Income Growth and the Distributional Effects of Urban Spatial Sorting*

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Abstract

We explore the impact of rising incomes at the top of the distribution on spatial sorting patterns within large U.S. cities. We develop and quantify a spatial model of a city with heterogeneous agents and non-homothetic preferences for locations with different amenities of endogenous quality. As the rich get richer, their increased demand for luxury amenities available downtown drives housing prices up in downtown areas. The poor are made worse off, either being displaced or paying higher rents for amenities that they do not value as much. Endogenous provision of private amenities amplifies the mechanism, while public provision of other amenities in part curbs it. We quantify the corresponding impact on well-being inequality. Through the lens of the quantified model, the change in the income distribution between 1990 and 2014 led to neighborhood change and spatial resorting within urban areas that increased the welfare of richer households relative to that of poorer households by an additional 1.7 percentage points on top of their differential income growth.

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1 Introduction

Over the last three decades income inequality in the United States has grown sharply, with income growth disproportionately concentrated at the top of the earnings distribution. During this same time period, the urban cores of American cities have attracted more college educated and higher income individuals. This latter trend has accompanied a renewed discussion of neighborhood change within many U.S. cities.\footnote{For instance, some municipalities, like New York City, have implemented policies to slow down neighborhood change associated with the influx of higher income residents into downtown areas. See “New York Passes Rent Rules to Blunt Gentrification”, New York Times, March 22, 2016.}

In this paper, we explore the link between rising incomes of the rich and their net in-migration to the downtown areas of American cities since 1990. To trace the effects of this change in spatial sorting on well-being inequality, we build a model of residential location choice within a city. The model features heterogeneous agents and heterogeneous neighborhoods and embeds two empirical regularities. First, local urban amenities, like restaurants or entertainment options, tend to be relative luxury goods.\footnote{For example, Aguiar and Bils (2015) estimate that restaurant meals and non-durable entertainment are among the goods with the highest income elasticities.} Second, downtown areas of major cities have a higher density of such amenities. As the incomes of the rich increase, their demand for urban amenities rises, and more of them choose to reside in downtown urban areas to be closer to these amenities. In turn, as the income composition of downtown urban areas changes, the supply of high quality urban amenities responds endogenously. This fuels further in-migration of the rich. It also drives up downtown rents imposing a pecuniary externality on low income residents of downtown areas. Given the empirical fact that most poor residents in downtown urban areas are renters, they do not reap the capital gains from rising house prices. Poorer residents have a choice between paying higher rents for a bundle of amenities that they do not value as much and moving out of the downtown area.

We quantify the model and find that the increased incomes of the rich are causing a phenomenon that looks like urban gentrification. In areas initially populated by poorer residents, the in-migration of higher income residents causes the amenity mix of neighborhoods to change.\footnote{Throughout the paper, we often use “neighborhood change” for low income neighborhoods and “gentrification” interchangeably. We realize that gentrification is a complex process with many potential definitions and drivers. Our interpretation is closest to the definition in the Merriam-Webster dictionary that defines gentrification as “the process of renewal and rebuilding accompanying the influx of middle-class or affluent people into deteriorating areas that often displaces poorer residents.” Our paper is not intended to explore all potential underlying causes of neighborhood gentrification. Rather, we wish to focus on the dimension of gentrification that follows the rise in top incomes. Specifically, we focus on the interaction of rising top incomes, non-homothetic preferences for urban amenities, and endogenous spatial responses.} We use the model to estimate the economic impact of rising incomes at the top of the distribution, mediated by these spatial sorting responses, on well-being inequality. We find that, because of changes in neighborhood quality and prices imposed by the in-migration of the rich, welfare estimates of increased income inequality are understated when spatial sorting responses are ignored. Our estimates suggest that welfare differences between those in the top decile of the income distribution and those at the bottom decile of the income distribution increased by an additional 1.7 percentage points between
1990 to 2014, once accounting for spatial responses, compared to a baseline increase of 19 percentage points between the two income deciles during this time period. Furthermore, we find that the neighborhood change within downtown areas that resulted from the rising incomes of the rich reduced the well-being of the average renter in the bottom decile of the income distribution by 0.50 percent in consumption equivalent terms. Most low income renters live in the suburbs. The welfare losses to renters in the bottom decile of the income distribution who actually live downtown are even larger at 1.5 percent in consumption equivalent terms.

We start by documenting a set of stylized facts on the residential choice and amenity consumption choice of households with different incomes. These facts motivate our model with non-homothetic preferences over urban amenities. First, focusing on the 100 largest CBSAs, we show that the propensity to live in downtown areas is U-shaped in household income. As is well-documented, poorer households are more likely to live downtown than middle-income households. However, we show that as household income increases above $100,000 (in 1999 dollars), the propensity to live downtown becomes monotonically increasing in income. This fact persists across different survey years of the U.S. Census, for a variety of definitions of downtown urban areas and income measures, as well as conditioning on household type, race, and age. We then document the fact that is at the heart of our analysis: between 1990 and 2014 rich households have become increasingly likely to live downtown even conditional on income - leading to an uptick in this U-shape that is more pronounced in CBSAs that saw greater income growth. Baum-Snow and Hartley (2017) and Couture and Handbury (2017) study the large shifts in demographic composition of downtown areas of the past two decades, and conclude that preferences for urban amenities play an important role in these shifts. These results motivate our particular focus on supply and demand of urban amenities. Our last stylized fact shows, in particular, that patterns of urban amenity consumption differ by income. Namely, the propensity to travel to restaurants and other entertainment options rises monotonically with household income, and does so more downtown than in the suburbs.

Building on these facts, we then propose a new model of within city residential choice with two key features. First, residential choice varies with household income. Second, neighborhood quality changes endogenously with the income composition of the city. The model is rich enough to speak to the stylized facts presented above and aims to formalize the link between income inequality growth and neighborhood change. It features heterogeneous households who differ in their level of income and in their idiosyncratic tastes for residential location. They choose where to live among neighborhoods that vary in how attractive they are. A key mechanism in the model is that desirable neighborhoods are luxury goods: in equilibrium, richer households disproportionately choose to live in high quality-high cost neighborhoods. The desirability of a neighborhood is determined by two main elements. It is first shaped by public amenities, like parks or schools. These benefit all residents of neighborhoods in a given location (e.g., downtown or in the suburbs). They are financed by a local government that collects property taxes and, as a result, evolve endogenously with the local income mix. The desirability of a neighborhood is also shaped by the quality of the housing stock and its proximity to private amenities, such as restaurants and entertainment.
Households visit amenities in their own neighborhood as well as others, so both the density and quality of amenities in a location increases the desirability of its neighborhoods. Private amenities of each quality level are provided endogenously by developers who respond to demand by building differentiated neighborhoods. In the model, neighborhoods are also horizontally differentiated, so a location is more attractive if it offers a higher variety of neighborhoods to choose from - guaranteeing a better match with one’s own idiosyncratic tastes. Households make their residential choice trading off higher desirability of a neighborhood with higher cost of living there. In the model, this cost depends on housing prices, taxes, and commuting costs to work.

In the third part of the paper, we take the model to the data. The first key elasticity in our model governs the extent of non-homotheticity in residential location choices. Our estimation exploits the differential location choice response, within cities, of individuals at differing levels of income to a CBSA-wide income shock. This estimation also offers an empirical validation of the gentrification mechanism at play in the model, as our results suggest a causal link between income growth and the relative urbanization of the rich. The second key elasticity governs the magnitude of gains from density in amenity consumption. This elasticity comes from an amenity gravity equation that we estimate with a rich database of smartphone location data. This data traces the extent to which individuals from different neighborhoods travel to different venues that provide urban amenities, and also allows us to create measures of neighborhood amenity quality. We use existing micro data sources to pin down other key parameters of the model. In a second stage, armed with these parameters, we calibrate the full model using method of moments. This procedure targets the whole U-shaped distribution of the propensity to reside downtown as a function of income, as well as the relative housing prices between different neighborhoods types and location, both in 1990. We show that the calibrated model can replicate these salient cross-sectional features of the data. In particular, the model accommodates the equilibrium that we observe in the data where downtown areas are disproportionately populated by both very low and very high earners. Low income households minimize costs of housing and commuting by residing downtown in low-quality neighborhoods. At the same time, higher income households are attracted downtown by the density of high-quality neighborhoods offered there. Finally, middle income individuals are over-represented in the mid-range options offered by suburbs, with good quality public amenities and reasonable costs.

