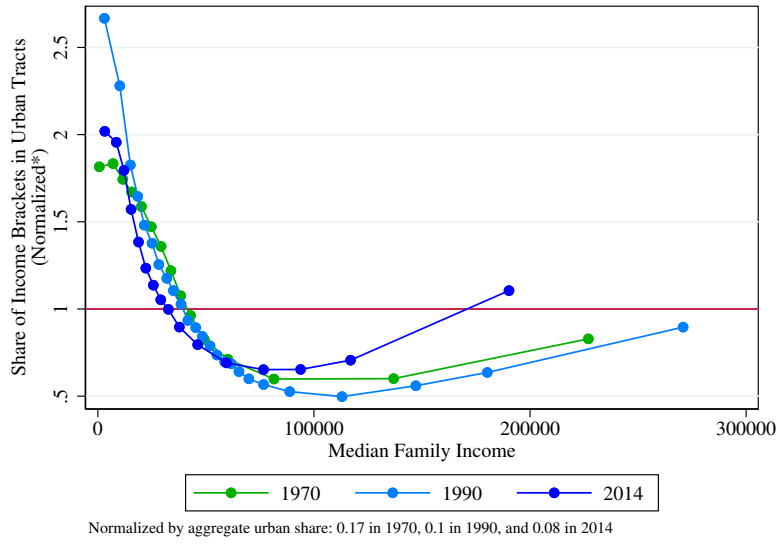
3.2 Downtown Residential Propensity and Household Income

We are interested in understanding how location choices, within a city, systematically vary with income. Figure 1 summarizes the Engel curve for residing downtown. It shows the relative propen-

US counties, and Fajgelbaum and Gaubert (2018) study optimal spatial policies in models with heterogeneous workers who have heterogeneous preferences over endogenous city amenities.

¹⁰We define the city center of each CBSA using the locations provided by Holian and Kahn (2012), who use the coordinates returned by Google Earth for a search of each CBSA’s principal city.

Figure 1: Downtown Residential Income Propensity by Income



Note: Table uses Census data on family income for the 100 largest CBSAs in 1970, 1990, and 2014. Urban tracts consists of all tracts closest to the city center that account for 10% of a CBSA’s population in 2000. Each dot in the Figure corresponds, on the x-axis, to the median family income within each Census bracket. We compute this median using IPUMS microdata for the corresponding year in the 100 largest CBSAs. All incomes are in real 1999 dollars.

sity of families to reside downtown by income, and its evolution over time. Each point represents the share of families, in a given census income bracket, that resides downtown in a given year – normalized by the share of all families that reside downtown that year.¹¹ The x-axis features the median family income for that bracket in the same year, in 1999 dollars, computed using IPUMS micro data: the number of points on the graph is limited by the number of income brackets reported by census for tract-level information.

Figure 1 reveals an interesting pattern: the propensity to reside downtown is a U-shaped function of income. To the left of the graph, we see that lower income families are much more likely to live in urban areas than other income groups. Families earning \$25,000 a year (in 1999 dollars) in 1970, 1990, and 2014 were between 1.5 and 2 times more likely to live downtown than other households. The propensity to live downtown then declines with income: middle-income families have the highest likelihood of living in the suburbs. However, for income above roughly \$100,000, the patterns reverses, and the propensity to live downtown starts to *increase* with income. Importantly, this U-shaped sorting pattern is not a new phenomenon. It is present in 1970, 1990, and 2014. The second interesting pattern displayed by figure 1 is apparent when comparing the curves over time. The uptick of the propensity to live downtown for high income families has become starkly more pronounced between 1990 and 2014. At the same time, the over-representation of the poorest households downtown has become less pronounced.

¹¹This normalization allows to abstract from the suburbanization of the population as a whole over this period. The share of families at all income levels that live downtown was 0.1 in 2000 – by construction of our downtown areas, but was 0.17 in 1970 and 0.08 in 2014

We note that these facts are robust to the definition of an urban area, CBSA sub-samples, and the use of household income rather than family income. One may think that these U-shape patterns reflect demographic characteristics that are correlated with income, and/or that the changes in the U-shape pattern over time simply reflect demographic shifts that are correlated with income and that took place between 1990 and 2014. For instance, Couture and Handbury (2017) find that solos and childless couples have a higher propensity to live downtown than families with children, and that they represent a rising share of the young and college-educated population. We find that these U-shape patterns and their evolution are largely invariant to controlling for socio-demographic characteristics such as age, race, and household composition. This suggests that the propensity of the rich to reside downtown and, in particular, the reinforcement of this pattern between 1990 and 2014 are not explained simply by demographic shifts. One of the questions we are interested in and study in the next sections of the paper is: how much of this change in the pattern of spatial sorting within cities between 1990 and 2014 can be traced back to the change in the *income distribution* and the disproportional increase of incomes at the top that took place over that period?

3.3 CBSA Income Growth and Changing Spatial Sorting by Income

If changes in the income distribution leads to spatial sorting changes, then one would expect that cities that experienced faster income growth over the period also experienced more changes in the sorting patterns of richer households. We provide suggestive evidence that this is the case using cross-city variation in the two stylized facts above.

To summarize the shift in the right-hand side of the U-shape in each city, we compute the 1990-2014 growth in the propensity of households with incomes greater than \$70,000 to reside downtown in each CBSA, relative to the growth in the propensity of all households to reside downtown in that CBSA.¹² We plot this growth against the CBSA-level growth in average household income over the same period. Figure 2 shows that CBSAs with higher aggregate income growth saw higher increases in the over-propensity of high income households to reside downtown. A 10 percent increase in CBSA income during the 1990-2014 period was associated with a 13 percent increase in the over-representation of richer households downtown.

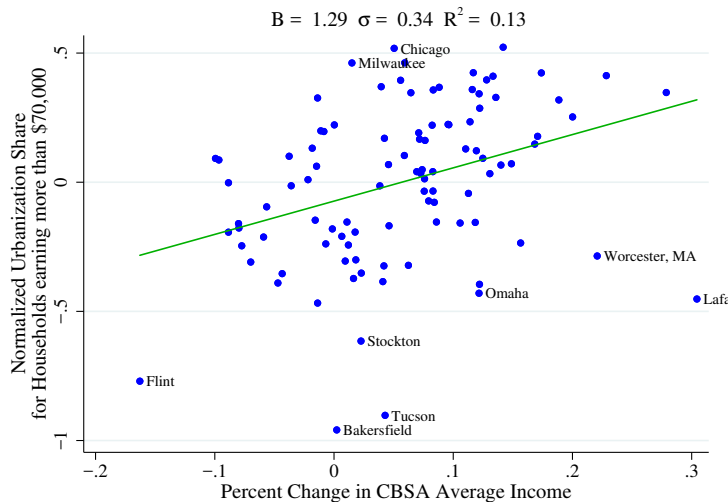
This correlation suggests that shifts in the income distribution observed during the 1990-2014 period may be a quantitatively important factor in drawing higher income individuals into downtown areas of major cities. Below, we develop and estimate a model that formalizes this link, and allows to quantify it.

4 Model

We propose here a model of a city which is flexible enough to capture the salient feature of the data, yet stylized enough to be a model of a *representative* city rather than matching quantitatively one

¹²We choose income greater than \$70,000 as the cut off because that is roughly the inflection point of the U-shape in Figure 1. Household income levels at the tract level come in bracketed form, so we use all brackets containing individuals with income greater than \$70,000.

Figure 2: Richer Household Propensity to Live Downtown in Response to a CBSA Level Change in Income 1990-2014



Note: Each observation in the figure is one of the 100 largest CBSAs. On the x-axis is the average CBSA real household income growth between 1990 and 2014. On the y-axis is change in the share of individuals earning \$70,000 or more residing downtown relative to the average individual between 1990 and 2014. A simple weighted regression through the scatter plot (where the weights are the CBSA 1990 population) yields a slope coefficient of 1.29 with a standard error of 0.34.

specific city. A city is comprised of two parts, a central district which we call “Downtown” and the rest of the city which we call the “Suburbs.” Households with different income levels choose their location of residence. Downtown offers easier access to jobs while the suburbs have nicer public amenities at the cost of a longer commute. In both areas, private developers develop neighborhoods featuring housing and retail outlets. The development of a richer variety of private urban amenities is fueled downtown by economies of density. Non-homotheticities in the consumption of urban amenities and in transportation leads to the sorting of heterogeneous households in different parts of the city.¹³ Downtown has an over-representation of both extremes of the income distribution. The model builds on Fajgelbaum et al. (2011) which we adapt to an urban context and extend to feature two sources of non-homotheticities.

4.1 Model setup

4.1.1 Choice of neighborhood

The city is comprised of neighborhoods indexed by r . Households choose a neighborhood where to live. A neighborhood r is characterized by the part of the town where it is located, downtown or the suburbs, as indexed by $n \in \{D, S\}$. Within these two broad areas, neighborhoods also differ by the quality of their housing stock and private amenities. Specifically, there are high quality

¹³Lower commute cost, and in particular the availability of transit, is the standard explanation for the over-representation of the poor in urban areas, see for instance LeRoy and Sonstelie (1983) and Glaeser et al. (2008). Modeling the endogenous development of luxury urban amenities is a contribution of our paper.

(H) and low quality (L) neighborhoods as indexed by $j \in \{H, L\}$.¹⁴ Within each level of quality, neighborhoods r are further differentiated horizontally.

4.1.2 Preferences

Households who live in neighborhood r of type (n, j) derive utility from the consumption of a freely traded composite good c , private urban amenities a consumed in different parts of the city, as detailed further below, as well as directly from the enjoyment of the non-rival amenities of their neighborhood, which require renting one unit of housing in r . The utility of household ω who lives in neighborhood r of type (n, j) is:

$$U_r(\omega) = Q_{j(r)} A_{n(r)} \left(\frac{a}{\alpha}\right)^\alpha \left(\frac{c}{1-\alpha}\right)^{1-\alpha} b_r(\omega). \quad (1)$$

In this expression, A_n is a shifter summarizing quality of life in downtown vs the suburbs (e.g., their differences in public amenities such as parks or schools) while Q_j is a shifter that summarizes the quality level of a neighborhood, in terms of the housing stock and private urban amenities. Q_j is higher in high quality neighborhoods. The shock $b_r(\omega)$ captures the idiosyncratic preference worker ω has for living in neighborhood r . Specifically, each household draws a vector $\{b_r(\omega)\}_r$ of idiosyncratic preference shocks, following a Generalized Extreme Value distribution:

$$F(\{b_r\}) = \exp \left(- \left[\sum_{n,j} \left(\sum_{r \in \mathcal{B}(n,j)} b_r^{-\gamma} \right)^{-\frac{\rho}{\gamma}} \right] \right),$$

where $\mathcal{B}(n, j)$ is the set of neighborhoods of quality j in part of the city n . With this nested structure of idiosyncratic preferences, the preferences of a given household are more correlated for neighborhoods of the same quality and located in the same part of the city, than they are for neighborhoods of different types. Specifically, the parameter ρ governs the variance of draws across types of neighborhoods (*across* n, j pairs) and γ governs the variance of idiosyncratic preference draws for neighborhoods of the same type (*within* n, j pairs). Consistency with utility maximization requires $\gamma > \rho > 1$.

Households consume amenities in different locations in the city. We assume that private amenities – restaurants and retail options – are differentiated across neighborhoods and that households have CES preferences over amenities located in various neighborhoods. Specifically, a household that resides in location r consumes $a_{rr'}$ amenities in neighborhood r' and chooses where to consume

¹⁴The model can be readily extended to include a greater range of neighborhood qualities, but we find that two levels of quality are sufficient to capture quantitatively the non-monotonic U-shaped patterns of location choice observed in the data (see section 5).

amenities so as to maximize their bundle of amenity consumption:

$$a_r = \left(\sum_{r'} (\beta_{j(r)j'(r')})^{\frac{1}{\sigma}} (a_{rr'})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $\sigma > 1$ is the elasticity of substitution between amenities from different neighborhoods and the term $\beta_{j(r)j'(r')}$ captures utility costs that are specific to a pair of neighborhoods. It depends on dissimilarity in quality between a household's own neighborhood and the destination neighborhood. This is meant to capture the notion that people value horizontal differentiation within a given quality range that corresponds to their preferred quality level, but might not value as much amenity options of a different quality. Furthermore, we assume that consuming amenities further away from one's residence is costly. Specifically, commuting to amenities entails an iceberg commuting cost that increases with distance at rate $\tilde{\delta}$, so that the consumer cost of consuming amenities in neighborhood r' , for someone living in r , is $d_{rr'}^{\tilde{\delta}} p_{r'}^a$, where $p_{r'}^a$ is the price of amenities in r' . The price index for amenities consumption for a household who lives in r is therefore:

$$P_r^a = \left(\sum_{r'} \beta_{j(r)j'(r')} \left(d_{rr'}^{\tilde{\delta}} p_{r'}^a \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

Given that we model a representative city, we will make the assumption that neighborhoods of a given type (n, j) are all symmetric in size and location, so that all neighborhoods of type (n, j) have the same price index for amenity consumption P_{nj}^a , and the same local price of amenities p_{nj}^a .¹⁵ Denote with N_{nj} the number of neighborhoods within a n, j pair. The price index for amenities in a given neighborhood can therefore be re-written as:

$$P_{nj}^a = \left(\sum_{n', j'} N_{n'j'} \beta_{jj'} \left(d_{nn'}^{\tilde{\delta}} p_{n'j'}^a \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}, \quad (2)$$

where $d_{n'n}$ is the representative distance between two neighborhoods, one located in location n and one in location n' , while $\beta_{jj'}$ is the disutility shifter associated with shopping at locations whose quality is different than one's own residential type.¹⁶ Note that under our symmetry assumption, we can write distance frictions as a constant utility function of space, such that

$$(d_{nn'})^{\tilde{\delta}} = \Delta (K_{n'})^{\delta}, \quad (3)$$

where $\Delta = 1$ if $n = n'$ and $\Delta > 1$ if $n \neq n'$. The term Δ captures the border friction, assumed to

¹⁵While this assumption does not allow us to speak to the actual detailed spatial patterns of gentrification within a location in a given city, it allows us to capture the salient features of neighborhood change in a representative city.

¹⁶We assume that $\beta_{jj} = 1$ while typically $\beta_{jj'} < 1$ if $j \neq j'$.

be symmetric, between downtown and the suburbs.¹⁷

4.1.3 Labor Income and Net Income

We derive here the total net income of workers which is impacted by their skill and their location choice as follows. Households supply labor inelastically and are heterogeneous in skill. We assume that labor income is an increasing function of skill, so that we can summarize the heterogeneity of households with their wage w . The number of households with income w who live in the city is given by $L(w)$. Our focus is to study how heterogeneous households sort into different neighborhoods in the city, given the overall distribution of skills $L(w)$. We take this aggregate distribution as a primitive of the model.¹⁸

Workers commute to work. We assume that commuting costs depend on the part of the city where one lives, summarized by n , and that the cost of commuting is proportional to labor income. It is captured by commuting costs τ_n so that net labor income is $(1 - \tau_n)w$ for a household with wage w living in n . We assume that $\tau_D < \tau_S$ to capture the fact that households living downtown have an easier access to jobs compared to those living in the suburbs.

Households also potentially derive income from owning real estate. We allow for the real estate portfolio –and the corresponding returns – to vary systematically by worker type, as captured by $\chi(w)$, which we take as given. Finally, households pay local taxes. We allow for taxes levied by the local government, $T_n(w)$, to be location and income specific. Overall, the net income m of a household w who lives in n is given by:

$$m_n(w) = (1 - \tau_n)w + \chi(w) - T_n(w), \quad (4)$$

Households choose their neighborhood of residence r by maximizing (1) subject to the budget constraint. Given the specification of income and the utility function, the indirect utility of a household ω whose wage is w is given by:¹⁹

$$\max_r (m_{n(r)}(w) - p_r^h) (P_r^a)^{-\alpha} A_n Q_j b_r(\omega)$$

The price p_r^h is the price of the unit of housing in neighborhood r that one must rent to live there, while the price of the freely traded good is taken as the numeraire. There are two sources of non-homotheticities in the model. First, the unit-housing requirement in the model generates non-homothetic demand. Low-income workers can only afford to live in low housing costs neighborhoods.

¹⁷The expression for the price index (2) therefore simplifies to

$$P_{nj}^a = p_{nj}^a (N_{nj})^{\frac{1}{1-\sigma}} K_n^{\frac{\sigma}{\sigma-1}}$$

under the assumption that households only consume amenities in neighborhoods of their own type.

¹⁸Specifically, we study how spatial sorting patterns in the city change (and in turn, how house prices and urban amenities change) when this primitive income distribution changes.

¹⁹In what follows, we simply use subscripts n and j when it is clear to do so. They are really functions of the neighborhood chosen: $j = j(r); n = n(r)$.

In contrast, higher income households self-select into high quality-high price neighborhoods. This force leads to an over-representation of the rich households in the highest-quality neighborhoods, typically the ones downtown.

Second, commuting costs generate another source of non-homotheticity. Living in the suburbs is nicer than downtown with respect to fixed amenities but more costly in terms of commuting time. Higher income workers are willing to take this trade-off while it is too costly for low-income workers who spend most of their income on housing rents and are close to a subsistence level. This generates an over-representation of the lower income households downtown. Taken together, these two mechanisms can generate a U-shaped distribution of the probability of living downtown as a function of income, provided that high-quality neighborhoods downtown are sufficiently attractive.

We now turn to describing the endogenous provision of differentiated neighborhoods by developers.

4.1.4 Land Markets and Developers

Neighborhoods are developed by private developers who use land to develop neighborhoods that feature housing units and retail amenities. They rent out housing units and operate retail stores and restaurants, which are marketed to households living in the neighborhood as well as in other parts of the city. The number of neighborhoods of each type is an endogenous outcome of the model.

Land is provided competitively by atomistic absentee landowners. Downtown and the suburbs differ in their elasticity of land supply ϵ_n that is typically lower downtown. We posit the following reduced-form land-supply equation:

$$K_n = K_n^0 (r_n)^{\epsilon_n}, \quad (5)$$

where r_n and K_n are respectively rents and land supply in location n , and K_n^0 is a n -specific exogenous shifter, which controls the relative size of downtown vs the suburbs. Developers use land in location n to build $H_{n,j}^h$ housing units of quality j as well as $H_{n,j}^a$ retail areas of quality j following:²⁰

$$H_{n,j}^h = \frac{K_{n,j}^h}{h_{n,j}^h} \quad \text{and} \quad H_{n,j}^a = \frac{K_{n,j}^a}{h_{n,j}^a}, \quad (6)$$

where a higher quality space is more expensive to build, as captured by $h_{n,H}^i > h_{n,L}^i$, for $i \in \{h, a\}$. Land market clearing pins down the rental price in location n :

$$r_n = \left(\sum_j \left(h_{n,j}^h H_{n,j}^h + h_{n,j}^a A_{n,j}^h \right) \right)^{\frac{1}{\epsilon_n}} \quad (7)$$

²⁰Land is understood here to be equipped land. The model can be easily extended to feature a production function for housing that relies on land and capital. Given that the calibration relies on matching the resulting housing supply elasticities between downtown and the suburbs, this extension does not affect our results.

Developers pay a fixed cost $f_{n,j}$ to develop a differentiated neighborhood r of type (n, j) . We assume that developers price housing, as well as amenities, according to monopolistic competition. Finally, the number of developers is pinned down by free entry. The number of neighborhoods of type (n, j) , $N_{n,j}$, adjusts so that developers' profits are driven to zero, where a developer profit in an (n, j) is:

$$\pi_{n,j}^h + \pi_{n,j}^a - f_{n,j} = 0 \quad (8)$$

4.1.5 Role of local government: provision of public amenities

We assume that the public amenities in location n are in part exogeneous, but also are in part financed by local governments. Specifically, we assume that amenities respond to taxes according to:

$$A_n = A_n^o (G_n)^\Omega,$$

where A_n^o is the exogeneous part of amenities and G_n is local government spending, which is equal to taxes levied in the city, i.e.:

$$G_n = \int L(w) \left(\sum_j \lambda_{n,j}(w) \right) T_n(w) dw$$

Embedding this mechanism in the model is important: it ensures that the model properly captures the notion that as a location becomes richer, its local amenities (crime, schools, parks...) arguably increase, which benefits all of the local inhabitants, irrespective of their income.

