Income Growth, Spatial Sorting and the Distributional Effects of Urban Gentrification*

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October 2, 2018

EVOLVING

Abstract

We explore the link between rising incomes at the top of the income distribution and urban gentrification. We develop and quantify a spatial model of a city with heterogeneous agents and non-homothetic preferences for endogenous differentiated privately provided neighborhood amenities (e.g., restaurants and entertainment). As the rich get richer, their increased demand for such luxury amenities drives housing prices up in downtown areas, where amenity development is fueled by economies of density. The poor, as a result, are made worse off either by being displaced or by paying higher rents for amenities that they do not value as much. Using our model, we find that the gentrification of urban areas during the last two decades increased the welfare of richer households relative to that of poorer households by an additional three percentage points above and beyond the differential income growth. We conclude that welfare estimates of increased income inequality are understated if spatial sorting responses are ignored.

*We thank Hero Ashman and Allison Green for outstanding research assistance. For useful comments, we thank Jonathan Dingel, Ed Glaeser, and Jacob Vigdor as well as seminar particpants at Berkeley, HEC Montreal, Wharton, the 2017 Federal Reserve Bank of Richmond conference on "Understanding Urban Decline," the 2018 European Urban Economic Association meetings, and the 2018 NBER Urban/Real Estate Summer Institute. Victor Couture and Cecile Gaubert thank the Fisher Center for Real Estate and Urban Economics at UC Berkeley for financial support. Jessie Handbury thanks the Zell-Lurie Real Estate Center for financial support. Authors contact information: couture@haas.berkeley.edu, cecile.gaubert@berkeley.edu, handbury@wharton.upenn.edu, and erik.hurst@chicagobooth.edu.

1 Introduction

Over the last three decades income inequality in the United States has grown sharply, with income growth being disproportionately concentrated at the top of earnings distribution.[1] During this same time period, American cities have attracted more college educated and higher income individuals (Couture and Handbury (2017); Baum-Snow and Hartley (2017)). This latter trend has accompanied a renewed discussion of gentrification within many U.S. cities. For instance, in response to the influx of higher income residents into downtown areas of major cities, some municipalities, like New York City, have implemented policies to slow down neighborhood gentrification.[2] In cities like Seattle, San Francisco, Chicago, or Atlanta, residents have organized protests against the gentrification of neighborhoods within their cities.

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. The paper builds on two empirical regularities. First, demand system estimates suggest that many privately provided local amenities are relative luxury goods.[3] Second, downtown areas of major cities have a higher density of such amenities. We build a model of residential sorting with heterogeneous agents and heterogeneous neighborhoods within a city that embeds these two empirical features. As the incomes of the rich increase, their demand for urban amenities increases, resulting in them choosing to reside in downtown urban areas so as to be closer to these amenities. As the income composition of downtown urban areas changes, the provision of high quality urban amenities increases endogenously there, further fueling the in-migration of the rich. The in-migration of higher income individuals 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 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 urban gentrification. Moreover, we estimate the economic impact of gentrification resulting from increased incomes of the rich on residents of downtown areas with differing income levels. One of the paper's main findings is that, because of the pecuniary externalities

[1] The literature documenting these facts are extensive. See, for example, the 2017 Economic Report of the President.

[2] See "New York Passes Rent Rules to Blunt Gentrification", New York Times, March 22, 2016.

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

imposed by the in-migration of the rich, welfare estimates of increased income inequality are *understated* when spatial sorting responses are ignored. Preliminary estimates suggest that welfare differences between those at the 90th percentile of the income distribution and those at the 10th percentile of the income distribution increased by an additional 3 percentage points once accounting for the changing nature of spatial sorting of the rich into downtown urban areas during the 1990 to 2013 period. As way of comparison, in our sample of large cities, the the nominal income gap between the 10th and 90th percentiles of the income distribution increased by about 18 percentage points during this time period. Moreover, we are finding that the resulting gentrification of downtown areas in response to the rising incomes of the rich reduced the utility of those at the 10 percentile of the income distribution by about 1.5 percent.

Our paper proceeds in four parts. In the first part of the paper, we document a set of facts highlighting cross-sectional and time series variation in the nature of spatial sorting within urban areas during the last few decades. We focus our attention on the 100 largest Census Bureau Statistical Areas (CBSA's) in the United States in 1990. We begin by showing that, within these CBSAs, the propensity to live in downtown areas is U-shaped in resident income. Poorer residents are more likely to live in downtown urban areas relative to middle-income residents. However, as resident family income increases above $100,000 (in 1999 dollars), the relationship between resident income and the propensity to live downtown becomes monotonically increasing. This fact persists across different survey years of the U.S. Census, for a variety of definitions of downtown urban areas, and for a variety of income measures. While stable in prior years, the relationship between income and the share of households living downtown has become steeper for the richest households by 2013. This suggests an increasing propensity for the rich to live in downtown urban in recent years, even conditional on a given income level.

Exploiting cross-CBSA variation, we document a strong relationship between *changes* in CBSA average income between 1990 and 2013 and *changes* in the share of that CBSA's high income residents living downtown during that same time period. When CBSA's become richer on average, there is a shift in spatial sorting patterns by income: poorer residents are more likely to locate outside of the downtown area, while richer residents are more likely to reside in the downtown area. These patterns are robust to the inclusion of CBSA-level controls as well as using a Bartik-style instrument for changes in CBSA income growth. Estimates from Bartik regressions suggest that the increasing incomes of the rich could be quantitatively important in explaining the changing U-shaped pattern of location choice between 1990 and 2013.

As a final stylized fact, we document that CBSA-level income growth is correlated with

CBSA gentrification in downtown urban areas. We define gentrifying neighborhoods to be those that had below median level of income in 1990, and saw a real income growth of at least 50 percent between 1990 and 2013. By this metric, the CBSAs with the most gentrifying downtown tracts include Seattle, San Francisco, Chicago, Washington, and New York. Gentrification is concentrated downtown and, outside of the downtown areas, low income tracts are not substantively more likely to gentrify as the CBSA gets richer. Collectively, these patterns suggest a tight non-monotonic relationship between individual income and the propensity to live downtown, as well as between changes in CBSA-level income, changes in spatial sorting, and neighborhood gentrification.

In the next part of the paper, we formalize the link between income inequality growth and urban gentrification. To do so, we build a model with heterogeneous agents and heterogeneous types of land. Individuals differ by their level of income. Land is comprised of downtown areas and suburban (non-downtown) areas which differ from each other in their bundle of fixed amenities, their proximity to jobs, and their housing supply elasticity. The suburbs have a higher endowment of fixed public amenities. Housing and associated endogenous amenities are also supplied more elastically in the suburbs. We model different quality neighborhoods within both the downtown and suburban areas. The quality of neighborhoods within each area indexes the quality of the housing and amenity bundles ("neighborhoods") that are provided, endogenously, by profit maximizing developers. Finally, within each area-quality pair, neighborhoods are horizontally differentiated and are accessible to all residents of neighborhoods of the same area and quality. So, households benefit from living in areas with a high density of neighborhoods of the same quality as the one in which they reside. In the model, individuals at different income levels make different location choices on average. The model lends itself naturally to welfare analysis, as it provides a unique welfare measure, for each level of income, that accounts for these location choices.

The key mechanism in the model is that high quality endogenous amenities are relative luxury goods. Given this, the model implies that urban areas of cities are disproportionately populated by both low income households who want to minimize commuting costs to jobs and reside in low-quality neighborhoods, and by higher income households who want to be close to the density of high quality neighborhoods. Middle income individuals disproportionately locate in the suburbs to take advantage of the higher fixed amenities there. One important assumption in our model is that economies of density fuel the attractiveness of urban amenities. Higher density allows for a greater variety of urban amenities in a given geographic area. While Princeton, New Jersey may have a handful of dining and entertainment options within a one-mile square radius, Manhattan has an order of magnitude more options within a similarly defined area. Given our love of variety preferences, this makes downtown urban

areas attractive for consuming such endogenous amenities.[4,5] In the model, downtowns have lower housing supply elasticities than to the suburbs, hence they grow through density rather than sprawl. As a result, as the city grows, downtown increases its comparative advantage compared to the suburbs in providing endogenous residential amenities.

We show that within our model, as incomes of richer households increase, richer households become more likely to move downtown where neighborhoods gentrify. Specifically, some existing downtown neighborhoods populated by poorer individuals are replaced by high quality ones, chosen by richer households. This increases the density of high quality neighborhoods available to residents of these neighborhoods downtown making these locations even more attractive to richer households. In that sense, increasing income levels of the rich lead to neighborhood gentrification in downtown areas. The influx of richer residents into downtown areas causes rents to increase, in both high and low quality neighborhoods, and the supply of low quality neighborhoods to shrink. Poorer incumbent households who remain in low quality neighborhoods downtown see their rents increase, while others choose to migrate out. On average, they are made worse off.

In the third part of the paper, we take the model to the data. In a first stage, we estimate the key elasticities of the model. Important among these are the elasticity of substitution between neighborhoods of the same type (high- or low-quality) in the same location (downtown or the suburbs) and the elasticity of substitution between neighborhoods of different types and different locations. We estimate these parameters, some of which are identified using the same type of empirical relationship identified in the first part of the paper. In a second stage, armed with these estimated elasticities, 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 by 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 facts from the data.

We then use the quantified model for welfare and counterfactual analysis. First, we assess how much of observed gentrification can be explained by the rising incomes of the rich through the lens of the model. To that end, we take the observed change in the income

[4]While quality is a fixed characteristic of any single neighborhood, the variety of neighborhoods accessible to residents of a given area-quality pair is isomorphic to (or can be interpreted as) a quality shifter that makes the area-quality pair more attractive as a whole.

[5]Within the model, we do not take a stand on what particular endogenous amenity is contributing to the non-homotheticity. Restaurants and entertainment options could be one component of these amenities. These consumptions goods are shown to have among the highest expenditure elasticities with respect to income out of all different consumption goods. But, our model is broad enough to encompass any differentiated endogenous amenity that individuals consider to be a relative luxury good (including high-quality schooling).

distribution from 1990 to 2013, feed it into the model and compute the corresponding new spatial equilibrium. We then use the model to compute the corresponding welfare effects for different income groups, inclusive of spatial sorting responses. While this section of the paper is still evolving, our preliminary estimates suggest that increases in the incomes of high income individuals were a substantive contributor to urban gentrification during the last 25 years within the U.S. Furthermore, our preliminary findings are that the gentrification resulting from the increased incomes of the rich did, in fact, make poorer residents worse off. In our base estimates, we find that the well-being of the the 10th percentile of the income distribution was reduced by about 1.5 percent in consumption equivalent units during the 1990-2013 period as a result of higher income individuals moving into downtown urban areas. Almost all of that decline was due to the increased housing prices that the poor had to pay in response to influx of the rich. While the model is stylized in many dimensions, it does suggest that gentrification has been welfare reducing for the poor. Additionally, our model finds that the gentrification effects actually made the rich better off due to the endogenous amenity response. Overall, we find that the welfare differences between the 90th percentile of the income distribution and the 10 percentile of the income distribution were 3 percentage points higher when accounting for the spatial sorting response of the rich as a result of their rising incomes during the 1990-2013 period.

Finally, we use the model to perform additional counterfactuals. We explore how residential sorting and gentrification is altered in response to changes in policy, and in response to further changes in income inequality. First, we use the model to assess the effect of implementing policies that aim at limiting gentrification of downtowns. Specifically, we simulate a policy in which high-quality neighborhoods downtown are taxed, and the tax levied is used to subsidize housing downtown for the poor. We find that such policies can be effective in shaping the income mix of urban residents. Even though tax policies can help mitigate the rise in well-being inequality qualitatively, we find that their well-being effects are quantitatively limited and are far from overturning the increase in well-being inequality that we found for 1990-2013 in our quantification exercise. Finally, we ask how the well-being of the poor and the downtown composition of residents would change if incomes of the rich were to continue to rise. Our model suggests that in this case, gentrification would continue to be a prominent feature of urban landscapes in the years to come.

2 Related Literature

Our paper draws from and contributes to a number of related literature, in particular to recent empirical work highlighting the importance of urban centers as a consumption good

for residents. Additionally, our paper contributes to the large literature on the causes and consequences of neighborhood change and gentrification. Finally, our quantitative spatial model with income sorting contributes to a large theoretical literature on spatial location choice.

Historically, cities were viewed as being centers of production. Recently, however, a literature has emerged documenting that cities also serve as centers of consumption. Glaeser et al. (2001) puts forth the notion of a "consumer city" where urban density facilitates the provision a larger variety of consumption opportunities. To that end, both Glaeser et al. (2001) and Couture and Handbury (2017) document the increased prevalence of individuals residing in downtown areas and commuting to the suburbs for work. Diamond (2016) shows that residents value local amenities and documents that local amenity values endogenously improve as higher income residents populate a neighborhood.

A large literature documents the pace of neighborhood change and explores its causes. Early contributions include Rosenthal (2008), who documents that neighborhoods frequently move from one income quartile to another, and Guerrieri et al. (2013), who document wide variation in house price growth across neighborhoods of the same city.[6] A number of papers document the rapid rise in the socio-economic status of downtown neighborhoods in the 2000s. Baum-Snow and Hartley (2017) and Couture and Handbury (2017) argue that rising values of local amenities drive this recent urban revival. Edlund et al. (2016) and Su (2017) argue instead that high-skilled workers moved downtown in search of shorter commutes, as a consequence of longer work hours for high-skill workers since the 1990s. Ellen et al. (2017) highlight the role of crime, and show that central cities that experienced faster violent crime decline in the 1990s had faster income and college growth in the 2000s. Our quantitative model is rich enough to nest all these hypotheses on the drivers of recent downtown gentrification. In the next section we provide evidence for our preferred gentrification mechanism, which combines rising top income and luxury urban amenities.

The existing literature on the consequences of gentrification focuses on identifying evidence of displacement. These studies find little evidence that individuals with low socio-economic status exit gentrifying neighborhood at a faster rate than they exit non-gentrifying neighborhoods.[7] Our paper's focus, however, is not on short-run displacement, but on long-run welfare change. We document a rapid decline in the absolute number of poor households

[6] Rosenthal (2008) highlight the role of aging housing stock and redevelopment in moving neighborhoods across the income distribution, while Lee and Lin (2018) show that natural amenities like beaches anchor high-income neighborhood. Guerrieri et al. (2013) show that the fastest house price appreciation occurs in poor neighborhoods in close proximity to rich neighborhoods.

[7] See, 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.

in gentrifying tracts, but our welfare results do not depend on whether these households are displaced or replaced. In fact, our model shows that poorer residents (most of whom are renters) who stay in gentrifying neighborhoods also experience lower welfare overall due to rising rents.

A limited number of papers study consequences of gentrification other than displacement. In gentrifying neighborhoods, Lester and Hartley (2014) find an overall gain in jobs with a shift away from manufacturing, Meltzer and Ghorbani (2017) find rising commute times, and Autor et al. (2017) find a decline in crime. Su (2017) is probably closest to our work in that he explores the welfare impact of rising value of time for high-skilled worker. Using a structural model, Su (2017) shows that the desire to minimize commuting costs draws richer residents downtown, bidding up land prices and causing adverse effects on the poorer residents who populate city centers. Berkes and Gaetani (2018) study the rise in income segregation within cities. They find that higher patent (innovation) intensity at the city level accounts for 20% of the rise in income segregation from 1990 to 2010, but that endogenous residential amenities again play the most important role. We differ from Su (2017) and Berkes and Gaetani (2018) in that we model the development of endogenous amenities, we focus on rising top income as a driving force, and we have luxury urban amenities play a direct role in gentrification.

A recent body of empirical work documents the rapid rise in the share of income accruing to the top of the income distribution (Piketty et al., 2018). This shift in high incomes lies at the core of the gentrification mechanism in our paper. Many papers explore the causes of this growth in income inequality, for instance Smith et al. (2017), but fewer papers explore its consequences. Two exceptions are Bertrand and Morse (2016) who show that rising incomes at the top of the distribution induced households lower in the income distribution to save less and consume a larger share of their income, and Gyourko et al. (2013) who show that the rising number of rich households nationally explains some of the rapid rise in house prices and income in "superstar" cities with low housing supply elasticities, like San Francisco, New York, and Boston. Our contribution is to use a quantitative structural model to measure the welfare consequences of an exogenous rise in high incomes, with a focus on endogenous spatial income sorting within cities.