We use the quantified model for welfare and counterfactual analysis. We aim to isolate how much the rising incomes of the rich can explain neighborhood change between 1990 and 2014 as well as the resulting change in spatial sorting patterns. To that end, we feed into the model a single (but complex) shock: the observed change in the whole distribution of incomes over that time period, which we refer to below as the “income inequality shock.” We then compute the corresponding new spatial equilibrium. We find that increases in the incomes at the top largely contributed to the changing within-city spatial sorting patterns by income levels in the U.S. during the last three decades. With an influx of high-income households, the relative demand for high-quality neighborhoods downtown increases, putting upwards pressure on housing prices. Poorer
incumbent households either remain in low quality neighborhoods downtown and see their rents increase, or they choose to migrate out. This mechanism is fueled by the endogenous provision of high quality downtown neighborhoods by developers, making downtown even more attractive to high earners. This type of amplification mechanism is not as pronounced in the suburbs, which grow through sprawl rather than density. As the city grows, downtown increases its comparative advantage in providing access to a dense variety of residential amenities compared to the suburbs. Finally, public amenities also feed back into these changes in spatial sorting. As downtown gets richer, public amenities increase. Incumbent households in low quality neighborhoods downtown benefit from this spillover, but at the same time, it puts upwards pressure on rents. Using the structure of the model, we compute the corresponding welfare effects at all levels of income. We find that the income inequality shock, mediated by change in neighborhoods and spatial sorting, triggered an even larger increase in well-being inequality.

Counterfactual analysis is then used to further validate the model and the income shock mechanism. We compare the model prediction to two additional empirical facts. First, we repeat the procedure above, but for the 1970-1990 change in income distribution. We find that our model predicts a more limited change in the U-shape pattern of spatial sorting compared to the 1990-2014 time period, and one that is also qualitatively different, like in the data. While incomes increased during the 1970-1990 period, our analysis suggests that there was not a sufficiently large increase in households at very high income levels to trigger much neighborhood change downtown. Second, we show that our model performs quite well at explaining cross-CBSA variation in spatial sorting during the 1990 to 2014 period. For this exercise, we recalibrate our model separately for each CBSA and feed in CBSA-specific changes in the income distribution between 1990 and 2014, to predict CBSA-level spatial sorting changes. Many aggregate stories that could be confounding our results get differenced out in a cross-CBSA analysis, making this a strong test of the model.

Finally, we show that our model can also be used to inform the current policy debate, sparked by large neighborhood changes in U.S. cities, on how to curb gentrification and keep city centers socially diverse. We simulate a policy that taxes housing in high-quality neighborhoods downtown to subsidize low-quality ones, as well as a form of zoning policy. We find that such policies can be effective in shaping the income mix of urban residents and keeping downtowns more affordable for the poor. However, their well-being effects are quantitatively limited, and are far from overturning the increase in well-being inequality that we find for 1990-2014. In contrast, a policy that relieves housing supply constraints in the CBSA mitigates the negative welfare impact of neighborhood change on the poor but does not curb gentrification.

This paper contributes to three main literatures. First, a growing literature studies how nominal income inequality can be accompanied by an even stronger real income inequality in models with non-homothetic preferences and monopolistic competition.\(^4\) We apply this logic to the endogenous provision of urban amenities within cities in response to a rise in income at the top of the income

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\(^4\)Faber and Fally (2017) show that more productive firms target wealthier households; Jaravel (2018) shows that innovation is skewed towards the growing top income market segment; Fajgelbaum et al. (2011), Fajgelbaum and Khandelwal (2016) and Faber (2014) study the welfare consequences of trade across the income distribution.
distribution. In doing so, we build on the literature that studies the observed changes in spatial sorting. In an early contribution, Gyourko et al. (2013) shows that the increase in high incomes nationally can explain the income growth and house price growth observed in supply-constrained “superstar cities.” Diamond (2016) shows that, across cities, homophily amongst the college educated amplifies sorting behavior and exacerbates well-being inequality. Following her insight, we study sorting patterns and well-being inequality within a city. Our main contribution to this line of research is to formalize a model of the endogenous supply of urban amenities over which households have non-homothetic preferences. Contemporaneous work also study welfare inequality within city. Fogli and Guerrieri (2017) focuses on the effect of segregation on educational outcomes, while Su (2017) emphasizes the rising value of time for high-skilled workers as a key engine for spatial sorting changes. Our focus on urban amenities follows the early insights of Brueckner et al. (1999) and Glaeser et al. (2001) that the comparative advantage of cities is not only in productivity, but also in consumption opportunities.

Second, we contribute to the quantitative spatial economics literature reviewed in Redding and Rossi-Hansberg (2017), more specifically to the strand that studies the internal structure of cities (Ahlfeldt et al. (2015); Redding and Sturm (2016); Allen et al. (2015)). These papers feature homogeneous workers with homothetic preferences and a reduced-form specification of urban amenities. One of the main contributions of our paper is to propose a new model of micro-founded endogeneous amenity provision with non-homothetic preferences. This allows us to study spatial sorting and well-being inequality across the full distribution of income. The model’s core mechanisms are drawn from Fajgelbaum et al. (2011)’s model of non-homothetic preferences and endogenous production of differentiated traded products and relate to Davis and Dingel (2014)’s assignment model, where complementarity between location attractiveness and income also drives the sorting of agents across and within cities. A recent contribution by Tsivanidis (2018) also uses non-homothetic preferences to study the distributional effects, across two skill groups, of transit infrastructure investment in Bogota.\(^5\) While these papers propose quantified models of specific cities, in which city and neighborhood boundaries are treated as fixed, we propose a stylized model of a representative city that allows us to endogenize the quantity and sprawl of neighborhoods of a city. Our framework retains the tractability of quantitative spatial models, which allows us to (i) take it to the data and (ii) quantify the impact of policies on neighborhood change and welfare.\(^6\) In this sense, our paper also complements recent work examining the welfare implications of urban public policies by Diamond et al. (2018), Eriksen and Rosenthal (2010), Baum-Snow and Marion (2009), Diamond and McQuade (2019) and Hsieh and Moretti (2019).

Third, there is a large body of empirical work studying the causes and consequences of gentrifi-

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\(^5\)In country-wide spatial equilibrium models, Peters et al. (2018) include non-homothetic preferences model to study the heterogenous impact of structural change across U.S. counties and Fajgelbaum and Gaubert (2018) study optimal spatial policies in models with heterogeneous but homothetic preferences over endogenous city amenities.

\(^6\)Gaigne et al. (2017) theoretically analyze an extension of a classic linear city model with jobs and amenities exogenously given at different locations on the line, in which non-homothetic preferences generates heterogeneous spatial sorting.
cation and neighborhood change within the United States.\textsuperscript{7} Within this literature, our paper builds on a growing strand showing that the increasing propensity of richer households to live downtown is not primarily driven by job location.\textsuperscript{8} Glaeser et al. (2001), Baum-Snow and Hartley (2017), and Couture and Handbury (2017) all conclude that amenities play a major role in driving the compositional changes of downtowns during the 1990s and 2000s. In particular, Couture and Handbury (2017) document rising average commute distance for high-wage workers from 2002 to 2011 despite their moving into downtown areas, and rising propensity to reverse-commute, i.e., to live downtown but work in the suburbs.\textsuperscript{9} These findings illustrate that changing job location or changing taste for short commutes alone are unlikely to rationalize the rising propensity of high-skilled workers to live downtown. We contribute to this literature by providing a model of neighborhood change through rising top incomes and non-homothetic demand for urban amenities, empirical evidence in support of that mechanism, and a quantification of the long-run consequences of the resulting neighborhood change on spatial sorting and well-being inequality.

2 Motivating Facts

In this section, we document that location choices, within a city, vary systematically with income. We confirm that there is strong spatial sorting within U.S. cities and highlight that these spatial sorting patterns display an interesting non-monotonic relationship with income. This non-monotonicity became more pronounced between 1990 and 2014, particularly in CBSAs that saw strong top income growth. We also document an Engel curve in non-tradable amenity consumption, that is steeper downtown than in the suburbs. These stylized facts motivate our development of a residential choice model with non-homothetic preferences, in the next section.

2.1 Data

The stylized facts we report below are based on data from the 1970, 1990, and 2000 U.S. Censuses, as well as from the 2012-2016 American Community Surveys (ACS). We refer to the 2012-2016 pooled ACS data as the 2014 ACS. We use census tract level data published by the National Historical Geographic Information System (NHGIS). All data are interpolated to constant 2010-boundary tracts and 2014-boundary CBSAs using the Longitudinal Tract Data Base (LTBD). We complement Census tables with microdata from the Integrated Public Use Micro-data Series

\textsuperscript{7}See, for example, Guerrieri et al. (2013), Edlund et al. (2016), Ellen et al. (2017), Berkes and Gaetani (2018), Vigdor et al. (2002), Lance Freeman (2005), McKinnish et al. (2010); Ellen and ORegan (2010), Ding et al. (2016); Brummet and Reed (2018), Meltzer and Ghorbani (2017), Lester and Hartley (2014), and Autor et al. (2017).

\textsuperscript{8}For instance, high skill job growth downtown is a potential explanation for gentrification. However, papers investigating the recent urban revival conclude that spatial job sorting has very little explanatory power. See, for example, Couture and Handbury (2017), Baum-Snow and Hartley (2017), and Su (2017). For instance Su (2017) does not find that high skilled jobs centralized from 1990 to 2013.