4.2 Equilibrium

4.2.1 Workers residential choice

Among workers with labor income w , the share of workers who locate in a particular neighborhood r of type (n, j) is:

$$\lambda_{n,j,r}(w) = \lambda_{n,j}(w) \lambda_{r|n,j}(w),$$

where the notation $\lambda_{r|n,j}$ indicates the share of workers who choose neighborhood r conditional on choosing a neighborhood of quality j in location n . Given the structure of the idiosyncratic preference shocks, the conditional probability of choosing r among other (n, j) choices is:²¹

$$\lambda_{r|n,j}(w) = \frac{V_r(w)^\gamma}{\sum_{r' \in \mathcal{B}(n,j)} V_{r'}(w)^\gamma}, \quad (9)$$

where $V_r(w)$ is the inclusive value of neighborhood r :

$$V_r(w) = (m_n(w) - p_r^h) (P_r^a)^{-\alpha} A_{n(r)} Q_{j(r)} \quad (10)$$

²¹In equilibrium, all neighborhoods are symmetric within type, so that $\lambda_{r|n,j}(w) = \frac{1}{N_{n,j}}$.

Second, the probability that the neighborhood chosen is of type (n, j) is:

$$\lambda_{n,j}(w) = \frac{V_{n,j}^\rho(w)}{\sum_{n',j'} V_{n',j'}^\rho(w)} \quad (11)$$

where $V_{n,j}$ is the inclusive value of all neighborhoods of type (n, j) . Note that the inclusive value of living in any neighborhood n, j is:

$$V_{n,j}(w) = \left(\sum_{r' \in \mathcal{B}(n,j)} V_{r'}(w)^\gamma \right)^{\frac{1}{\gamma}} = A_n Q_j N_{nj}^{\frac{1}{\gamma}} (P_r^a)^{-\alpha} (m_n(w) - p_r^h). \quad (12)$$

To drive intuition, we can specialize the equations for a moment to the case where households only consume amenities in their own type of neighborhood (n, j) . In this case, we get:

$$V_{n,j}(w) \propto Q_j A_n \frac{N_{nj}^{\frac{1}{\gamma} + \frac{\alpha}{\sigma-1}} K_n^{\frac{-\alpha\delta}{\sigma-1}}}{(p_{nj}^a)^\alpha} (m_n(w) - p_r^h).$$

We see that the number of neighborhoods N_{nj} acts as an agglomeration force for two reasons. First, a higher N_{nj} increases utility through a love of variety effect in the choice of residential neighborhoods. With more neighborhoods to choose from, residents can find a better match for their idiosyncratic preference draws. The strength of this force is mitigated by the elasticity $\frac{1}{\gamma}$. Second, a higher N_{nj} also drives a love of variety effect in the choice of neighborhoods to visit to consume urban amenities. With more neighborhoods available, residents can visit more neighborhoods to consume their differentiated urban amenity bundle. The strength of this force is mitigated by $\frac{\alpha}{\sigma-1}$. This second benefit of having more variety in neighborhood choice is dampened by distance. In the suburbs, where the extension in the number of neighborhoods leads to sprawl, K_n increases faster than in downtown, mitigating the welfare impact of expanding the number of neighborhood options in the suburbs. The same forces are at play in the general case, where, in addition, welfare depends on amenity options in other neighborhood types, as captured by the price index P_r^a defined in equation (2).

Finally, the model lends itself naturally to welfare analysis. The average welfare of a household with wage w is the same irrespective of its location choice:

$$V(w) = \left(\sum_{n',j'} V_{n',j'}^\rho(w) \right)^{1/\rho}. \quad (13)$$

Note that higher-income households will be over-represented in costly neighborhoods, as income and housing prices are complement in equation (11).²² Since higher quality neighborhoods will

²²The complementarity can be seen from $\frac{\partial \log \lambda_{n,j}(w,p)}{\partial w \partial p} > 0$, which means that higher income workers are disproportionately located in higher p neighborhoods.

endogenously, in equilibrium, have higher demand hence higher housing prices, they will attract high-income households disproportionately. This first feature of the model can rationalize why higher income households disproportionately locate in high quality downtown neighborhoods, where the quality of urban amenities is reinforced by economics of density. Second, rewriting the same expression as:

$$V_{n,j}(w) = A_{n(r)} Q_{j(r)} N_{n,j}^{\frac{1}{\gamma}} (P_r^a)^{-\alpha} ((1 - \tau_n)) \left[w + \frac{\chi(w)}{(1 - \tau_n)} - \frac{p_r}{(1 - \tau_n)} \right]$$

shows that commuting cost makes the real cost of living in the suburbs higher ($\frac{p_r}{(1 - \tau_n)} > p_r$). Provided that the quality of life in the suburbs is high enough to justify such a commute, it will be so only for workers with high enough income because, again, income and prices are complement in this expression. This force will generate the disproportionate sorting of lower income workers away from the suburbs and into downtown housing units.

4.2.2 Developers

We close here the model by describing the pricing and entry behaviors of developers. Details are provided in Appendix B.0.1. Given CES demand for amenities, developers price amenities at a constant markup over marginal costs, that is:

$$p_r^a = \frac{\sigma}{\sigma - 1} h_{n(r),j(r)}^a r_{n(r)}, \quad (14)$$

Furthermore, they price housing by maximizing their profits on the residential market, under a monopolistically competitive market structure. On this market, using (10), (9) and (11) leads to the following housing pricing formula:

$$p_r^h = \frac{\gamma}{\gamma + 1} h_{n,j}^h r_n + \frac{1}{\gamma + 1} \mathcal{I}_{n,j}(p_r^h), \quad (15)$$

where the term $\mathcal{I}_{n,j}(p_r^h)$ is a measure of demand for neighborhood r .²³ By symmetry, all neighborhoods of type (n, j) have the same price in equilibrium, which we denote as $p_{n,j}^h$.

Given these prices, developers' operating profits are pinned down. Free entry drives down developers' total profits to zero, which pins down the number of developers entering in location n at quality j :

$$N_{n,j} = \frac{1}{f_{n,j}} \left[\int_w \lambda_{n,j}(w) \left(p_{n,j}^h - h_{n,j}^h r_n + \frac{\alpha^a}{\sigma} (w - p_{n,j}^h) \right) dL(w) \right] \quad (16)$$

A few comments are in order here. First, note that free entry creates a feedback loop. Take for instance neighborhoods of high quality downtown. The higher the demand for living there, the more developers enter and offer horizontally differentiated high quality neighborhoods - i.e., $N_{D,H}$

²³ Specifically, $\mathcal{I}_{n,j}(p) = \frac{\int_w \Lambda_{n,j}(p,w)[(1-\tau_n)w+\chi(w)]dF(w)}{\int_w \Lambda_{n,j}(p,w)dF(w)}$ with $\Lambda_{n,j}(p,w) = \frac{\lambda_{n,j,r}(w)L(w)}{[(1-\tau_n)w+\chi(w)-p]}$.

in (28) increases. This, in turn, raises the demand for this type of neighborhood by a love of variety effect (captured by equations (11) and (12)). Second, the intensity of this feedback loop depends on the elasticity of substitution between neighborhoods where to live, γ , and the elasticity of substitution between urban amenities, σ . The lower these elasticities, the larger the entry feedback loop - as neighborhoods are less substitutable, for housing or for amenity consumption. Third, the intensity of this feedback loop also depends on whether the density of neighborhoods increases or not in response to higher demand, as captured by the distance friction in (2). The model captures the idea that when new neighborhoods are developed through an increase in density, households living in the location have an easy access the corresponding urban amenities, even outside of their own neighborhood. The presence of nearby differentiated neighborhoods increases the appeal of residing in a given location. This is the case downtown, where land supply is fixed. The number of neighborhoods expands by filling up a constant space, so that accessibility to these varieties is high. In contrast, new neighborhoods developed in the suburbs are built, in part, over new land, as land is supplied more elastically there. Sprawl limits the amenity value of expanding the number of neighborhoods in the suburbs, as it reduces the accessibility to amenities.

This concludes the set up of the model. An equilibrium of the model is a distribution of location choices by income $\lambda_{n,j}(w)$, housing and amenity prices $p_{n,j}^i$, land rents $r_{n,j}$, number of neighborhoods $N_{n,j}$ such that (i) households maximize their utility (ii) developers maximize profits and (iii) land and housing markets clear.

Given the structure of the model, it is straightforward to show that an equilibrium of the model can be expressed in relative changes compared to another reference equilibrium, with different primitives (e.g., different city-level distribution of income, or different exogenous levels of amenities). We detail this approach and leverage it in section 6.1, where we analyze a series of counterfactual equilibria, starting from an initial one calibrated from the data. We now describe this calibration.

5 Model Parametrization

We now take the model to the data. We first describe how we match the model concepts of quality and location to their empirical counterparts. We then detail how we parametrize the model in two stages. In a first stage, we estimate the key model elasticities, and calibrate others using existing estimates from the literature. In a second stage, we use method of moments to fully calibrate the remaining parameters of the model.

5.1 Model Notions of Space

Throughout the empirical analysis, we equate the notion of neighborhoods, in the model, to census tracts, in the data. As discussed in section 3, we define the downtown (D) area as all census tracts surrounding the city center that contained 10% of the CBSA population in 2000. We take two approaches to segmenting high and low quality census tracts within the downtown and suburban areas. First, we define high quality neighborhoods based on the demographic composition of res-

idents. We draw from Diamond (2016), who shows that the college-educated share can proxy for endogenous amenities. Specifically, we define a high quality neighborhood as a neighborhood where at least 40 percent of residents between the ages of 25 and 65 have at least a bachelor’s degree. Under this definition, 15, 22 and 32 percent of census tracts in the downtown areas of the top 100 CBSAs are respectively classified as high quality in 1990, 2000 and 2014.

As a second measure, we define high quality neighborhoods based on the quality of amenities provided in the neighborhood. We measure the quality of local amenities – specifically, restaurants – leveraging novel smartphone movement data (Couture et al., Work in Progress), as detailed below. The smartphone data comes from aggregating GPS geolocation from multiple apps locational services used by a given smartphone device. This smartphone data allows us to identify billions of visits to the 100 largest restaurant chains from 2016 to 2018. We combine this data with the geocoded location of these restaurants in 2000 and 2012 from the National Establishment Time-Series (NETS). We use this data again to identify our amenity demand system in section 5.2.2. We provide additional details on the smartphone data in Appendix A.²⁴

Within the smartphone data, we define a person’s home as being the residential location where the phone spends most of the night. We construct a “restaurant chain quality index” that measures the propensity of residents living in a high income block group to visit a given restaurant chain, relative to the propensity of the average person. We define high income blocks as having median income higher than \$100,000. We measure the number of visits from each block group to each chain after controlling for proximity to venues within that chain, in order to isolate chains that high income people like from chains that simply co-locate with them. Given this, a chain quality index larger than 1 indicates that all else equal, people in high income block groups are more likely to visit a chain than the average person. In order to isolate the choice of visiting a chain from other considerations of travelers (e.g., eating during lunch at work), we restrict our sample of chain visits to only trips starting from a person’s home.²⁵ We also experiment with adding controls for race, age, education, and income similarity between the person’s home block group and the block group in which the closest venue in a given chain is located. We describe the procedure in details in Appendix C. We compute this index for the largest 100 chains that we can find both in the smartphone and NETS data. Among the restaurant chains with the highest quality are smaller gourmet chains like Shake Shack (1st), Zoës Kitchen (2nd) and California Pizza Kitchen (3rd),

²⁴Athey et al. (2018) and Chen and Rohla (2018) use similar smartphone data from a different provider. Athey et al. (2018) models restaurant demand in San Francisco, while Chen and Rohla (2018) investigate the impact of Donald Trump’s election on the length of Thanksgiving dinners in the United States. We refer to Couture et al. (Work in Progress) for evidence that the spatial distribution of smartphone devices provides a balanced representation of the US population along a number of dimensions (CBSA, income, race, education), that smartphones visit distance resembles that from the NHTS travel survey, and that the basemap of commercial establishments in the data is relatively complete.

²⁵We may not observe all movements for a given device if a user shuts off their phone or does not bring it with them when consuming certain amenities. Additionally, our geocoding data does not map office buildings, schools, and hospitals so we miss these trips. Given this, we are not able to distinguish easily a person’s place of work versus any other retail establishment. To remedy this, we define a trip starting from home as occurring when the last location prior to the amenity visit is home and there is at most one hour between the last observation at home and the first in the consumption venue.

as well as large national chains like Chipotle (6th), Panera Bread (7th), and Starbucks (14th).²⁶ Using this chain quality index, we define a high quality (H) census tract as having average chain quality higher than 1.1. Under this definition, 13 and 34 percent of census tracts with non-missing quality in the top 100 CBSAs are classified as high quality, respectively, in 2000 and 2012.²⁷

Defining high quality tracts inherently involves some judgment. Given that, we pursue multiple approaches to measure high quality neighborhoods. Despite the two methods being conceptually different and having different strength and weaknesses, we find very similar estimates of our key parameters across both methods for segmenting tracts into quality tiers. Finally, we have also explored segmenting high quality neighborhoods based on the value of housing. Given that below we assess the fit of our calibrated model by comparing the model’s prediction of house price changes over time for each $\{n, j\}$ pair with the actual data, we have chosen not to use house prices to segment neighborhoods into quality tiers.

5.2 Parametrization: First Stage

In this section, we discuss our parametrization of the key elasticities of the model. Specifically, we discuss how we estimate or calibrate the 12 parameters highlighted in Table 1 using several micro data sources or drawing on the existing literature. The role played by these parameters in driving sorting patterns and welfare results is discussed in section 6.4.2.

5.2.1 Estimation of Elasticity of Demand Between Neighborhood Types (ρ)

We begin by discussing how we estimate ρ , the elasticity of substitution of demand between neighborhood of different types. We first present the estimating equation, then discuss data and measurement of the variables, before detailing our empirical strategy and discussing the results.

Estimating Equation. We derive the estimating equation for ρ using equations (11) and (12) of the model. We take logs of equation (11) and difference it between downtown and the suburbs, as well as between two equilibria, corresponding to two time periods. We obtain the following estimating equation:²⁸

$$\Delta \ln \left(\frac{\lambda_{cDj}(w)/\lambda_{cDj}}{\lambda_{cSj}(w)/\lambda_{cSj}} \right) = \psi_{cj} + \rho \Delta \ln \left(\frac{w - p_{cDj}^h}{w - p_{cSj}^h} \right) + \epsilon_{cj}(w), \quad (17)$$

²⁶For the 53 restaurant chains for which both the *MPI* index in Couture and Handbury (2017) and our smartphone quality index is defined, the correlation between both is 0.87. Couture and Handbury (2017) define restaurant chain quality using the Market Potential Index *MPI* of 61 local restaurant chains. The *MPI* calculated by Esri ArcGIS uses data from the *Survey of American Consumers* to measure the propensity of individuals residing in different neighborhoods to visit a given chain relative to the average American, so it potentially confounds preferences for chains with co-location.

²⁷We choose a value of 1.1 as the cutoff for chain quality index so that the 2012 share of high quality downtown neighborhoods matches the 2014 high quality downtown share based on the education mix of residents described above.

²⁸Specifically, we start with (11) and plug in the value of V_{nj} using (12), before taking logs and differencing. For simplicity, we assume away commuting costs here.

Table 1: Key Model Parameters

Parameter	Description	Value	Source
<u>Location Substitution Elasticities</u>			
ρ	Between-type neighborhood substitution elasticity	3.3	Estimated
γ	Within-type neighborhood substitution elasticity	6.5	Assumption
<u>Amenity Demand</u>			
α	Amenity share	0.15	CEX
σ	Substitution elasticity across neighborhoods	6.5	Assumption
δ	Distance elasticity across neighborhoods	0.2	Estimated
<u>Public Amenity Supply</u>			
T_D	Downtown local property tax	0.2	IPUMS 2000
T_S	Suburban local property tax	0.3	IPUMS 2000
Ω	Public amenity supply elasticity	0.05	Assumption
<u>Land and Housing Supply Elasticities</u>			
ϵ_D	Downtown land supply elasticity	0.6	Calibrated to Saiz (2010)
ϵ_S	Suburban land supply elasticity	1.3	Calibrated to Saiz (2010)
<u>Transportation Costs</u>			
τ_D^C	Commute costs as share of labor income downtown	0.044	Authors' calculation
τ_S^C	Commute costs as share of labor income suburbs	0.059	Authors' calculation

This equation relates the propensity of a CBSA- c household earning income w to reside in downtown tracts of quality j relative to their propensity to reside in a suburban tract of quality j to the relative disposable income that the household will have after paying quality- j housing prices downtown relative to that after paying quality- j housing prices in the suburbs.

The first term ψ_{cj} is a city-quality fixed effect. It captures changes in the desirability of downtown quality- j neighborhoods, relative to suburban quality- j neighborhoods, in city c over time. Recall that this desirability is driven, in the model, by a shifter that combines the level of public and private amenities as well as the price of amenities. Importantly, it is constant for all residents within a given CBSA-quality tier, and can therefore be controlled for with a fixed effect. With this CBSA-quality fixed-effect, all the identifying variation for ρ comes from variation in how location choices correlate with house prices differently across income groups within a CBSA. We estimate a larger ρ if richer households tend to locate more in areas with higher housing prices, conditional on neighborhood quality j .

The ϵ_{cj} captures measurement error and any time-varying variables with a differential impact across income groups missing from the model.

Data. We describe all data sources in Appendix A and variable construction in detail Appendix C, and summarize them here. To run specification (17) in the data, we measure house prices using the Zillow Home Value per Square Foot index in 2000 and 2014.²⁹ We normalize the price index to 1999 dollars, as with income.³⁰ Specifically, we compute p_{cnj} as the annual user cost of a median-sized housing unit in area-quality pair nj within CBSA c .³¹ We then compute $\Delta \ln((w - p_{cDj})/(w - p_{cSj}))$, setting w as the median household income within each constant CPI-adjusted census bracket. We calculate this median using 2000 IPUMS microdata from the 100 largest CBSAs, and hold it fixed over time and across CBSAs. In total, our estimation includes at most 2000 observations (100 CBSAs, ten income brackets, and two quality tiers).³² In many specifications, we have less than 2000 observations given the presence of missing data at the CBSA-area-quality triplet.

²⁹The Zillow house price index is not available prior to 1996, and our measure of restaurant quality is not available prior to 2000, so our preferred time period for estimation is 2000 to 2014. For robustness, we run estimate using 1990 to 2014 changes. For this specification, and again in the calibration, we impute 1990 house prices and 1990 restaurant quality assuming that house prices and restaurant quality remained fixed between 1990-1996 and 1990-2000 respectively.

³⁰In the model, prices and income are expressed in terms of the tradable numeraire good. The urban CPI excluding shelter tracks the urban CPI for all goods broadly at a decadal frequency between 1990 and 2014, so we use the CPI for all goods to maintain the comparability of our results with those from other studies.

³¹This computation holds unit size and user cost constant across area-quality-CBSA triplet, so that all variation in p_{cnj} comes from the per square foot price of housing. Using Zillow data, we find that the median size of a housing unit in the 100 largest CBSAs is 1529 square feet in 2000 and 1565 square feet in 2014. The annual user cost of housing is 4.7 percent of house prices in 2000, and 4.6 percent in 2014 according to data from the Lincoln Institute of Land Policy.