Finally, our paper contributes to a theoretical literature on the location of different income groups within a city. These models are generally extensions of the monocentric city model, reviewed in Duranton and Puga (2015). In the basic version of this model, richer individuals consume more land, and therefore choose to live away from the city center, where land is cheaper. Brueckner et al. (1999) show that adding amenities at the city center can reverse this income sorting pattern. Gaigne et al. (2017) propose a linear polycentric city model with jobs and amenities at different locations, and non-homothetic Stone-Geary preferences.

Their model, like ours, can match the non-monotonic income sorting patterns observed in reality. Important contributions outside the linear city framework include LeRoy and Sonstelie (1983) and Glaeser et al. (2008). They show that transit availability in cities and the high cost of commuting by cars to suburbs make downtown attractive to poor individuals. Our model draws from this insight in that downtowns attract poor individuals due to higher commute costs in suburbs.

Instead of using the linear city framework, our model builds on recent developments in quantitative spatial economics, reviewed in Redding and Rossi-Hansberg (2017). We add individual income heterogeneity to a quantitative spatial model of a city. More specifically, we extend Fajgelbaum et al. (2011)'s model of international trade with non-homothetic preferences to an urban context. Closest to our work is Tsivanidis (2018) that uses a spatial sorting model with heterogeneous residents to analyze the distributional effects of urban transit networks.

3 Data and Definitions

Our primary data source to measure urban gentrification comes from the 1970, 1990, and 2000 *U.S. Censuses* and from the 2011-2015 *American Community Surveys* (ACS). When measuring variables at the census tract level, we use published tables from the *National Historical Geographic Information System* (NHGIS). When measuring variables at the Core-Based Statistical Area (CBSA) level, we either aggregate census tract level variables from the NHGIS, or we aggregate microdata from the 1% *Integrated Public Use Micro-data Series* (IPUMS) in 1970, the 5% IPUMS sample of the 1990 and 2000 Censuses and the 5% IPUMS sample from the 2011-2015 ACS surveys. From henceforth, we refer to the 2011-2015 pooled ACS data as the 2013 ACS. All data are interpolated to constant 2010-boundary tracts and constant 2013-boundary CBSAs using the *Longitudinal Tract Data Base* (LTBD). We limit our analysis to the 100 largest CBSAs based on population in 1990. All dollar values are adjusted to 1999 dollars. We use the Census and ACS data to measure the location choice of households with differing levels of income, housing prices at different levels of location aggregation, and location specific neighborhood characteristics such as the share of residents with a bachelor's degree. In some robustness specifications, we also exploit Census/ACS commuting time data by income group.

We complement Census and ACS data with information on house prices, amenity quality, and travel patterns. To measure location specific house price growth, we use, in addition to Census median house prices, the Zillow House Value Index for all homes in 1996 (the first year this index is available), 2000 and 2013, which measures median house prices at the zip

code level.[8]

To measure travel patterns, we use confidential geocoded microdata from the 2009 *National Household Transportation Survey* (NHTS). The NHTS data comes from travel diaries on daily trips taken in a 24-hour period for each individual in participating households. We use this data to measure commuting times associated with both work and leisure activities. In some specifications, we measure amenity quality in a census tract using data on the location of 61 restaurant chains from the National Establishment Time-Series (NETS), a geo-coded census of establishments in 2000 and 2010. We match each restaurant chain with its *Market Potential Index* (MPI) from the 2010 Esri ArcGIS business analyst, which captures the propensity of high-income individuals to visit that chain.[9] Our measure of average restaurant quality in a tract assigns higher weight to restaurants closer to a tract centroid.[10]

To measure urban gentrification, we need to formalize our notion of an urban area. When defining urban areas, we focus on the downtown area of the CBSA's main city. We often refer to downtowns and urban areas interchangeably in what follows. For example, for the Chicago CBSA, we define the downtown area as the set of census tracts surrounding the center of the city of Chicago.[11] For our primary measure of a downtown area, we use the set of tracts closest to the city center accounting for 10 percent of a CBSA's population in 2000. We fix this definition of downtown area across all other years. 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 their size and density. However, we explore the robustness of all of our key facts to alternate definitions of downtown areas including those census tracts with centroids within a three mile radius of the city center as in Baum-Snow and Hartley (2017). For each CBSA, we refer to all remaining non-downtown tracts as being suburban tracts.

[8]We map the Zillow zip code data to 2010 tract geography using a crosswalk from the U.S. Department of Housing and Urban Development (HUD). We also expand the dataset beyond tracts that Zillow covers by defining tract groups as in Ferreira and Gyourko (2011). That is, we calculate the average house price index within a tract-group for tracts covered by Zillow, and apply this average to tracts that are not covered by Zillow. Tract groups are a set of three to four neighboring tracts, as defined in Ferreira and Gyourko (2011).

[9]These measures are as in Couture and Handbury (2017). Esris MPIs come from the Survey of American Consumers, a proprietary marketing survey from GfK MRI. Esri ArcGIS business analyst divides each neighborhood in the U.S. into market segments and assigns a *Market Potential Index* (MPI) to each chain in each segment based on the Survey of American Consumers data. The MPI measures the propensity of each segment's inhabitants to visit a given chain relative to the average American. We use the MPIs in segments with average income above $\$100,000$ to identify the restaurants that high-income individuals are most likely to visit.

[10]The weights are from Couture (2017) and based on observed travel behavior in the NHTS. The tract average includes restaurants up to a 45 minute walk from the tract centroid, but such long trips are infrequently taken and therefore receive little weight.

[11]We define the city center of each CBSA using the locations provided by Holian and Kahn (2012), obtained by entering the name of each CBSA's principal city into Google Earth and recording the returned coordinates.

Our definition of suburban is quite broad in that it simply reflects non-downtown tracts. In all work that follows, all tracts in a CBSA are either classified as downtown *(D)* or suburbs *(S)*. In Appendix C, Figure 14 shows downtown tracts in dark blue and suburban tracts in light green for New York, Chicago, Philadelphia, San Francisco, Boston, and Las Vegas CBSAs. Appendix Appendix A provides additional detail on all data sources and variable construction.

4 CBSA Income Growth and Urban Gentrification During 1990-2013

In this section, we establish a set of facts about recent income growth and the increasing prevalence of urban gentrification during the last two decades within the United States. We also document a strong relationship between CBSA level income growth and CBSA level urban gentrification, which persists when using a standard Bartik instrument for income growth. Finally, we provide some evidence that urban amenities are relative luxury goods. Collectively, these set of facts will help to motivate and discipline the model that we develop in the following sections.

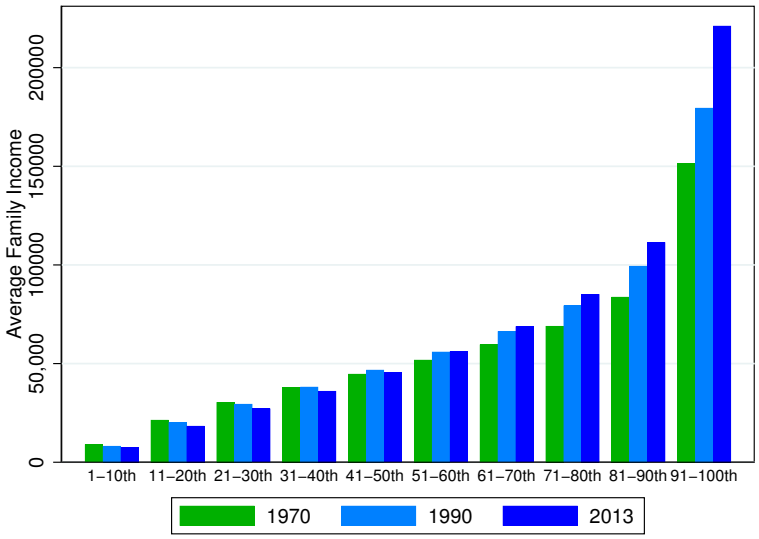
4.1 CBSA Income Growth Concentrated at Top of Income Distribution

Figure 1 shows the average real family income within each income decile in the pooled sample of the largest 100 CBSAs in 1970, 1990 and 2013.[12] As with all values in the paper, income is reported in 1999 dollars. Like the country as a whole, the largest 100 CBSA's have become both richer and more unequal during the last half century. Real incomes were essentially unchanged over time in the bottom 50 percentiles of the family income distribution. However, for the upper percentiles, there was large income growth. For example, real average incomes within the top decile of the family income distribution in the top 100 CBSAs increased from about $150,000 in 1970 to about $225,000 in 2013. Also consistent with aggregate data, most of the growth in the top decile occurred between 1990 and 2013 as opposed to between 1970 and 1990.

The change in CBSA income growth documented in Figure 1 will be the driving force

[12]We use family instead of household income, because household income is missing from IPUMS microdata in 1970. One important difference between household and family income is that the latter excludes solo households. We verified that household and family income deliver similar results in 1990 and 2013, in which both are available.

Figure 1: Mean income by Decile in Largest 100 CBSA's Over Time



Note: Figure shows real average family income by family income decile for the 100 largest CBSAs over time. Data comes from 1970, 1990, and 2011-2015 IPUMS microdata. When computing statistics, we pool families from the 100 largest CBSAs together. All incomes are in real 1999 dollars.

in the quantitative assessment of the model that we develop below. In particular, we are interested in assessing the spatial sorting response generated by the rising concentration of income at the top of the distribution between 1990 and 2013. We will take these changes in the income distribution as exogenous for our quantitative exercise.

4.2 Downtown Residential Propensity and Household Income

Figure 2 measures the propensity of families with differing levels of income to live in downtown census tracts.[13] To help interpret the units, we normalize the data by the fraction of families of all income levels living downtown. Formally, let $\lambda_{Dc}(w)$ equal the share of families earning income w living in the downtown area of a given CBSA c during a given period.[14] Let λ_{Dc} be the share of all families in CBSA c living in D in a given period regardless of income. Given our primary definition of downtown areas, λ_{Dc} is equal to 0.1 in year 2000. However, given trends in the propensity to live downtown by all income groups over time, λ_{Dc} need not equal 0.1 in 1970, 1990, or 2013. Formally, we define the normalized share of families earning income w living downtown relative to the suburbs in a given CBSA, $\bar{\lambda}_{Dc}(w)$, as:

[13] We replicate these results for household income instead of family income in 1990 and 2013.

[14] We suppress the time subscripts to facilitate exposition.

$$\bar{\lambda}_{Dc}(w) \equiv \frac{\lambda_{Dc}(w)}{\lambda_{Dc}} \tag{1}$$

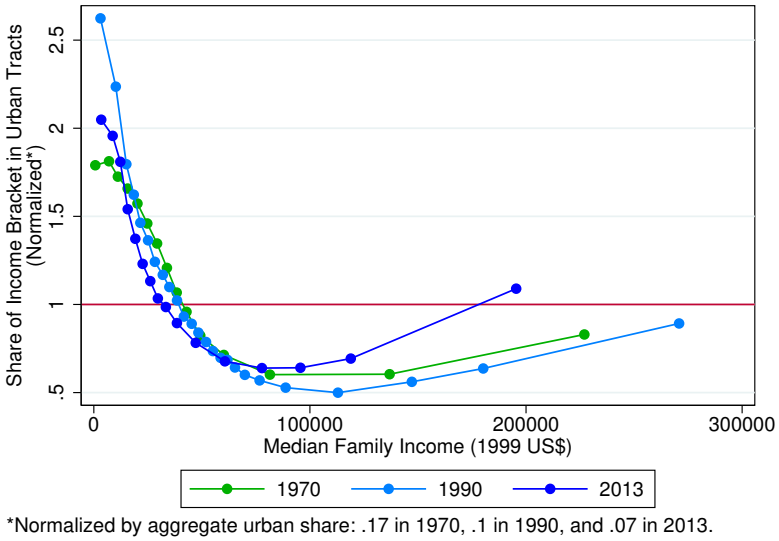
In equation (1), if $\bar{\lambda}_{Dc}(w) = 1$ it means that families with income w is exactly as likely to live in downtown areas as the average family, while $\bar{\lambda}_{c}(w) > 1$ means that families with income w are overrepresented in downtown areas. Using Census tables in 1970, 1990, and 2013, each w corresponds to a different CPI-adjusted family income bracket. Specifically, we define w to equal the median income within that bracket in the 100 largest CBSAs, which we find using IPUMS microdata from the corresponding year.

In Figure 2, we show data for a representative CBSA constructed by aggregating families over the largest 100 CBSAs, but we can document similar patterns for individual CBSAs. The figure shows a U-shaped propensity to live in urban areas as a function of median family income w within each bracket in 1970, 1990, and 2013. Lower income families are much more likely to live in urban areas. For example, families earning $25,000 a year in 1970, 1990, and 2013 were between 1.5 and 2 times more likely to live in downtown urban areas than other households. As their income increases, residents are increasingly more likely to live in the suburbs. However, when income gets above roughly $100,000, households start to move back downtown.

Figure 2 has a number of noteworthy features. First, the U-shaped patterns are present in 1970, 1990, and 2013. Second, the propensity for high income households to reside in downtown urban areas is larger in 2013 than it is in 1970 and 1990. This pattern is consistent with the discussion of increased gentrification in recent years. Third, the U-shaped pattern in resident income is a quite robust feature of the data. Specifically, we have explored a number of robustness exercises including controlling for other demographic factors such as age of the household head and the size of the household.

We will calibrate the model that we develop below to match the U-shape pattern in 1990. Given that, our model will need mechanisms to explain both why the poor and the rich are more likely to live downtown (relative to middle income groups). We will also ask, through the lens of the model, how much of the change in the U-shape pattern between 1990 and 2013 can be explained by the change in the income distribution that occurred during that time period.

Figure 2: Downtown Residential Income Propensity by Income



Note: Table uses Census data on family income for the 100 largest CBSAs in 1970, 1990, and 2013. 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.

4.3 CBSA Income Growth and Changing Spatial Sorting by Income

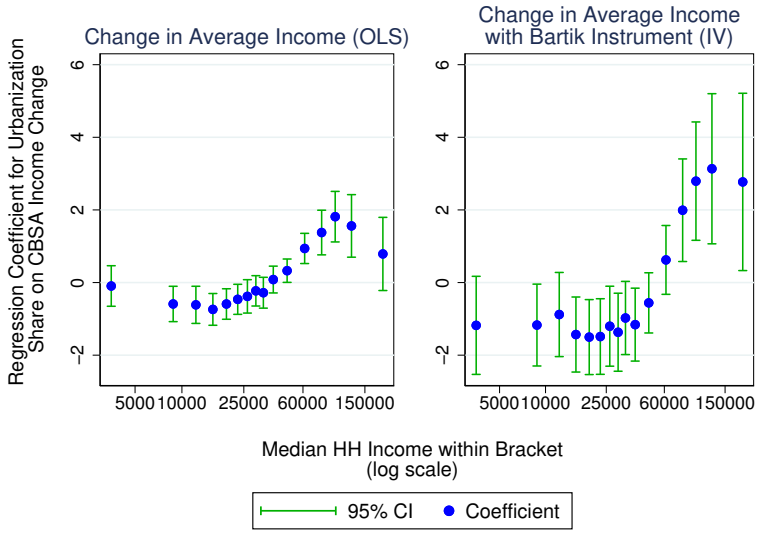
In this sub-section, we show the relationship between *changes* in CBSA income growth from 1990 to 2013 and *changes* in the propensity of households at different income levels to reside downtown. Specifically, we are asking whether rising income at the city level has a more positive impact on the propensity of rich households to move downtown than on that of poor households. To assess this reduced form relationship, we estimate the following equation in first-difference from 1990 to 2013:

$$\Delta \ln \left(\bar{\lambda}_{cD}(w) \right) = \alpha_w \Delta \ln(Income_c) + \epsilon_c, \tag{2}$$

where $\ln(Income_c)$ is the log mean CBSA income. $\bar{\lambda}_{cD}(w)$ is defined as above, but the first-difference specification requires constant brackets with median income w, so we define 16 such brackets that whose bounds are the same in 1990 and 2013.[15] The coefficient α_w for each income group w that measures the extent to which income group w increases their

[15]The 16 brackets are based on the 1999 dollar bounds of the brackets reported in the 2000 census data. We infer the share in each of these brackets in 1990 and 2013 using the IPUMS micro data for each of these years. Figure 3 plots the coefficient for each bracket against the median income in that bracket in 2000.