\textsuperscript{9}Data from the U.S. Census shows that commuting times increased the most for downtown CBSA residents in the top income deciles between 1990 and 2014 (author’s calculations). These patterns are consistent with the conclusions in Couture and Handbury (2017) that commuting times did not fall for high income CBSA residents despite their migration into downtown urban areas.
(Ruggles et al., 2018). We use the 1% IPUMS sample in 1970, and the 5% IPUMS samples in 1990, 2000, and 2012-2016. In what follows, all income measures are CPI-adjusted to 1999 dollars. With this data, we measure the location choice of households with differing levels of income.

Central to our analysis is the notion of the dense urban center of a CBSA, which we refer to as the “downtown,” “urban areas,” or “urban center” interchangeably in the paper. Our baseline definition of an urban center is as follows. In each CBSA, we focus on the CBSA’s main city, and within this main city on its city center.\footnote{We define the city center of each CBSA using the locations provided by Holian and Kahn (2012), who use the coordinates returned by Google Earth for a search of each CBSA’s principal city.} We then classify as downtown the set of tracts closest to the city center that accounted for 10 percent of the CBSA’s population in 2000. This defines a spatial boundary of downtown, which we keep constant across all years. For each CBSA, we refer to all remaining non-downtown tracts as being suburban tracts: tracts are either classified as downtown ($D$) or suburban ($S$). Note that our notion of the downtown area of a city is measured in population units, as opposed to distance, given that CBSAs differ in size and density. Our key motivating facts are robust, however, to alternative definitions of downtown areas, including defining downtown as census tracts with centroids within a three mile radius of the city center as in Baum-Snow and Hartley (2017). Appendix G features maps of New York, Chicago, Philadelphia, San Francisco, Boston, and Las Vegas where tracts are classified as downtown and suburban based on our definition.

### 2.2 Downtown Residential Propensity and Household Income

We are interested in understanding how location choices, within a city, systematically vary with income. Figure 1 summarizes the Engel curve for residing downtown. It shows the relative propensity of families to reside downtown by income, and its evolution over time. Each point represents the share of families, in a given Census income bracket, who reside downtown in a given year – normalized by the share of all families who reside downtown that year.\footnote{This normalization allows to abstract from the suburbanization of the population as a whole over this period. The share of families at all income levels that live downtown was 0.1 in 2000 (by construction) but was 0.17 in 1970 and 0.08 in 2014.} The x-axis features the median family income for that bracket in the same year, in 1999 dollars, computed using IPUMS micro data. The number of points on the graph is limited by the number of income brackets reported by the Census for tract-level information.

Figure 1 reveals an interesting pattern: the propensity to reside downtown is a U-shaped function of income. To the left of the graph, we see that lower income families are much more likely to live in urban areas than other income groups. Families earning $25,000 a year (in 1999 dollars) in 1970, 1990, and 2014 were between 1.5 and 2 times more likely to live downtown than other households. This implies that approximately 20 percent of all families living in a CBSA earning $25,000 per year live in downtown urban areas. The propensity to live downtown then declines with income: middle-income families have the highest likelihood of living in the suburbs. However, for income above roughly $100,000, sorting patterns reverse, and the propensity to live downtown starts to
increase with income. Importantly, this U-shaped sorting pattern is not a new phenomenon. It is present in 1970, 1990, and 2014. The second interesting pattern displayed by Figure 1 is apparent when comparing the curves over time. The uptick of the propensity to live downtown for high income families has become starkly more pronounced between 1990 and 2014. At the same time, the over-representation of the poorest households downtown has become less pronounced.

We note that these facts are robust to the definition of an urban area, CBSA sub-samples, and the use of household income rather than family income. One may think that these U-shape patterns reflect demographic characteristics that are correlated with income, and/or that the changes in the U-shape pattern over time simply reflect demographic shifts that are correlated with income and that took place between 1990 and 2014. As reported in detail in the online appendix, we find that these U-shape patterns are even more pronounced at the top of the income distribution after controlling for socio-demographic characteristics such as age, race, native born status, and household composition. The change in the U-shape also largely persists after adding these controls, and in fact, we observe a U-shaped location pattern with an uptick between 1990 and 2014 within every socio-demographic group we looked at (e.g., 45-65 year olds, the foreign born, by race, etc). This suggests that the propensity of the rich to reside downtown and the reinforcement of this pattern between 1990 and 2014 are not explained simply by omitted demographic controls. Our paper instead asks: how much of this change in spatial sorting patterns within cities between 1990 and 2014 can be traced back to the change in the income distribution and the disproportional increase of incomes at the top that took place over that period?
2.3 CBSA Income Growth and Changing Spatial Sorting by Income

If changes in the income distribution lead to changes in spatial sorting, one would expect that cities that experienced faster income growth over the period also experienced faster changes in the sorting patterns of richer households. We provide suggestive evidence that this is the case using cross-city variation in the two stylized facts above. To that end, we summarize the shift in the right-hand side of the U-shape in each city by computing the 1990-2014 growth in the propensity of households with incomes greater than $70,000 to reside downtown in each CBSA, relative to the growth in the propensity of all households to reside downtown in that CBSA. We then plot this growth against the CBSA-level growth in average household income over the same period. Figure 2 shows that CBSAs with higher aggregate income growth saw higher increases in the over-propensity of high income households to reside downtown. A 10 percent increase in CBSA income during the 1990-2014 period was associated with a 13 percent increase in the over-representation of richer households downtown. This correlation suggests that shifts in the income distribution observed during the 1990-2014 period may be a quantitatively important factor in drawing higher income individuals into downtown areas of major cities. Our model estimation in section 4 offers more detailed evidence on how CBSA income shocks have a differential impact on the urbanization of different income groups. Our use of Bartik instruments in that section also provide further evidence for a causal link between income shocks and the influx of high income individuals into downtown urban areas. Below, we develop and estimate a model that formalizes this link and allows for quantification.

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

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

At the heart of the model below is the notion that urban amenities like restaurants and entertainment options are relative luxury goods, which finds a large support in 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 increase their spending share on restaurant and entertainment.

Trip level data from the 2009 National Household Travel Survey (NHTS) provide additional support for the view that urban amenities like restaurants and entertainment are more important for richer households, and also show that this effect is stronger downtown than in the suburbs. Figure 3 reports the average number of daily trips to non-tradable services (including restaurants and entertainment activities) for individuals at different income levels. Results are presented separately for individuals living in downtown areas of CBSAs and suburban areas of CBSAs (as defined above). Three findings emerge from Figure 3. First, individuals in the highest NHTS income bracket earning more than $100,000 take more than twice as many daily trips to non-tradable services as the poorest individuals. Second, rich urban residents travel to non-tradable service destinations more than once per day (this is a higher travel frequency than that for work purposes.) Third, urban residents take...
more trips to non-tradable services than suburban residents, but this positive urban-suburban gap is only present for rich households. These findings are consistent with the importance of non-homothetic preferences for urban amenities, and they motivate a key gentrification mechanism in the model: downtown urban areas more easily provide these luxury amenities.

3 Model

We propose a model of a city which is flexible enough to capture salient features of the data, yet stylized enough to be a model of a representative city rather than matching quantitatively one specific city. The representative 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; land supply elasticities are lower downtown than in the suburbs. Non-homotheticities in the consumption of urban amenities and in transportation lead to the sorting of heterogeneous households to different parts of the city. Downtown has an over-representation of both extremes of the income distribution.

3.1 Model setup

3.1.1 Choice of neighborhood

The city is comprised of neighborhoods indexed by \( r \). They are characterized by the part of the town where they are located, downtown or the suburbs, as indexed by \( n \in \{D, S\} \). Within these two broad areas, neighborhoods also differ by the quality of their housing stock and private amenities. Specifically, there are high quality (H) and low quality (L) neighborhoods as indexed by \( j \in \{H, L\} \). We write \( B(nj) \) is the set of neighborhoods of quality \( j \) in part of the city \( n \). Within each \( B(nj) \), neighborhoods, \( r \) are differentiated horizontally, but are symmetric.