³²We drop all households with income smaller than \$25,000 per year from our model calibration. Given the presence of public housing, such households are not well represented by our model. For consistency, we exclude them from this regression as well. This leaves us with 10 income groups in the estimation. We also remove any observation with $w - p_{cnj}^h < 0$ (1.4% of our sample). We then censor the top and bottom 1 percent of $\Delta \ln(w - p_{cnj}^h)$.

Identification Strategy. Equation (17) directly estimates a key equation from the model, assuming no model misspecification. But one could be worried that forces that are outside of our modeling framework are in part driving the relationship between house prices and location choices. Specifically, recall that ψ_{cj} controls for any change in neighborhood characteristics that would be valued equally by all households if they had the same income. But it could be that richer households have intrinsically different preferences than poorer households, even controlling for income differences. In this case, it could be that amenity changes for which richer households have a higher taste than poorer households could confound our estimates, driving both house price growth and in-migration of the rich.

To deal with this potential endogeneity concern, we instrument $\Delta \ln((w - p_{cDj}^h)/(w - p_{cSj}^h))$ with a CBSA-level shift-share per-capita income shock, interacted with individual income bracket dummies. The CBSA-level shift-share shock predicts average earnings change in a given CBSA using national trends (excluding that CBSA) in average earnings for each industry projected on the local industry mix. Our first-stage depends on how, when a CBSA gets an exogenous shock to labor demand which increases per-capita income, residents of differing incomes in that CBSA adjust their location choice. Our exclusion restriction is that, conditional on ψ_{cj} , the shift-share shock changes the relative propensity of a given income group to live in D_j relative to S_j only through its impact on relative real incomes driven by differential house price variation across the n, j pairs. This would imply, for example, that the extent to which city planners improve downtown amenities preferred by the rich is orthogonal to our CBSA level shift-share shock. Overall, our instrument isolates variation in relative house prices in downtown versus suburbs associated with plausibly exogenous movements in CBSA-level income that are at the heart of our model’s gentrification mechanism.³³

Reduced Form Regression. To understand the variation that facilitates our identification, our instrument offers a useful reduced-form representation of the structural equation (17). In this reduced-form, we estimate the direct impact of CBSA-level Bartik per capita income shocks on the urbanization of household within each income bracket. To illustrate this variation, we run the following regression:

$$\Delta \ln \left(\frac{\lambda_{cD}(w)/\lambda_{cD}}{\lambda_{cS}(w)/\lambda_{cS}} \right) = \mu_w^0 + \mu_w^1 \widehat{\Delta \text{Income}_c}^{\text{Bartik}} + \epsilon_{cw}. \quad (18)$$

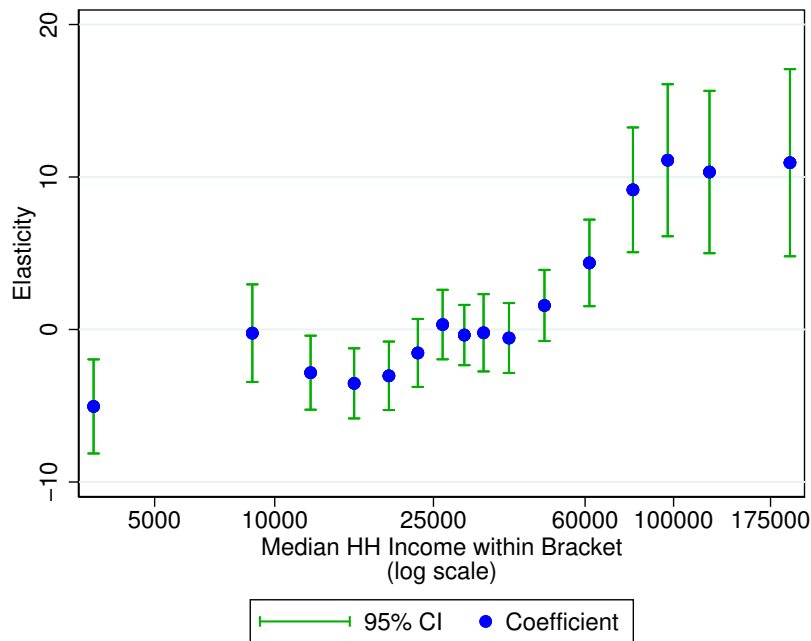
The regression above measures the extent to which individuals with income w change their relative propensity to live downtown (as opposed to the suburbs) as CBSA predicted income change increases. We estimate equation (18) separately for each of our bracketed income groups. Finally,

³³There is a growing literature discussing the potential pros and cons of using a shift-share (Bartik) instrument to isolate parameters exploiting cross-region variation. See, for example, Ado et al. (2018), Borusyak et al. (2018), and Goldsmith-Pinkham et al. (2018). Many of these papers discuss the potential that initial industry mix is also correlated with other CBSA specific factors that may also be driving variation in the dependent variable of interest. These papers, however, are less relevant for our analysis. Given that our estimation includes CBSA fixed effects (which proxies for other CBSA specific factors), we are using the shift-share instrument to exploit within CBSA variation across different income groups. It is this interaction that facilitates our identification.

we estimate this regression both for changes between 2000 and 2014 and for changes between 1990 and 2014. To estimate equation (18), we use the same definition of λ as in our U-shape plot of Section 3, which is consistent with the model above. $\mu_w^1 > 0$ implies that when CBSA income increases, the propensity of income group w to live downtown as opposed to the suburbs rises relative to that of the average CBSA resident. Our model implies that μ_w^1 should be increasing as w increases. Moreover, given that the relationship is in normalized shares, if higher income individuals have $\mu_w^1 > 0$, lower income individuals must have $\mu_w^1 < 0$. Finally, we wish to stress that there is nothing tautological about these regressions. If spatial sorting responses are unrelated to income, μ_w^1 could equal zero for all income groups.

Figure 3 depicts the reduced-form estimates from equation (18), along with their 95 percent confidence bounds, where all changes are defined over the 2000 to 2014 period. The results show that CBSA per-capita income shocks are associated with differential spatial sorting patterns of the rich and the poor, and provide empirical validation for our model. For all the top five income bins, $\mu_w > 0$ and all estimates are statistically significant at the 5 percent level. Conversely, all the bottom five income bins have estimates of $\mu_w < 0$, and all estimates but one are statistically significant. We find the same patterns of relative urbanization of the rich and suburbanization of the poor following an income shock for the 1990 to 2014 period and in regressions replacing the Bartik shock with actual per-capita income growth.

Figure 3: Reduced-form: Elasticity of Change Urban Share on Bartik Income Shock for each Income Bracket, 2000 to 2014



Note: Plot depicts income bracket-specific coefficients from equation (18).

Table 2: Estimation of elasticity ρ

	Quality Definition: College Share		Quality Definition: Restaurant Chain	
	(1) OLS	(2) IV	(3) OLS	(4) IV
$\hat{\rho}$	1.34 (0.09)	3.19 (0.20)	1.38 (0.13)	3.38 (0.27)
δ_{cj}	Yes	Yes	Yes	Yes
R ²	0.84		0.87	
KP F-Stat		45.37		48.02
Obs	1,599	1,599	1,434	1,434

Notes: Data from 100 largest CBSAs in 2000 and 2014. Observations are CBSA-population weighted. Standard errors, in parentheses, are clustered at CBSA-level. KP F-Stat = Kleinberger-Papp Wald F statistic.

Estimation Results Our main estimation results of ρ from equation (17) are reported in Table 2. Because of the data limitations explained above, we report results for changes during the 2000 to 2014 period.³⁴

Columns (1) and (2) reports the estimates when we define as high quality neighborhoods the census tract with at least 40 percent of residents with more than a bachelor’s degree. Columns (3) and (4) uses the alternative definition of neighborhood quality that relies on local restaurant quality. Within each quality measure, we show both the OLS estimates and the IV estimates where we use our Bartik instrument for $\Delta \ln \left(\frac{w-p_{cDj}^h}{w-p_{cSj}^h} \right)$. As seen in Table 2, our IV estimates of ρ are stable across our two measures of neighborhood quality, and range from 3.2 to 3.4. Therefore, for our base specification, we set $\rho = 3.3$. As we show later, ρ is an important parameter determining our welfare results. Therefore, in our counterfactual exercises we show the sensitivity of our results to alternate values of ρ .

We have explored the robustness of the results in Table 2 to additional controls. One potential concern with our instrument is that predicted rising average income in some CBSAs comes from a concentration of typically urbanized industries that recently experienced high national wage growth (e.g., technology or FIRE). The growth of these urbanized industries could then drive both the income growth at the CBSA level and the shift of the wealthy downtown in the cities where these industries were overrepresented in 1990. Specifically, if the technology sector was booming during the 2000s and technology jobs are more likely to be located downtown and employ high income people, we may observe high income people moving downtown in response to the positive shift share shock to minimize their commute as opposed to consuming urban amenities. To investigate

³⁴The estimates we obtain – with less reliable data– for the 1990 to 2014 period are similar.

whether such a concern is warranted, we compute Bartik instruments that leave out technology or FIRE industries. Our results from these leave out Bartiks are very similar to those from Figure 3.³⁵

5.2.2 Estimation and Parametrization of Amenity Demand (α , δ , σ)

We begin this section by discussing how to estimate the amenity demand elasticities (δ and σ) using a model-implied gravity equation. We then talk about how we can use expenditure data to parameterize α , the share of expenditure that households allocate to residential amenities above and beyond what they pay for housing. Throughout, we define residential amenities as non-tradable services such as restaurants, bars, entertainment venues (movie theater, shows, etc), gyms, and other personal services. When thinking of residential amenities, we exclude retail consumption at apparel, grocery, and other merchandise stores. Non-tradable services like restaurants and entertainment venues most closely match our model’s amenity that are luxurious, endogenous, locally-provided, and subject to strong economies of density.³⁶

The model delivers the following gravity equation for amenity demand:

$$\ln\left(\frac{a_{rr'}}{a_{rr}}\right) = \overbrace{\ln\left(\frac{\beta_{rr'}^q}{\beta_{rr}^q}\right)}^{\beta_{j(r)\neq j(r')}} + \sigma\delta \ln\left(\frac{d_{rr'}}{d_{rr}}\right) + \overbrace{\sigma \ln\left(\frac{p_{r'}^a}{p_r^a}\right)}^{\theta_r + \theta_{r'}}. \quad (19)$$

The first term captures the possibility that people place less value on consuming amenities of a quality type other than their preferred type. We proxy this with a dummy variable $\beta_{j(r)\neq j(r')}$ equal to 1 when the home neighborhood r is of different quality type than neighborhood r' where amenities are consumed. The second term captures the travel distance required to access amenities in neighborhood r' relative to the travel distance required to consume within the home neighborhood r . The third term captures the relative amenity prices in neighborhood r' and r . Given that amenity price is constant within neighborhood, we can proxy for this third term with an origin r and a destination r' fixed-effect, θ_r and $\theta_{r'}$. Importantly, these fixed-effects can absorb any unobserved tract characteristics. We then obtain the following estimating equation:

$$\ln\left(\frac{a_{rr'}}{a_{rr}}\right) = \beta_{j(r)\neq j(r')} + \sigma\delta \ln\left(\frac{d_{rr'}}{d_{rr}}\right) + \theta_r + \theta_{r'} + \epsilon_{rr'}, \quad (20)$$

Estimating (20) requires information on the origin and destination of a large number of trips to consume amenities, which is not available in conventional travel surveys like the National Household Travel Survey. To circumvent this issue, we again use the new smartphone movement data.

³⁵These results are consistent with Couture and Handbury (2017), Baum-Snow and Hartley (2017) and Su (2017) who all find evidence that spatial job sorting plays little to no role in explaining the recent movement of high income individuals downtown.

³⁶As discussed before, Aguiar and Bilal (2015) identify non-tradable services like restaurant and entertainment as having steep Engel curves, Couture and Handbury (2017) identify non-tradable services in particular as the key driver of the downtown location choice of the college-educated.

This smartphone data allows us to identify 2.3 billion trips to commercial establishments that we classify as non-tradable services, namely restaurants, gyms, theaters, and outside amenities, from 87 millions of devices for which we identify a permanent home location. We provide additional details on the dataset in Appendix A.

In order to isolate the choice of consuming amenities from other considerations of travelers, we study the robustness of our estimates to restricting the sample to only trips starting from home, to trips starting from home and coming immediately back home, or to trips that take place on weekends. We again define neighborhoods as census tracts, so $a_{rr'}$ is the number of trips by people living in tract r to non-tradable service establishments located in tract r' . We define $d_{rr'}$ as the haversine distance from the centroid of tract r to that of tract r' and δ_{rr} as half the radius of the home tract. Each observation in our regression is a tract pair rr' and we limit the choice set of each person to tracts available within its CBSA. Note that $\delta\sigma$ is large if people make few trips far from home, either because the cost of distance δ is large or because amenities are highly substitutable (i.e., σ is large).

Table 3 shows the estimation results. The coefficients $\delta\sigma$ are stable and remain within -1.17 and -1.57 across all estimations. Interestingly, our amenity trip gravity coefficients are similar, albeit somewhat larger, to those from the trade literature, which center around -1 (Disdier and Head, 2008) and resemble the estimate of -1.29 for regional trade in the US from Monte et al. (forthcoming).³⁷

The coefficients on $\beta_{j(r)\neq j(r')}$ are consistently negative and significant, indicating a distaste for visiting neighborhoods with quality other than one's home neighborhood, and providing some evidence that our quality definition captures relevant features of household's preference for amenities. In fact, using our preferred quality definition based on college-educated share, people living in high quality tracts take 81 percent of their trips to other high quality tracts, and people living in low quality tract also take 81 percent of trips to other low quality tracts. Our $\delta\sigma$ estimates are robust to adding additional controls for tract pair characteristics, such as an index of racial dissimilarity and median age difference.

The above gravity equation estimates $\sigma\delta$. However, for our calibration, we need estimates of σ and δ separately. We are not aware of existing estimates of δ in the literature, but estimates of σ for amenities are available. Atkin et al. (2018) find an elasticity of substitution of 3.9 for retail stores in Mexico, Einav et al. (2018) find 6.1 for offline stores in the US, Su (2018) and Couture (2016) find 7.5 and 8.8 respectively for restaurants in the US. We pick a value of 6.5 in the middle of this range, and explore robustness over the range of values above. Using our estimates of $\sigma\delta = 1.3$ from Table 3, we obtain $\delta = 0.2$.

Finally, we use data from the Consumer Expenditure Survey (CEX) to discipline α , the share of expenditures net of housing costs and transportation to work that is spent on residential amenities such as restaurants, bars, entertainment venues, gym memberships, and other personal services.

³⁷The only comparable estimates we are aware of are from Agarwal et al. (2017), who obtain much smaller distance elasticities of around -0.4 for different consumption sectors using credit card transaction data at the census place level. They exclude the home place for their regression and include all transactions up to 120km away.

Table 3: Estimation of gravity parameter $\sigma\delta$

	Quality Definition: College Share				Quality Definition: Restaurants Chain			
	All (1)	Home (2)	Weekend (3)	Home-Home (4)	All (5)	Home (6)	Weekend (7)	Home-Home (8)
$\hat{\delta}\sigma$	-1.57 (0.00)	-1.42 (0.00)	-1.20 (0.00)	-1.18 (0.00)	-1.56 (0.00)	-1.40 (0.00)	-1.18 (0.00)	-1.17 (0.00)
$\beta_{j(r)\neq j(r')}$	-0.14 (0.00)	-0.12 (0.00)	-0.10 (0.00)	-0.09 (0.00)	-0.04 (0.00)	-0.03 (0.00)	-0.03 (0.00)	-0.03 (0.00)
R^2	0.91	0.87	0.88	0.85	0.91	0.87	0.88	0.85
Obs	22,791,347	6,403,153	11,924,874	3,050,752	19,858,033	5,645,813	10,419,101	2,696,680

Notes: From smartphone data on trips to non-tradable services in 100 largest CBSAs in 2016-2018. All: sample of all trips, Home: trips starting from home, Weekend: trips taken on weekend, Home-Home: trips starting from home and returning directly back home. See main text for a description of the regression and Appendix A for data details.

In the 2013 CEX, food away from home and entertainment fees and admission represent 6.2% of spending out of the average individual total expenditures. Given that housing is about 27 % of total expenditures (including utilities) and transportation to work is about nine percent of total expenditures, restaurant and entertainment spending alone represent 10 percent of expenditure net of housing costs and transportation. Adding in other residential amenities such as bars, gym memberships, and other personal services yields roughly another few percentage points of expenditures net of housing and transportation. As a result, our base calibration uses $\alpha = 0.15$, and we investigate the robustness of our results to $\alpha \in [0.10, 0.30]$. The lower bound makes the narrow assumption that our residential amenities only include restaurants and entertainment. The upper bound allows for the fact that there are other luxury residential amenities (like a reduction in crime) that households are willing to pay for and that also evolve endogenously. As we show below, the higher the value of α , the larger the amplification in welfare differences between the rich and the poor predicted from the model due to the spatial sorting response that results from rising income inequality. Appendix C again provides detailed expenditure definitions.

5.2.3 Parametrization of Elasticity of Demand Between Neighborhoods (γ)

Given the assumptions on idiosyncratic preference shocks, ρ must be lower than γ . This bounds γ from below. Second, existing research suggests that there is less socio-economic diversity within census tracts than there is within retail establishments such as grocery stores and restaurants.³⁸ Through the lens of our model, this implies the substitution elasticity for residential amenities (σ) is an upper bound on our estimate of γ . Given our above estimation, this implies that γ will lie in the range between 3.3 and 6.5. The lower the value of γ the larger the endogenous response

³⁸Handbury et al. (2015) find that Nielsen panelists who are from college- and non-college educated households are more likely to co-locate in grocery stores than in census tracts. This is consistent with Davis et al. (Forthcoming) who find a higher rate of racial segregation across residential neighborhoods than restaurants within NYC.

of amenities to the changing income distribution. For our base assumption, we use a conservative value of $\gamma = 6.5$. As a robustness exercise, we present the sensitivity of our results to alternative parametrizations.

5.2.4 Parametrization of Land and Housing Supply Elasticities

In the model, the elasticity of land supply ϵ_n directly governs the elasticity of housing supply. We directly calibrate the latter. Saiz (2010) provides housing supply elasticity estimates ϵ_c for 95 large Metropolitan Statistical Areas, based on geographical constraints and housing regulations. We match 83 of these to our sample. Unfortunately, these are not estimated separately for downtown and suburban areas. To calibrate ϵ_D and ϵ_S , we posit that housing supply elasticities systematically vary, in equilibrium, with average household density ($density_c$), and estimate the following log-linear regression of ϵ_c on $density_c$:

$$\ln(\epsilon_c) = 1.97 - \underset{(0.07)}{0.30} \ln(density_c) + \xi_c^e, R^2 = 0.21 \quad (21)$$

We rely on cross-CBSA variation to estimate this equation. We then define $\hat{\epsilon}_D$ and $\hat{\epsilon}_S$ as the fitted values from equation (21) computed at typical density of D and S neighborhoods in the 100 largest CBSAs. We find $\hat{\epsilon}_D = 0.60$ and $\hat{\epsilon}_S = 1.33$.³⁹ We use these values in our baseline calibration and test the sensitivity of our results to alternative parameter values.

5.2.5 Parametrization of Commuting Costs

To estimate the commuting costs, we use data on trip time to work by car from the geo-coded 2009 National Household Travel Survey to estimate area-specific τ'_n s. Specifically, the average daily commute time for drivers living in the suburbs of the top 100 CBSAs is 64 minutes while it is 47 minutes for those living downtown. We compute τ_n by assuming that each worker allocates 9 hours per day to working and commuting, and by valuing an hour of commuting at half of the hourly wage as recommended by Small et al. (2007). This implies a per labor hour commute cost of $\tau_n = 0.5 * \text{CommuteTime}_n / 9$, or $\tau_D = 0.0435$ and $\tau_S = 0.059$.