Figure 3: Propensity to Live Downtown in Response to a CBSA Level Change in Income 1990-2013



Note: Table uses data for the 100 largest CBSAs. Urban tracts consists of the 10% of tracts closest to the city center. Each dot in the figure represents the estimates of α_w for each income bracket plotted against the median income of that bracket in 2000. The left panel estimates equation (2) via OLS while the right panel estimates equation (2) using a Bartik instrument for the change in average income at the CBSA level.

propensity to live downtown in response to a CBSA level change in income. If $\alpha_w = 0$, an increase in CBSA level income does not alter the propensity of income group w to live downtown relative to the suburbs. If $\alpha_w > 0$, income group w is relatively more likely to live downtown compared to other income groups when CBSA income increases.

We estimate equation (2) using our sample of the top 100 CBSAs, weighting each CBSA observation by its 1990 population, first in OLS and then using a Bartik instrument. The left-hand panel of Figure 3 depicts the OLS estimates along with their 95 percent confidence bounds. The results support the hypothesis that CBSA per capita income growth is associated with differential spatial sorting patterns of the rich and the poor. For all of the top 6 income bins, $\alpha_w > 0$ and, aside from the top bin which has fewer observations, all are statistically significant at the 5 percent level. Conversely, all of the bottom six income bins have estimates of $\alpha_w < 0$ and, aside from bottom bin, all are statistically significant at the 5 percent level. These coefficients imply that, as a city's inhabitants get richer on average, rich households urbanize relative to poor households.

We do not make any causal claims about the causality of the correlations depicted in Figure 3. The direction of causality would depend on the source of the cross-CBSA variation in income growth that we use to estimate the α_w coefficients. For example, the patterns

above could be driven by local policies that made downtown areas more attractive for high income individuals, which themselves attracted high income people to the CBSA raising its average income. We can make some progress, however, by instrumenting for each CBSA's income growth between 1990 and 2013 with the CBSA's 1990 industrial mix. Specifically, we instrument for CBSA-level income growth with predicted growth in the average CBSA wage generated by interacting the initial 1990 CBSA-level industry shares with their respective industry-level national wage growth between 1990 and 2013.[16] This Bartik (1991)-style instrument isolates movements in CBSA income to those driven by cross-industry variation in national trends.[17]

The IV coefficients are for equation (2) are shown in the right panel of Figure 3. The IV estimates across the income groups display the same pattern as the OLS estimates but are larger in magnitude and less precisely estimated. In any case, both the OLS and IV results show that high income households are more likely to re-locate downtown relative to other households in CBSAs with higher average income growth.

As a back of the envelope exercise, we can assess whether our estimates shown in Figure 3 are of the right order of magnitude to explain the *change* in the U-shape pattern between 1990 and 2013 documented in Figure 2. In other words, was the collective per capita inocme change observed in the top 100 CBSAs large enough to explain the change in the aggregate U-shape pattern between 1990 and 2013 given our estimates of (2). To assess this, we compute a predicted change in $\Delta \ln\left(\bar{\lambda}_{cD}(w)\right)$ as follows:

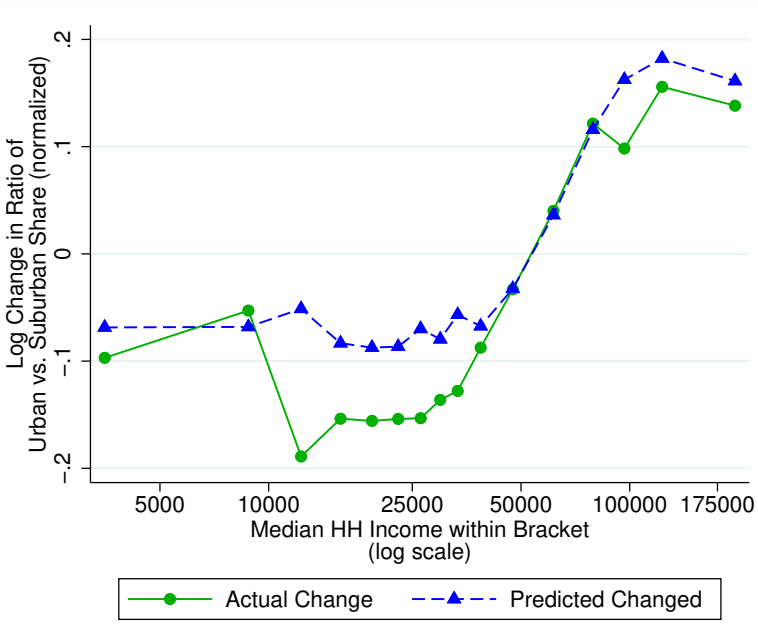
$$\Delta \ln \widehat{\left(\bar{\lambda}_{cD}(w)\right)} \equiv \hat{\alpha}_w \Delta \ln(Income_{1\bar{0}0}), \tag{3}$$

where $\hat{\alpha}_w$ corresponds to our IV estimates shown in the right panel of Figure 3 and $\Delta \ln(Income_{1\bar{0}0})$ is the change in mean income in the largest 100 CBSAs as a whole from 1990 to 2013. Figure

[16] This instrument is a significant predictor of average income. The first-stage F statistic for these regressions is 22.7, which is above the critical values for weak instrument reported in Stock and Yogo (2005).

[17] Goldsmith-Pinkham et al. (2018) show that the identifying variation in Bartik instruments depends almost entirely on initial industry shares, and they suggest standard tests of the identifying assumption. We are planning to investigate the source of our identifying assumption further in future versions of this draft. For now, we note that whether industry shares satisfy the exclusion restriction depends on the context. Here, a key concern is that 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 and the shift of the wealthy downtown in the cities where they were overrepresented in 1990. To investigate this, we compute Bartik instruments that leave out technology or FIRE industries. The IV coefficients from these leave out Bartiks are very similar to those from Figure 4. We also note that Couture and Handbury (2017), Baum-Snow and Hartley (2017) and Su (2017) all conclude that spatial job sorting plays little to no role in explaining recent downtown gentrification. Su (2017), for instance, does not find any evidence that high skilled jobs centralized from 1990 to 2013.

Figure 4: Actual vs. Fitted Downtown Residential Propensity By Income Bracket



Note: All data shown in the Figure from the largest 100 CBSAs. The predicted change is computed from equation (3), using the Bartik IV coefficients from equation (2) and the aggregate change in average income. The actual change is computed from the change in the share in equation (1) from 1990 to 2013.

4 compares the actual 1990-2013 changes in the relative downtown residential propensity of different income groups with our back of the envelope predicted estimates of these changes based on average income growth in the largest 100 CBSAs. The actual change in downtown residential propensity for different income groups is just the log difference between the 1990 and 2013 curves in Figure 2. Figure 4 shows that our predicted estimates are very similar to the actual relative shift in residential sorting patterns during this period for households at different levels of income.

Again, we cannot claim that the positive relationship between income growth and the urbanization of rich relative to poor households documented in this subsection are entirely causal. However, we note that this positive relationship is even stronger when using alternative income growth definitions that directly capture disproportionate income growth at the top, and robust to alternative samples of CBSAs, and to the addition of controls like CBSA population growth.[18] Therefore, the overall evidence suggests that shifts in the income distribution observed during the 1990-2013 period may be a quantitatively important factor in

[18]For instance, we observe the same pattern of relative urbanization of richer households if we define $\Delta \ln(Income_c)$ as the change in the share of income going to the top decile of the income distribution in CBSA c, or else as a change in the ratio of income at the 95th percentile over that at the 20th percentile. Our results also hold in a sample of all CBSAs (instead of the largest 100), and in unweighted regressions.

drawing higher income individuals into downtown areas of major cities. Below, we formalize a model that does just that. Additionally, the patterns that we document in this subsection will be useful in helping to discipline some of the model parameters.

4.4 CBSA Income Growth and Urban Gentrification

The above section shows that CBSA-level income growth urbanizes rich households relative to poor households. What the above section did not show was whether when rich households relocate downtown in response to a CBSA-level income growth, they do so by migrating into neighborhoods previously occupied by the poor. In other words, do CBSA-level income shocks result in increased urban gentrification?

To explore this question, we must first adopt a measure for gentrification. Specifically, we measure the fraction of low income tracts within area n of CBSA c that gentrifies from 1990 to 2013 (where n is either downtown D or suburbs S). A tract is characterized as gentrifying if (i) its median household income was below the median across all tracts in the same CBSA in 1990 and (ii) it experienced at least a 50 percent growth in median income between 1990 and 2013. This definition captures initially poor tracts that experienced rapid median income growth. Table 1 shows the extent of urban gentrification by this definition in the 20 most populous CBSAs in 1990. The share of eligible tracts that gentrified ranges from zero in Riverside (whose downtown lacks the scale of that in CBSAs of comparable size) to above 40% in Seattle and San Francisco.[19]

Our measure of gentrification is based on tract level income growth. In Table 2 we compare eligible downtown tracts in the top 100 CBSAs that we classified as gentrifying between 1990 to 2013 to other eligible downtown tracts that did not gentrify by our definition along a variety of additional economic and demographic margins. Compared to non-gentrifying eligible tracts, the tracts that we identify as gentrifying based on tract level income growth experienced much faster growth in population, house prices, and the share of residents with at least a bachelor's degree. Gentrifying tracts also saw a rapid outflow of households from the lowest income decile, a decline in the fraction of renters, and increasing penetration by the kind of restaurants that richer individuals have a high propensity to visit relative to non-gentrifying eligible tracts.

We now turn to our application of this definition and ask whether CBSA-level income shocks are associated with urban gentrification. Figure 5 shows the relationship between the

[19]Appendix Figure 15 motivates our focus on gentrification in urban areas: gentrification was highly concentrated downtown between 1990 and 2013 in the set of large CBSAs depicted (New York City, Cook County (Chicago), Philadelphia County, San Francisco County, Suffolk County (Boston), and Clark County (Las Vegas)).

Table 1: Share of Eligible Downtown Tracts that Gentrify from 1990 to 2013 in Largest 20 CBSAs

		Share of Eligibile Downtown Tracts Gentrifying			Share Eligibile Downtown Tracts Gentrifying
1	Seattle	0.44	11	Philadelphia	0.12
2	San Francisco	0.43	12	Pittsburgh, PA	0.10
3	Chicago	0.35	13	Miami	0.10
4	Washington	0.34	14	Minneapolis	0.09
5	New York	0.34	15	Cleveland	0.07
6	Houston	0.27	16	St. Louis, MO	0.05
7	Atlanta	0.25	17	Detroit	0.04
8	Baltimore	0.18	18	Los Angeles	0.03
9	Boston	0.16	19	Phoenix	0.03
10	Dallas	0.13	20	Riverside	0.00

Note: Downtown tracts consists of all tracts closest to the city center that account for 10% of CBSA population in 2000. Eligible gentrifying tracts are tracts in the bottom 50% of the median income distribution in their CBSA which also experienced at least 50% real median income growth from 1990 to 2013. The percentages in the table are out of all eligible tracts in the downtown area of the CBSA.

share of eligible tracts that gentrified in downtown areas (blue circles) and suburban areas (orange triangles) as a function of log CBSA average income growth. As CBSA income rises, poor downtown neighborhoods are gentrifying with a much higher frequency than suburban neighborhoods. Note that there is nothing mechanical about this cross-CBSA relationship. Eligible suburban tracts do not gentrify at the same increased rate as eligible downtown tracts when per capita CBSA incomes rise. Combining the results from Figures 3 and 5, we find that as CBSA income grows, higher income households are more likely to locate in downtown urban areas and poorer downtown neighborhoods gentrify. These facts motivate our modeling choices and will be used to help discipline the parameters of our model.

4.5 Urban Amenities as Relative Luxury Goods

At the heart of our model below is the assumption that urban amenities like restaurants and entertainment options are relative luxury goods. There is large support for such an assumption within the literature. For example, using detailed spending categories from the Consumer Expenditure Survey, Aguiar and Bils (2015) find that nondurable entertainment activities (e.g., movie and concert tickets, museum fees, sporting events) and food away from home (which includes restaurant meals) are two of the spending categories with the highest expenditure elasticities. These micro estimates suggest that as households get richer, they

Table 2: Changes in Economic Conditions By Gentrification Status, 1990-2013

	Gentrifying	Non-Gentrifying	p-val of diff
Growth in Population	17 %	-3%	< 0.01
Change in Fraction w/ Bachelor's Degree	36 p.p.	11 p.p.	< 0.01
Growth in Census Median House Price	108%	48%	< 0.01
Growth in Zillow All Home Index (1996-2013)	88%	27%	< 0.01
Growth in # of Households in the Lowest Income Decile	-29%	2%	< 0.01
Change in Fraction of Renters	-8 p.p.	3 p.p.	< 0.01
Growth in Chain Restaurant Quality (2000-2010)	18%	7%	< 0.01

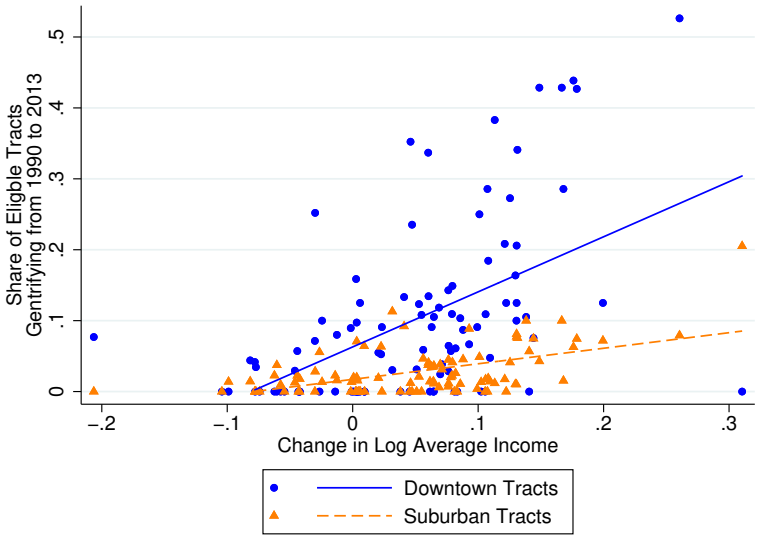
Note: Table shows data for 100 largest CBSAs in 1990. Gentrifying tracts are located in the downtown area of their CBSA, in the bottom half of the CBSA median income distribution, and experienced at least 50 percent real median income growth from 1990 to 2013. Non-gentrifying tracts are all other downtown tracts in the bottom half of the median income distribution in their CBSA. See text for variable descriptions.

increase the share of their expenditure towards restaurant and entertainment options. The key gentrification mechanism in our model is that downtown urban areas more easily provide these luxury consumption goods.

Trip level data from the 2009 NHTS provide additional support for the view that urban amenities like restaurants and entertainment are more important for the rich than for the poor and more important downtown than in the suburbs. Figure 6 shows the average number of daily trips to non-tradable services (including restaurants and entertainment activities) for individuals at different income levels. We show this number separately for individuals living in urban areas and the suburbs.[20] Two findings emerge from Figure 6. First, individuals in the highest NHTS income bracket earning more than $100,000 take more than 3 times as many daily trips to non-tradable services as the poorest individuals. Second, urban residents take more trips to non-tradable services than suburban residents, but this positive urban-suburban gap is only present for rich households. Both findings are consistent with non-homothetic preferences for urban amenities, and they motivate the key gentrification mechanism in our model.

[20]For this analysis, we define urban areas as being those tracts that surround the city center than comprise 15 percent of the CBSA's population. Patterns are similar using our base 10 percent urban area definition, but confidence intervals are wider due to smaller sample sizes.

Figure 5: CBSA Income Growth and Share of Tracts Gentrifying

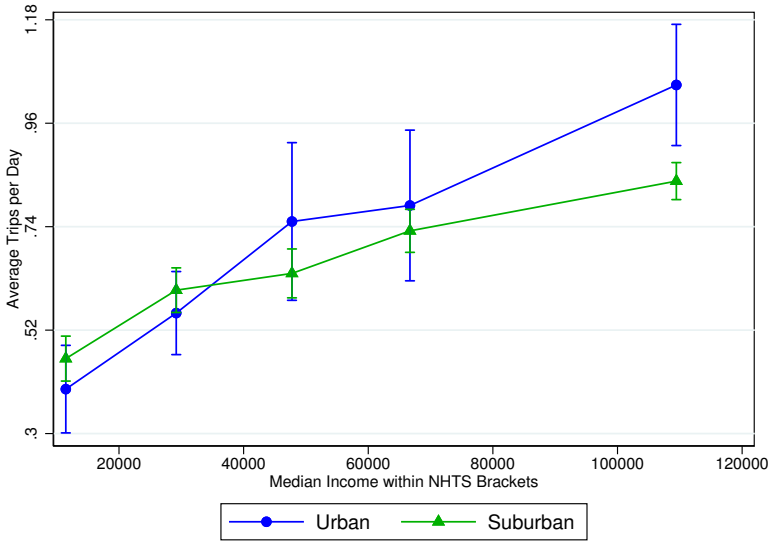


Note: Plot depicts the share of a CBSA's eligible (i.e., below median income) downtown (blue circles) and suburban (yellow triangles) tracts that gentrified (i.e., had 50% or more income median growth) between 1990 and 2013 against the change in that CBSA's log average income. Weighted regression lines through the scatter plots are shown where the weights are CBSA population in 1990. The slopes of the regression lines for the downtown and suburban gentrification shares are 0.78 and 0.22, respectively, with standard errors of 0.13 and 0.04.