3.1.2 Preferences

Households who live in neighborhood \( r \) of type \((n, j)\) derive utility from the consumption of a freely traded composite good \( c_r \), private urban amenities \( a_r \) consumed in different parts of the city, as well as directly from the enjoyment of the non-rival amenities of their neighborhood. This requires renting one unit of housing in \( r \). The utility of household \( \omega \) who lives in neighborhood \( r \) of type

\[ \text{Utility} = c_r + a_r + \text{non-rival amenities} \]

\[^{12}\text{Lower commute costs, and in particular the availability of transit, is the standard explanation for the over-}
\text{representation of the poor in urban areas, see for instance LeRoy and Sonstelie (1983) and Glaeser et al. (2008).}
\text{Modeling the endogenous development of luxury urban amenities is a contribution of our paper.}\]

\[^{13}\text{The model can be readily extended to include a greater range of neighborhood qualities, but we find that two}
\text{levels of quality are sufficient to capture quantitatively the non-monotonic U-shaped patterns of location choice}
\text{observed in the data (see section 4).}\]
\( (n,j) \) is:
\[
U_r(\omega) = Q_j(r) A_n(r) \left( \frac{a_r}{\alpha} \right)^{\alpha} \left( \frac{c_r}{1-\alpha} \right)^{1-\alpha} b_r(\omega).
\]

The shifter \( A_n \) summarizes quality of life in downtown vs. the suburbs (e.g., their differences in public amenities such as parks and schools) while \( Q_j \) summarizes the quality level of a neighborhood, in terms of its housing stock and private urban amenities. The shock \( b_r(\omega) \) captures the idiosyncratic preference worker \( \omega \) has for living in neighborhood \( r \). Specifically, each household draws a vector \( \{b_r(\omega)\}_r \) following a Generalized Extreme Value distribution:
\[
F(\{b_r\}) = \exp \left( - \left[ \sum_{n,j} \left( \sum_{r \in B(nj)} b_r^{-\gamma} \right)^{-\frac{\gamma}{\gamma}} \right] \right).
\]

With this nested structure, the preferences of a given household are more correlated for neighborhoods of the same quality and located in the same part of the city, than they are for neighborhoods of different types. Specifically, the parameter \( \rho \) governs the variance of draws across types of neighborhoods (across \( n,j \) pairs) and \( \gamma \) governs the variance of idiosyncratic preference draws for neighborhoods of the same type (within \( n,j \) pairs). As we discuss in detail later, \( \rho \) determines the strength of the non-homotheticity for neighborhood quality and \( \gamma \) determines the love of variety effects over neighborhoods within an \( nj \) pair. Consistency with utility maximization requires \( \gamma > \rho > 1 \).

Households consume private amenities – e.g., restaurants and entertainment options – in different locations in the city. Specifically, a household that resides in location \( r \) consumes \( a_{rr'} \) urban amenities in neighborhood \( r' \) and chooses where to consume them so as to maximize a CES bundle of amenity consumption:
\[
a_r = \left( \sum_{r'} \left( \beta_{jj(r)r'(r')} \right)^{\frac{1}{\sigma}} \left( a_{rr'} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},
\]
where \( \sigma > 1 \) is the elasticity of substitution between amenities from different neighborhoods and the disutility term \( \beta_{jj(r)r'(r')} \) depend on the dissimilarity in quality between a household’s own neighborhood and the destination neighborhood.\(^{14}\) Furthermore, we assume that consuming amenities further away from one’s residence is costly. Commuting to amenities entails an iceberg commuting cost that increases with distance at rate \( \delta \), so that the consumer cost of consuming amenities in neighborhood \( r' \), for someone living in \( r \), is \( d_{rr'}^\delta p_{r'}^n \), where \( p_{r'}^n \) is the price of amenities in \( r' \).

Given that all neighborhoods in \( B(nj) \) are assumed to be symmetric, they offer the same price index for amenity consumption \( P_{nj}^a \), and the same local price of amenities \( p_{nj}^a \).\(^{15}\) Furthermore,

\(^{14}\)We assume that \( \beta_{jj} = 1 \) while typically \( \beta_{jj'} \leq 1 \) if \( j \neq j' \). People value horizontal differentiation within their preferred quality level and value to a lesser degree amenity options of a different quality.

\(^{15}\)While this assumption does not allow us to speak to the actual detailed spatial patterns of gentrification within a location in a given city, it allows us to capture the salient features of neighborhood change in a representative city. In terms of notation, in what follows, we simply use subscripts \( n \) and \( j \) when it is clear to do so. They are really
again, thanks to symmetry, we can write distance frictions as a function of the land areas $K_n$ for $n \in D, S$:

$$(d_{nn'})^\delta = \Delta (K_n')^\delta,$$  \hspace{1cm} (2)

where $d_{nn'}$ is the representative distance between two neighborhoods, one located in location $n$ and one in location $n'$, $\Delta = 1$ if $n = n'$ and $\Delta > 1$ if $n \neq n'$. The term $\Delta$ captures the border friction, assumed to be symmetric, between downtown and the suburbs. If land area is smaller, it is cheaper to consume amenities from different neighborhoods because they are closer. Denote with $N_{nj}$ the number of neighborhoods within a $n, j$ pair. The price index for amenities in a given $n, j$ neighborhood is therefore:

$$P_{nj} = \left( \sum_{n', j'} \Delta N_{n'j'} \beta_{j'} \left( K_{n'} P_{n'j'}^{a} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$ \hspace{1cm} (3)

### 3.1.3 Labor Income and Total Net Income

Households supply labor inelastically and are heterogeneous in skill. We assume that labor income is an increasing function of skill, summarized with wage $w$. Our focus is to study how heterogeneous households sort into different neighborhoods in the city, given the overall distribution of skills that we write $L(w)$. We take this aggregate distribution as a primitive of the model.  

Workers commute to work. We assume that commuting costs depend on the part of the city where one lives, summarized by $n$, and that the cost of commuting is proportional to labor income. It is captured by commuting costs $\tau_n$ so that net labor income is $(1 - \tau_n) w$ for a household with wage $w$ living in $n$. We assume that $\tau_D < \tau_S$ to capture the fact that households living downtown have an easier access to jobs compared to those living in the suburbs. Households also potentially derive income from owning real estate. We allow for the real estate portfolio – and the corresponding returns – to vary systematically by worker type, as captured by $\chi(w)$, which we take as given. Finally, households pay local taxes. We allow for taxes levied by the local government, $T_n(w)$, to be location and income specific. Overall, the net income $m$ of a household $w$ who lives in $n$ is given by:

$$m_n(w) = (1 - \tau_n) w + \chi(w) - T_n(w),$$ \hspace{1cm} (4)

Households choose their neighborhood of residence $r$ by maximizing (1) subject to the budget constraint: $p^h_r + p^a r + c = m_n(w)$. The price $p^h_r$ 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. Given the specification of income and the utility function, the indirect utility of a household $\omega$ functions of the neighborhood chosen: $j = j(r); n = n(r)$.

16 By taking the income distribution as given, we do not allow for neighborhood change to alter the labor market opportunities for low skilled urban residents. While this assumption is made for tractability, it is also consistent with recent evidence from New York City by Meltzer and Ghorbani (2017). They find that gentrification has little overall employment impact on incumbent low income residents, despite a significant decline in low wage jobs near gentrifying tracts. These findings suggest taking the income distribution as exogenous is not grossly at odds with the existing empirical work on the labor market effects of gentrification.
whose wage is $w$ is given by:

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

### 3.1.4 Land Markets and Developers

Neighborhoods are developed by private developers. They use land to develop neighborhoods that feature housing units and retail amenities. Developers rent out housing units, and operate retail stores and restaurants that are marketed both to households living in the neighborhood as well as in other parts of the city. There is free entry of developers in each market $n, j$.

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

$$K_n = K_n^0 (R_n)^{\epsilon_n},$$

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

$$H_{n,j}^h = \frac{K_{n,j}^h}{h_{n,j}^h},$$

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

$$R_n = \left( \sum_j \left(h_{n,j}^h H_{n,j}^h + h_{n,j}^a A_{n,j}^h\right) \right)^{1/\epsilon_n}$$

Developers pay a fixed cost $f_{n,j}$ to develop a differentiated neighborhood $r$ of type $(n, j)$. In each $n, j$, both the housing and the amenities markets are monopolistically competitive. The number of neighborhoods of type $(n, j)$, $N_{n,j}$, adjusts so that developers’ profits are driven to zero, where a developer profit in an $(n, j)$ is:

$$\pi_{n,j}^h + \pi_{n,j}^a - f_{n,j} = 0.$$  

### 3.1.5 Role of local government: provision of public amenities

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

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

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

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

Embedding this mecha-
nism in the model is important: it ensures that the model properly captures the notion that as a location becomes richer, its local amenities (safety, schools, parks, etc.) improve, which benefits all of the local inhabitants, irrespective of their income.