5.2.6 Parametrization of Public Amenities and Homeownership

We calibrate local taxes to match the unit-level average real estate taxes paid as a share of annualized housing costs in 2000. This implies a local property tax rate of 20% in the suburbs and 30% downtown. We set the elasticity of the endogenous component of the public amenity with respect to these tax revenues to 0.05 (Fajgelbaum et al., 2018). In our base parametrization, we assume that all housing rents in the city (land rents and fixed costs of development) accrue to an

³⁹In our downtowns, the average CBSA population-weighted household density is 4,300 households per square mile, versus 300 in the suburbs. The highest density CBSA, New York, has 850 households per square mile, so the average density in D is out-of-sample. However, $\hat{\epsilon}_D = 0.60$ turns out to equal the elasticity of housing supply in Miami, which is the metropolitan area with the most inelastic housing supply in Saiz (2010).

absentee landlord and none are transferred to the city residents, i.e., that $\chi(w) = 0$ for all w . In our counterfactual analysis, we want to account for the heterogeneous rate of home ownership in contributing to spatial sorting responses. Doing so allows agents who own their home to reap the benefits associated with rising house prices. To that end, we transfer to households at each labor income level capital gains corresponding to their average real estate portfolio. This corresponds to the average rent growth of neighborhoods where households of that income lived in the previous period, which is then scaled by the share of households who were homeowners according to the 2000 IPUMS data. Note that this calibrated share of home ownership increases systematically with labor income. To summarize, a household earning labor income w , receives a transfer of $\chi(w) = OS(w)\lambda_{1999,nj}(w) \sum_{nj} (p_{2014,nj}^h - p_{1990,nj}^h)$, where $OS(w)$ is the share of households with income w who reported owning homes in the 2000 IPUMS data. This allows us to forgo taking a stance on the initial level of $\chi(w)$ and instead only focus on the changes in $\chi(w)$ over time that results from house price growth due to the income inequality shock that we study.

5.3 Second Stage: Method of Moments

Calibration. Armed with estimates for the key elasticities of the model, we then conclude the calibration of the model using a method of moments. That is, we set the remaining parameters that allow, conditional on the model elasticities, to minimize the distance between the model moments and their empirical counterparts. The model is flexible enough to exactly match some of these moments, while others will be targeted without being fully matched.

Specifically, we exactly match two shares taken from the equilibrium read from the data. The first, which we denote S_{nj}^{mk} , is the share of amenity expenditures of households living in a neighborhood of type (n, j) spent on amenities consumed in a neighborhood of type (m, k) .⁴⁰ The second the share of equipped land $s_{n,j}^i$, within each location, used by activity $i \in a, h$ of quality j .⁴¹ Beyond these shares that the model exactly replicates, we target the following set of moments: (i) the whole distribution, by income level, of the share of workers living downtown in 1990 presented in the stylized facts section 3.2, and (ii) the median house price by neighborhood type, also in 1990, also employed in the demand elasticity estimation and described in section 5.2.1. These two moments summarize the key economic concepts we aim to capture.

To accurately capture the location choices of higher-income households, we seek to match the downtown share of households at a finer income grid than the Census income brackets represented in the stylized facts section 3.2. To this end, we construct the same curves but for finer, 1999\$5,000 income brackets using the micro IPUMS data. The additional detail in the income dimension comes at the expense of precision in the spatial dimension and, as a result, we are limited to studying 27 CBSAs of our original 100 in the calibration and counterfactual exercises.⁴² We drop households

⁴⁰We proxy for these expenditure shares using trip shares from the smartphone data described earlier in this section.

⁴¹We have $\sum_{i,j} s_{n,j}^i = 1$ for $n = D$ or S and $\sum_{m,k} S_{nj}^{mk} = 1$, for $n = D, S$ and $j = H, M, L$.

⁴²The IPUMS data identifies the locations of respondents at the PUMA (Public Use Microdata Area), each of which contains approximately 100,000 individuals, relative to the 4,000 contained in each Census tract. To replicate the urban share for each fine income brackets, we first construct a cross-walk between PUMAs and our tract-based

earning less than \$25,000 in 1999 dollars. Given the presence of public housing, such households are not well represented by our model.⁴³

The method of moments allows us to back out two key composite model variables: (i) the relative values of effective neighborhood quality in each location for each neighborhood type in the baseline equilibrium:

$$\tilde{q}_{n,j} = A_n Q_j N_{nj}^{\frac{1}{\gamma}} (P_r^a)^{-\alpha}, \quad (22)$$

without separately identifying the individual terms and (ii) the price of housing in each location for each neighborhood type ($p_{n,j}^h$). Combined with the model elasticities, these variables pin down the calibrated value for location choice $\lambda_{n,j}(w)$ in the model. Furthermore, using the equilibrium relationship (27), these composite variables also pin down $h_{n,j}^h r_n$, the land prices of the model.

Importantly, we note that this calibration does not identify all of the deep parameters of the model separately. Rather, it identifies a set of composite variables $\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{nj}^{mk}, s_{n,j}^i\}$ that is just sufficient, conditional on estimates for the model elasticities $\{\rho, \gamma, \epsilon_n, \sigma, \alpha, \tau_n\}$, to compute any counterfactual equilibrium of the same model that relies on different primitives, using exact hat algebra following the method popularized by Dekle et al. (2007). Intuitively, these composite variables embed just the right level of information on the deep parameters of the model, such as the exogenous quality of different neighborhoods A_n and Q_j or the fixed cost of building neighborhoods f_{nj} that ultimately determines the variety of neighborhoods $N_{n,j}$, to compute relevant counterfactuals. This step is described in more detail in section Appendix B.1 below.

The identification of the model in this second stage is quite straightforward. First, it is clear how the house price moments is directly informative for the calibration of $p_{n,j}^h$. Note though that since the model is over-identified, the price moment cannot be matched perfectly. Depending on the weight put on moments (i) and (ii), the procedure trades-off a better fit of the U-shape for location choices against a better fit for housing prices. Then, conditional on prices, the U-shape pattern of the location choice data helps identify the relative quality (all included) of different types of neighborhoods (that is, $\tilde{q}_{n,j}$). This is a quite intuitive revealed preference approach, applied to our non-homothetic demand function: the same level of price and quality of a neighborhood generates different demand patterns at different levels of income. Of course, this reasoning is conditional on prices that are in part informed by the other moment. Concretely, the identification relies on the following equation for all (n, j) :

$$\frac{\lambda_{n,j}(w)}{\lambda_{S,L}(w)} = \frac{\tilde{q}_{n,j}^\rho \left[(1 - \tau_n)w - p_{n,j}^h \right]^\rho}{\tilde{q}_{S,L}^\rho \left[(1 - \tau_S)w - p_{S,L}^h \right]^\rho}$$

Given τ_n and w , the calibration backs out the $\tilde{q}_{n,j}$ and $p_{n,j}^h$ that allow to match best the data

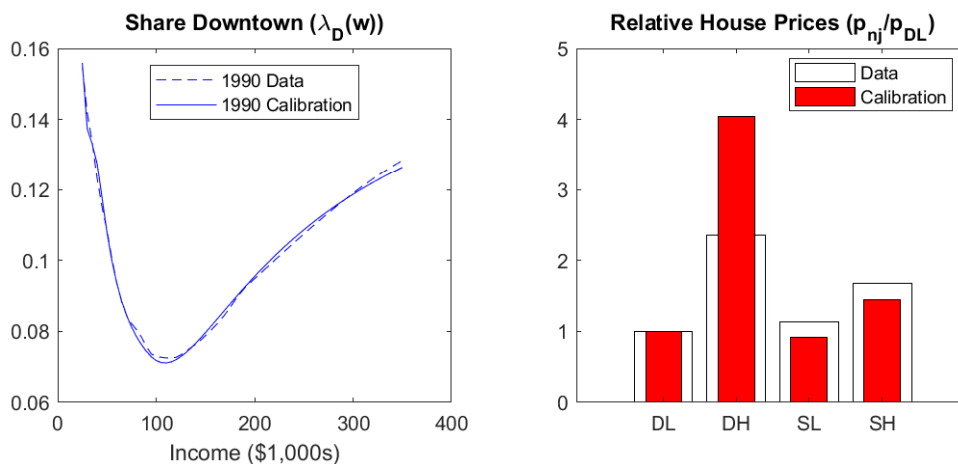
downtown areas. There are 27 CBSAs in which PUMAs are small enough relative to the downtown definition so as to allow for useful inference here. See the data appendix for more details.

⁴³For instance, data from the department of Housing and Urban Development shows that in our downtowns in 2014, about 30 percent of households earning between \$5000 and \$14000 in 1999 dollars lived in subsidized housing.

distribution of location choices, $\frac{\lambda_{n,j}(w)}{\lambda_{L,S}(w)}$. These vectors are pinned down up to a normalization level, whose value does not impact the counterfactuals done in the following section.

Moment Fit. The moment fit is presented in Figure 4. Despite a sparse specification, the calibrated model is able to match remarkably well the rich non-monotonic U-shape patterns of location choice by households of various incomes. Furthermore, we note that the model matches the relative housing prices in the suburbs well, though the model values tend to be slightly below those in the data. The model has a harder time matching the high quality housing prices downtown, and calls for prices in high quality downtown neighborhood that are higher than those in the data.

Figure 4: Calibration to 1990 Urban Shares and Neighborhood Prices



6 Counterfactual Analysis

Armed with the quantified model, we are now ready to study the effects of an increase in top income inequality on spatial sorting and well-being inequality. We briefly describe how we use the structure of the model and its 1990 calibration to compute counterfactual equilibria, before turning to analyzing our counterfactual exercises of interest.

6.1 Computing Counterfactuals

Our main counterfactual exercise of interest isolates the impact of a change in the income distribution in the city on the within-city spatial equilibrium. We solve for a counterfactual equilibrium of the model that corresponds to an income distribution $L'(w)$ in the city that is different from the 1990 one. In the new equilibrium, price of housing and quality of urban amenities change endogenously in response to this change in demand, and households at all levels of the (new) income distribution choose where they want to live, given these new parameters. The model therefore predicts the counterfactual sorting patterns that would have prevailed in response to a given income

distribution shock that we study in isolation. A approach similar to the one we describe here can be used for solving for counterfactual equilibria that correspond to other shocks to the economy, for instance, one where the relative quality of public amenities downtown increases exogenously compared to the one in the suburbs ; or one that implements a specific change in tax and transfer policy.

The information necessary to perform this step are (i) the model elasticities $\{\rho, \gamma, \epsilon_n, \sigma, \alpha, \tau_n\}$, and (ii) the calibrated values at the initial equilibrium for: population distribution, house prices, and share of land, for each neighborhood type, as well as the share of amenities trips taken in different types of neighborhoods: $\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{n,j}^{mk}, s_{n,j}^i\}$.⁴⁴ They were parametrized in the previous section.

We write a counterfactual equilibrium in changes relative to the initial equilibrium, denoting by $\hat{x} = \frac{x'}{x}$ the relative change of the variable x between the two equilibria. We show in Appendix B that given the structure of the model, the counterfactual equilibrium is the solution to the set of equations (29)-(33) for $\{(p_{n,j}^h)'\}$, $\{\lambda'_{n,j}(w), L'_{n,j}\}$ (or, equivalently, their “hat” values) as well as all the auxiliary variables $\{\hat{P}_{n,j}^a, \hat{r}_n, \hat{N}_{n,j}\}$, which is fully determined conditional on the model elasticities and $\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{n,j}^{mk}, s_{n,j}^i\}$. Details of the procedure as well as the corresponding set of equations are given in Appendix B.

6.2 Computing Welfare Measures

Having solved for a counterfactual equilibrium of interest, we are interested in computing welfare measures at various levels of income, to trace out the effect of the shock we are studying on well-being inequality. To that end, we compute a measure of compensating variation (CV) that is more readily interpretable than the welfare measure of the model. Let i denote a percentile in the income distribution and $m_t(i)$ denote the corresponding income in equilibrium t , where $t = 2$ in the new equilibrium (e.g., a 2014 counterfactual), and $t = 1$ in the initial one (the 1990 calibration).

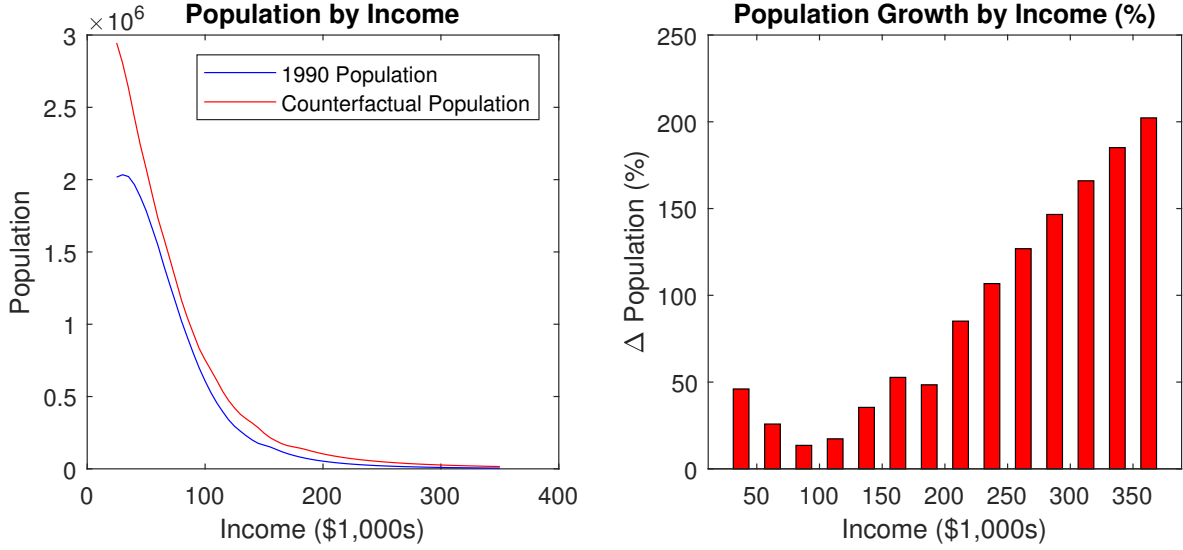
The CV measure is defined as follows:

$$\begin{aligned} CV(i) &= e(p_2, V_2(i)) - e(p_2, V_1(i)) \\ &= m_2(i) - V_2^{-1}(V_1(m_1(i))), \end{aligned}$$

where V , defined in (13), is utility and $e(\cdot)$ is the expenditure function. This compensating variation measures the gain in well-being between the two periods of a household at percentile i of the income distribution, in dollar equivalent and $t = 2$ prices. We then compare this Compensating Variation

⁴⁴We denote with $L_{n,j}$ is the total population living in neighborhoods of type $\{n, j\}$, i.e., $L_{n,j} = \int L(w)\lambda_{n,j}(w)dw$

Figure 5: Income and Population Changes from 1990 to 2014



measure to CPI-adjusted income growth:⁴⁵

$$\Delta \mathcal{W}^c(i) = \frac{CV(i) - (m_2(i) - m_1(i))}{m_1(i)}$$

Whenever $\Delta \mathcal{W}^c(i) > 0$, income growth measures *understate* increases in well-being.

6.3 Counterfactual 1: Changing Population and Income

Population and Income Shock Between 1990 and 2014, the population of major US cities grew by 29 %, i.e. faster than the rest of the US. At the same time, the distribution of incomes grew disproportionately at the top: the 2014 income distribution is characterized by a fatter right tail than the 1990 one. Overall, total income grew by 39 % for the CBSAs we study. These changes are summarized in Figure 5. In this paper, we take this growth as given and do not attempt to explain why urban population and income inequality of major centers grew faster than the rest of the US.⁴⁶ We start by studying the model’s prediction for the change in the spatial distribution of population within a representative CBSA, following this combined shock in income and population, both taken as exogenous.

Counterfactual This counterfactual is interesting in that it helps quantify how much of the change in spatial sorting patterns over the period, documented in Figure 1, can be ultimately traced

⁴⁵ Note that we also compute a measure of equivalent variation (EV), that is how much income would a worker i have needed, in period 1, to get the utility they get in period 2. Equivalent variation is measured as $EV(i) = e(p_1, W_2(i)) - e(p_1, W_1(i))$. This approach leads to similar insights. We report the corresponding results in the Appendix.

⁴⁶See Diamond (2016) for a study of the forces behind the sorting of workers of heterogenous skill *across* cities over the past few decades.

back, through the lens of the model, to socio-demographic trends summarized by population growth and income changes between 1990 and 2014 – as opposed to other economic shocks that have been studied elsewhere in the literature, such as changes in jobs location, crackdown on crime preceding neighborhood change, etc.⁴⁷ It is not our base counterfactual though: our preferred counterfactual is one where we hold population fixed to isolate the impact of the change in the income distribution itself. We discuss this counterfactual next, in section 6.4. For now, we recompute the equilibrium of the quantified model that corresponds to the new income distribution and the new population in 2014, holding all other exogenous parameters of the model constant.

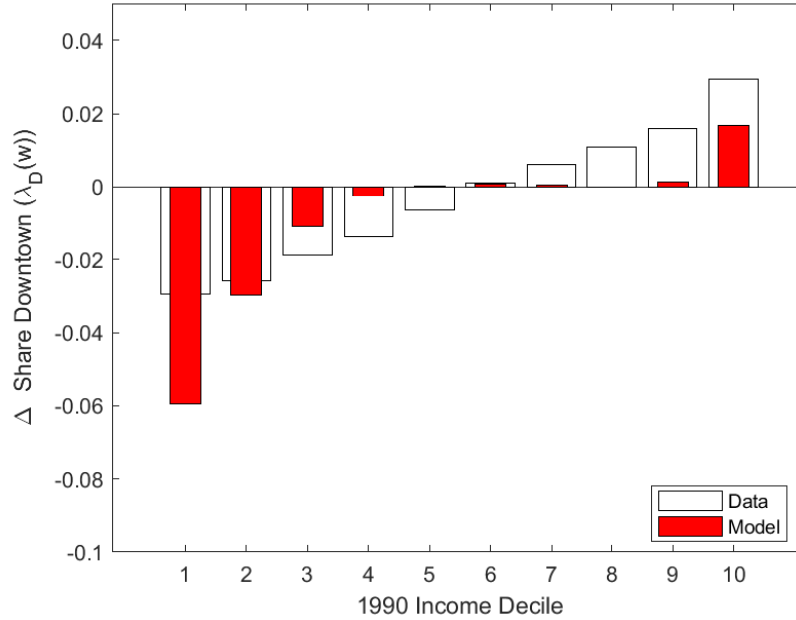
Figure 6 plots the predicted change in spatial sorting of households at various levels of the income distribution. The plots group individuals into income deciles based on the 1990 income distribution. For each income decile, we show two statistics: the change in the propensity to live in downtown areas between 1990 and 2014 in the data ($\Delta\lambda_D(w)$), using clear wide bars, and the model-implied ones, in red skinnier bars. The clear bars summarize the shift in the U-shape shown in Figure 1.

In response to population growth and increase in income inequality, the model predicts that poorer households move out of downtown and into the suburbs, while richer households do the opposite. This tilts the initial U-shape. This pattern strongly resembles, qualitatively, what happened in the data over that period. Quantitatively, the model suggests that these economic shocks have the potential to explain a substantial part of spatial changes over the period. At the top of the income distribution, the income and population shock explains in itself between one-half and three-quarters of the increased urbanization rate between 1990 and 2014. At the very bottom of the distribution, the sorting responses predicted by the model are somewhat stronger than what observed in the data for the bottom of the income distribution. Two elements are likely driving this result. In the model, as a result of population growth and income shifts, prices of housing downtown rise faster than those in the suburbs, leading to poorer households ultimately migrating out. In the data, despite a very strong price growth, we note that the relative propensity of low income households to live downtown has gone down, but less than in the model prediction. We note, first, that housing subsidies, rent control and public housing likely play a significant role in explaining the fact that some poorer households stay downtown despite market forces pushing in the other direction. This force is absent of the model. Second, our model features unit housing consumption as a source of non-homothetic consumption patterns. If this is a tractable and intuitive way to model location choices, it comes at a cost: it does not allow poorer household to adjust to price shocks on the intensive margin, by reducing square footage. This is a margin that households at the lower end of the income distribution have arguably used in recent years to be able to afford to stay downtown.⁴⁸

⁴⁷Edlund et al. (2016) and Su (2017), for example, provide evidence that longer work hours for high-skilled workers drove them into urban areas in the 1990s, as a way to reduce their travel cost to jobs. Ellen et al. (2017) show that central cities with a faster decline in crime in the 1990s experienced rising shares of high-income and college-educated residents.