This mechanism is finally supported by an emerging literature demonstrating the importance of non-tradable services in making urban area desirable places to live. Murphy (2017) provides theoretical and empirical support for the notion that urban residents consume non-tradable services as a substitute for home production (i.e., urban residents eat at restaurants while suburban residents cook at home.) Couture (2016) measures gains from restaurant density and suggests that non-tradable service variety accounts for most of the consumption value of cities. Couture and Handbury (2017) quantify the importance of non-tradable services as as a driver of the urbanization of the young and college-educated in the 2000s, and find such services to be more important than jobs, house prices, tradable retail amenities, or public amenities like school and crime. Baum-Snow and Hartley (2017) also find that local urban amenities drive recent urban gentrification.

We want to be clear that, in our model below, households have non-homothetic preferences over urban amenities broadly defined. In this subsection, we highlight evidence from the literature documenting that households have non-homothetic preferences over one important set of urban amenities - restaurants and entertainment options. However, the key insights from the model and quantitative exercises that follow hold if households have non-homothetic preferences over a broad bundle of urban amenities. For example, if richer

Figure 6: Propensity to Travel to Non-Tradable Services by Income and Location.



Note: The Figure shows the average number of daily trips to non-tradable services of individuals in different income brackets living downtown (in blue) and in the suburb (in green). The data comes from the the 2009 NHTS survey and includes all members of participating households who are 25 to 65 year old and live in the 100 largest CBSAs. The downtown definition includes all tracts closest the the city center accounting for 15% of the population. Trips to non-tradable services include trips to restaurants, to go out/hang out (e.g., bars, entertainment), to gym/sports, to personal services, and to buy services (e.g., laundry, garage).

households prefer low-crime more than poorer households and crime falls when rich people move downtown, this force will be embedded in the model's amplification mechanism.

4.6 Alternative Explanations for Urban Gentrification

We want to end this section by addressing two other forces in the literature that have been discussed as a cause of urban gentrification. First, Edlund et al. (2016) and Su (2017) 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. Our model allows for work commute costs to vary between suburban and downtown residents and to increase with income. So, as the income of the rich increases, it becomes more expensive for them to commute from the suburbs. However, we do not focus on this mechanism as a primary motive of urban gentrification because empirically commuting times have not fallen for the rich during this period. Specifically, Couture and Handbury (2017) show that the average commute distance for high-wage workers actually *increased* slightly from 2002 to 2011, with the most positive percentage change in commute distance for workers living closest to the

city center.[21] The reason for this is that, while the rich are more likely to move downtown, they are reverse commuting to the suburbs with increased propensity. This is consistent with downtown amenities being more important than commuting costs in determining the patterns of sorting by income within a CBSA.[22] In order to simplify the model, we abstract from reverse commuting. Given that commuting costs for individuals of differing income levels did not change much (on net), we feel that we are not missing too much by abstracting from this force in our model.

Another potential story for recent urban gentrification was put forth by Ellen et al. (2017) who show that central cities with a faster decline in crime in the 1990s experienced rising shares of high-income and college-educated residents. Again, our model has an amplification mechanism that captures endogenous amenities that the rich value more than the poor generally, such as crime. However, unlike urbanized luxury amenities like restaurants and entertainment, crime cannot explain the relatively high propensity of rich families to live downtown even during the high urban crime eras of 1970 and 1990 in Figure 2. It could be that a policy change occurred that reduced crime in downtown urban areas in the 1990s, and that this attracted some high income individuals back to downtown urban areas. We find such a story plausible although it is not a force that we focus on in our model. Our goal is not to explain all factors that generated gentrification during the 1990s and 2000s. Instead, we focus on one important force and discipline that force using moments of the micro data that we think are connected to the mechanism that we highlight. Accordingly, while our mechanism explains much of the change in urban sorting by income during the last few decades in the US, it does not explain it all. Given this, there is room for these other forces to have contributed to the large amount of urban gentrification that occurred within the U.S. during the last few decades.

5 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

[21] We performed our own analysis of the relationship between changes in commuting time and household income of residents who were 25-54 years old living in metropolitan areas using commuting data from the Censuses and ACS. Our findings reinforce the patterns in Couture and Handbury (2017). In particular, we find that both median and 95th percentile commute times are stable for workers within all income deciles during the 1990-2013 period except for the top two deciles that experienced an *increase* in commute times over the last two decades.

[22] Recent findings in (Gaigne et al., 2017) support the view that richer individuals' desire to minimize commuting costs can only explain a small fraction of the in increase in urban gentrification during the 2000s (holding the sorting based on amenities fixed).

quantitatively one 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. 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.

5.1 Model setup

5.1.1 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. We assume that there are two levels of quality (low and high) and index them by $j \in \{L, H\}$. Within each level of quality, neighborhoods r are further differentiated horizontally.[23]

5.1.2 Preferences

A worker who lives in neighborhood r of type (n, j) derives utility from the consumption of a freely traded composite good c as well as directly from the enjoyment of non-rival urban amenities that require renting one unit of housing in r. The utility of worker ω who lives in neighborhood r of type (n, j) is:

$$U_r(\omega) = c\, A_n\, b_{n,j,r}(\omega), \tag{4}$$

where 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, as well as their size difference) and $b_{n,j,r}(\omega)$ is the value of the private urban amenity associated with living in neighborhood r

[23]The 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 6).

for worker ω. Workers value each horizontally-differentiated neighborhood differently, which we capture by assuming that $b_{n,j,r}(\omega)$ is a random variable that is i.i.d. across workers. Specifically, each household draws a vector $\{b_{n,j,r}(\omega)\}$ of idiosyncratic preference shocks, following a Generalized Extreme Value distribution:

$$F(\{b_{n,j,r}\}) = \exp\left(-\left[\sum_{n,j}\left(\sum_{r\in\mathcal{B}(n,j)}\frac{q_j}{\mathcal{L}_n}b_{n,j,r}^{-\gamma_j}\right)^{-\frac{\rho}{\gamma_j}}\right]\right),$$

where $\mathcal{B}(n,j)$ is the set of neighborhoods of quality j in part of the city n.

Two remarks are in order here. First, with this nested structure of idiosyncratic preferences, the preferences of a given worker 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_j governs the variance of idiosyncratic preference draws for neighborhoods of the same type (*within* n,j pairs), where consistency with utility maximization requires $\gamma_j > \rho > 1$. Furthermore, we can allow for different scope and taste for neighborhood differentiation in high and low quality neighborhoods (i.e., $\gamma_H \neq \gamma_L$) [24]

Second, we allow the mean of these preference shocks to be location n- and quality j-specific. The mean urban amenity value of a neighborhood of type (n,j) is given by $\frac{q_j}{\mathcal{L}_n}$, where q_j captures the quality level of the neighborhood - higher quality neighborhoods provide on average higher amenities than low quality neighborhoods. $\frac{1}{\mathcal{L}_n}$ is the density of that part of the city where $\mathcal{L}_n$ is the land area of location n. This reduced-form density shifter captures the notion that the denser an area is, the closer and more accessible the amenities of nearby neighborhoods are, which makes the area more attractive to live in with respect to consuming residential amenities.

5.1.3 Labor Income and Net Income

Workers are heterogeneous in skill. They supply labor inelastically. We assume that labor income is an increasing function of worker skill, so that we can summarize the heterogeneity of workers through their wage w. The number of workers 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.[25]

[24] The parameter γ is inversely related to the variance of the draws.

[25] Specifically, 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.

Workers commute to work. We assume that commuting costs depend on the part of the city where the worker lives, summarized by n. We assume that the cost of commuting is proportional to labor income and captured by commuting costs τ_n, so that net labor income is $(1-\tau_n)\,w$ for a worker with wage w who lives 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 own a share of the city-wide real estate portfolio. We allow this share to vary systematically by worker type, as captured by $\chi(w)\Pi$ where Π is the total returns to the real estate portfolio and $\chi(w)$ is the fraction owned by a worker of type w. Market clearing for asset ownership requires that $0 \leq \int \chi(w)L(w)dw \leq 1$.[26]

Households choose their neighborhood of residence r by maximizing (4) subject to the budget constraint. Given the specification of income and the utility function, the indirect utility of a worker ω whose wage is w is given by:[27]

$$\max_r \left((1-\tau_n)w + \chi(w)\Pi - p_r\right)A_n b_{n,j,r}\left(\omega\right)$$

The price p_r 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. 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.

[26]The total share can be less than one, the rest being owned by absentee landlords.

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

5.1.4 Land Markets and Developers

Neighborhoods are developed by private developers who rent out housing units; the number of neighborhoods of each type is an endogenous outcome of the model. Developers combine land and capital to develop neighborhoods, which are a set of housing units, together with urban amenities such as restaurants, cafes, and retail outlets that make the neighborhood appealing to potential renters.

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

$$\mathcal{L}_n = \mathcal{L}_n^0 \left(r_n\right)^{\epsilon_n}, \tag{5}$$

where r_n and $\mathcal{L}_n$ are respectively rents and land supply in location n, and $\mathcal{L}_n^0$ is a $n-$specific exogenous shifter, which shifts the relative size of downtown vs the suburbs. We assume that land supply is inelastic downtown (i.e., $\epsilon_D = 0$) while it is elastic in the suburbs ($\epsilon_S > 0$). Developers combine land $\mathcal{L}$ and capital K in a Cobb-Douglas production function to build H_j housing units of quality j:

$$H_{n,j} = \frac{1}{h_{n,j}} \mathcal{L}_{n,j}^{\alpha} K_{n,j}^{1-\alpha}, \tag{6}$$

where a higher quality neighborhood is more expensive to build, as captured by $h_{n,H} > h_{n,L}$. Capital is provided by absentee capitalists and has exogenous price r_K, constant over space. Define $H_{n,j}$ the total demand for housing units in (n, j), and $E_n \equiv \sum_j h_{n,j} H_{n,j}$ the total demand for equipped land in n. The unit cost of housing in neighborhood (n, j) is then a constant elasticity function of equipped land in location n:[28]

$$R_{n,j} = \kappa_{o,n} h_j E_n^{\frac{\alpha}{1-\alpha+\epsilon_n}}, \tag{7}$$

where the constants are $\kappa_{o,n} = r_K^{1-\alpha} \left(\frac{\alpha r_K^{1-\alpha}}{\mathcal{L}_n^0}\right)^{\frac{\alpha}{1-\alpha+\epsilon_n}}$.

Developers pay a fixed cost $f_{n,j}$ to develop a differentiated neighborhood r of type (n, j). Housing rents are p_r, and demand for housing units in neighborhood r is denoted $d_r(p_r)$. A

[28] Specifically, it follows from (6) that the unit cost of housing in neighborhood (j, n) is $R_{n,j} = h_j r_n^{\alpha} r_K^{1-\alpha}$ (where h_q has been re-normalized by a constant term). Denote by $\mathcal{L}_{n,j}$ the the total demand for land in n, j and $\mathcal{L}_n$ the demand for land in n. Clearing the land market requires that $r_n \mathcal{L}_{n,j} = \alpha R_{n,j} H_{n,j}$, which aggregates across qualities to $\mathcal{L}_n = \alpha r_n^{\alpha-1} r_K^{1-\alpha} E_n$.

Combining this land demand equation to the land supply equation in (5) leads to equilibrium prices of land as a function of housing demand $r_n = \kappa_{1,n} E_n^{\frac{1}{1-\alpha+\epsilon_n}}$, where $\kappa_{1,n} = \left[\frac{\alpha r_K^{1-\alpha}}{\mathcal{L}_n^0}\right]^{\frac{1}{1-\alpha+\epsilon_n}}$. In turn, equilibrium cost of housing and land supply are respectively $R_{n,j} = \kappa_{2,n} h_j E_n^{\frac{\alpha}{1-\alpha+\epsilon_n}}$ and $\mathcal{L}_n = \kappa_3 E_n^{\frac{\epsilon_n}{1-\alpha+\epsilon_n}}$, where the constants are $\kappa_{2,n} = \left(\kappa_n^1\right)^{\alpha} r_K^{1-\alpha}$ and $\kappa_3 = \alpha \kappa_1^{\alpha-1} r_K^{1-\alpha}$

developer's profit function for a neighborhood of type j in location n is therefore:

$$\pi_{n,j,r} = d_r(p_r)\left(p_r - R_{n,j}\right) - f_{n,j}. \tag{8}$$

Developers price housing according to monopolistic competition. There is free entry of developers: the number of neighborhoods r of type (n, j) adjusts so that developers' profits are driven to zero.

5.2 Equilibrium

5.2.1 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. We examine these terms in turn.

First, given the structure of the idiosyncratic preference shocks, we know that the conditional probability of choosing r among other (n, j) choices is:

$$\lambda_{r|n,j}(w) = \frac{V_r(w)^{\gamma_j}}{\sum_{r' \in \mathcal{A}(n,j)} V_{r'}(w)^{\gamma_j}}, \tag{9}$$

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

$$V_r(w) = A_n \left(\frac{q_j}{\mathcal{L}_n}\right)^{\frac{1}{\gamma_j}} \left[(1-\tau_n)w + \chi(w)\Pi - p_r\right], \tag{10}$$

In equilibrium, all neighborhoods are symmetric within type, so that $\lambda_{r|n,j}(w) = \frac{1}{N_{n,j}}$ where $N_{n,j} = |\mathcal{B}(n, j)|$ is the endogeneous number of neighborhoods of type (n, j).

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

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

where $V_{n,j}$ is the inclusive value of all neighborhoods of type (n, j) :

$$V_{n,j}(w) = \left[\sum_{r\in\mathcal{A}(n,j)} (V_r(w))^{\gamma_j}\right]^{\frac{1}{\gamma_j}} = A_n \left(\frac{q_j N_{n,j}}{\mathcal{L}_n}\right)^{\frac{1}{\gamma_j}} [(1-\tau_n)w + \chi(w)\Pi - p_r] \tag{12}$$

Finally, the model lends itself naturally to welfare analysis. The average welfare for a worker of wage w is the same irrespective of his location choice:

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

Note that higher-income workers will be over-represented in costly neighborhoods, as income and housing prices are complement in equation (11).[29] Since higher quality neighborhoods will endogenously, in equilibrium, have higher demand hence higher housing prices, they will attract high-income workers disproportionately. This first feature of the model can rationalize why higher income workers 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:

$$V_{n,j}(w) = A_n((1-\tau_n)) \left(\frac{q_j N_{n,j}}{\mathcal{L}_n}\right)^{\frac{1}{\gamma_j}} \left[w + \frac{\chi(w)\Pi}{(1-\tau_n)} - \frac{p_r}{(1-\tau_n)}\right]$$

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 (i.e., $A_S(1-\tau_S) > A_D(1-\tau_D)$), it will be so only for higher-income workers as, 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.

5.2.2 Developers

Developers compete according to monopolistic competition. They maximize profits, not recognizing the impact of their pricing on the price index. That is, they maximize (8) where their demand is

$$d(p_r) = \int_w \lambda_{n,j,r}(w)\, L(w) dw.$$

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

[29] The 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.

$$p_r = \frac{\gamma_j}{\gamma_j + 1} R_{n,j} + \frac{1}{\gamma_j + 1} \mathcal{I}_{n,j}(p_r), \tag{14}$$

where the term $\mathcal{I}_{n,j}(p_r)$ is a measure of demand for neighborhood r.[30] By symmetry, all neighborhoods of type (n, j) have the same price in equilibrium, which we denote as $p_{n,j}$. Finally, the number of developers of neighborhoods of type (n, j) is pinned down by free entry.

$$N_{n,j} = \frac{\int_w \lambda_{n,j}(w) L(w) dw}{f_{n,j}} (p_{n,j} - R_{n,j}) \tag{15}$$

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., $N_{n,j}$ in (15) 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 γ_j. Entry generates a smaller feedback loop for neighborhoods that are more substitutable - intuitively, the lower quality neighborhoods. 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 term $\frac{1}{\mathcal{L}_n}$ in (12)). The idea that the model captures here is 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 built in the suburbs are built, in part, over new land, as land is supplied 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 $\lambda_{n,j}(w)$, house prices $p_{n,j}$, land rents R_n, 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

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

levels of amenities). We detail this approach and leverage it in section 7, where we analyze a series of counterfactual equilibria, starting from an initial one calibrated from the data. We now describe this calibration.