3.2 Equilibrium

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

$$\lambda_{r|nj}(w) = \frac{V_r(w)^{\gamma}}{\sum_{r' \in B(nj)} V_{r'}(w)^{\gamma}},$$

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

$$V_r(w) = (m_n(w) - p^{b_h}_r) (P^a_r)^{-\alpha} A_{n(r)} Q_j(r)$$

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

$$\lambda_{nj}(w) = \frac{V_{nj}^p(w)}{\sum_{n',j'} V_{n',j'}^p(w)}$$

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

$$V_{nj}(w) = \left( \sum_{r \in B(nj)} V_r(w)^{\gamma} \right)^{\frac{1}{\gamma}} = A_n Q_j N_{nj}^{\frac{1}{\sigma}} (P^a_{nj})^{-\alpha} (m_n(w) - p^{b_h}_{nj}).$$

To drive intuition, we can specialize the equations for a moment to the case where households only consume amenities in their own type of neighborhood $(n, j)$. In this case, we get $V_{nj}(w) \propto Q_j A_n N_{nj}^{\frac{1}{\sigma} + \frac{\alpha}{\sigma-1}} K^\frac{\alpha}{\sigma-1} (P^a_{nj})^{-\alpha} (m_n(w) - p^{b_h}_{nj})$. We see that the number of neighborhoods $N_{nj}$ acts as an agglomeration force for two reasons. First, a higher $N_{nj}$ increases utility through a love of variety effect in the choice of residential neighborhoods. With more neighborhoods to choose from, residents can find a better match for their idiosyncratic preference draws. The strength of this force is mitigated by the elasticity $\frac{1}{\gamma}$. Second, a higher $N_{nj}$ also drives a love of variety effect in the choice of neighborhoods to visit to consume urban amenities. With more neighborhoods available, residents can visit more neighborhoods to consume their differentiated urban amenity bundle. The strength of this force is mitigated by $\frac{\alpha}{\sigma-1}$. This second benefit of having more variety

---

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

---
in neighborhood choice is dampened by distance. In the suburbs, where the extension in the number of neighborhoods leads to sprawl, $K_n$ increases faster than in downtown, mitigating the welfare impact of expanding the number of neighborhood options in the suburbs. The same forces are at play in the general case, where, in addition, welfare depends on amenity options in other neighborhood types, as captured by the price index $P_{nj}^a$ defined in equation (3).

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

$$V(w) = \left( \sum_{n',j'} V_{n',j'}^\rho(w) \right)^{1/\rho}. \tag{12}$$

Note that higher-income households will be over-represented in costly neighborhoods, as income and housing prices are complement in equation (10).\(^{19}\) Since higher quality neighborhoods have higher demand and hence higher housing prices in equilibrium, they attract high-income households disproportionately. This first feature of the model can rationalize why higher income households disproportionately locate in high quality downtown neighborhoods, where the quality of urban amenities is reinforced by economics of density. Second, rewriting the same expression as $V_{nj}(w) = A_{n(r)} Q_{j(r)} N_{nj}^{\gamma} (P_{nj}^a)^{-\alpha} ((1 - \tau_n)) \left[ w + \frac{\lambda(w) - T_n(w)}{1 - \tau_n} - \frac{p_r}{1 - \tau_n} \right]$ shows that commuting cost makes the real cost of living in the suburbs higher, all else equal. That is, $\frac{p_r}{1 - \tau_n} > p_r$. Provided that the quality of life in the suburbs is high enough to justify such a commute, it will be so only for workers with high enough income because, again, income and prices are complement in this expression. This force will generate the disproportionate sorting of lower income workers away from the suburbs and into downtown housing units.

### 3.2.2 Developers

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

$$p_{nj}^a = \frac{\sigma}{\sigma - 1} h_{nj}^a R_n, \tag{13}$$

Furthermore, they price housing by maximizing their profits on the residential market, under a monopolistically competitive market structure. On this market, using (9), (8) and (10) leads to the following housing pricing formula:

$$p_{nj}^h = \frac{\gamma}{\gamma + 1} h_{nj}^h R_n + \frac{1}{\gamma + 1} T_{nj}(p_{nj}^h), \tag{14}$$

\(^{19}\)The complementarity can be seen from $\frac{\partial \log \lambda_{nj}(w,p)}{\partial w} > 0$, which means that higher income workers are disproportionately located in higher $p$ neighborhoods.
where the term $\mathcal{I}_{nj}(p_{nh}^j)$ is a measure of demand for a neighborhood of type $n, j$. By symmetry, all neighborhoods of type $(n, j)$ have the same price in equilibrium, which we denote as $p_{nh}^j$.

Given these prices, developers’ operating profits are pinned down. Free entry drives down developers’ total profits to zero so that the number of developers entering location $n$ at quality $j$:

$$N_{nj} = \frac{1}{f_{nj}} \left[ \int_w \lambda_{nj}(w) \left( p_{nh}^j - h_{nj}^h R_n + \frac{\alpha a}{\sigma} (w - p_{nj}) \right) dL(w) \right]$$

(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., $N_{D,H}$ in (A.7) increases. This, in turn, raises the demand for this type of neighborhood by a love of variety effect (captured by equations (10) and (11)). Second, the intensity of this feedback loop depends on the elasticity of substitution between neighborhoods where to live, $\gamma$, and the elasticity of substitution between urban amenities, $\sigma$. The lower these elasticities, the larger the entry feedback loop, as neighborhoods are less substitutable. Third, the intensity of this feedback loop also depends on whether the density of neighborhoods increases or not in response to higher demand, as captured by the distance friction (2).

The model captures the idea that when new neighborhoods are developed through an increase in density, households living in the location have an easy access the corresponding urban amenities, even outside of their own neighborhood. The presence of nearby differentiated neighborhoods increases the appeal of residing in a given location. This is the case downtown, where land supply is constrained. The number of neighborhoods expands by filling up space, so that accessibility to these varieties is high. In contrast, new neighborhoods developed in the suburbs are built, in part, over new land, as land is supplied more elastically there. Sprawl limits the amenity value of expanding the number of neighborhoods in the suburbs, as it reduces the accessibility to amenities.

This concludes the set up of the model. An equilibrium of the model is a distribution of location choices by income $\lambda_{nj}(w)$, housing and amenity prices $p_{nh}^j$, land rents $r_{nj}$, number of neighborhoods $N_{nj}$ such that (i) households maximize their utility (ii) developers maximize profits and (iii) land and housing markets clear. Given the structure of the model, it is straightforward to show that an equilibrium of the model can be expressed in relative changes compared to another reference equilibrium, with different primitives (e.g., different city-level distribution of income, or different exogenous levels of amenities). We detail this approach and leverage it in section 5.1, where we analyze a series of counterfactual equilibria, starting from an initial one calibrated from the data.

We now describe this calibration.\footnote{Specifically, $\mathcal{I}_{nj}(p) = \frac{\int \lambda_{nj}(p, w)(1 - r_{nj})w + \chi(w))dF(w)}{\int \lambda_{nj}(p, w)dF(w)}$ with $\lambda_{nj}(p, w) = \frac{\lambda_{nj}(w)L(w)}{[(1 - r_{nj})w + \chi(w)] - p}$.}\footnote{If the agglomeration effects at play in the model driven by love of variety are too strong compared to the dispersion forces, driven by the housing supply (in-)elasticity and the idiosyncratic preference for locations-quality types, the model may give rise to multiple equilibria. Around our parameter values, we have not found evidence for such multiple equilibria, suggesting that the calibrated $\epsilon_n$ and $\rho$ are low enough for equilibrium uniqueness.}
4 Model Parameterization

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

4.1 Model Notions of Space

Throughout the empirical analysis, we equate the notion of neighborhoods, in the model, to census tracts, in the data. As discussed in section 2, we define the downtown ($D$) area as all census tracts surrounding the city center that contained 10% of the CBSA population in 2000. Defining high quality tracts inherently involves some judgement. Given that, we pursue multiple approaches to segmenting high and low quality census tracts within the downtown and suburban areas. First, as our baseline approach, 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 32 percent of census tracts in the downtown areas of the top 100 CBSAs are respectively classified as high quality in 1990, 2000 and 2014.

As a second robustness measure, we define high quality neighborhoods based on the quality of amenities provided in the neighborhood. We measure the quality of local amenities – specifically, restaurants – leveraging novel smartphone movement data (Couture et al., Work in Progress), as detailed below. The smartphone data comes from aggregating GPS geolocation from the locational services of multiple applications used by smartphone devices. This smartphone data allows us to identify billions of visits to the 100 largest restaurant chains from 2016 to 2018. We combine this data with the geocoded location of these restaurants in 2000 and 2012 from the National Establishment Time-Series (NETS). We use this data again to identify our amenity demand system in section 4.2.2. We provide additional details on the smartphone data in Appendix A.\textsuperscript{22}

Within the smartphone data, we define a person’s home as being the residential location where the phone spends most of the night. We construct a “restaurant chain quality index” that measures the propensity of residents living in a high income block group to visit a given restaurant chain relative to the propensity of the average person. We define high income blocks as those blocks with median resident income higher than $100,000. We measure the number of visits from each block group to each chain after controlling for proximity to venues within that chain, in order to isolate

\textsuperscript{22}Athey et al. (2018) and Chen and Rohla (2018) use similar smartphone data from a different provider. We refer to Couture et al. (Work in Progress) for evidence that the spatial distribution of smartphone devices provides a balanced representation of the U.S. population along a number of dimensions (CBSA, income, race, education); the distance traveled to different destinations implied by the smartphone data resembles that from the NHTS travel survey; and that the mapping of commercial establishments visited by smartphone users to the business registry is relatively complete.
chains that high income people like from chains that simply co-locate with them. Given this, a chain quality index larger than 1 indicates that, all else equal, people in high income block groups are more likely to visit a chain than the average person. In order to isolate the choice of visiting a chain from other considerations of travelers (e.g., eating during lunch at work), we restrict our sample of chain visits to only trips starting from a person’s home. We also experiment with adding controls for race, age, education, and income similarity between the person’s home block group and the block group in which the closest venue in a given chain is located. We describe the procedure in details in Appendix C. We compute this index for the largest 100 chains that we can find both in the smartphone and NETS data. Among the restaurant chains with the highest quality are smaller gourmet chains like Shake Shack (1st), Zoës Kitchen (2nd) and California Pizza Kitchen (3rd), as well as large national chains like Chipotle (6th), Panera Bread (7th), and Starbucks (14th). Using this chain quality index, we define a high quality (H) census tract as having average chain quality higher than 1.1. Under this definition, 13 and 34 percent of census tracts with non-missing quality in the top 100 CBSAs are classified as high quality, respectively, in 2000 and 2012. Despite these two methods being conceptually different and having different strength and weaknesses, we find very similar estimates of many of our key parameters across them.