⁴⁸We have experimented with a Stone-Geary utility function for housing rather than a unit housing requirement. Because the Stone-Geary demand function features a minimum housing requirement, the extensive margin ending

Figure 6: Counterfactual: 1990-2014 Population and Income Change



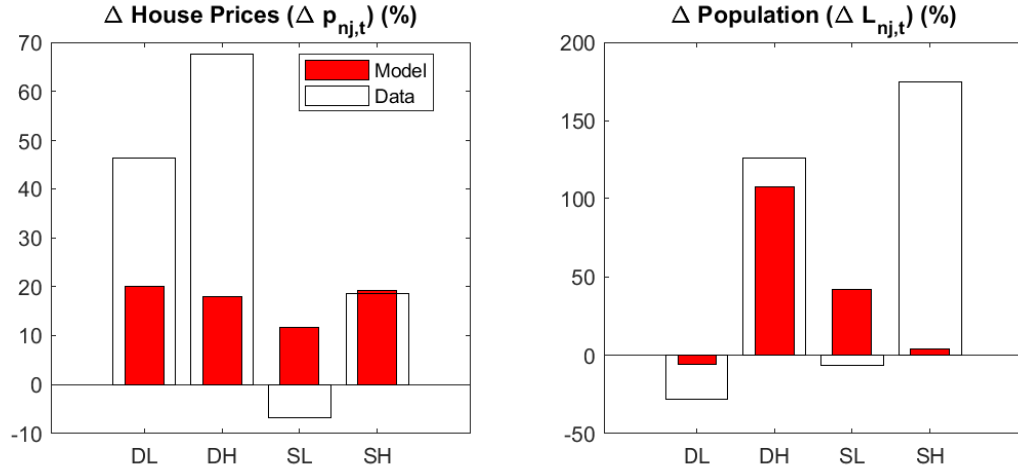
The out-migration of lower income households from downtown is driven by the increase in housing costs there, relative to the suburbs. Figure 7 compares our model predictions of housing price growth in each location-quality pair - isolating the population and income change mechanism alone - against the actual change in housing prices in those areas. Consistent with the differential housing supply elasticities between D and S , and with qualitative patterns in the data, housing prices grew more in downtown low quality areas relative to suburban low quality areas (20 vs. 10 percent). Second, our model predicts house price growth downtown in response to the population and income shock, of about 20 percent. This price growth is more limited than what happened overall in the data, where prices in downtown low and high quality neighborhoods have increased by roughly 40 and 60 percent between 1990 and 2014. This suggests that other economic mechanisms drive the housing price dynamics downtown, beyond the population and income trends captured here. We also note that the high cyclical nature of the housing prices that drive, in part, the data we report, might mask the long run trends that the model aims to capture.⁴⁹

Overall, we conclude from this analysis that the change in income distribution together with aggregate population growth between 1990 and 2014 has the potential to explain a substantive portion of the shift in the composition of downtowns over the same period. We are highlighting one important force that explains part of the neighborhood change within metropolitan areas. Our results also suggest that other mechanisms are at play at the same time.

up playing a large role for poor households in this case too.

⁴⁹Appendix Figure 18 demonstrates that house prices in high-quality downtown neighborhoods recovered from the housing crisis faster between 2010 and 2014 than other neighborhood types.

Figure 7: Model Predictions of Prices and Quality Sorting

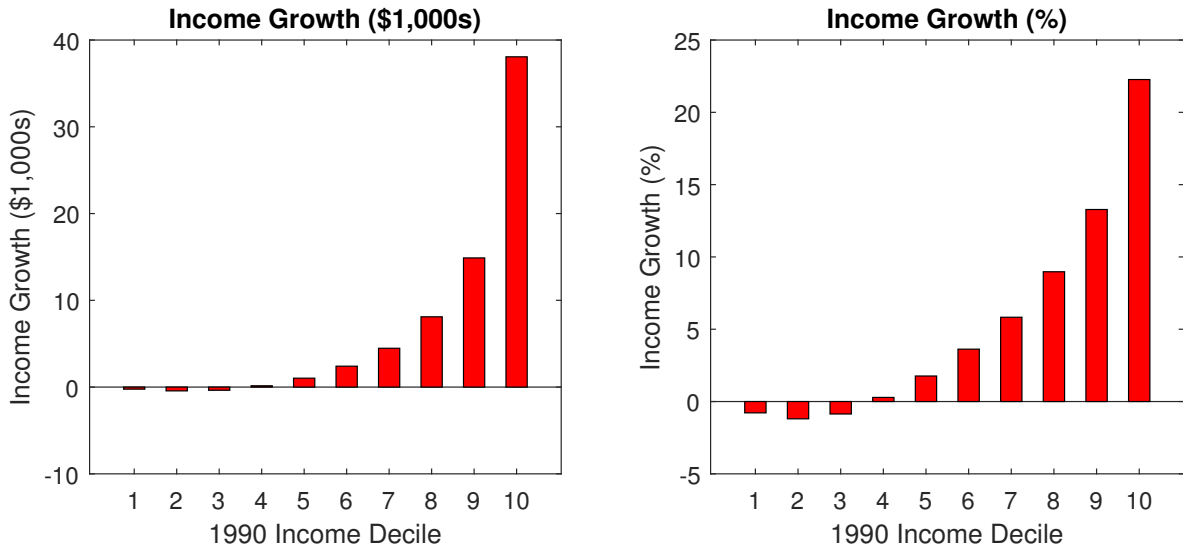


6.4 Counterfactual 2: Changing Only the Income Distribution

Income Distribution Shock We now turn to isolating the impact of changes in the income distribution, separate from population growth. To do so, we run the same counterfactual as above, but normalize the counterfactual population to its 1990 level. Our goal is in particular to estimate the welfare implications of the changing nature of spatial sorting in response to the rising incomes of the rich. To that end, we compute compensating variation (CV) between the initial equilibrium and this counterfactual at each percentile of the income distribution, as explained in section 6.2, and refer to this CV measure as “welfare” or “well-being”, to simply contrast it with the simple change in income over time. This measure reflects changes in well-being associated not only with changing income, but also with changing housing costs, and changes in endogenous amenity quality. Figure 8 plots the shock that we consider in this counterfactual. The left panel shows the dollar change in average income within each income decile between 1990 and 2014. The right panel shows the percentage change in income growth earned within each income decile during this period. Similar to what has been documented extensively within the literature for the economy as a whole, income inequality has increased within the largest CBSAs over the last 25 years in the United States. For the bottom decile of the income distribution for our sample, income actually fell slightly by approximately 0.5 percent. For the top decile, income increased by a little over 21 percent. Overall, there was an 22 percentage point increase in the income gap between the top and bottom decile in our sample since 1990.

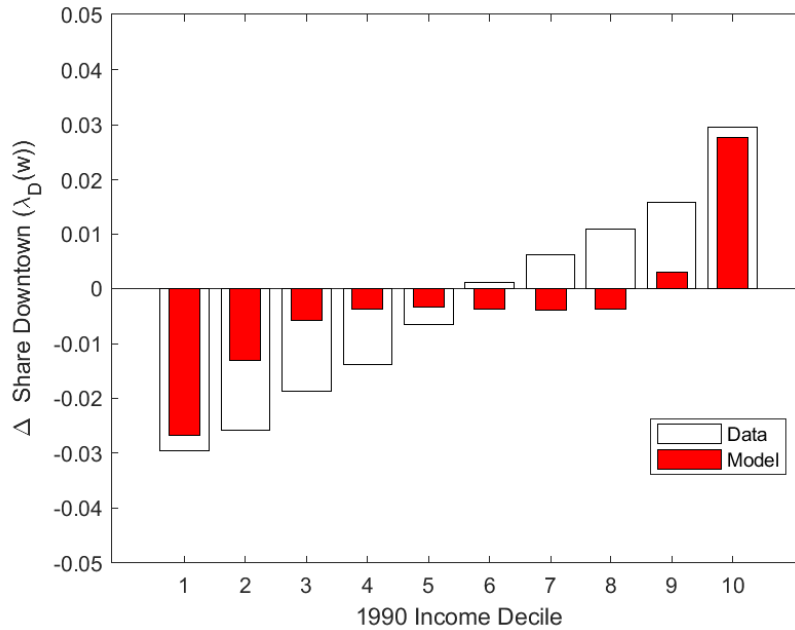
Impact on Spatial Sorting We compute the counterfactual spatial equilibrium that would have prevailed, through the lens of the model, if the only shock to the economy between 1990 and 2014 had been the change in the income distribution. Figure 9 shows that the 1990-2014 change in income distribution, in itself, results in a shift in location choices that has the same qualitative properties as the general trend we observe in the data. Top earners move in downtown, while

Figure 8: Income Changes from 1990 to 2014



households at lower income levels tend to move out. The predictive power of this shock alone on the change in spatial sorting patterns observed in the data is quite high.

Figure 9: Counterfactual impact of shift in income distribution (at constant population)



Welfare Impact Figure 10 shows our headline results, i.e. the welfare gains, above and beyond income change, accruing to different income deciles due to the spatial sorting response to rising

incomes of the rich. The right hand panel shows results assuming that everyone is a renter, while the left hand panel instead assumes that some households are homeowners. In this case, they reap the gains from the price appreciation of the housing stock between 1990 and 2014, which increases their total income. Specifically, as described in Section 5, we allocate the profits from increased house prices to each income decile based on their ownership shares by location type in 1990. This panel includes the full welfare to each income group accounting for the fact that homeowners are potentially made better off when neighborhoods gentrify.

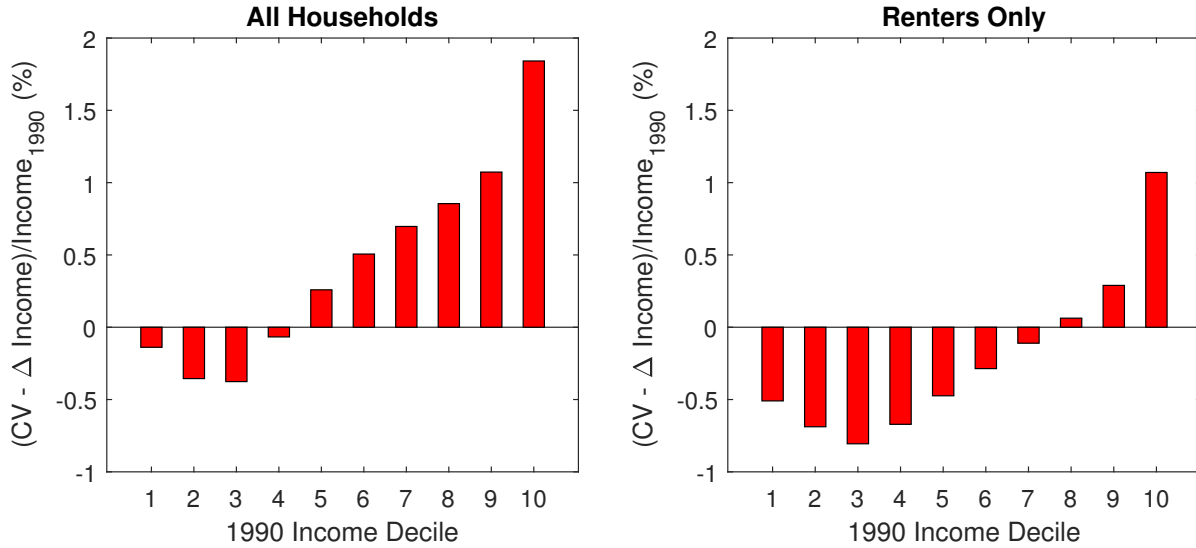
A few results are striking from Figure 10. The spatial sorting response amplifies the differences in well-being between the rich and the poor during this time period. In the top decile of the income distribution, well-being grew more than income, by 1.8 percentage points including the capital gains of the house price increase (left panel). As high earners move into downtown areas, the private amenities that they value endogenously respond, making them better off. House prices increase, but incumbents are compensated by the fact that they own. Even high-income renters, however, gain from gentrification. They see 1 percentage point welfare growth in spite of higher housing costs (right panel). The amenity effect dominates the price effect, at the top of the income distribution. At the bottom of the income distribution, on the other hand, households' well-being grew less than what income suggests. Renters well-being growth is 0.8 percentage points lower than income growth. For these households, the price effect dominates the amenity effect, on net. Note that about 30 percent of individuals from the lowest income decile who resided downtown in 1990 owned their home. They are compensated for the housing cost increases by house price appreciation, so that their utility losses are smaller. On net, individuals from the bottom three income deciles are between 0.1 and 0.3 percentage points worse off from the rising incomes of the rich (left panel).

Overall, well-being inequality between the top and bottom deciles of the income distribution increased by an additional 2.0 percentage points - compared to income inequality growth (22 percent) - because of spatial sorting responses within cities. The key finding of our paper is that ignoring within city spatial sorting leads to understating the welfare differences between the rich and the poor of rising income inequality.

6.4.1 Mechanisms

Summary What drives these results in the model? There are four important components here. First, as the rich get richer, they move downtown to consume urban amenities. This puts upward pressure on housing prices downtown. Given that the poor initially live downtown, this makes poor renters worse off if they remain downtown. Second, as the rich move downtown, the number of high quality neighborhoods increases. Some of this entry is at the cost of exit (or gentrification) of poorer neighborhoods. Given love of variety preferences, the additional entry of high quality neighborhoods downtown makes high income households better off and the associated gentrification makes low income households worse off. Third, as downtown gets richer, taxes collected are higher and public amenities respond. This increases amenities for all households downtown, including the

Figure 10: Welfare Changes From Spatial Sorting Response to Changing Income Distribution

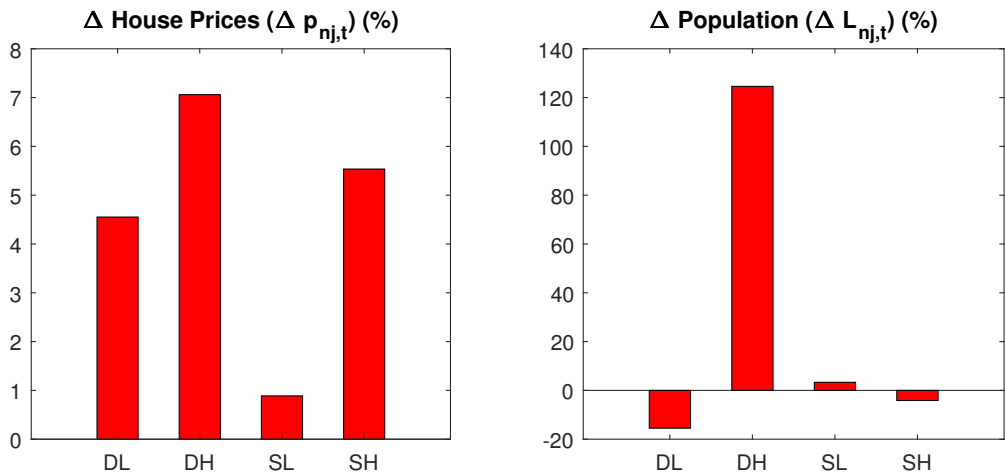


poorest ones. Absent price responses, this would make both richer and poorer households better off downtown, but housing price responses to this amenity increase tend to hurt poorer households. Finally, some of the low income households choose to relocate to lower quality neighborhoods in the suburbs. In doing so, they incur additional commute costs and move to a location that, by revealed preference in the initial equilibrium, they enjoy less. This mechanism is captured in the model by idiosyncratic utility shocks. These are reduced-form shocks that can capture attachment to a place as well as proximity to family and social networks and the access to social insurance they provide. These all matter strongly in location decisions and are arguably important in analyzing the well-being consequences of gentrification.

Price Effects The left-hand panel of Figure 11 shows the prediction of house prices within our model from the changing income distribution for different neighborhood types. A few things are of note. First, the change in the income distribution only explains some of the change in house prices observed in the data highlighted above. Given that we have shut down population growth in this counterfactual, it is not surprising that we are getting less house price growth. The large population increase within the largest CBSAs puts much more upward pressure on house prices. Second, our model is predicting that the shift in the income distribution alone is resulting in a roughly 10 percent increase in house prices in both low and high quality downtown neighborhoods. It is this increase in house prices generated by the shift in incomes of the rich that contribute to the welfare losses of the poor renters who remain downtown. Additionally, the house prices in low quality downtown areas increase more than the house prices in low quality suburban areas. Land is more elastic in the suburbs moderating house price growth.

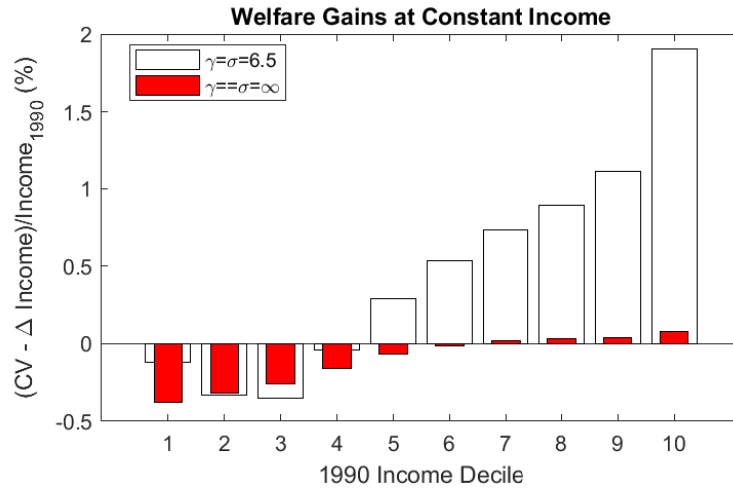
Neighborhood Change The right hand side of Figure 11 shows the share of households that reside in high and low quality housing in each area. Our model predicts a decline in the population residing in low quality downtown neighborhoods and a corresponding increase in the population in high quality neighborhoods in response to the shift in the income distribution. These shifts are the model analog of gentrification. As the rich get richer, high quality downtown neighborhoods expand while low quality downtown neighborhoods contract. Love of variety for high quality amenities and neighborhoods make this effect positive for richer households. Poorer households might benefit from it as well, to the extent that they consume some of these amenities themselves.