6 Model Calibration

In this section, we 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 calibrate the model in two stages. In a first stage, we estimate a series of key elasticities. In a second stage, we use the method of moments to calibrate the remaining model parameters.

6.1 Calibration Preliminaries

There are three notions of space within our model. First, as discussed above, a representative metropolitan area is divided into two areas indexed by n: downtown (D) and the suburbs (S). Second, within each area n, there are two levels of neighborhood quality indexed by j: high quality (H) and low quality (L). Finally, within each $\{n, j\}$ pair, there is a continuum of r differentiated neighborhoods. As discussed in section 3, we empirically define neighborhoods as census tracts and the downtown (D) area as all census tracts surrounding the center city of a CBSA that contain 10 percent 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 residents. 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 31 percent of census tracts in the downtown areas of the top 100 CBSAs are respectively classified as high quality in 1990, 2000 and 2013. We choose 40 percent as a focal point given that over this period roughly 35 percent of adults aged 25 and 65 have a bachelor's degree. We chose a threshold slightly higher than the national average.

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 using the *Market Potential Index* (MPI) of local restaurant chains, as described in section 3. Specifically, we take the average MPI of restaurant chains within walking distance of a tract centroid. A chain's MPI measures the likelihood of a high income American to visit that

chain relative to the average American.[31] The five restaurant chains with the highest MPI are California Pizza Kitchen, Cheesecake Factory, Panera Bread, Chipotle, and Starbucks. Amenity quality and household location are determined in equilibrium, so these MPIs capture both the propensity of high income individuals to visit and locate near a given chain and the type of chains that choose to locate near them (given that propensity to visit a chain declines with travel time). We define a high quality census tract as being those census tracts with average MPI greater than 1. Under this definition, 18 and 39 percent of census tracts with non-missing quality in the top 100 CBSAs are classified as high quality, respectively, in 2000 and 2010, the two years for which this measure is available.[32]

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, they yield quite similar classification of tracts into quality levels. For example, in 2013, the simple tract-level correlation between the two measures exceeded 0.5. As we highlight below, 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.

6.2 Calibration: First Stage

6.2.1 Estimation of ρ and γ

Two important elasticities of the model are ρ and γ that govern, respectively, the substitutability *between* area/quality pairs $(n, j) \in \{(D, H), (D, L), (S, H), (S, L)\}$, and the substitutability between neighborhoods *within* an area/quality pair. We detail here how we estimate these key elasticities. We first discuss how we estimate ρ from the following equation implied by equation 9 of the model:[33]

[31] Our MPI measure may be noisy, because as explained in section 3, we do not recover MPIs directly from the underlying proprietary marketing survey. Instead, we measure the MPI of each chain as the average MPI in all Esri's geographic segments in which the average income is above $100,000.

[32] Tracts with missing restaurant MPI have very low population density and no chains within walking distance. Our robustness tables in the appendix show results assigning all missing tracts to either L or H.

[33] To derive equation (16), we start with (9), drop the commuting cost and mutual fund terms for simplicity, take logs, difference over time and across the two areas in a CBSA, and finally add a CBSA-quality fixed effect δ_{cj} and an error term ϵ_{cj} to capture measurement error and any time-varying variables with a differential impact across income groups missing from the model.

$$\Delta \ln \left(\frac{\lambda_{cDj}(w)/\lambda_{cDj}}{\lambda_{cSj}(w)/\lambda_{cSj}} \right) = \delta_{cj} + \rho \Delta \ln \left(\frac{w - p_{cDj}}{w - p_{cSj}} \right) + \epsilon_{cj}(w). \tag{16}$$

With the CBSA/quality fixed-effect δ_{cj}, all the identifying variation is across income groups. We estimate a larger ρ if richer households tend to locate in areas with higher housing prices, conditional on neighborhood quality j.

Equation (16) takes our model literally and interprets the relationship between changes in the propensity to live downtown and changes in house prices as being driven by non-homothetic preferences for urban amenities (broadly defined). Other forces, however, could be driving house prices and location choices outside of our model. δ_{cj} captures the changes in demand for area/quality pairs that are common across income groups, but any downtown demand shocks that affect the rich more than the poor could confound our estimates.

We therefore instrument $\Delta \ln((w - p_{cDj})/(w - p_{cSj}))$ with a CBSA-level Bartik income shock. This 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. In this sense, equation (16) is the structural counterpart of the reduced-form equation (2) that motivates our model. Our exclusion restriction is that, conditional on δ_{cj}, the Bartik shock changes the relative propensity of a given income group to live in Dj relative to Sj only through its impact on relative house prices. As with the reduced-form estimation in section 4.3, we will finalize our investigation of the Bartik identifying variation and of the confounding impact of job sorting by skills in future versions of this draft. Our results so far on that front are reassuring. Our estimates are robust to Bartik instruments that leave out urbanized high wage growth industries like FIRE and technology.[34]

While we believe that our estimation strategy allows us to uncover ρ, our approach to estimating γ at this time is more speculative. We estimate a version of equation (16) with a CBSA instead of a CBSA*quality fixed-effect, which allows for the joint estimation of ρ and γ. In particular, the model implies:

$$\Delta ln \left(\frac{\lambda_{cDj}(w)/\lambda_{cD}}{\lambda_{cSj}(w)/\lambda_{cS}} \right) = \delta_c + \frac{\rho}{\gamma} \Delta \ln \left(\frac{N_{cD,j}/\mathcal{L}_{cD}}{N_{cS,j}/\mathcal{L}_{cS}} \right) + \rho \Delta \ln \left(\frac{w - p_{cDj}}{w - p_{cSj}} \right) + \epsilon_{cj}(w). \tag{17}$$

In this specification, we again identify ρ with our Bartik instrument. We can then recover

[34] Su (2017) finds no increase from 1994 to 2010 in the share of high skill jobs located downtown relative to the suburbs, or in the share of high relative to low skill jobs downtown. He uses the Zip Code Business Patterns from the 25 largest MSAs, and defines high skilled jobs as being in occupations with at least 40% of workers with a college degree. He defines downtowns as all zipcodes with centroid within 5 miles of the city center, which is roughly the scale of our 10% downtown definition for cities of this size.

γ from our estimate of ρ/γ. The coefficient on ρ/γ is smaller than 1 if the elasticity of substitution between neighborhoods (whose substitution is governed by γ) is smaller than the elasticity of substitution between downtown and the suburbs (whose substitution is governed by ρ). In this case, a rising share of j neighborhoods in D relative to S generates a less than proportional rise in the number of households in Dj relative to Sj. The impact of $\Delta \ln((N_{cDj}/\mathcal{L}_{cD})/(N_{cSj}/\mathcal{L}_{cS}))$ is constant across income groups and the fixed-effect δ_c captures all changes in the relative attractiveness of downtowns versus suburbs, so remaining identification concerns are area-specific changes in demand for a given quality level.

For example, if there is an increase in the demand for quality j in D relative to S for reasons outside of our model, this could simultaneously increase both the share of land allocated to j in D relative to S as well as the share of people living in Dj relative to Sj. As of now, we do not have a straight-forward way to rule out this identification concern. So, we proceed by estimating (17) only instrumenting for $\Delta \ln(w - p_{cDj})/(w - p_{cSj})$ using our Bartik instrument and estimating $\Delta \ln((N_{cDj}/\mathcal{L}_{cD})/(N_{cSj}/\mathcal{L}_{cS}))$ without an instrument. We then explore the robustness of our results to alternate quantitative results below with alternate values of γ. As the paper evolves, we plan on fine-tuning our estimation of γ.

To estimate equations (16) and (17), we use the same definition of λ as in our reduced-form work of section 4, which is consistent with the model above. To compute $\Delta \ln((w - p_{cDj})/(w - p_{cSj}))$, we again set w as the median household income within each constant CPI-adjusted census bracket.[35] As a result, w is fixed over time and across CBSAs. We use the Zillow all home price index in 2000 and 2013 as well as the prevailing mortgage rate in a given year to compute annual housing costs p_{cnj} associated with the median house price in each $\{n, j\}$ pair within a CBSA.[36] For equation (17), we proxy for $(N_{cnj}/\mathcal{L}_{cn})$ in each CBSA with the total share of the geographical area n that is of quality j. In total, our estimation includes at most 2000 observations (100 CBSAs, 10 income groups, and 2 quality tiers).[37] In many specifications, we have less than 2000 observations given the presence of missing data at the CBSA-income group-quality triplet.[38] We provide additional details on all variable

[35] As mentioned in section 4, we calculate this median using 2000 IPUMS microdata from the 100 largest CBSA.

[36] The Zillow Home Value Index for all homes in 2000 and 2013 measures the median home value at the zip code level. We first map it to census tracts, and then compute a population-weighted median house price over all census tracts within $\{n, j\}$. Finally, we compute the first annual mortgage payment associated with this house price for a standard 30 year-fixed rate mortgage with a 20% downpayment at the prevailing mortgage rate in a given year.

[37] We have 10 income groups in this estimation, instead of 16 as in the reduced-form empirical work of section 4.3. This is because we 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.

[38] We also remove any observation with $w - p_{cnj} < 0$ (1.4% of our sample). Within each year and quality type, we then censor the top and bottom 1% of $w - p_{cnj}$. Censoring the top and bottom 5% instead leads

Table 3: OLS and IV Estimation of ρ and γ

	Tract College Share > 40%				Local Restaurant Chain Quality			
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
$\hat{\rho}$	0.99	2.44	1.47	2.67	0.26	2.40	0.82	2.14
	(0.15)	(0.57)	(0.10)	(0.17)	(0.35)	(0.72)	(0.11)	(0.22)
$\widehat{\rho/\gamma}$	0.60	0.62			0.66	0.67		
	(0.05)	(0.05)			(0.07)	(0.07)		
Implied $\hat{\gamma}$	1.66	3.91			0.40	3.59		
	(0.26)	(0.97)			(0.53)	(1.25)		
δ_c	Yes	Yes			Yes	Yes		
δ_{cj}			Yes	Yes			Yes	Yes
R2	0.61		0.79		0.56		0.83	
KP F-Stat		7.44		65.49		6.66		49.53
Obs	1,363	1,363	1,368	1,368	1,295	1,295	1,297	1,297

Notes: Data from 100 largest CBSAs in 2000 and 2013. Observations are CBSA-population weighted. Standard errors, in parentheses, are clustered at CBSA-level. Standard error on $\hat{\gamma}$ computed with the delta method. KP F-Stat = Kleinberger-Papp Wald F statistic.

construction in Appendix A.

Our main estimation results of ρ and γ are in Table 6. Columns (1)-(4) segment neighborhood quality using whether a census tract has at least 40 percent of residents with at least a bachelor's degree. Columns (5)-(8) segment tracts based on the restaurant quality index. Within each quality measure, we estimate both equation (16) and (17). The former is designed to only estimate ρ by including CBSA-quality fixed effects while the latter estimates both ρ and γ and includes only CBSA fixed effects. Finally, for each type of regression we show both the OLS estimates and the IV estimates where we use our Bartik instrument for $\Delta ln((w - p_{cSj})/(w - p_{cSj}))$.

A few things are of note from the results in Table 6. First, our IV estimates of ρ are very stable across specifications. Our IV estimates are our preferred estimates. Across both our estimates of (16) and (17) and with both measures of neighborhood quality, our estimates of ρ range from 2.14 through 2.67. For our base specification, we set $\rho = 2.5$ which is around the average of the estimates. However, we show robustness of our calibration results for a

to similar estimates.

range of values of ρ. Second, we note that the instrument is relevant; the CBSA-level Bartik shock is a highly significant predictor of faster house price increase downtown relative to the suburbs. Edlund et al. (2016) find a similar result. We report robust Kleinberger-Paap (KP) Wald statistics for all our IV regressions.[39] As would be consistent with measurement error in our OLS specification, our estimates of ρ rise with our instrumenting procedure. Finally, our estimates of γ in columns (4) and (8) are quite similar at a value of 3.91 and 3.59 despite the different quality measures being used to segment tracts. As noted above, we are still working to refine our estimates of γ. We note here that reassuringly, the un-instrumented coefficient ρ/γ takes almost the same value in the IV and OLS specifications, and for both quality definitions. In our base specification, we will set $\gamma = 3.75$. However, we will also explore a wide range of alternate values of γ in a variety of robustness exercises. Appendix C includes additional robustness tables with a number of variations in data, specifications, controls, and quality cut-offs.[40]

6.2.2 Estimation of ϵ_n and α

To calibrate the elasticity of land supply ϵ_n and the share of land in housing α, we first note that they are related to the housing supply elasticity β_n following:

$$\beta_n = \frac{1 - \alpha + \epsilon_n}{\alpha}. \tag{18}$$

Saiz (2010) provides housing supply elasticity estimates β_c for 95 large Metropolitan Statistical Areas, based on geographical constraints and housing regulations. We can therefore assign β_c to 83 of the largest 100 CBSAs in our sample, and rely on this cross CBSA variation to infer values of β_D, β_S. In particular, we find that the Saiz elasticities β_c decline with average household density ($density_c$). This suggests that $\beta_D < \beta_S$.

To formalize this argument, we estimate the following log-linear regression of β_c on $density_c$:

$$\ln(\beta_c) = 1.97 - \underset{(0.07)}{0.30} \ln(density_c) + \epsilon_c, \; R^2 = 0.21 \tag{19}$$

We then define $\hat{\beta}_D$ and $\hat{\beta}_S$ as the fitted values from equation (19) computed at typical

[39] The instrument in equation (16), which identifies ρ alone, is strong with KP statistics above 50. The KP statistic falls to around 7 for the joint estimation in equation (17) but importantly both equations deliver similar estimates of ρ. Increasing the sample to all CBSAs increases the KP statistic in the joint estimation to around 8 or 9 and assigning all missing restaurant quality tracts to H or L increases it above 10.

[40] In particular, in particular, we obtain very similar coefficients using Census house prices and 1990 to 2013 changes, but the F-stat falls to around 5 in the joint estimation. The rest of our estimation uses 2000 to 2013 changes because neither our restaurant quality index nor our preferred Zillow house price index are available in 1990.

density of D and S neighborhoods in the 100 largest CBSAs. We find $\hat{\beta}_D = 0.60$ and $\hat{\beta}_S = 1.33$.[41] We assume that land supply is fixed downtown, which corresponds to $\epsilon_D = 0$. We can then use equation (18) together with the estimates $\hat{\beta}_n$ to pin down $\alpha = 0.625$ and $\epsilon_S = 0.45$. We use these values in our baseline calibration and test the sensitivity of our results to alternative parameter values.[42]

6.2.3 Other Parameters and Summary

There are two remaining sets of parameters that we calibrate in the first stage. First, we estimate area-specific commute costs τ_n using data on trip time to work by car from the geo-coded 2009 National Household Travel Survey.[43] Second, in our base calibration, we assume that all housing rents in the city (land rents and fixed costs of development) accrue to an absentee landlord and none are transferred to the city residents, i.e., that $\chi(w)$ =0 for all w.[44] This concludes the first stage of the calibration. The full set of parameters calibrated

[41] In 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, $\hat{\beta}_D = 0.60$ 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).

[42] Combes et al. (2017) estimate a housing production function that is close to Cobb-Douglas and constant returns to scale. They find a share of land in housing production of 0.27 for French cities with population larger than 500,000. Albouy and Ehrlich (2018) find a cost share of land in housing production of around 0.35 in a sample of all MSAs in the United States. Our values of α are larger, consistent with the production of neighborhoods (that include private amenities and public spaces) being relatively more land intensive than that of housing units.

[43] 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 $\tau_S = 0.059$.