4.2 Parametrization: First Stage

In this section, we discuss our parametrization of the key elasticities of the model. Specifically, we discuss how we estimate or calibrate the 12 parameters highlighted in Table 1 using several micro data sources or drawing on the existing literature. The role played by these parameters in driving sorting patterns and welfare results is discussed in section 5.3.2.

4.2.1 Estimation of Elasticity of Demand Between Neighborhood Types ($\rho$)

We begin by discussing how we estimate $\rho$, the elasticity of substitution of demand between neighborhoods of different types ($nj$ pairs). This estimation also serves to illustrate and validate the key sorting mechanism in our model. We first present the estimating equation, then detail our empirical strategy before discussing data, measurement of the variables, and the results.  

---

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

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

25 We choose a value of 1.1 as the cutoff for chain quality index so that the 2012 share of high quality downtown neighborhoods matches the 2014 high quality downtown share based on the education mix of residents described above.
Table 1: Key Model Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Location Substitution Elasticities</strong></td>
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</tr>
<tr>
<td>$\rho$</td>
<td>Between-type neighborhood substitution elasticity</td>
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<td>Estimation</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Within-type neighborhood substitution elasticity</td>
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<td>Assumption = $\sigma$</td>
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<tr>
<td>$\alpha$</td>
<td>Amenity share</td>
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<td>CEX</td>
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<tr>
<td>$\sigma$</td>
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<td>Estimation+literature</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Distance elasticity across neighborhoods</td>
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<td>Estimation+literature</td>
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<td><strong>Public Amenity Supply</strong></td>
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</tr>
<tr>
<td>$T_D$</td>
<td>Downtown local property tax</td>
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<td>IPUMS 2000</td>
</tr>
<tr>
<td>$T_S$</td>
<td>Suburban local property tax</td>
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<td>IPUMS 2000</td>
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<td>Literature</td>
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<td>$\epsilon_D$</td>
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<td><strong>Transportation Costs</strong></td>
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<td>Commute costs as share of labor income downtown</td>
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<tr>
<td>$\tau_S$</td>
<td>Commute costs as share of labor income suburbs</td>
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<td>Authors’ calculation</td>
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</table>
Estimating Equation. We derive the estimating equation for \( \rho \) using equations (10) and (11) of the model. Defining \( B_{nj} = A_n Q_{nj}^{1/\gamma} (P^\alpha_{nj})^{-\alpha} \) and \( D(w) = 1/\sum_{n',j'} V_{n',j'}^\rho(w) \), we can express \( \lambda_{nj}(w) \) as follows:\(^{26}\)

\[
\lambda_{nj}(w) = D(w)B_{nj}(w - p^h_{nj})^\rho
\]  

(16)

Note that the parameter \( \rho \) governs the strength of the sorting (non-homothetic location choice) effects in the model: with a high \( \rho \), higher income households disproportionately choose more expensive neighborhoods. Our estimation of \( \rho \) exploits cross CBSA variation. We index different CBSAs by \( c \).\(^{27}\) Interpreting different time periods as different steady states of the model, we take log differences of (16) across two time periods. Given that \( B_{nj,c} \) and \( D_c(w) \) are unobservable, we difference (16) in two additional ways. First, we take the difference between the choice of an individual with a given income level \( w \) within a CBSA to live downtown (\( \Delta \ln \lambda_{Dj,c}(w) \)) and their choice to live in the suburbs (\( \Delta \ln \lambda_{Sj,c}(w) \)). Doing so differences out any common factors at the CBSA level (i.e., \( \Delta \ln D_c(w) \)). Second, consider two income groups \( w \) and \( w' \). We take differences in location choice across these income groups within a CBSA. Comparing the propensity to live in a given \( n,j \) pair between individuals earning income \( w_m \) and individuals earning income \( w_{m'} \) differences out any common CBSA-specific neighborhood quality fixed effects (i.e., \( \Delta \ln B_{nj,c} \)). The resulting estimating equation is:

\[
\Delta \ln \left( \frac{\lambda_{Dj,c}(w_m)}{\lambda_{Sj,c}(w_m)} \right) - \Delta \ln \left( \frac{\lambda_{Dj,c}(w_{m'})}{\lambda_{Sj,c}(w_{m'})} \right) = \rho \left[ \Delta \ln \left( \frac{w_m - p^h_{Dj,c}}{w_m - p^h_{Sj,c}} \right) - \Delta \ln \left( \frac{w_{m'} - p^h_{Dj,c}}{w_{m'} - p^h_{Sj,c}} \right) \right] + \epsilon_{j,c}(w_m, w_{m'})
\]

(17)

Identification Strategy. We lack micro panel data, so we cannot observe how the location choice of a given individual changes as their income \( w \) changes. Instead, we identify \( \rho \) from changes in net disposable income – wage income net of housing costs – stemming from changes in the cost of housing in a given area, \( p^h_{nj,c} \), using repeated cross sectional variation. A given change in housing prices yields a smaller percentage change in net income for individuals with higher \( w \) relative to individuals with lower \( w \). If housing prices rise downtown, the model predicts that lower income households should be more likely to migrate to the suburbs than higher income households given their larger change in net income, with \( \rho \) governing the strength of the response.

Taking the model literally, there is no error term. In the empirical exercise, however, both data mismeasurement and model mispecification can bias our OLS estimates of (17). There is likely attenuation bias from classical measurement error in our measure of within CBSA-quality house price growth. In addition, there may be endogenous movements in house prices that our model’s quality bins fail to capture. For example, suppose that rich households move downtown to minimize

\(^{26}\)For ease of exposition, we ignore commuting costs as well as local taxes and transfers.

\(^{27}\)Variation of outcomes across cities in the model (duplicated for each city) comes from cities differing in parameters such as housing supply elasticity, parameters that govern endogenous amenity provision, and income distribution.
commute time to high-skilled jobs, or to access to amenities specifically designed for them, above and beyond what is captured in the model. This will cause a rise in house prices downtown relative to the suburbs. Such reverse causality will bias our estimate of $\rho$ upwards.

To deal with these potential biases, we instrument the independent variable in (17) with a CBSA-level shift-share per-capita income (Bartik) shock. The Bartik shock predicts average earnings change in a given CBSA using national trends (excluding that CBSA) in average earnings for each industry projected on the initial CBSA industry mix. The logic of the instrument comes from the model: as CBSA residents are hit with an exogenous income shock, their demand for housing increases, which drives up local housing prices. Because of a lower housing supply elasticity downtown, house prices rise disproportionately downtown relative to the suburbs. We provide evidence for this first-stage mechanism and come back to discussing the exclusion restriction below.

Data. We describe all data sources in Appendix A and variable construction in detail in Appendix C, and summarize them briefly here. For the dependent variable in (17), we measure population shares $\lambda(w_m)_{nj,c}$ using Census counts by income bracket in 1990 and 2014, as in section 2. 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 the model. For consistency, we exclude them from this regression as well, which leaves us with 10 income groups in the estimation. Given this, the use of 10 income brackets yields 45 distinct potential pairs of $w_m$ and $w_{m'}$ for each quality tier $j$. We organize the data such that $w_m > w_{m'}$. As a result, the maximum number of observations in each of our regressions is 9000, though in many specifications, we have less given missing data at the CBSA-area-quality triplet.

To measure changes in net disposable income within each census income bracket in the independent variable, we use variation in house prices measured from the Zillow 2 Bedroom Home Value Index. Focusing on housing units of a given size helps control for the changing composition of housing units across different areas within a CBSA over time. House prices from Zillow are not available prior to 1996. As a result, we measure house prices in our initial period pooling over years 1996 through 1998 and for our ending period pooling over years 2012 through 2016. Specifically, we compute $p_{cnj}^{h}$ as the annual user cost of a median priced 2 bedroom house in area-quality pair $nj$ within CBSA $c$. We then compute $\Delta \ln(w - p_{nj,c})$ for each income bracket ($w$), and each $nj$ pair ($DH$, $DL$, $SH$, and $SL$) within each CBSA. We set $w$ as the median household income within each constant CPI-adjusted census bracket. We calculate this median using 2000 IPUMS

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28For instance, data from the department of Housing and Urban Development shows that in our downtowns in 2014, about 30 percent of households earning between $50000 and $140000 in 1990 dollars lived in subsidized housing.