Figure 11: Mechanisms



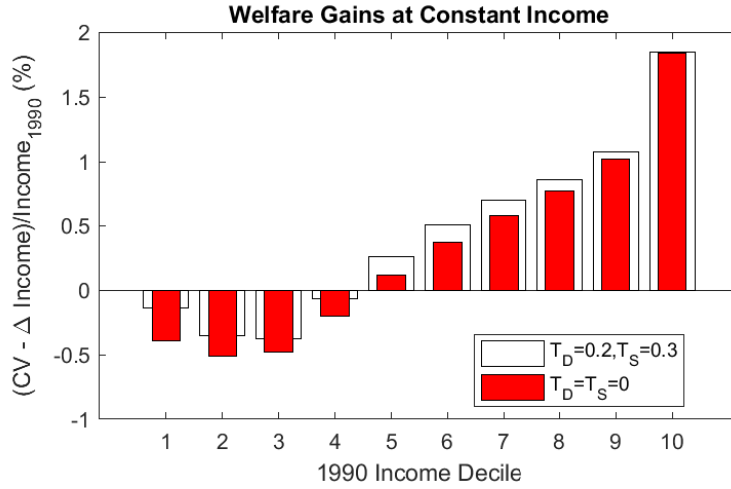
To tease out the respective roles played by endogenous neighborhood entry and price changes in driving the welfare results at various levels of the income distribution, we study the changing welfare measures in a calibration that shuts down love of variety effects across neighborhoods by setting the two between-neighborhood substitution elasticities, γ and σ , to infinity. Recall that γ governs the elasticity of substitution across neighborhoods for residential choice while σ governs the elasticity of substitution of consuming amenities from other neighborhoods. We do this for the specification where we account for homeownership. These results are shown in Figure 12 (red bars). For ease of comparison, we redisplay our base welfare results inclusive of homeownership (clear bars) in the background. In this counterfactual, prices and land area respond to changes in the income distribution, but there is no increase in neighborhood (or associated amenity) variety. The welfare gap across income groups is mitigated substantially when the love of variety effects are shut down. Specifically, the well-being growth gap between households in the top vs. the bottom decile of the income distribution in 1990, is 0.5 percentage points without love of variety effects, vs. 2 percentage point in the baseline suggesting that about three-quarters of the welfare gap in our base results stems from the endogenous private amenities response. Interestingly, the absolute welfare losses for the bottom decile are increased from -0.14 to -0.38 percentage points, since they benefit less from the positive amenities that accompany the influx of the wealthy (both public and private).

Figure 12: Shutting Down Amplification



Public amenities As richer households move in downtown, tax revenues increase and public amenities are enhanced in response. Therefore, endogenous public amenities arguably curb the negative effect of gentrification on poorer households. Note though that this channel will also end up impacting real estate prices and rents downtown, as it makes the area more desirable. Therefore, it is unclear a priori whether, on net, the public amenity channel mitigates the well-being inequality that accompanies gentrification. We turn to our model to quantify this net effect. Figure 13 reports a counterfactual with no endogenous response in public amenities, and compares it to the baseline. We see that the public amenities channel in itself tends to mitigate the welfare losses for low-income households, which are more than double (-0.4 vs. -0.14 percentage points) when endogenous public amenities are shut down, without much effect on the top decile. For poorer households, the benefit of an increase in publicly provided amenities is higher than the corresponding price increase it triggers. This suggests that endogenous public amenities mitigate the effect of gentrification, but are far from overturning the general tendency of spatial sorting responses to increase well-being inequality.

Figure 13: Shutting Down Public Amenities



6.4.2 Robustness

Which elasticities are important in driving the magnitudes of our distributional welfare results? To explore this question, we examine the sensitivity of our welfare results to alternate parameter values. Table 4 summarizes the sensitivity of our two main results to variation in key parameter values. Specifically, we focus on the sensitivity of (1) the absolute change in welfare that results from spatial sorting in response to the change in the income distribution for households in the top and bottom decile of the income distribution and (2) the relative change in welfare between these deciles. This table highlights the key mechanisms that are driving our welfare estimates.

ρ is the parameter we feel we identify best using the underlying variation in spatial sorting across neighborhood types in response to exogenous CBSA-wide income shocks. Our base estimate is $\rho = 3.3$. Table 4 shows the sensitivity of our results when we set $\rho = 2.5$ and $\rho = 4$. At higher levels of ρ , neighborhoods of different types are more substitutable with each other. As individuals get richer, they are more likely to move downtown when ρ is lower. Additionally, the poor are more likely to migrate out in response to the price increase associated with rich moving downtown as ρ is higher. Therefore, higher values of ρ amplify our welfare results. But, it is interesting to note that even when $\rho = 2.5$ the increase in the welfare gap is large when spatial sorting responses are ignored.

The elasticities of substitution between neighborhoods for housing and non-tradable amenity consumption, γ and σ , were studied above (Figure 12). In Table 4, we show the sensitivity of our results to different values of γ and σ pairs. For lower value of γ or σ , there is even more love of neighborhood variety effects and even more endogenous amplification of amenities downtown. This amplifies our welfare results. We note that changing δ has very little effect on our welfare estimates. This is because the share of household spending on non-tradable amenities is relatively small ($\alpha = 0.15$ in our base case). The corresponding channel is therefore quantitatively limited in the model. The higher the value of α the larger the well-being inequality increase, and the more σ and δ matter

Table 4: Robustness of Welfare Estimates to Key Parameters

	$(\Delta CV - \Delta Inc)/Inc_{1990}$						
	All Households			Renters Only			
	Decile:	Top	Bottom	Diff.	Top	Bottom	Diff.
Base Specification		1.84	-0.14	1.98	1.07	-0.51	1.58
Elasticity of Substitution between Neighborhood Types (base: $\rho = 3.3$)							
$\rho = 2.5$		1.69	-0.06	1.75	1.02	-0.50	1.52
$\rho = 4$		2.04	-0.12	2.15	1.23	-0.48	1.71
Elasticity of Substitution between Same-Type Neighborhoods (base: $\gamma = 6.5$)							
$\gamma = 5$		2.81	0.37	2.45	1.94	-0.24	2.18
$\gamma = 8$		1.51	-0.22	1.72	0.82	-0.60	1.43
$\gamma = \infty$		0.45	-0.29	0.75	0.07	-0.89	0.96
Elasticity of Substitution between Private Amenities (base: $\sigma = 6.5$)							
$\sigma = 5$		2.08	-0.06	2.13	1.30	-0.45	1.75
$\sigma = 8$		1.71	-0.18	1.90	0.94	-0.55	1.49
$\sigma = \infty$		1.25	-0.35	1.60	0.49	-0.69	1.18
Distance Elasticity of Amenity Consumption (base: $\delta = 0.2$)							
$\delta = 0.1$		1.85	-0.14	1.99	1.08	-0.51	1.58
$\delta = 0.3$		1.83	-0.14	1.97	1.06	-0.51	1.57
Amenity Expenditure Share (base: $\alpha = 0.15$)							
$\alpha = 0.05$		1.68	-0.09	1.77	1.04	-0.26	1.30
$\alpha = 0.25$		1.92	-0.15	2.07	1.09	-0.64	1.73
Housing/Land Supply Elasticities (base: $\epsilon_D = 0.6, \epsilon_S = 1.33$)							
$\epsilon_D = 0.1, \epsilon_S = 1.33$		1.84	-0.14	1.98	1.05	-0.53	1.59
$\epsilon_D = \epsilon_S = 1.33$		1.85	-0.13	1.98	1.09	-0.47	1.57
$\epsilon_D = 1.33, \epsilon_S = 3$		1.96	0.03	1.93	1.34	-0.13	1.47
Public Amenity Elasticity (base: $\Omega = 0.05$)							
$\Omega = 0$		1.68	-0.20	1.88	0.91	-0.57	1.48
$\Omega = 0.03$		1.78	-0.16	1.94	1.01	-0.53	1.54
$\Omega = 0.08$		1.94	-0.10	2.04	1.17	-0.48	1.64
Property Tax Rates (base: $T_D = 0.2, T_S = 0.3$)							
$T_D = T_S = 0$		1.83	-0.39	2.22	1.09	-0.83	1.91
$T_D = 0.15, T_S = 0.25$		1.90	-0.14	2.04	1.13	-0.52	1.65
$T_D = 0.25; T_S = 0.25$		1.84	-0.25	2.09	1.10	-0.61	1.71

for our welfare results. In our base calibration, the main love of variety effect at play quantitatively is the on the choice of neighborhood where to live (governed by γ), rather than on the choice of neighborhood where to go consume amenities (governed by σ).

The elasticity of housing supply downtown versus the suburbs play an important role in the welfare effects for poor renters. This is not surprising. Much of the welfare effect on the poor stems from them paying higher rents downtown as the rich move in. The more inelastic is the downtown housing supply, the more house prices move and the larger the welfare results. However, when price growth is higher, poor owners are made better off. Changing the land supply elasticity does not affect the welfare gaps between the poor and the rich on average. However, the land supply elasticity is crucial for understanding the welfare losses to lower income renters.

Finally, the response of our welfare estimates to the elasticity of the endogenous component of public amenities confirms that low-income households benefit from the increases in local tax revenues that accompany gentrification. Increased efficiency of the public sector benefits the poor in absolute terms, but it in fact benefits the wealthy by more, so the welfare gap actually grows by more when Ω increases.

Overall, this variation in our welfare estimates to different parameter values is useful for understanding the forces driving our results. However, we note that over reasonable parameter ranges, our welfare results are fairly stable. Our main qualitative results are not reversed by any of these perturbations: poor households (particularly renters) are worse off in both absolute terms and relative to the wealthy from the spatial sorting response to top income growth between 1990 and 2014.

6.5 Welfare Impact of Alternative Income and Population Change

In the above sub-sections we have focused on the welfare effects of feeding in changes in the observed income distribution holding all other potential driving forces constant. In this sub-section, we explore the welfare implication of total population change itself. We also explore alternative changes in income distribution, to tease out what characteristic of the 1990-2014 income shock are important in driving our result.

Table 5 reports the results for those alternative shocks. Row 1 re-displays our base line results. In the second row, we feed in the actual population change and change in the income distribution between 1990 and 2014. This is the first counterfactual we discussed above. The third row isolates the effects of population growth separately from income growth, by feeding in only the observed change in population, holding the underlying income distribution constant. Table 5 shows that accounting for growth in population results in a larger increase in welfare inequality between rich and poor households compared to our baseline. The larger increase stems from two forces. First, population growth amplifies the love of variety effects. As there are more people, developers provide more neighborhoods of differing varieties. The increased varieties makes downtown high quality neighborhoods even more attractive which further draws richer households downtown. Just as above, these variety effects enhance the welfare of the rich relative to the poor. In addition, the

increases in population drives up rents everywhere but more so in the downtown areas where land is more constrained. Given our unit housing assumption, this reduces the welfare of the poor by making their housing less affordable. In particular, changing both population and income increases the well-being gap between high and low income residents by over 6 percentage points (on a base of 22 percentage points) – a roughly 30 percent increase. Additionally, poorer renters are made worse off in absolute terms by an amount equal to 3.3 percent of their lifetime income. While shifting the income distribution alone had a sizable effect on the welfare gap between high and low income individuals, general population growth is also resulting in sizable welfare differences between rich and poor households through a spatial sorting response.

In the fourth row of the table, we hold population growth fixed and assume that all household experienced the same income growth equal to the 1990-2014 per capita average. Under this alternative income change, the welfare of the poor in general, and poor renters in particular, are made much more worse off in absolute terms. The reason for this is that when making the increase in income broad based, many middle class individuals in the suburbs also want to move up their residential Engel curves. This causes even more individuals to want to live downtown putting further upward pressure on house prices. In our baseline counterfactual very few households are treated with the income increase. The more broad based the treatment of income growth, the larger the spatial sorting response. As a result, the increase in welfare inequality due to spatial responses is higher than in the baseline case, at about 3.8 percent (instead of 2.0).

In the final rows (5 through 7) of table we explore crude predictions about the potential future of neighborhood change. Specifically, we hold population growth fixed and ask what happens through the lens of our model when income growth increases by an additional 10, 20 and 30 percent for everyone, respectively, starting from the actual 2014 income distribution. These counterfactuals shed some light on the potential effects of future economic growth on the spatial distribution of residents within cities. Holding population fixed, the quantified model suggests that the spatial sorting response from a rise in income of 10 percent for all individuals (which does not impact income inequality) increases well-being inequality. Accounting for within city spatial responses reduces the welfare of those in the bottom decile of income distribution by 0.7 percentage points compared to an income-based measure. At the same time, accounting for these spatial responses leads to a well-being growth that is 1.7 percentage points higher than income growth, for the richer households. Welfare inequality increases by 2.4 percentage points. The mechanisms are the same as what we highlight above. As some households get sufficiently rich, they want to move downtown to consume amenities provided in high quality neighborhoods. This puts upward pressure on rents making poorer households worse off. Simultaneously, the variety of high quality neighborhoods will increase making high income households better off. The larger the income growth, the more the welfare gaps between the rich and poor will diverge due to the spatial sorting response. Our model predicts that if income growth in the US continues, additional gentrification and within city neighborhood change will be an enduring feature of the urban landscape.

Table 5: Welfare Estimates under Different Counterfactual Income Distributions

		$(\Delta CV - \Delta Inc)/Inc_{1990}$					
		All Households			Renters Only		
Decile:		Top	Bottom	Diff.	Top	Bottom	Diff.
[1]	Base Specification ($\Delta Pop = 0$)	1.84	-0.14	1.98	1.07	-0.51	1.58
Alternative Driving Forces (1990-2014)							
[2]	Actual 2014 Income Distribution	6.32	-0.08	6.40	3.62	-3.26	6.88
[3]	$\Delta HHI_{inc} = 0$	3.69	-0.13	3.81	1.92	-2.80	4.72
[4]	$\Delta Pop = 0$ & $\Delta HHI_{inc_i} = \Delta Mean(HHI_{inc_i})$	2.75	-0.29	3.04	2.51	-1.16	3.67
Projected Further Welfare Changes from Further Income Growth from 2014 Onward							
[5]	Additional $\Delta HHI_{inc} = 10\%$	1.71	-0.69	2.39	4.41	2.49	1.92
[6]	Additional $\Delta HHI_{inc} = 20\%$	7.02	-1.57	8.59	8.79	1.11	7.68
[7]	Additional $\Delta HHI_{inc} = 30\%$	10.64	-2.66	13.30	10.88	-1.79	12.67

6.6 Gentrification Curbing Policy

Finally, we turn to analyzing the impact of policies that aim to shape the spatial sorting of heterogeneous households within the city. As an example, we use the model to study what would be the impact of systematically taxing the high-quality housing developments downtown while subsidizing poorer households who choose to live downtown. This is a stylized “anti-gentrification” policy. It aims to limit the development of high-quality neighborhoods downtown while helping poorer households to remain located in the city. Specifically, we assume that the local government imposes a tax t on housing prices downtown, for housing units in high-quality neighborhoods. The tax levied is then fully redistributed as a place-quality-specific subsidy for households who choose to locate downtown, but in low-quality neighborhoods.⁵⁰ We recompute the spatial equilibrium of the city, implementing the policy with a tax of 5%. We focus on the environment of our preferred counterfactual, with the 2014 distribution of household income but no population growth. Figure 14 shows that the policy has the effect of stemming part of the gentrification of downtown neighborhoods. As seen from the right panel, compared to the case without policy, there is less increase in population of high quality neighborhoods, and less decrease in low quality neighborhoods. Furthermore, the policy is effective at stemming part of the land price increase in low income neighborhoods downtown.⁵¹ Turning to the well-being effect of this policy, we find that, unsurprisingly, it reverses some of the gains for higher income households (figure 15). But it has only marginal benefits for

⁵⁰That is, the price perceived by household for D,H houses is $p_{DH}(1+t)$ while the one perceived for D,L houses is $p_{DL} - \delta$, where:

$$\delta = \frac{\int L(w)\lambda_D(w)\lambda_{DH}(w)tp_{DH}dF(w)}{\int L(w)\lambda_D(w)\lambda_{DL}(w)dF(w)}.$$

⁵¹In addition, mechanically, effective housing costs increase by less than the price increase for low quality housing residents downtown, who receive the redistribution of the tax revenues, and increase by more for high-quality housing residents downtown, who bear the incidence of the tax.

low-income households. Overall, perhaps unsurprisingly, the redistributive motive is not sufficient to warrant such a policy. The policy intervention is large, but its welfare implications are clearly insufficient to cancel out the large redistributive impacts of the neighborhood change associated with growing nominal income inequality. Put differently, the increase in well-being inequality could arguably be targeted more efficiently by direct redistribution. On the other hand though, we note that the policy does contribute to limiting neighborhood change and spatial resorting. To the extent that governments intrinsically value social diversity within their downtowns, this suggests that these policies can help achieve some of these targets.

Figure 14: Mechanisms under “Anti-Gentrification” Policy

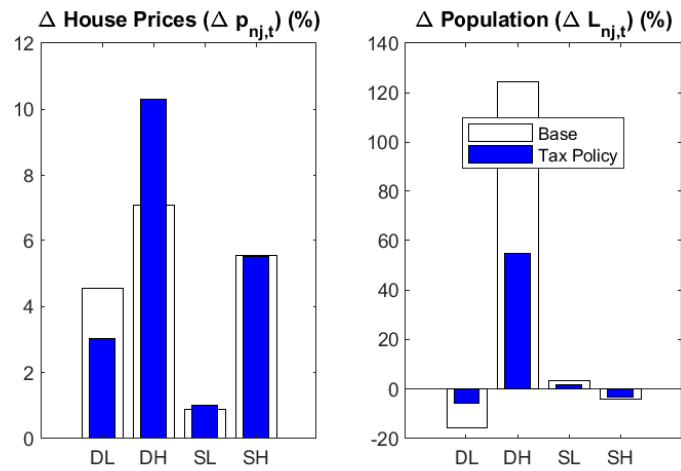
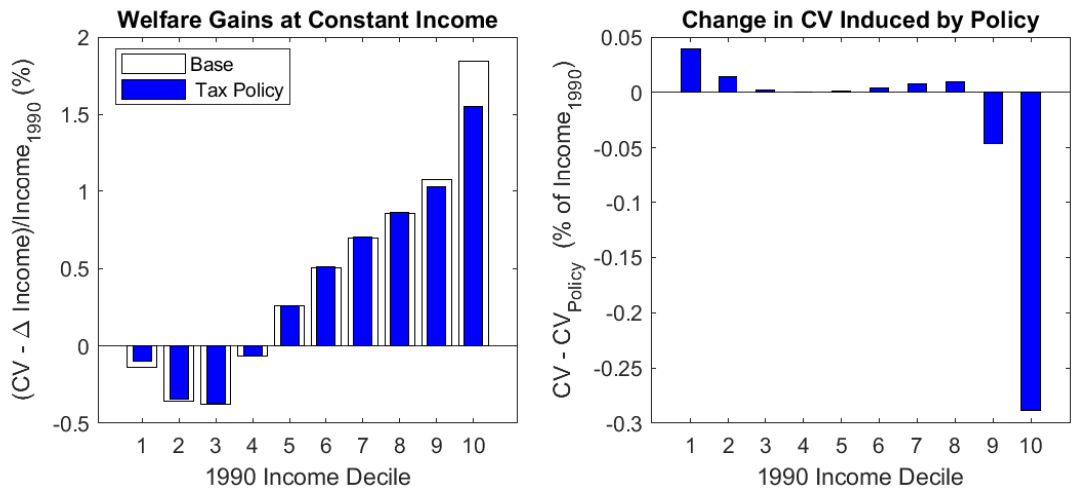


Figure 15: Well-Being Effects of “Anti-Gentrification” Policy



7 Conclusion

We set out to explore the link between rising incomes at the top of the income distribution and the changes that have happened over the past few decades in the urban cores of US cities: high income households have been moving into downtowns, housing prices have gone up while neighborhoods have been changing dramatically, leading to anti-gentrification protests and a renewed reflection among policy circles about maintaining social diversity in urban neighborhoods. To study this phenomenon, we develop a spatial model of a city with heterogeneous agents, neighborhoods of different qualities, and non-homothetic preferences. We quantify the model using detailed location and income data, at the tract level, on the largest cities in the US. We then use the quantified model to tease out how much of the change in spatial sorting patterns by income over time can be plausibly traced back to changes in the income distribution, tilted towards higher incomes.

In the model, as the rich get richer, their increased demand for urban amenities drives up housing prices in downtown areas, where the development of these amenities is fueled by economies of density. The poor are either displaced or end up paying higher rents, making them worse off. Our estimates suggest that increases in the incomes of high income individuals was a substantive contributor to increased urban neighborhood change during the last 25 years within the U.S. Furthermore, our analysis suggests that the neighborhood change resulting from the increased incomes of the rich did, in fact, make poorer residents worse off. We explore possible policy responses to the rise in gentrification, and find that policies that contain gentrification seem to only lead to a very modest mitigation of the increase in well-being inequality, which could arguably be targeted more efficiently by direct redistribution. On the other hand, it is effective in maintaining social diversity in urban neighborhoods, arguably one of the goals of such a policy.