[44] For robustness, we calibrate the share $\chi(w)$ of the real estate portfolio using home ownership data from IPUMS. We first compute the total share of this real estate portfolio owned locally, as opposed to owned by absentee landlords, by matching the share of housing wealth that is owned, rather than rented, in 1990 in the data. This pins down $\int \chi(w)L(w)dw = 62.505\%$. Second, we set $\chi(w)$ so that the model matches the share of households that were reported homeowners in the 2000 IPUMS data for each income bracket. Specifically, given our assumption of a common real estate portfolio owned in different proportions by households of different incomes, this leads to $\chi(w) \propto OS(w)$, where $OS(w)$ is the share of ownership in the data for income w. We use this data assuming that these ownership rates are fixed between 1990 and 2013. Allowing for returns from ownership in this manner increases the disposable income of all households, helping with the fit of the data in two respects. First, the mutual fund distributions are larger for high labor income households than for low labor income households, who tend to have lower home ownership rates (which range from approximately 30% amongst households earning $25,000 (US$ 1999) to over 90% amongst households earning above $200,000). High-income households therefore mechanically enjoy more of the gains from house price growth than low-income households and this disproportionate increase in disposable income amplifies the shift in their tendency to move downtown as well as their relative welfare improvement. Second, the mutual fund distributions to low-income households, while smaller than those to high-income households, are very large relative to their labor income. When prices increase from 1990 to 2013, this increase in spending

Table 4: Model Parameters

Parameter	Description	Value	Source
ρ	Between-type neighborhood substitution elasticity	2.6	Estimated (see sec 6.2.1)
γ	Within-type neighborhood substitution elasticity	4	Estimated (see sec 6.2.1)
ϵ_D	Downtown land supply elasticity	0	
ϵ_S	Suburban land supply elasticity		Authors' calcs (see sec 6.2.2)
$1-\alpha$	Share of capital in housing production		Authors' calcs (see sec 6.2.2)
r_K	Rental rate of capital	1	Normalization
τ_D^C, τ_S^C	Commute costs as share of labor income	0.0435,0.059	Authors' calcs (see sec 6.2.3)
$\chi(w)$	Fraction of land rents and fixed costs to homeowners	0	N/A

in the first stage is summarized in Table 4.

6.3 Second Stage: Method of Moments

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. We target the following to set of moments: (i) the whole distribution, by income level, of the share of workers living downtown in 1990, as described in the stylized facts section 4.2, and (ii) the median house price by neighborhood type, also in 1990. These two moments summarize the key economic concepts we aim to capture.

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

$$\tilde{q}_{n,j} = A_n \left(\frac{q_j N_{n,j}}{\mathcal{L}_n} \right)^{\frac{1}{\gamma_j}}, \tag{20}$$

without separately identifying the individual terms, and (ii) the price of housing in each location for each neighborhood type ($p_{n,j}$). 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 (14), these composite variables also pin down $R_{n,j}$, the land prices of the model, and Π the value of the real estate portfolio.

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 $\{p_{n,j}, \lambda_{n,j}(w), R_{n,j}, \Pi\}$

power implies that the lowest income households can still afford the unit housing requirement and amplifies their displacement to the low-quality housing in the suburbs, which is still more costly than the low-quality housing downtown.

that is just sufficient, conditional on estimates for the model elasticities, 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 $N_{n,j}$) 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 moment (ii). Note though that since the model is over-identified, the price moment cannot be perfectly matched. 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 of different types of neighborhoods ($\tilde{q}_{n,j}$), perceived by different income groups. 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):

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

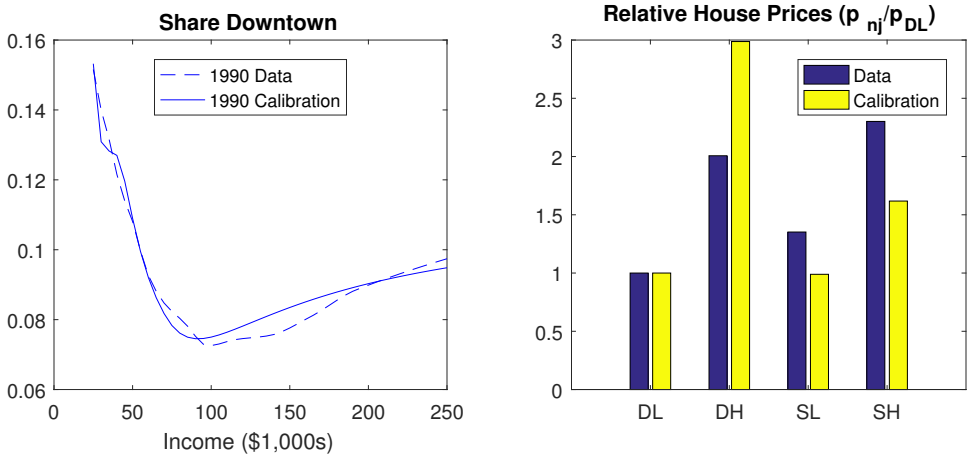
Knowing τ_n, w, and Π, which is set by a fixed point of the procedure as it depends on prices,[45] the calibration backs out the $\tilde{q}_{n,j}$ and $p_{n,j}$ that allow to match best the data distribution of location choices, $\frac{\lambda_{n,j}(w)}{\lambda_{L,S}(w)}$.[46]

The moment fit is presented in Figure 7. Despite a sparse specification, the calibrated model is able to match the rich non-monotonic U-shape patterns of location choice by households of various incomes. To be able to match these sorting patterns, the model calls for housing prices in the suburbs that are below those in the data, and for high quality housing prices downtown that are above those in the data.

[45] Specifically, $\Pi = \sum_{n,j} L_{n,j} p_{n,j}$ with $L_{n,j} = \int L(w)\lambda_{n,j}dw$.

[46] These vectors are pinned down up to a normalization level, whose value does not impact the counterfactuals of section 7.

Figure 7: Calibration to 1990 Urban Shares and Neighborhood Prices



7 Counterfactual Analysis

In this section, we use the calibrated model to analyze the impact of spatial sorting on welfare inequality. We first describe how we use the structure of the model and its 1990 calibration to compute counterfactual equilibria. We then describe and analyze a series of counterfactual exercises.

7.1 Computing Counterfactuals

We summarize here how to compute a counterfactual equilibrium for a different income distribution $L'(w)$ in the city, conditional on (i) an initial calibration corresponding to the income distribution $L(w)$, and (ii) on the model elasticities $\{\rho, \gamma_j, \epsilon_n, \alpha\}$. A similar approach can be used for solving for a counterfactual equilibrium where, for instance, the exogenous value of A_D/A_S changes, or one that implements a specific tax and transfer policy. Details of the procedure as well as the corresponding set of equations are given in Appendix Appendix B.

Specifically, the information necessary to perform this step are the model elasticities and the calibrated values at the initial equilibrium for $\{p_{n,j}, \lambda_{n,j}(w), L_{n,j}, R_{n,j}, \Pi\}$, where $L_{n,j}$ is the total population living in neighborhoods of type $\{n, j\}$ in the initial equilibrium, i.e.:

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

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 Appendix B that given the structure of the model, the counterfactual equilibrium

is the solution to the set of equations (21)-(26) for $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}, \Pi'\}$ (or, equivalently, their "hat" values) that is fully determined conditional on the model elasticities and $\{p_{n,j}, \lambda_{n,j}(w), L_{n,j}, R_{n,j}, \Pi\}$.

7.2 Computing Welfare Measures

Before turning to describing the outcome of the counterfactual analysis, we detail here the measure of welfare inequality we use in what follows. A goal of our analysis is to compare changes in well-being inequality, which take into account changes in prices and spatial sorting, to simple measures of changes in income inequality. Since the welfare measure delivered by the model is hard to interpret as is, we instead compute a measure of compensating variation (CV) to guide our well-being analysis.

Let i denote a percentile in the income distribution. Let $m_1(i)$ denote the corresponding income in the initial equilibrium (and $m_2(i)$ in the second equilibrium). More generally, subscript 2 indicates the new equilibrium (e.g., a 2013 counterfactual), and subscript 1 the initial one (the 1990 calibration).

The CV measure is defined as follows:

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

This measures tells us, in 2013 dollars (i.e., at 2013 prices), how much additional income a worker at percentile i of the income distribution would need to go from his 1990 welfare level to his 2013 welfare level (where welfare is captured by V, defined in (13)).

We compare this measure to the change in income of a worker at this percentile of the income distribution, by computing the percentage point difference between the two relative income (or CV) changes:

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

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. This leads

to similar insights. We report the corresponding results in the Appendix.[47]

7.3 Counterfactual 1: Changing Both Population and Income

We start by studying the model's prediction for the change in the spatial distribution of the population within a CBSA and resident welfare, following a change in total CBSA population and a shift in the income distribution that mimics the observed changes between 1990 and 2013. This counterfactual is what drives the spatial sorting responses of residents over this period as depicted in Figure 2. This counterfactual is done for illustrative purposes to understand the forces in our model; however, it will not be our base counterfactual. Our preferred counterfactual is instead one where we isolate the effect of changes to the shape of the income distribution holding total CBSA population fixed. We discuss that counterfactual in section 7.4.

To perform the counterfactual in this subsection, we recompute the equilibrium of the quantified model that corresponds to the new income distribution of 2013 and the new population in 2013, holding all exogenous parameters of the model constant. Recall that the 2013 income distribution is characterized, in particular, by a fatter right tail than the 1990 income distribution, as discussed in section 4. There was also 16 percent population growth between 1990 and 2013 within our sample the top 100 CBSAs, which had associated price effects that will also drive the sorting response in this initial counterfactual.

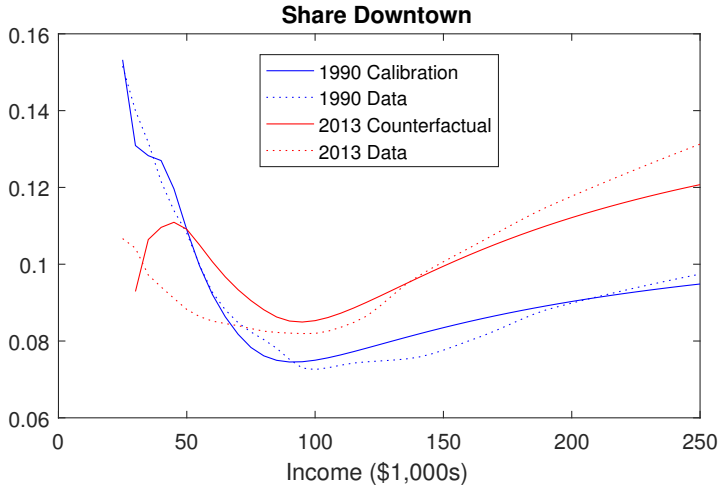
Figure 8 presents the model's prediction for the share of workers living downtown by income level for this new distribution of income. The figure also shows, for reference, the calibrated share of workers living downtown in 1990 and the actual shares living downtown in 2013.

Our quantified model predicts that the growth in income at the upper-end of the distribution between 1990 and 2013 results in a spatial redistribution of higher-income households downtown, as well as the displacement of lower-income households to the suburbs. Qualitatively, these patterns are overall consistent with that observed in the data. Of course, other changes - beyond a change in the income distribution and the population - happened over the last two decades. We interpret the predictions of our model as being indicative of what *part* of the spatial shifts of the past two decades are plausibly attributable to the growth in population and income inequality that took place over this time period.

[47] Equivalent variations are measured as:

$$\begin{aligned} EV(i) &= e(p_1, W_2(i)) - e(p_1, W_1(i)) \\ &= W_1^{-1}(W_2(m_2(i))) - m_1(i) \end{aligned}$$

Figure 8: Illustrative Counterfactual



Quantitatively, we find that the model predicts most of the observed shift downtown for households earning between $100,000 and $125,000, and approximately two thirds of this shift at higher income levels at incomes between $125,000 and $250,000. Turning to the bottom of the income distribution, the model predicts some displacement of lower income households to the suburbs, but less so than in the data. Specifically, the poorest households are displaced outside of downtown, both in the data and in the model, but the model predicts that households at intermediate levels of income remain downtown, more so than in the data.

Overall, we conclude from this analysis that the change in income distribution together with aggregate population growth between 1990 and 2013 has the potential to explain a large part of the shift in the composition of downtowns over the same period, though we note that it does not explain well the increased suburbanization of households at intermediate levels of income.[48]

7.4 Counterfactual 2: Changing Only the Income Distribution

The results from the first counterfactual summarize the joint effects of the observed growth in the aggregate population and the income distribution and are useful for testing the predictive power of the model. We now turn to isolating the contribution of changes in the income distribution, separate from population growth. It is in this exercise that we compute our welfare effects from the changing nature of spatial sorting. To do so, we run the same counterfactual as above, but normalize the counterfactual population to its 1990 level.

In particular, our goal is to estimate the welfare implications of the changing nature

[48] In further iterations of this draft, we will investigate quantitatively whether a change in other primitives of the model, beyond the income distribution, can explain this shift.

of spatial sorting in response to the rising incomes of the rich. To that end, we compute compensating variation (CV) for households at each percentile of the income distribution in 1990, as explained in section 7.2. This measure reflects changes in well-being associated not only with changing income, but also with housing costs, and endogenous amenity quality.[49] We refer to this CV measure as "welfare" or "well-being", to simply contrast it with the simple change in income over time.

7.4.1 Results

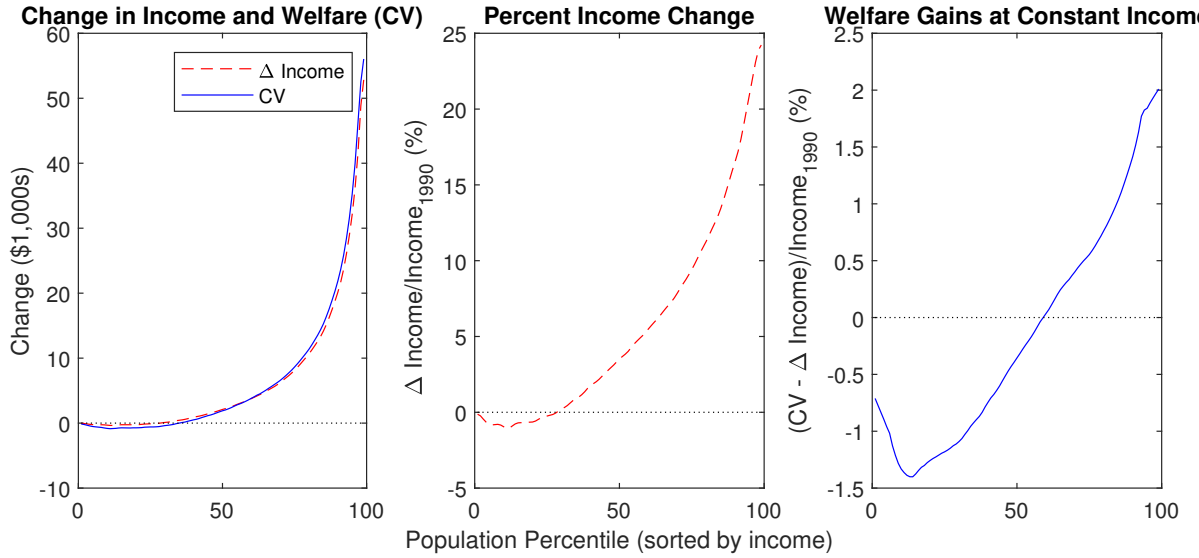
Figures 9 shows our headline results. Specifically, the left hand panel of Figure 9 represents the change in well-being measure in actual dollars, in solid blue, together with the raw change in income, in dotted red, at all percentiles of the income distribution. Note that the welfare measure is slightly tilted, compared to the change in income: the changes in well-being inequality represented in the figure are *larger* than the underlying changes in income.

To see that point more clearly, we represent two additional panels of results. In the middle panel, we show the percentage change in income that occurred between the two time periods at each percentile of the income distribution. As has been documented extensively within the literature for the economy as a whole, income inequality has increased within the top 100 largest CBSAs over the last 25 years in the United States. For the 10th percentile of the income distribution for our sample, income actually fell slightly by 1 percent. For the 90th percentile, income increased by 17 percent. Overall, there was an 18 percentage point increase in the income gap between the 10th and 90th percentile within our sample since 1990.