29We also remove any observation with $w - p_{cnj}^{h} < 0$ (1.4% of our sample). We then censor the top and bottom 1 percent of $\Delta \ln(w - p_{cnj}^{h})$.

30We pool over years to minimize transitory fluctuations in the local housing price indices. Also, given the data limitations, we match 1990-2014 changes in residential location with 1996-2014 changes in house prices. House prices were generally flat over the 1990 to 1995 period suggesting that this measurement issue unlikely to bias our results in any meaningful way.

31The annual user cost of housing is 4.7 percent of house prices in 2000, and 4.6 percent in 2014 according to data from the Lincoln Institute of Land Policy.
microdata from the 100 largest CBSAs, and hold it fixed over time and across CBSAs, so that for each income bracket pair, all variation in the independent variable comes from changes in house prices. Housing prices and income are converted to 1999 dollars using the urban CPI.\footnote{In the model, prices and income are expressed in terms of the tradable numeraire good. The urban CPI excluding shelter tracks the urban CPI for all goods broadly at a decadal frequency between 1990 and 2014, so we use the CPI for all goods to maintain the comparability of our results with those from other studies.} For our base analysis we define neighborhood quality based on the education composition of residents. In the appendix, we also discuss the robustness of our results to defining neighborhood quality using our restaurant chain index.

**Reduced Form Regressions.** To understand the variation that facilitates our identification, we perform two exercises. First, we note that the first stage of our IV estimation comes from the Bartik income shock raising house prices more in downtown areas relative to suburban areas for a given quality level. The downtown versus suburban house price variation is what drives the variation in the independent variable in equation (17). The left panel of Figure 4 plots our Bartik shock between 1990 and 2014 for each CBSA (on the x-axis) against $\Delta \ln(p_{Dj,c}^h/p_{Sj,c}^h)$ (on the y-axis). There are 200 observations in the figure: 2 quality tiers within each of our 100 CBSAs. As the model predicts, more positive income shocks within a CBSA raise housing prices downtown relative to the suburbs within a quality tier. This variation underlies our use of the Bartik shocks to identify $\rho$.

Second, before estimating the structural equation (17), we estimate the corresponding reduced-form. It shows how individuals of differing incomes change their residential choices in response to CBSA level Bartik shocks. Specifically, we run:

$$\Delta \ln \left( \frac{\lambda_{cD}(w)}{\lambda_{cS}(w)} \right) = \mu_0^w + \mu_1^w \Delta \text{Income}_{c}^{\text{Bartik}} + \epsilon_{cw}. \quad (18)$$

To build intuition, we estimate equation (18) separately for each of our 10 bracketed income groups. $\mu_1^w < 0$ implies that following a positive CBSA Bartik shock, the propensity of income group $w$ to live downtown falls relative to that of the average CBSA resident.\footnote{The relationship is in normalized shares, so if lower income individuals have $\mu_1^w < 0$, higher income individuals must have $\mu_1^w > 0$.} The right panel of Figure 4 reports estimates from equation (18), along with their 95 percent confidence bounds, where all changes in residential choice are defined over the 1990 to 2014 period. We find that CBSA per-capita income shocks are associated with differential spatial sorting patterns for the rich vs. the poor. These differential sorting patterns are consistent with our model predictions. The mechanism behind this reduced-form prediction is illustrated in our first stage above (the left panel of Figure 4): the Bartik shock raises house prices downtown relative to the suburbs, which has a larger impact on poor households, for whom housing represents a large share of net income. As a result, consistent with the model, $\mu_1^w$ should be increasing as $w$ increases, so that higher income households are more likely than lower income households to move downtown in response to an exogenous income shock. This is indeed what we find. For all the top five income groups, $\mu_0^w > 0$ and all estimates are statistically significant at the 5 percent level. Conversely, all the bottom
five income groups have estimates of $\mu_w < 0$, with all but the middle income group estimate being statistically significant. We wish to stress that there is nothing tautological about these regressions. If spatial sorting responses are unrelated to income, $\mu_w^1$ could be zero for all income groups.

Figure 4: Reduced Form Results - Bartik Income Shock vs House Prices and Urban Shares.

Estimation Results  Our base estimation results of $\rho$ from equation (17) are reported in the first two columns of Table 2. Column 1 shows our OLS estimate and column 2 shows our IV estimate. We weight both OLS and IV regressions by the number of observations in each cell. This down weights cells with fewer individuals where measurement error may be higher.

A few things are of note from our base estimates of $\rho$. First, our OLS estimate is slightly lower than our IV estimates (2.5 vs. 3.0). As noted above, measurement error in our house price measure could attenuate our OLS estimates of $\rho$. Second, our instrument has strong first stage predictive powers with the cluster robust F-stat equaling 36. Finally, we could have estimated the regression 90 separate times for each possible $w_m - w_m'$ income pair and for each quality level, instead of
Table 2: Estimation of elasticity $\rho$

<table>
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<td>2.49</td>
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<td>3.92</td>
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<td>Omit FIRE Industries</td>
<td>Omit Hi-Tech Industries</td>
<td>Omit Manufacturing Industries</td>
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<td>$R^2$</td>
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<td>KP F-Stat</td>
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<td>27.2</td>
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<td>5,916</td>
<td>5,916</td>
<td>5,916</td>
</tr>
</tbody>
</table>

Notes: Data from 100 largest CBSAs. Each observation is weighted by the number of households in the income bracket with the fewest households amongst the four brackets in each independent variable. Standard errors clustered at the CBSA-quality level are in parentheses. KP F-Stat = Kleinberger-Papp Wald F statistic. Our estimation focuses on the 1990-2014 period and we define neighborhood quality based on the education mix of residents running the pooled regression (17). We find that our weighted median OLS and IV estimate of $\rho$ in these 90 regressions are 2.6 and 3.4. Importantly, we find that $\rho$ estimates are uncorrelated with the difference in gross income between the $w_m - w_{m'}$ pairs in the regression. This invariance is a strong test of the functional form assumptions embedded in the model. To summarize, we use our preferred IV estimate in column 2 and set $\rho = 3.0$ in our model calibration. In our online appendix, we explore the robustness of our estimates of $\rho$ to many different specifications, including different time periods and different house price measures. These robustness estimates are all within two standard error bands of our preferred estimate. As we show later, $\rho$ is an important parameter determining our welfare results. In our counterfactual exercises we show the sensitivity of our results to alternate values of $\rho$ between 2 and 4 which encompass the two standard deviation bands of our estimate in column 2.

We conclude this section with a discussion of potential violation of the exclusion restriction. Suppose that variation in our Bartik instrument comes disproportionately from industries that were concentrated downtown in 1990, and that experienced high wage growth from 1990 to 2014. In that case, wage growth in these urbanized industries could drive both our Bartik instrument and our error term $\epsilon_{j,c}(w_m, w_{m'})$ through the urbanization of high wage workers. To investigate whether such a concern is warranted, we perform several robustness exercises which are summarized in columns (3)-(6) of Table 2.\textsuperscript{34} First, we define our Bartik shock excluding the top quartile of

\textsuperscript{34}Many of our robustness exercises are similar in spirit to those suggested by Goldsmith-Pinkham et al. (2018). Goldsmith-Pinkham et al. (2018) suggest exploring the underlying industry variation that is driving the variation in Bartik shocks across regions.
urbanized industries.\textsuperscript{35} We find little impact on our IV estimates. Second, we recompute our Bartik instrument leaving out technology and finance, insurance, and real estate (FIRE) industries. These industries disproportionately employ higher skilled workers. We also recompute our Bartik instrument excluding manufacturing which disproportionately employs lower skilled workers. Our estimates of $\rho$ using these alternate Bartiks as instruments are similar to our base results (columns 4-6). The similarity of these robustness specifications to our main results is reassuring; it suggests that our instrument is not correlated with labor demand shocks that are concentrated in urban centers of CBSAs and that disproportionately effect high income individuals. These results are also consistent with Couture and Handbury (2017), Baum-Snow and Hartley (2017), and Su (2017) who all find evidence that spatial resorting of jobs plays little role in explaining the recent movement of high income individuals downtown.