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Appendix A Data Appendix

Appendix A.1 Census Data and ACS Data

Census Tract Data For our work at the neighborhood level, we assemble a database of constant 2010 geography census tracts using the Longitudinal Tract Data Base (LTDB) and data from the National Historical Geographic Information System (NHGIS) for the 1970-2000 censuses and the 2012-2016 ACS. In each of the censuses from 1970 to 2000, some tracts are split or consolidated and their boundaries change to reflect population change over the last decade. The LTDB provides a crosswalk to transform a tract level variable from 1970 to 2000 censuses into 2010 tract geography. This reweighting relies on population and area data at the census block level, which is small enough to ensure a high degree of accuracy. We combine these reweighted data with the 2012-2016 ACS data, which already uses 2010 tract boundaries.

CBSA Definitions Core Based Statistical Areas (CBSAs) refer collectively to metropolitan and micropolitan statistical areas. CBSAs consist of a core area with substantial population, together with adjacent communities that have a high degree of economic and social integration with the core area. We assign 2010 census tracts to CBSAs based on 2014 CBSA definitions. Our model estimation sample consists of metropolitan area CBSAs with the largest population in 1990s.

IPUMS Data PUMA geography is also not constant from 1990 to 2014, so we use a crosswalk between PUMAs (Public-Use Microdata Areas) and CBSAs in each year to link each PUMA to a CBSA. To construct constant downtowns from PUMAs across years, we develop the following methodology. We first intersect PUMA geographies in 1990 and 2014 with our constant downtown geography described in the main text, defined out of tracts closest to the city center accounting for 10 percent of a CBSA's population in 2000. PUMAs generally intersect with both the urban and suburban area of a CBSA, so we assign an urban weight to each PUMA equal to the percentage of that PUMA's population falling within the urban area (i.e., downtown) of that CBSA. We compute the urban and suburban population of each PUMA using the population of all census blocks whose centroid falls in a given area.

In most of the 100 CBSAs, PUMAs are too large to accurately represent downtowns. We therefore enforce an inclusion criteria where we only keep CBSAs for which 60% of the urban population lives in PUMAs whose population is at least 60% urban. Under this restriction, we find a set of 27 CBSAs for which we can define urban areas in 1990 and 2014.

Appendix A.2 Smartphone movement data

The smartphone movement data is from October 2016 to August 2018. Our data provider aggregates data from multiple apps' location services. Each visit comes from raw movement data intersected with a basemap of polygons (usually buildings). Each visit receives a unique location, device, and time stamp.

We define the permanent home location of each device as in Couture et al. (Work in Progress), using 90 billion visits to residential establishments. We first identify a device’s weekly home location as the residential location where it spends most night hours, conditional on visiting that location at least three different nights that week. We then assign a permanent home location to any device that has the same weekly home location for three out of four consecutive weeks. We are able to identify permanent homes for 87 million devices between 2016 and 2018. We refer to this location as the person’s home location.

We have 9.6 billion visits to commercial establishments in our sample. Of these, our amenity demand estimation uses 2.3 billion that are to non-tradable amenities, defined as restaurants, gyms, movie theaters, and outdoor amenities (we exclude all retail locations.) To identify visits starting from home, we use the time stamp and duration of each visit. We define a trip as from home if the previous visit was to home and ended less than 60 minutes earlier. That procedure identifies 220 million of trips to non-tradable services that start from home.⁵² Finally, for our quality estimation, we restrict the sample to 600 million visits to chain restaurants, 60 million of which start from home. We refer to Couture et al. (Work in Progress) for additional details on that data.

Table 6 shows the number of establishments in the smartphone data basemap for the ten largest restaurant chains, compared with recent estimates of the actual number that we found online. This comparison shows that the smartphone basemap is nearly complete, with one exception, Starbucks, where almost half of the establishments are missing from the smartphone basemap.

Appendix A.3 NETS Data

The 2012 National Establishment Time-Series (NETS) Database includes 52.4 million establishments with time-series information about their location, industries, performance and headquarters from 1990-2012. The NETS dataset comes from annual snapshots of U.S. establishments by Duns and Bradstreet (D&B). D&B collects information on each establishment through multiple sources such as phone surveys, Yellow Pages, credit inquiries, business registrations, public records, media, etc. Walls & Associates converts D&B’s yearly data into the NETS time-series. The NETS data records the exact address for about 75 percent of establishments. In the remaining cases, we observe the establishments zip code and assign it’s location to the zip code centroid.

Neumark et al. (2007) assess the NETS reliability by comparing it to other establishment datasets (i.e., QCEW, CES, SOB and BED data). Their conclusions support our use of the NETS data to compute a long 12-year difference from 2000 to 2012. They report that NETS has better coverage than other data sources for very small establishments (1-4 persons), which is often the size of consumption amenity establishments.

Table 6 suggests that the NETS database is less complete than the smartphone basemap, but some of this difference is due to the earlier count. The NETS contains a majority of establishments

⁵²We do not observe all travel by devices, so visit duration is a lower bound and missing in some cases. This explains why we are only able to ascertain 10 percent of trips as starting from home, whereas for instance about 30 percent of trips to restaurants in the NHTS start from home.

Table 6: Ten Largest Restaurant Chains in NHTS vs Smartphone Data

Chain	NETS 2012 Rank	Smartphone 2016 Rank	NETS 2012 Count	Smartphone 2016 Count	Most Recent Actual Count
Subway	1	1	10,946	25,889	24,000+
McDonalds	2	2	9,889	14,914	14,000+
Starbucks	3	3	6,581	7,636	14,000+
Pizza Hut	4	6	5,754	6,695	7500+
Burger King	5	5	5,660	7,011	6500+
Wendys	6	8	4,127	5,683	5000+
Dunkin Donuts	7	4	4,030	7,418	8500+
KFC	8	14	3,997	3,157	4000+
Taco Bell	9	7	3,544	6,102	6000+
Dairy Queen	10	10	3,380	4,199	3500+

Notes: The data source from the most recent actual count obtained on 19 December 2018 from the following websites:

Subway: <https://www.subway.com/en-US/exploreourworld>

McDonald: <https://news.mcdonalds.com/our-company/restaurant-map>

Starbucks: <https://www.loxcel.com/sbux-faq.html>

Pizza Hut: <https://locations.pizzahut.com/>

Burger King: <https://locations.bk.com/index.html>

Wendys: <https://locations.wendys.com/united-states>

Dunkin Donuts: <https://www.dunkinonuts.com/en/about/about-us>

KFC <http://www.yum.com/company/our-brands/kfc/>

Taco Bell: <http://www.yum.com/company/our-brands/taco-bell/>

Dairy Queen: <https://www.qsrmagazine.com/content/23-biggest-fast-food-chains-america>

for eight of the ten largest chains, with the exceptions of McDonalds and Starbucks where the NETS misses more than half the actual number of establishments. We further assess the precision of the NETS by considering aggregate growth of chain establishments. For instance, Chipotle had nearly 100 stores in 2000 and grew to about 1000 stores in 2010. The NETS reports 21 Chipotle stores in 2000 and around 840 in 2012. Together, these numbers show that the NETS data captures general growth patterns, but we struggle to identify all chains due to merging on inconsistent establishment names and lags in D&B recording new locations.

Appendix A.4 Zillow House Price Indexes

We use the Zillow House Value Index (ZHVI) for all homes, as well as the per square foot version of that index. The ZHVI index intends to measure a median value for all homes (i.e., single family, condominium, and cooperative) and is available monthly for 14,417 zip codes in 1996, 14,421 zip codes in 2000, and 15,500 zip codes in 2014.⁵³ For each zip code in the Zillow data, we compute a yearly index by averaging over all months of the year. We map zip codes to tracts with a crosswalk from HUD. We compute the tract-level index as the weighted average of the home value index across all zip codes overlapping with the tract, using as weights the share of residential address in the tract falling into each zip code. For tracts falling partly into missing zip codes, we normalize the residential share in zip codes with available data to one. The final data set contains home value indexes for 52,186 tracts in 1996, 52,193 tracts in 2000, and 54,417 tracts in 2014.

Appendix B Model Appendix

Appendix B.0.1 Entry of Developers

Given CES demand for amenities, developers price amenities at a constant markup over marginal costs, that is:

$$p_r^a = \frac{\sigma}{\sigma - 1} h_{n(r),j(r)}^a r_{n(r)}, \quad (23)$$

so that in equilibrium, operational profits made on the amenities market by a developer of type (n, j) is:

$$\pi_{n,j}^a = \frac{\alpha^a}{\sigma} \int_w \frac{\lambda_{n,j}(w) (w - p_{n,j}^h)}{N_{n,j}} dL(w)$$

and the land used by amenities of type (n, j) is:

$$r_n K_{n,j}^a = \frac{\sigma - 1}{\sigma} \alpha^a \int_w \lambda_{n,j}(w) (w - p_{n,j}^h) dL(w) \quad (24)$$

⁵³We collected the data in February 2019. The index and methodology are available at: <http://www.zillow.com/research/data/>.

Similarly, the land used by housing of type (n, j) is:

$$r_n K_{n,j}^h = \int_w \lambda_{n,j}(w) h_{n,j}^h r_n dL(w) \quad (25)$$

and the price of housing is pinned down by profit maximization of developers on the housing market given demand:

$$\pi_r^h = \left[\int_w \lambda_r(w) dL(w) \right] \left(p_r^h - h_{n,j}^h r_n \right) \quad (26)$$

Using (10), (9) and (11) leads to the following pricing formula:

$$p_r^h = \frac{\gamma}{\gamma + 1} h_{n,j}^h r_n + \frac{1}{\gamma + 1} \mathcal{I}_{n,j}(p_r^h), \quad (27)$$

where the term $\mathcal{I}_{n,j}(p_r^h)$ is a measure of demand for neighborhood r .⁵⁴ By symmetry, all neighborhoods of type (n, j) have the same price in equilibrium, which we denote as $p_{n,j}^h$.

This leads to:

$$N_{n,j} = \frac{1}{f_{n,j}} \left[\int_w \lambda_{n,j}(w) \left(p_{n,j}^h - h_{n,j}^h r_n + \frac{\alpha^a}{\sigma} (w - p_{n,j}^h) \right) dL(w) \right] \quad (28)$$

Appendix B.1 Computing Counterfactuals

We describe here how to compute a counterfactual equilibrium for a different income distribution $L'(w)$, conditional on (i) an initial calibration corresponding to the income distribution $L(w)$, and (ii) on the model elasticities $\{\rho, \gamma, \epsilon_n, \sigma, \alpha, \tau_n\}$. The information necessary to perform this step are the calibrated values at the initial equilibrium for $\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{n,j}^{mk}, s_{n,j}^i\}$, where $L_{n,j}$ is the total population living in neighborhoods of type $\{n, j\}$ in the initial equilibrium, i.e.:

$$L_{n,j} = \int L(w) \lambda_{n,j}(w) dw,$$

and where we have defined three shares measured in the initial equilibrium. First, $S_{n,j}^{mk}$ is the share of amenity expenditures of households living in a neighborhood of type nj spent on amenities consumed in a neighborhood (m, k) . Second, within location n , $s_{n,j}^i$ is the share of equipped land used by activity $i \in a, h$ of quality j in location n .⁵⁵

We write a counterfactual equilibrium in changes relative to the initial equilibrium, denoting by $\hat{x} = \frac{x'}{x}$ the relative change of the variable x between the two equilibria. The counterfactual equilibrium is the solution to the following set of equations for $\{(p_{n,j}^h)'\}$, $\{\lambda'_{n,j}(w), L'_{n,j}\}$ (or, equivalently, their “hat” values).

⁵⁴ Specifically, $\mathcal{I}_{n,j}(p) = \frac{\int_w \Lambda_{n,j}(p, w) [(1-\tau_n)w + \chi(w)] dF(w)}{\int_w \Lambda_{n,j}(p, w) dF(w)}$ with $\Lambda_{n,j}(p, w) = \frac{\lambda_{n,j,r}(w)L(w)}{[(1-\tau_n)w + \chi(w) - p]}$.

⁵⁵ We have $\sum_{i,j} s_{n,j}^i = 1$ for $n = D$ or S and $\sum_{m,k} S_{n,j}^{mk} = 1$, for $n = D, S$ and $j = H, M, L$.

First, given (7), changes in housing costs are given by:

$$\hat{r}_n = \left(\sum_j s_{n,j}^h \hat{r}_n \hat{L}_{n,j} + s_{n,j}^a \hat{r}_n \hat{K}_{n,j}^a \right)^{\frac{1}{1+\epsilon_n}}, \quad (29)$$

where we have used the notation $s_{n,j}^i$ to denote the shares of land used by usage $i \in \{h, a\}$ and quality j within location n in the initial equilibrium, that is:

$$s_{n,j}^i = \frac{K_{nj}^i}{\sum_{j',i'} K_{nj'}^{i'}}.$$

Note that $\hat{L}_{n,j} = \frac{\int \lambda'_{n,j}(w) dL'(w)}{\int \lambda_{n,j}(w) dL(w)}$ while $\hat{r}_n \hat{K}_{n,j}^a = \frac{\int \lambda'_{n,j}(w) (w - (p_{n,j}^h)') dL'(w)}{\int \lambda_{n,j}(w) (w - p_{n,j}^h) dL(w)}$, where $\lambda'_{n,j}(w)$ is unknown and a solution of the system of equations described here, while the counterfactual distribution of income $L'(w)$ is taken as given.

Second, the housing prices in the new equilibrium are defined by⁵⁶:

$$\left(p_{n,j}^h \right)' = \frac{\gamma}{\gamma+1} h_{n,j}^h r_n \hat{r}_n + \frac{1}{\gamma+1} \mathcal{I}'_{n,j} \left((p_{n,j}^h)' \right), \quad (30)$$

where the function $\mathcal{I}'_{n,j}(p)$ is defined by:

$$\mathcal{I}'_{n,j}(p) = \frac{\int_w \Lambda'_{n,j}(p, w) [(1 - \tau_n)w + \chi(w)'] L'(w) dw}{\int_w \Lambda'_{n,j}(p, w) L'(w) dw}, \quad (31)$$

with $\Lambda'_{n,j}(p, w) = \frac{\lambda'_{n,j,r}(w)}{[(1 - \tau_n)w + \chi(w) - p]}$. Note here that τ_n and $\chi(w)$ are assumed constant between the two equilibria.

Third, the change in overall neighborhood quality $\tilde{q}_{n,j}$ is driven in particular by changes in number of neighborhoods of different types $\hat{N}_{n,j}$ and the change in density \hat{K}_n . Starting from (22), simple algebraic manipulations lead to:

$$\tilde{q}_{n,j} = \hat{N}_{nj}^{\frac{1}{\gamma}} \left(\hat{P}_{n,j}^a \right)^{-\alpha} \quad (32)$$

In this expression, the change in the number of neighborhoods is given by:

$$\hat{N}_{n,j} = s_{n,j}^{\pi,h} \hat{L}_{n,j} \frac{\left(p_{n,j}^h \right)' - h_{n,j}^h r_n'}{p_{n,j}^h - h_{n,j}^h r_n} + \left(1 - s_{n,j}^{\pi,h} \right) \frac{X'_{n,j} - \left(p_{n,j}^h \right)' L'_{n,j}}{X_{n,j} - p_{n,j}^h L_{n,j}},$$

⁵⁶Note that $h_{n,j}^h r_n$ is known in the initial equilibrium using equation 27 and the known variables $p_{n,j}^h, \lambda_{n,j,r}(w), L(w)$

where we define $X_{n,j}$ to be total income in n, j :

$$X_{n,j} = \int_w \lambda_{n,j}(w) w dL(w),$$

and we have defined the initial shares in profits made on the housing (vs amenities) market:

$$s_{n,j}^{\pi,h} = \frac{\left(p_{n,j}^h - h_{n,j}^h r_n\right) L_{n,j}}{\left(p_{n,j}^h - h_{n,j}^h r_n\right) L_{n,j} + \frac{\alpha}{\sigma} \left(X_{n,j} - p_{n,j}^h L_{n,j}\right)}.$$

Furthermore, the change in the price index for amenities in a neighborhood of type n, j is found combining 2, 3 and 23:

$$\left(\hat{P}_{n,j}^a\right)^{1-\sigma} = \sum_{j'n'} S_{n,j}^{n'j'} \hat{N}_{n'j'} \hat{K}_{n'}^{-\delta} (\hat{r}_{n'})^{1-\sigma},$$

where $S_{n,j}^{mk}$ is the share of expenditure on amenities spent on neighborhood of type m, k for households living in neighborhood of type n, j :

$$S_{n,j}^{mk} = \frac{N_{m,k} K_m^{-\delta} (r_m)^{1-\sigma}}{\sum_{n',j'} N_{n',j'} K_{n'}^{-\delta} (r_{n'})^{1-\sigma}}.$$

Finally, the counterfactual location choice of workers can be simply expressed as a function of initial location choices $\lambda_{n,j}$, changes in neighborhood quality and prices defined above, and changes in income, which we take as an exogenous input to the counterfactual. Specifically, changes in location choices are given by:

$$\hat{\lambda}_{n,j}(w) = \frac{\widehat{q}_{n,j}^{\rho} [w(1-\tau_n) + \chi'(w) - p_r']^{\rho}}{\widehat{V}^{\rho}(w) [w(1-\tau_n) + \chi'(w) - p_r]^{\rho}}, \quad (33)$$

In parallel, we get the change in welfare given by:

$$\widehat{V}^{\rho}(w) = \sum_{n,j} \widehat{q}_{n,j}^{\rho} \frac{[(1-\tau_n)w + \chi'(w) - p_r']^{\rho}}{[(1-\tau_n)w + \chi(w) - p_r]^{\rho}} \lambda_{n,j}(w), \quad (34)$$

Values for $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}\}$ are the solutions of equations (29)-(33) that define a counterfactual equilibrium of the economy corresponding to an alternative distribution of income $L'(w)$ in the city.

Appendix C Variable definition

This appendix details the computation of variables used in our analysis.

Appendix C.1 CBSA level wage Bartik shock

We use a Bartik wage shock to predict CBSA-wide average income growth between 1990-2014 and 2000-2014. We determine industry growth using 3-digit Census industry codes in 1990. The Census Bureau provides crosswalks between 2000, 2012, and 1990 industry codes. Examples of 3-digit industry categories includes "Aluminum production and processing", "Shoe Stores", "Retail Florists", and "Real Estate".

To calculate national wage growth for each industry between 1990-2014 or 2000-2014, we use person-level IPUMS data in 1990, 2000, and 2014. We keep the sample of people between 25 and 55 years who work at least 35 hours a week in a non-farm profession. We use annual pre-tax wage and salary income for individual earners. As is standard we compute a CBSA-leave out growth for each CBSA.

For both the Bartik shock from 1990-2014 and 2000-2014, we fix the share of people working in each 3-digit census industry for each CBSA in 1990. We then compute the Bartik predicted wage growth as average industry leave-out wage growth weighted by initial 1990 industry shares in each CBSA. We also computed the Bartik shock leaving out three major industry categories for some robustness specifications: Finance, Real Estate and Insurance (1990 industry codes 700-712), Manufacturing (1990 industry codes 100-399), and Technology.⁵⁷

Appendix C.2 Median income within Census table brackets

The U-shape plot in Figure 1 shows median income within each family income brackets from the NHGIS Census tables. To find the median income within each Census bracket, we use the distribution of family income within the 100 largest CBSAs in the IPUMS microdata in the corresponding year. To adjust for topcoding in IPUMS, we estimate the shape of the IPUMS income distribution above the 95th percentile assuming a Pareto distribution.