The right panel shows the actual change in well-being above and beyond the income change due to the spatial sorting responses within our model. As discussed above, the spatial sorting response amplifies the differences in well-being between the rich and the poor during this time period. In particular, as the rich got richer, they moved into downtown urban areas making the poor worse off. Households at the 10th percentile of the income distribution have 1.3 percent lower utility from the movement of higher income individuals into urban areas as a response to their rising incomes. Households at the 90th percentile are actually 1.4 percentage points better off. As they move into downtown areas, amenities which they value endogenously respond making them better off. In total, the spatial sorting response increases inequality as measured by the 90-10 gap by an additional 2.7 percentage points. In other words, the true difference in well-being between the 10th and the 90th percentile increased

[49] Recall that we have assumed zero returns from the housing mutual fund. So, these welfare measurements do not include any welfare effects associated with ownership of any housing assets. Including these effects, the growth in welfare inequality would be even greater than measured here, since high-income households are more likely to be homeowners.

Figure 9: Welfare Changes From Spatial Sorting Response to Changing Income Distribution



by 19.7 percent (17 percent plus 2.9 percent). The key finding of our paper is that ignoring spatial sorting substantively understates the welfare differences between the rich and the poor of rising income inequality.

7.4.2 Mechanisms

What drives these results in the model? There are three 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 the poor 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 the 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. Finally, some of the poor may choose to relocate to lower quality neighborhoods in the suburbs. In doing so, the poor will incur additional commute costs and, if there is some autocorrelation in the idiosyncratic neighborhood utility draws, moving costs as they move from their preferred downtown locations.

The left-hand panel of Figure 10 shows the prediction of house prices within our model from the changing income distribution for different n,j pairs. The darker colored bars show the predictions of the model. We also show the actual change in house prices from the data in the lighter colored bars in the background. A few things are of note. First, the change

in the income distribution only explains some of the change in house prices in the data. This is not surprising given that a lot of the population growth in all areas is determined by the net increase in population within CBSAs during this period. Given we have shut down population growth in this counterfactual, it is not surprising that we are not matching all of house price growth. Second, our model is predicting that the shift in the income distribution alone is having a much larger effect on house prices in downtown areas (both high and low quality) relative to the suburban areas. It is this increase in house prices generated by the shift in incomes of the rich that will contribute to the welfare losses of the poor who remain downtown.

The right hand side of Figure 10 shows the share of high and low quality housing in each area. The change in this share is a model analog to gentrification. Within a given area (downtown or suburbs), housing is part of either a high or a low quality neighborhood. Our model predicts a decline in low quality downtown neighborhoods and a corresponding increase in high quality neighborhoods in response to the shift in the income distribution. As the number of high quality neighborhoods increase, this increases the utility of all downtown residents given our love of variety preferences.

To tease out the respective roles played by increasing prices and increasing variety in driving the welfare results at various levels of the income distribution, we proceed to decompose our changing welfare measures into two components: one due to changing housing prices and another due to changing neighborhood "varieties." These results are shown in Figure 11. For ease of comparison, we redisplay our base welfare results in the figure (blue line). The red dotted line is the well-being measure that would occur if we allow housing prices to adjust but held quality and variety constant, between 1990 and 2013. The red dashed line corresponds, conversely, to holding prices constant but allowing quality and variety of neighborhoods to change as predicted by the model. Comparing two red lines, we see that the increased welfare gap (depicted in blue) is gap is almost entirely due to changes in the neighborhood composition, that is, the gentrification of low quality neighborhoods downtown that is valued more by the rich than the poor.[50]

7.5 Counterfactual 3: Redistributive Policy (preliminary)

We finally turn to analyzing the impact of policies that shape the spatial sorting of heterogeneous households within the city. Specifically, 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-

[50]The effects of housing price and neighborhood variety changes each taken in isolation do not sum to the total effect because there are some non trivial interaction effects between the two changes.

Figure 10: Mechanisms

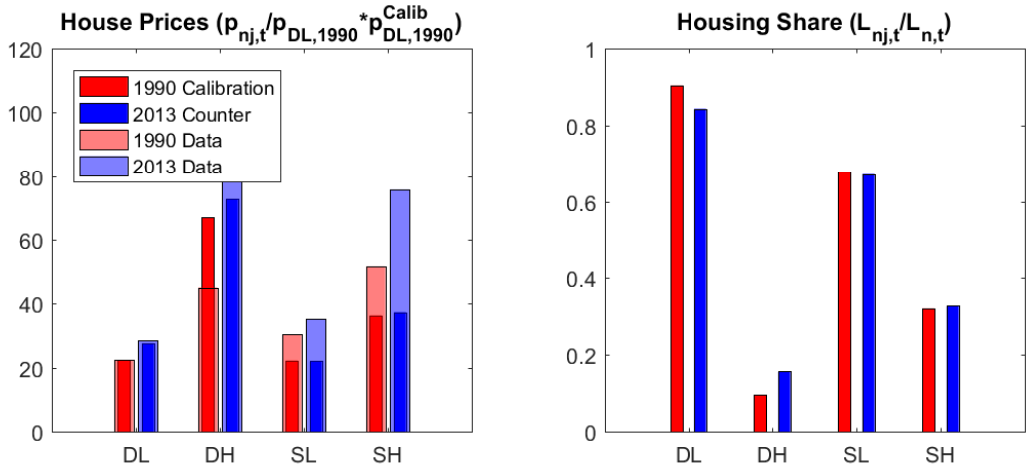
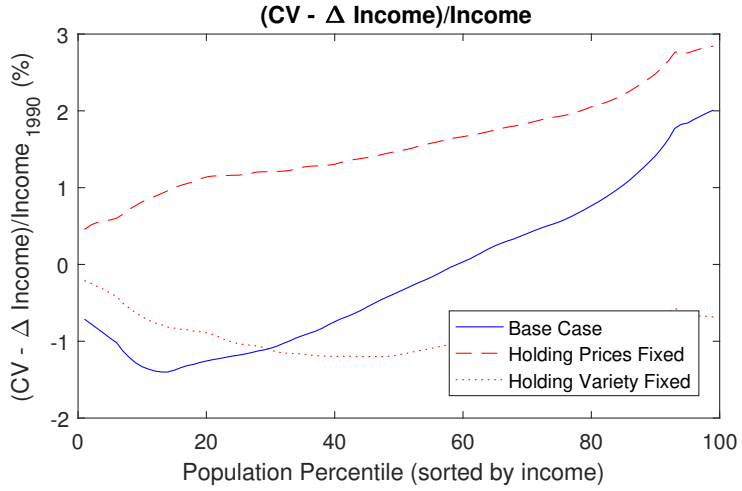


Figure 11: Price vs. Neighborhood Variety Holding Population Fixed



Note: The red-dotted line is the well-being measure that would correspond to the change in prices computed between 1990 and 2013, holding quality and variety at their 1990 level. The red dashed line is the well-being measure that would correspond to the change in quality and variety computed between 1990 and 2013, holding prices fixed at their 1990 level.

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 implement the following policy. We assume that the local government imposes a tax t on housing prices downtown, for houses in high-quality neighborhoods. The tax levied is then redistributed as a place-quality-specific subsidy for households who choose to locate downtown, but in low-quality neighborhoods. That 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:

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

We recompute the spatial equilibrium of the city, with the distribution of household income that corresponds in shape to that in 2013 but holds population fixed at its 1990 level, implementing the policy with a tax of 7.5%. Figure 12 shows that the policy has the effect of stemming approximately half of the gentrification of downtown neighborhoods (the transfer in housing share from low to high quality neighborhoods downtown). Post-transfer, the policy also prevents land price increases in downtown neighborhoods, where effective housing costs are now cheaper since low quality residents downtown receive the redistribution of the tax revenues. Turning to the well-being effect of this policy, we find that, unsurprisingly, it stems some of the losses to the poorest households and reverses some of the gains for higher income households (figure 13). Note though that low-to-middle income households are also worse off under this policy. This is because the development of their preferred housing option (low quality suburban neighborhoods) is crowded out by an increase in high quality suburban housing development, the preferred tax-free alternative for high-income households to high quality neighborhoods downtown. "That is, the policy generates a form of gentrification of the suburbs.

Contrasting the welfare results (in consumption equivalent) to the ones in Figure 9, however, we see that the welfare implications of such a large policy are insufficient to counteract the redistributive impacts of the spatial re-sorting associated with growing nominal income inequality. Even if such a policy could in principle contain some of the gentrification (and income composition changes) of downtowns, its re-distributive effects would be quantitatively limited.

We conclude that even if such a policy could in principle contain some of the change in income composition of the downtowns, its re-distributive effects would be quantitatively limited.

7.6 Counterfactual 4: Looking Forward

To be completed.

Figure 12: Mechanisms under "Anti-Gentrification" Policy

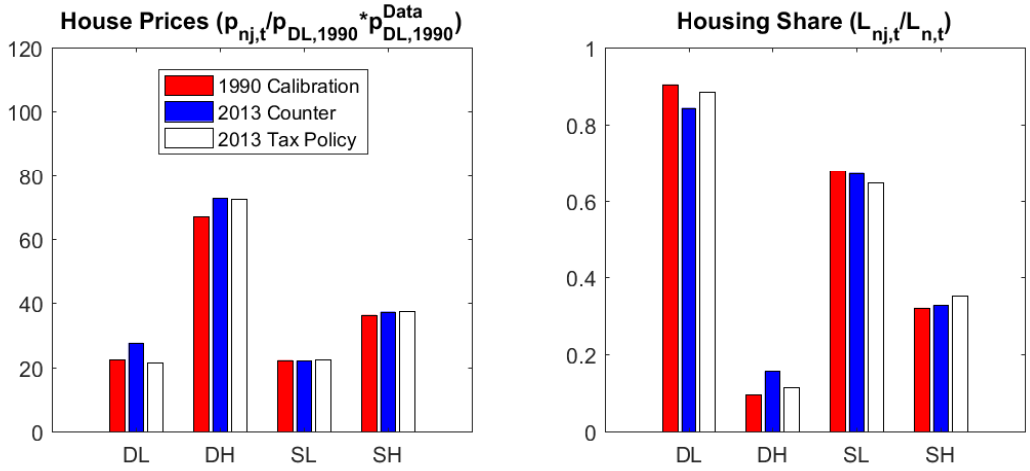
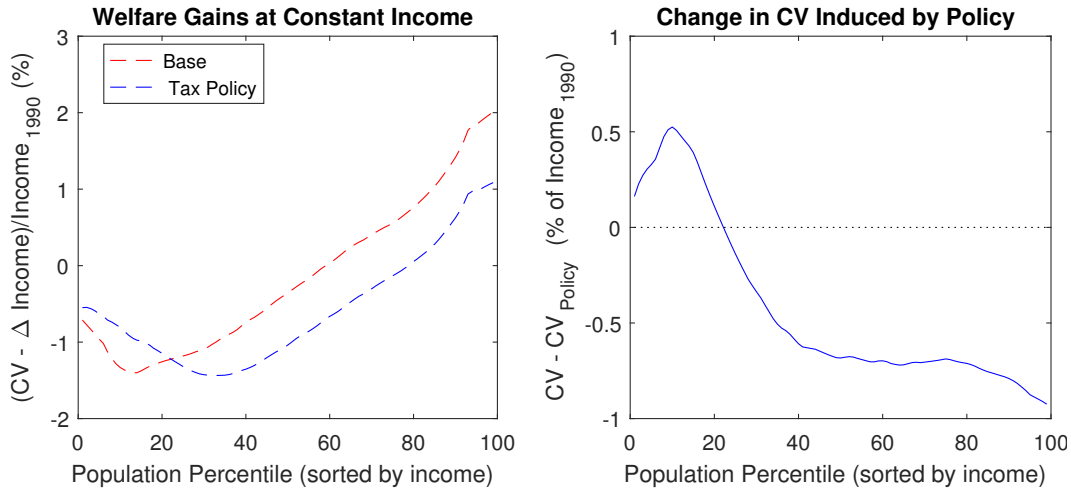


Figure 13: Well-Being Effects of "Anti-Gentrification" Policy



8 Conclusion

In order to explore the link between rising incomes at the top of the income distribution and urban gentrification, we write down a spatial model of a city with heterogeneous agents and non-homothetic preferences. We quantify the model using detailed location and income data, at the tract level, on the the top 100 CBSA's in the US. We then use the quantified model to tease out how much of the change in spatial sorting, and gentrification, 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 preliminary estimates suggest that increases in the incomes of high income individuals was a substantive contributor to increased urban gentrification during the last 25 years within the U.S. and that the gentrification 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.

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Appendix A Data Appendix

To be completed.

Appendix B Model Appendix

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 $\{\rho, \gamma_j, \epsilon_n, \alpha\}$.The information necessary to perform this step are the calibrated values at the initial equilibrium for $\{p_{n,j}, \lambda_{n,j}(w), L_{n,j}, R_{n,j}, \Pi\}$, where $L_{n,j}$ is the total population living in neighborhoods of type $\{n, j\}$ in the initial equilibrium, i.e.:

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

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 $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}, \Pi'\}$ (or, equivalently, their "hat" values).

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

$$\widehat{R}_{n,j} = \left(\sum_j s_{n,j}\widehat{L}_{n,j}\right)^{\frac{\alpha}{1-\alpha+\epsilon_n}}, \tag{21}$$

where we have used the notation $s_{n,j}$ to denote the following shares from the initial equilibrium: $s_{n,L} = \frac{L_{n,j}}{\left(R_{n,H}/R_{n,L}\right)L_{n,H}+L_{n,L}}$ and $s_{n,H} = 1 - s_{n,L}$. Note that $\widehat{L}_{n,j} = \frac{\int L'(w)\lambda'_{n,j}(w)dw}{\int L(w)\lambda_{n,j}(w)dw}$, where $\lambda'_{n,j}(w)$ is unknown and a solution of the system of equations described here, while $L'(w)$ is exogenously given.

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

$$p'_{n,j} = \frac{\gamma_j}{\gamma_j + 1}R'_{n,j} + \frac{1}{\gamma_j + 1}\mathcal{I}'_{n,j}(p'_{n,j}), \tag{22}$$

where we get $R'_{n,j} = \widehat{R}_{n,j}R_{n,j}$ from above, and the function $\mathcal{I}'_{n,j}(p)$ is defined by:

$$\mathcal{I}'_{n,j}(p) = \frac{\int_w K'_{n,j}(p,w)\left[(1-\tau_n)w + \chi(w)\Pi'\right]L'(w)dw}{\int_w K'_{n,j}(p,w)L'(w)dw}, \tag{23}$$

with $K'_{n,j}(p,w) = \frac{\lambda'_{n,j}(w)L'(w)}{[(1-\tau_n)w+\chi(w)\Pi'-p]}$. Note here that τ_n and $\chi(w)$ are assumed constant between the two equilibria. The value of the real estate portfolio Π', on the other hand, is endogenous and defined by:

$$\Pi' = \sum_{n,j} L'_{n,j}p'_{n,j} \tag{24}$$

Third, the change in overall neighborhood quality $\tilde{q}_{n,j}$ is driven by changes in number of neighborhoods of different types $\widehat{N}_{n,j}$ and the change in density $\widehat{\mathcal{L}}_n$. Starting from (20), simple algebraic manipulations lead to:[51]

$$\widehat{\tilde{q}}_{n,j} = \left(\frac{\widehat{L}_{n,j}\frac{p'_{n,j}-R'_{n,j}}{p_{n,j}-R_{n,j}}}{\widehat{R_n}^{\frac{\epsilon_n}{\alpha}}}\right)^{\frac{1}{\gamma_j}} \tag{25}$$

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:

$$\widehat{\lambda}_{n,j}(w) = \frac{\widehat{\widetilde{q_{n,j}}^{\rho}}}{\widehat{V}^{\rho}(w)}\frac{[w(1-\tau_n)+\chi(w)\Pi'-p'_r]^{\rho}}{[w(1-\tau_n)+\chi(w)\Pi-p_r]^{\rho}}, \tag{26}$$

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

$$\widehat{V}^{\rho}(w) = \sum_{n,j}\widehat{\widetilde{q_{n,j}}}\rho\frac{[(1-\tau_n)w+\chi(w)\Pi'-p'_r]^{\rho}}{[(1-\tau_n)w+\chi(w)\Pi-p_r]^{\rho}}\lambda_{n,j}(w), \tag{27}$$

Values for $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}, \Pi'\}$ are the solutions of equations (21)-(26) that define a counterfactual equilibrium of the economy corresponding to an alternative distribution of

[51] Specifically, equation (25) follows from $\widehat{\tilde{q}}_{n,j} = \left(\frac{\widehat{N}_{n,j}}{\widehat{\mathcal{L}}_n}\right)^{\frac{1}{\gamma_j}}$, combined with (XX) that leads to the expression for the change in number of neighborhoods $\widehat{N}_{n,j} = \widehat{L}_{n,j}\frac{p'_{n,j}-R'_{n,j}}{p_{n,j}-R_{n,j}}$ while (XX) leads to the expression for the change in land area, $\widehat{\mathcal{L}}_n = \left(\widehat{R}_n\right)^{\frac{\epsilon_n}{\alpha}}$.

income $L'(w)$ in the city.

Appendix C Additional Figures and Tables

Table 5: Cutoff Sensitivity for OLS and IV Estimation of ρ and γ

	Tract College Share				Local Restaurant Chain Quality			
	$> 30\%$	$> 40\%$	$> 50\%$	$> 60\%$	> 0.9	> 1	> 1.1	> 1.2
	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$\hat{\rho}$	2.53	2.44	2.02	1.63	3.67	2.40	2.47	2.18
	(0.62)	(0.57)	(0.47)	(0.41)	(0.92)	(0.72)	(0.68)	(0.79)
$\widehat{\rho/\gamma}$	0.75	0.62	0.49	0.55	0.43	0.67	0.65	0.91
	(0.08)	(0.05)	(0.05)	(0.10)	(0.05)	(0.07)	(0.13)	(0.17)
Implied $\hat{\gamma}$	3.38	3.91	4.10	2.97	8.62	3.59	3.81	2.40
	(0.92)	(0.97)	(0.98)	(0.94)	(2.57)	(1.25)	(1.53)	(0.91)
δ_c	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP F-Stat	6.10	7.44	5.70	5.58	5.39	6.66	3.54	4.60
Obs	1,451	1,363	1,321	1,216	1,505	1,295	1,150	1,030

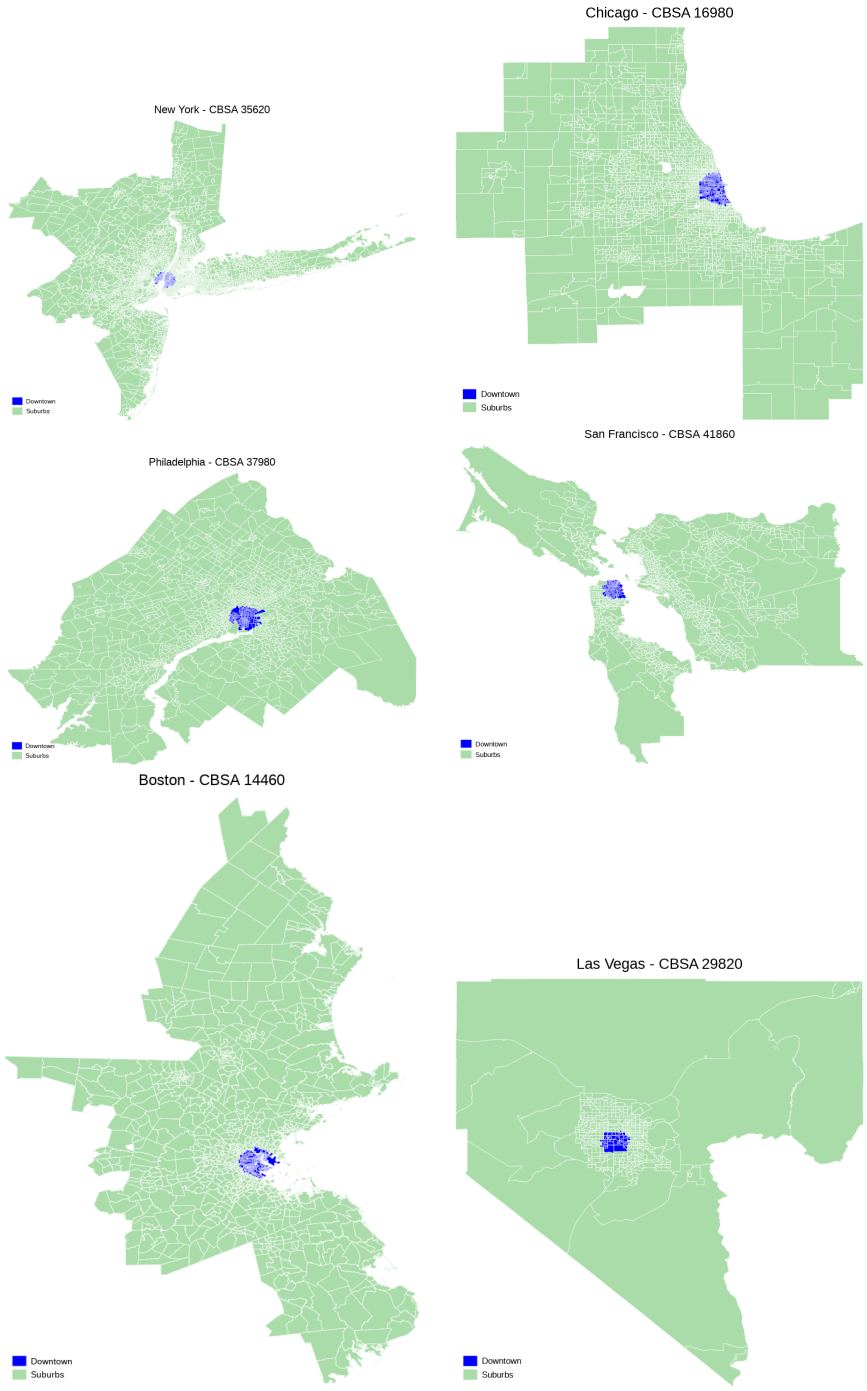
Notes: Data from 100 largest CBSAs in 2000 and 2013. Observations are CBSA-population weighted. Standard errors, in parentheses, are clustered at CBSA-level. Standard error on $\hat{\gamma}$ computed with the delta method. KP F-Stat = Kleinberger-Papp Wald F statistic.

Table 6: Alternative Specifications of OLS and IV Estimation of ρ and γ

			School and	Alt N/L=	MPI		Commute Costs	
	Census 1990-2013	No CBSA FE	Crime No FE	Share Change	Missing= High Qual	Missing= Low Qual	$\tau_S = .05$ $\tau_D = 0$	$\tau_S = .059$ $\tau_s = .043$
	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$\hat{\rho}$	2.82	2.85	3.40	2.92	2.91	2.23	2.46	2.40
	(1.24)	(0.93)	(1.37)	(0.77)	(0.78)	(0.64)	(0.62)	(0.72)
$\widehat{\rho/\gamma}$	0.64	0.72	0.63	1.10	0.78	0.74	0.67	0.67
	(0.07)	(0.09)	(0.12)	(0.05)	(0.05)	(0.07)	(0.06)	(0.07)
Implied $\hat{\gamma}$	4.41	3.95	5.39	2.65	3.74	3.00	3.68	3.59
	(1.91)	(1.40)	(2.14)	(0.76)	(1.03)	(0.98)	(1.11)	(1.25)
δ_c	Yes	No	No	Yes	Yes	Yes	Yes	Yes
KP F-Stat	4.66	6.40	9.78	10.35	11.04	11.45	8.36	6.66
Obs	1,681	1,451	474	1,451	1,478	1,450	1,431	1,295

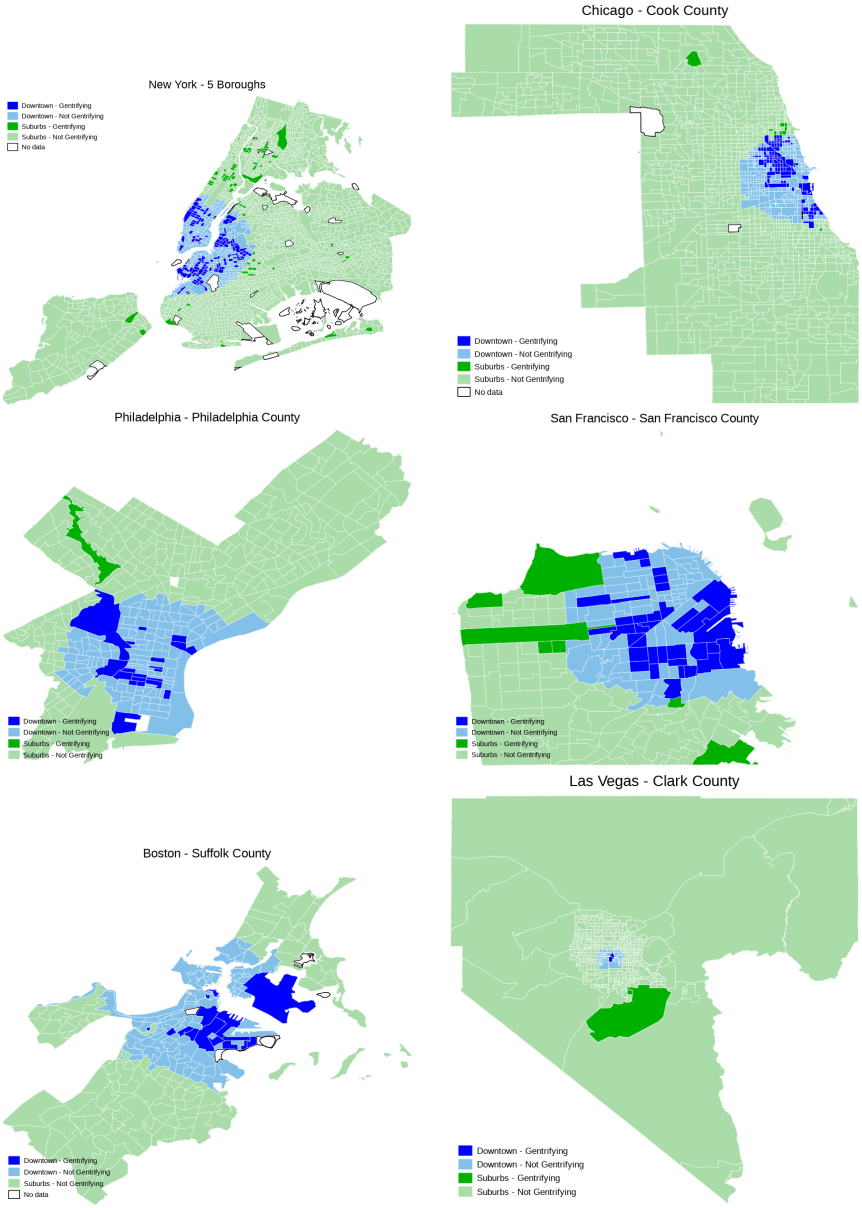
Notes: Data from 100 largest CBSAs. Estimation period 2000-2013 for columns 2-8 and 1990-2013 for column 1. Observations are CBSA-population weighted. Standard errors, in parentheses, are clustered at CBSA-level. Standard error on $\hat{\gamma}$ computed with the delta method. KP F-Stat = Kleinberger-Papp Wald F statistic.

Figure 14: 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 15: 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 consists of all tracts closest to the city center and accounting for 10% of total CBSA population in 2000. A tract is gentrifying if its median household income in 1990 was in the bottom half of the CBSA income distribution, and if it experienced median household income growth of 50% growth between 1990 and 2013.

Appendix D Counterfactual Robustness

The figures below study the robustness of our headline welfare result (the right-hand panel of Figure 9) to different parameter values and other assumptions. The results are robust to shifts in key parameters, to the bounds of our estimates of the demand elasticities (γ and ρ) and to reasonable alternatives for the land supply elasticity and land share of housing production (ϵ_S and α). The results are also robust to alternative classifications of the data into high and low quality as discussed in section 6.1.

Figure 16: Robustness to Different Values of γ Values

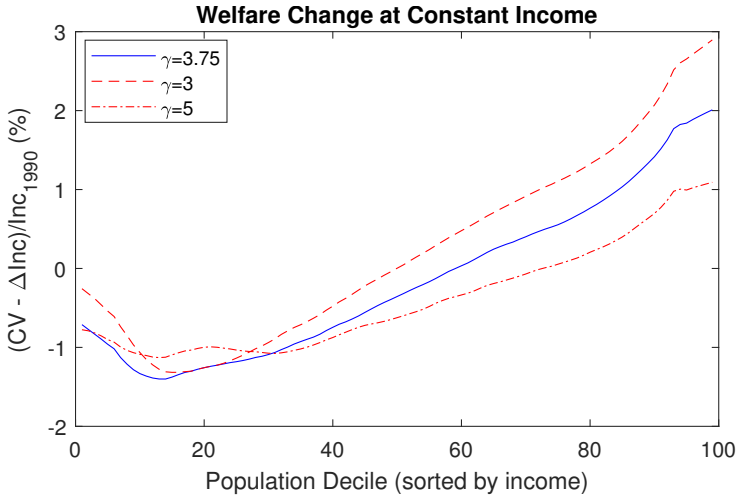


Figure 17: Robustness to Different Values of ϵ

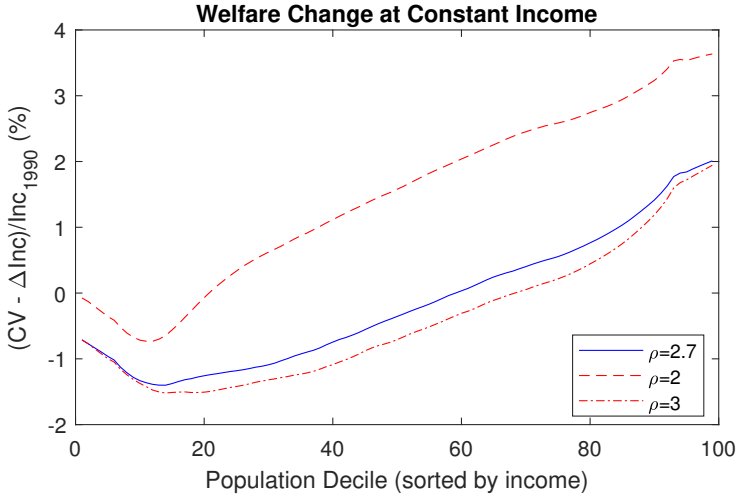


Figure 18: Robustness to Different Values of ϵ

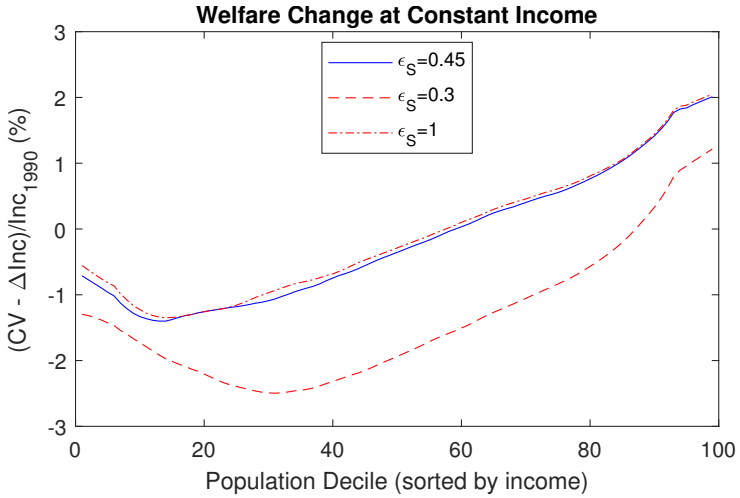


Figure 19: Robustness to Different Values of α

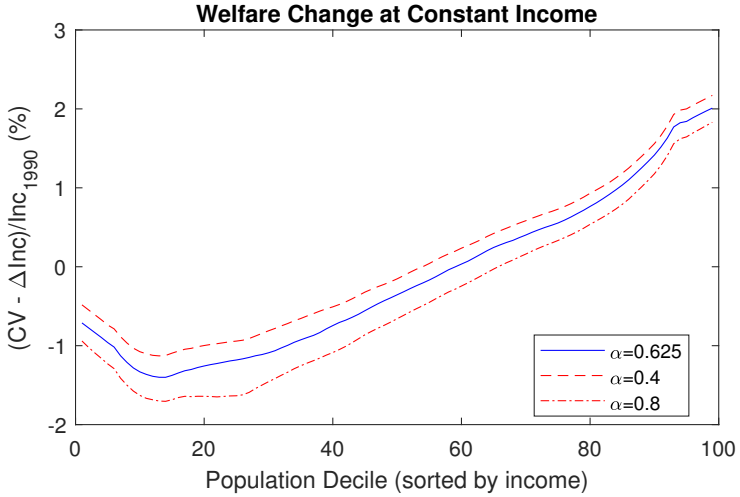


Figure 20: Robustness to Different Neighborhood Quality Definitions