The estimation of ρ also requires median income within each census bracket. In this case, however, the estimation requires constant bracket over time. To do this, we assume that households are uniformly distribution within all bracket, except for the top bracket. Using the uniform distribution, we can map the CPI-adjusted census brackets in 1990 and 2000 onto to 2014 bracket definitions. For all bracket except the top bracket, the median income w used in estimation is the mid-point of these constant brackets. For the top bracket (above \$140,600 in 1999 dollars), we determine median income using 2000 IPUMS microdata.

⁵⁷181 = Pharmaceuticals; 342 = Electronic component and product manufacturing ; 352 = Aircraft and Parts ; 362 = Aerospace products and parts manufacturing ; 891 = Scientific research and development services ; 732 = Computer systems design and related services + Software Publishing + Data processing, hosting, and related services; 882 = Architectural, engineering, and related services.

Appendix C.3 Yearly user cost of housing for a median sized unit by quality, location and CBSA (p_{njc}).

Median house size in each year We find the median house size in each zip code by dividing the Zillow median house value by the Zillow median price per square foot. We map zip codes to tract as described in Appendix A and compute a population-weighted median over all tracts in the 100 largest CBSAs in each year. We find a median house size of 1510, 1529, and 1565 square feet in 1996, 2000, and 2014 respectively.

Computing p_{nj} We find house value for a median sized unit in each tract by multiplying the per square foot Zillow index by the median house size in the corresponding year. We then compute a population weighted-average over all tracts in a given area quality pair in a given CBSA. To obtain p_{njc} that we use in estimation and calibration, we multiply this average house value by a user cost of housing equal to 4.8 percent of house value in 1996, 4.7 percent in 2000 and 4.6 percent in 2014. These rent-price ratios come from the Lincoln Institute of Land Policy.⁵⁸

Appendix C.4 Share of expenditures on amenities α

Table 2 in Aguiar and Bils (2015) reports Engle curve estimates for 20 expenditure categories using 1994-1996 CEX data. Both "entertainment" and "restaurants" have expenditure elasticities higher than 1. Entertainment has the second highest elasticity at 1.74 (the highest is cash contributions, such as charitable donation), and restaurants has the seventh highest elasticity at 1.32. Based on CEX 2013 tables, entertainment fees and admission have a mean expenditure share of 1.1 percent, and food away from home has a mean share of 5.1 percent, excluding alcohol away from home.⁵⁹ In the model, α is net of expenditures on transportation to work and housing costs. The CEX share of expenditure on direct shelter is 19.7 percent with an additional 7.3 percent in utilities. This gives a combined housing share of 27 percent. The share on transportation is 17.6 percent, and if we assume that 40 percent of it is for work, we find $0.5 \times 17.6 = 8.8$ percent of expenditure on work transportation.⁶⁰ Putting this together we obtain $(0.051 + 0.011) / (1 - 0.088 - 0.270) = \alpha = 0.10$, which is our lower bound for α in the text.

Appendix C.5 Tract level quality index.

Appendix C.5.1 Estimating chain quality

We define quality for the 100 largest restaurant chains, with the most establishments in the smartphone data basemap. We index block groups by i , venues by j , and chains by c . We denote by N_{ic} the total number of visits by devices living in block i that start from home and end in venues in

⁵⁸Data collected in October 2018 from <https://datatoolkits.lincolninst.edu/subcenters/land-values/rent-price-ratio.asp>

⁵⁹<https://www.bls.gov/cex/2013/combined/income.pdf> Accessed on 6 January 2019

⁶⁰In the NHTS 2009, travel to work represents only about 30 percent of trips, and 50 percent of total distance traveled for 25 to 55 year olds..

chain c within its CBSA. Our main specification has two controls for proximity of block i to venues in chain c : first the normalized straightline distance between the centroid of block i and the closest venue j in chain c , denoted by $dist_{ic(closest)}$, and second the normalized number of establishments in chain c within 5 miles of block i , denoted by $num5mil_{ic}$.⁶¹ Our estimation sample consists of 2.3 million block*chain pairs with at least one within-CBSA visit from home. In a first step, we purge the number of visits from the impact of proximity to chains by running:

$$\ln N_{ic} = \beta_1 + \beta_2 \ln(dist_{ic(closest)}) + \beta_3 \ln(num5mil_{ic}) + \epsilon_{ic}.$$

We then compute a number of visits purged of proximity as:

$$\widehat{N}_{ic} = \exp\left(\ln N_{ic} - \widehat{\beta}_2 \ln(dist_{ic(closest)}) - \widehat{\beta}_3 \ln(num5mil_{ic})\right)$$

In the next step, we compute the relative propensity of high income devices to visit each chain, relative to the average device. We assign income at the block group level, and define as high income block groups that had median income of \$100,000 per year in 1999 dollars in the latest ACS (2014). The share of visits to chain c out of total visits to the 100 largest chains, among devices living in high income block groups, is:

$$S_c^{High} = \frac{\sum_{i \in I_c} \widehat{N}_{ic}^{High}}{\sum_{c=1}^{100} \sum_{i \in I_c} \widehat{N}_{ic}^{High}},$$

where I_c is the set of block groups with a positive number of visits to chain c . We can then define the quality of chain c as the propensity of devices in high income block groups to visit chain c relative to that of devices in the average block:

$$Quality_c = \frac{S_c^{High}}{S_c},$$

where $Quality_c = 1$ means that high income devices are as likely to visit chain c as the average device, controlling for differences in proximity to venues in chains c .

We perform a number of robustness checks. First, we note that excluding block*chain pairs with zero visits from home is likely to bias our quality index against chains that locate far from high income residents. We experiment with including all block*chain pairs with zero visits in our regression and index computation, and obtain an index with a correlation of 0.94 with our preferred index.⁶² We also experiment with different income cut-off and find that an index defining high income blocks as having median income above \$75,000 has a correlation of 0.93 with our

⁶¹We normalize $dist_{ic(closest)}$ to equal 1 at the median distance of the closest venue for that chain, computed across all blocks with at least one visit to that chain. The variable $dist_{ic(closest)}$ is then in multiples of that median distance. We do this to ensure that our distance-adjusted number of visits remains unchanged for a block at median distance from chain c .

⁶²In that case, $N_{ic} = 0$ gets adjusted upward if the closest venue to block i is farther than median distance, and therefore included as a positive number of visits in the index computation, possibly creating the opposite bias as in our preferred specification. We use the invert hyperbolic sine transform to allow for log of zeros.

preferred index. Finally, we experiment with adding controls for number of chains farther away than 5 miles, and for demographic similarity between block i and the block in which the closest venue in chain c is located (median income difference, age difference, share college difference, EDD measure of racial dissimilarity in Davis et al. Forthcoming). The correlation of these indices with our preferred chain quality index is above 0.98.

Appendix C.5.2 From a chain quality to a tract quality index.

In the NETS data, we can find all of the 100 largest chains in the smartphone data in 2012, accounting for 64,000 establishments, and 96 chains in 2000, accounting for 49,000 establishments.⁶³ We compute quality at the tract level as the average quality of all chains within the tract. If a tract contains fewer than 3 chains, we take the average over all tracts with centroid within 0.25 mile from the tract, and so on in further 0.25 mile increment until there are at least 3 chains. We set a limit of 1.5 miles in urban areas, and 3 miles in suburban areas, below which we set quality to missing if there are still fewer than 3 chains within that limit. This procedure generates 4 percent missing tracts in urban areas, and 15 percent in suburban areas.⁶⁴

Appendix D Estimating δ

Combining data on restaurant trips, prices, and expenditures with existing empirical estimates of value of travel time, Couture (2016) finds that a significant majority (59%) of trips to a restaurant from home take between 5 and 15 minutes, and that over this range of travel times, the total price of amenity rises by 27% due to travel costs. If we similarly calibrate our δ such that tripling distance increases travel cost by 27% percent, we obtain:⁶⁵

$$\frac{d_{rr'}^\delta p^a}{d_{rr''}^\delta p^a} = \left(\frac{15}{5}\right)^\delta = 1.27$$

and recover $\delta = 0.22$.

Appendix E Additional Figures and Tables

Appendix E.1 Robustness of Counterfactual Results to Restaurant Quality Cutoff

Throughout the paper, we use two separate measures of neighborhood quality. First, we define high quality neighborhoods as those that contain 40 percent of residents with at least a bachelor's degree. Second, we define high quality neighborhoods as those that have a chain restaurant index greater than 1.1. In the main text, we show our baseline counterfactuals using the education definition. However, essentially all the key results in the paper are robust to using the restaurant chain index.

To illustrate this, Table 7 redisplayes Table 4 from the main text using our chain restaurant index to segment neighborhoods. As seen from this table, our results are nearly identical in all specifications using this alternate procedure to define high quality neighborhoods.

⁶³The earliest NETS data is in 1992, but we cannot reliably define tract quality so far back in the past, because too many of the largest chains in our 2016-2018 smartphone data only experienced national growth after 1992.

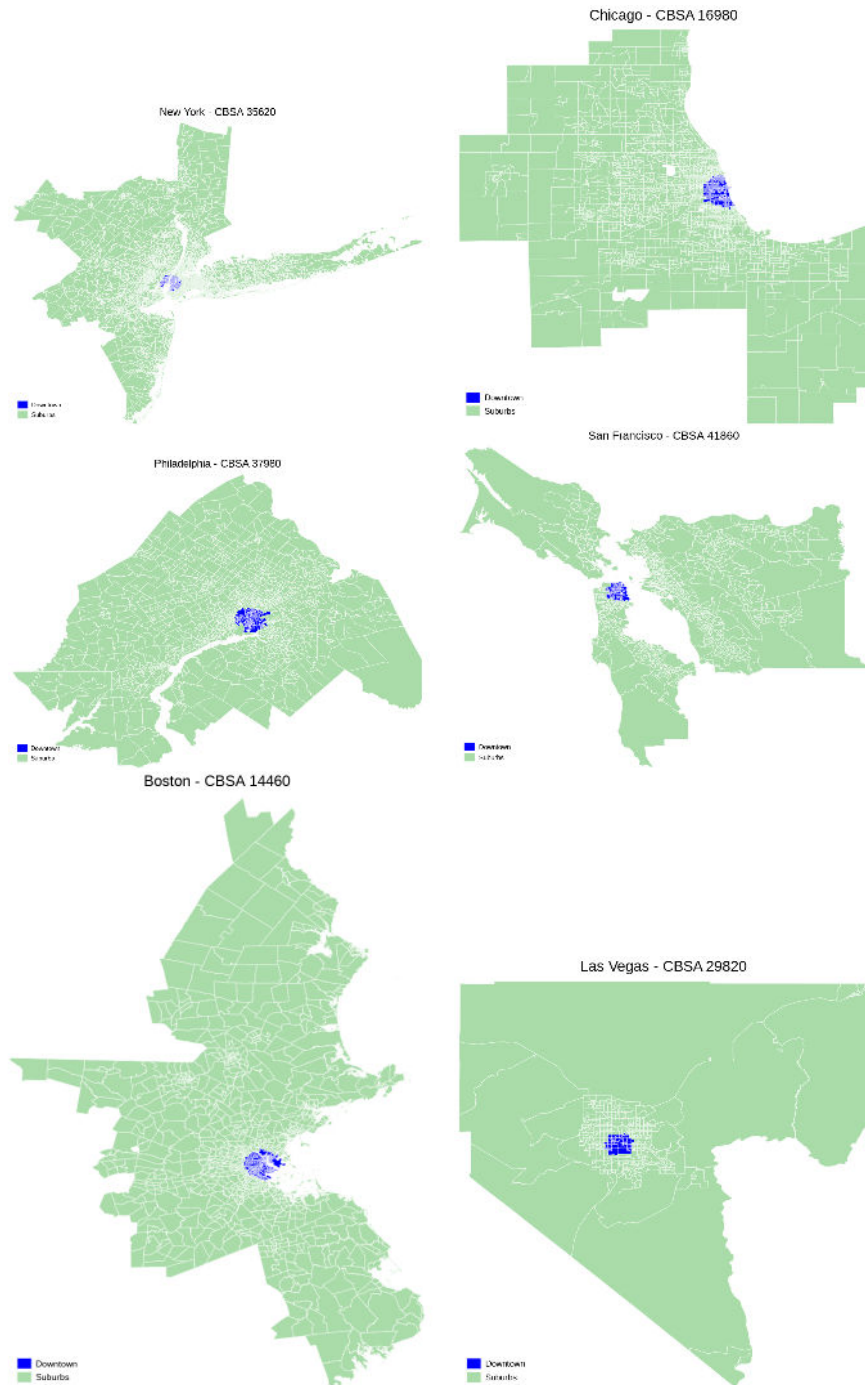
⁶⁴For urban tract, there are at least three chains within tract for 15 percent of tracts, within 0.5 miles for 29 percent of tracts, and within 1 mile for 73 percent of tracts. For suburban tracts, there are at least three chains within tracts for 20 percent of tracts, within 0.5 miles for 25 percent of tracts, within 1 mile for 55 percent of tracts, and within 2 miles for 86 percent of tracts.

⁶⁵This result is not reported by Couture (2016), but can be computed with the data reported in that paper.

Table 7: Robustness of Welfare Estimates to Key Parameters using Restaurant Quality Cutoff

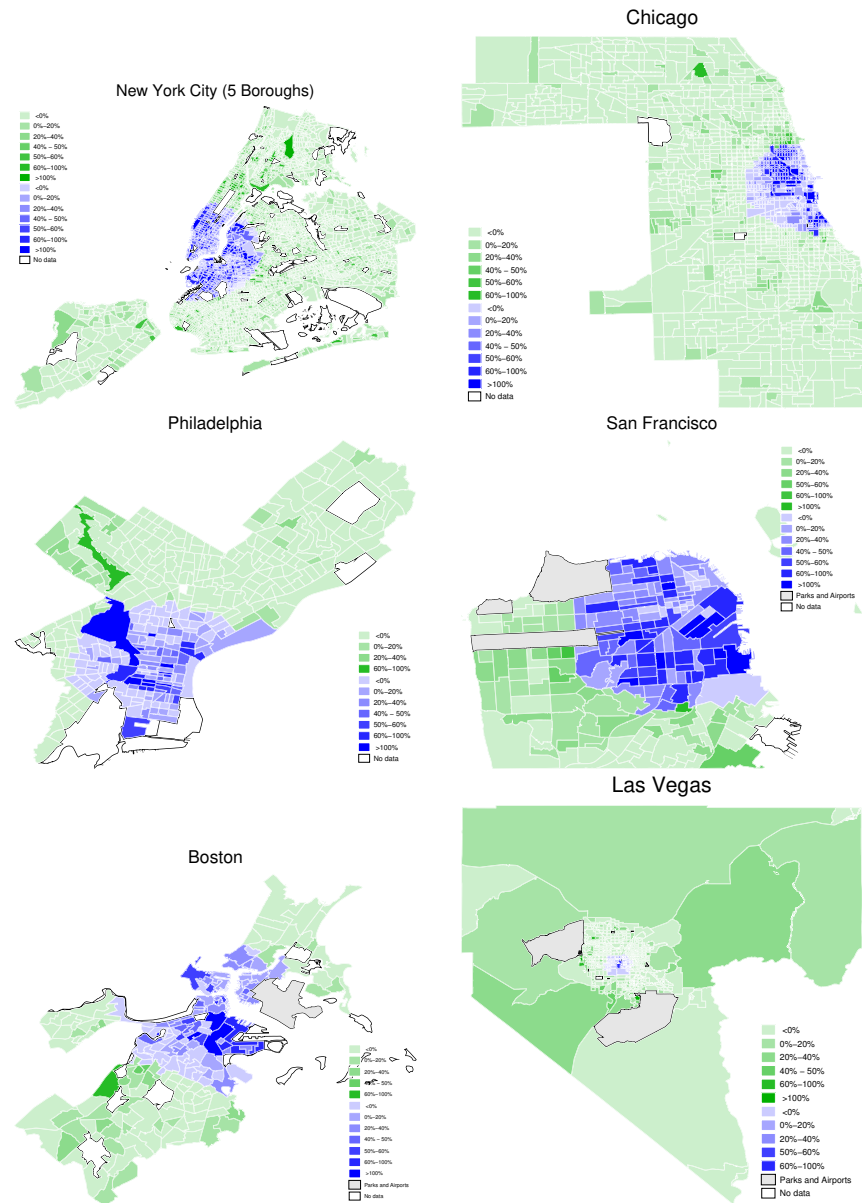
	$(\Delta CV - \Delta Inc)/Inc_{1990}$						
	Decile:	All Households			Renters Only		
		Top	Bottom	Diff.	Top	Bottom	Diff.
Base Specification	1.99	0.16	1.83	1.33	-0.45	1.78	
Elasticity of Substitution between Neighborhood Types (base: $\rho = 3.3$)							
$\rho = 2.5$	2.07	-0.46	2.53	0.93	-1.18	2.10	
$\rho = 4$	3.78	-0.59	4.37	2.89	-2.56	5.46	
Elasticity of Substitution between Same-Type Neighborhoods (base: $\gamma = 6.5$)							
$\gamma = 5$	2.88	0.62	2.26	2.05	-0.22	2.28	
$\gamma = 8$	1.51	-0.08	1.59	0.91	-0.56	1.47	
$\gamma = \infty$	0.49	-0.23	0.71	0.11	-0.86	0.97	
Elasticity of Substitution between Private Amenities (base: $\sigma = 6.5$)							
$\sigma = 5$	2.23	0.24	2.00	1.56	-0.40	1.96	
$\sigma = 8$	1.85	0.12	1.73	1.19	-0.48	1.68	
$\sigma = \infty$	1.52	0.01	1.51	0.88	-0.56	1.44	
Distance Elasticity of Amenity Consumption (base: $\delta = 0.2$)							
$\delta = 0.1$	1.99	0.16	1.83	1.33	-0.45	1.78	
$\delta = 0.3$	1.98	0.16	1.82	1.32	-0.45	1.77	
Amenity Expenditure Share (base: $\alpha = 0.15$)							
$\alpha = 0.05$	1.71	0.13	1.58	1.20	-0.21	1.42	
$\alpha = 0.25$	2.12	0.17	1.95	1.37	-0.59	1.95	
Housing/Land Supply Elasticities (base: $\epsilon_D = 0.6, \epsilon_S = 1.33$)							
$\epsilon_D = 0.1, \epsilon_S = 1.33$	1.99	0.17	1.82	1.33	-0.45	1.77	
$\epsilon_D = \epsilon_S = 1.33$	1.99	0.17	1.83	1.35	-0.42	1.77	
$\epsilon_D = 1.33, \epsilon_S = 3$	2.09	0.33	1.76	1.58	-0.03	1.61	
Public Amenity Elasticity (base: $\Omega = 0.05$)							
$\Omega = 0$	1.82	0.12	1.71	1.16	-0.50	1.66	
$\Omega = 0.03$	1.92	0.14	1.78	1.26	-0.47	1.73	
$\Omega = 0.08$	2.08	0.19	1.90	1.42	-0.42	1.85	
Property Tax Rates (base: $T_D = 0.1, T_S = 0.2$)							
$T_D = T_S = 0$	2.05	0.05	2.00	1.35	-0.76	2.11	
$T_D = 0.15, T_S = 0.25$	1.91	0.10	1.82	1.27	-0.47	1.74	

Figure 16: Downtown and Suburban Tracts in Selected CBSAs.



Note: Downtown tracts in dark blue consists of all tracts closest to the city center and accounting for 10% of total CBSA population in 2000.

Figure 17: Gentrifying Tracts in Central County of Selected CBSA



Note: Each map shows the central county of a given CBSA, except for New York which shows the five counties (boroughs) of New York City. Downtown tracts in blue consist of all tracts closest to the city center and accounting for 10% of total CBSA population in 2000. The shading of each tract shows its percent growth in median household income between 1990 and 2014.

Figure 18: Zillow Monthly Per Square Foot House Price Index by Neighborhood Type