4.2.2 Estimation and Parametrization of Amenity Demand ($\alpha$, $\delta$, $\sigma$)

We begin this section by discussing how to estimate the amenity demand elasticities ($\delta$ and $\sigma$) using a model-implied gravity equation. We then parameterize $\alpha$, the share of net disposable income spent on urban amenities. Throughout, we define residential amenities as non-tradable services such as restaurants, bars, entertainment venues (movie theater, shows, etc), gyms, and other personal services. When thinking of residential amenities, we exclude retail consumption at apparel, grocery, and other merchandise stores. Non-tradable services like restaurants and entertainment venues most closely match our model’s amenity that are luxurious, endogenous, locally-provided, and subject to strong economies of density.\textsuperscript{36}

The model delivers the following gravity equation for amenity demand:

$$\ln \left( \frac{a_{rr'}}{a_{rr}} \right) = \ln \left( \frac{\beta_j(r) \neq j(r')}{\beta_j(r')} \right) + \sigma \delta \ln \left( \frac{d_{rr'}}{d_{rr}} \right) + \theta_r + \theta_{r'} + \sigma \ln \left( \frac{p_{rr'}}{p_{rr}} \right). \quad (19)$$

The first term captures the possibility that households value differently urban amenities of quality different than their reference quality, defined as the quality of their neighborhood of residence. We proxy this with a dummy variable $\beta_j(r) \neq j(r')$ equal to 1 when the home neighborhood $r$ is of different quality type than the destination neighborhood $r'$. The second term captures the travel distance required to access amenities in neighborhood $r'$ relative to the travel distance required to consume within the home neighborhood $r$. The third term captures the relative amenity prices in neighborhood $r'$ and $r$. Given that amenity price is constant within neighborhood, we proxy for this third term with an origin $r$ and a destination $r'$ fixed-effect, $\theta_r$ and $\theta_{r'}$. Importantly,

\textsuperscript{35}Strickly speaking, we remove industries in which residents of urban areas are most likely to work. We do not observe workplace location with enough geographical precision in IPUMS to match workers with their urban or suburban job location. The online appendix highlights the most and least urbanized industries in our sample.

\textsuperscript{36}As discussed before, Aguiar and Bils (2015) identify non-tradable services like restaurant and entertainment as having steep Engel curves, Couture and Handbury (2017) identify non-tradable services in particular as the key driver of the downtown location choice of the college-educated.
these fixed-effects can absorb any unobserved tract characteristics. We then obtain the following estimating equation:

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

(20)

Estimating (20) requires information on the origin and destination of a large number of trips to consume amenities, which is not available in conventional travel surveys. To circumvent this issue, we again make use the new smartphone movement data. It allows us to identify 2.3 billion trips to commercial establishments that we classify as non-tradable services, namely restaurants, gyms, theaters, and outside amenities, from 87 millions of devices for which we identify a permanent home location. We provide additional details on the dataset in Appendix A. In order to isolate the choice of consuming amenities from other considerations of travelers, we study the robustness of our estimates to restricting the sample to only trips starting from home, to trips starting from home and coming immediately back home, or to trips that take place on weekends. We again define neighborhoods as census tracts, so $a_{rr'}$ is the number of trips by people living in tract $r$ to non-tradable service establishments located in tract $r'$. We define $d_{rr'}$ as the haversine distance from the centroid of tract $r$ to that of tract $r'$ and $\delta_{rr}$ as half the radius of the home tract. Each observation in our regression is a tract pair $rr'$ and we limit the choice set of each person to tracts available within its CBSA. Note that $\delta \sigma$ is large if people make few trips far from home, either because the cost of distance $\delta$ is large or because amenities are highly substitutable (i.e., $\sigma$ is large).

Table 3 shows the estimation results. The coefficients $\delta \sigma$ are stable and remain within -1.17 and -1.57 across all estimations. Interestingly, our amenity trip gravity coefficients are similar, albeit somewhat larger, to those from the trade literature, which center around -1 (Disdier and Head, 2008), and resemble the estimate of -1.29 for regional trade in the U.S. from Monte et al. (forthcoming). The coefficients on $\beta_{j(r) \neq j(r')}$ are consistently negative and significant, indicating a distaste for visiting neighborhoods with quality other than one’s home neighborhood, and providing some evidence that our quality definition captures relevant features of household’s preference for amenities. In fact, using our preferred quality definition based on college-educated share, people living in high quality tracts take 81 percent of their trips to other high quality tracts, and people living in low quality tract also take 81 percent of trips to other low quality tracts. Our $\delta \sigma$ estimates are robust to adding additional controls for tract pair characteristics, such as an index of racial dissimilarity and median age difference.

The above gravity equation estimates $\sigma \delta$. However, for our calibration, we need estimates of $\sigma$ and $\delta$ separately. We are not aware of existing estimates of $\delta$ in the literature, but estimates of $\sigma$ for amenities are available. Atkin et al. (2018) find an elasticity of substitution of 3.9 for retail stores in Mexico, Einav et al. (2018) find 6.1 for offline stores in the U.S., Su (2018) and Couture (2016) find 7.5 and 8.8 respectively for restaurants in the U.S.. We pick a value of 6.5 in the middle of

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37The only comparable estimates we are aware of are from Agarwal et al. (2017), who obtain much smaller distance elasticities of around -0.4 for different consumption sectors using credit card transaction data at the census place level. They exclude the home place for their regression and include all transactions up to 120km away.
Table 3: Estimation of gravity parameter $\sigma\delta$

<table>
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<th>Quality Definition: College Share</th>
<th>Quality Definition: Restaurants Chain</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All (1)</td>
<td>All (5)</td>
</tr>
<tr>
<td></td>
<td>Home (2)</td>
<td>Home (6)</td>
</tr>
<tr>
<td></td>
<td>Weekend (3)</td>
<td>Weekend (7)</td>
</tr>
<tr>
<td></td>
<td>Home-Home (4)</td>
<td>Home-Home (8)</td>
</tr>
<tr>
<td>$\delta\sigma$</td>
<td>-1.57 (-0.00)</td>
<td>-1.56 (-0.00)</td>
</tr>
<tr>
<td>$\beta_{j(r)\neq j(r')}$</td>
<td>-0.14 (0.00)</td>
<td>-0.04 (0.00)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td>Obs</td>
<td>22,791,347</td>
<td>19,858,033</td>
</tr>
</tbody>
</table>

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

this range, and explore robustness over the range of values above. Using our estimates of $\sigma\delta = 1.3$ from Table 3, we obtain $\delta = 0.2$.

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

4.2.3 Parametrization of Elasticity of Demand Between Neighborhoods ($\gamma$)

Given the assumptions on idiosyncratic preference shocks, $\rho$ must be lower than $\gamma$. This bounds $\gamma$ from below. Second, existing research suggests that there is less socio-economic diversity within
census tracts than there is within retail establishments such as grocery stores and restaurants.\footnote{Handbury et al. (2015) find that Nielsen panelists who are from college- and non-college educated households are more likely to co-locate in grocery stores than in census tracts. This is consistent with Davis et al. (Forthcoming) who find a higher rate of racial segregation across residential neighborhoods than restaurants within NYC.}

Through the lens of our model, this implies the substitution elasticity for residential amenities (\( \sigma \)) is an upper bound on our estimate of \( \gamma \). Given our above estimation, \( \gamma \) lies between 3.3 and 6.5. The lower the value of \( \gamma \) the larger the endogenous response of amenities to the changing income distribution. For our base assumption, we use a conservative value of \( \gamma = 6.5 \). As a robustness exercise, we present the sensitivity of our results to alternative parametrizations.

4.2.4 Parametrization of Land and Housing Supply Elasticities

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

\[
\ln (\epsilon_c) = 1.97 - 0.30 \ln (\text{density}_c) + \xi_c, \quad R^2 = 0.21 \tag{21}
\]

We rely on cross-CBSA variation to estimate this equation. We then define \( \hat{\epsilon}_D \) and \( \hat{\epsilon}_S \) as the fitted values from equation (21) computed at typical density of \( D \) and \( S \) neighborhoods in the 100 largest CBSAs. We find \( \hat{\epsilon}_D = 0.60 \) and \( \hat{\epsilon}_S = 1.33 \).\footnote{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, \( \hat{\epsilon}_D = 0.60 \) turns out to equal the elasticity of housing supply in Miami, which is the metropolitan area with the most inelastic housing supply in Saiz (2010). We use these values in our baseline calibration and test the sensitivity of our results to alternative parameter values.

4.2.5 Parametrization of Commuting Costs

To estimate the commuting costs, we use data on trip time to work by car from the geo-coded 2009 National Household Travel Survey to estimate area-specific \( \tau_n \)'s. Specifically, the average daily commute time for drivers living in the suburbs of the top 100 CBSAs is 64 minutes while it is 47 minutes for those living downtown. We compute \( \tau_n \) 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 \( \tau_S = 0.059 \).
4.2.6 Parametrization of Public Amenities and Homeownership

We calibrate local taxes to match the unit-level average real estate taxes paid as a share of annualized housing costs in 2000, using tract-level data from the 2000 Census. This implies a local property tax rate of 20% in the suburbs and 30% downtown. We set the elasticity of the endogenous component of the public amenity with respect to these tax revenues to 0.05 (Fajgelbaum et al., 2018). In our base parametrization, we assume that all housing rents in the city (land rents and fixed costs of development) accrue to an absentee landlord and none are transferred to the city residents, i.e., that $\chi(w) = 0$ for all $w$. In our counterfactual analysis, we want to account for the heterogeneous rate of home ownership in contributing to spatial sorting responses. Doing so allows agents who own their home to reap the benefits associated with rising house prices. To that end, we transfer to households at each labor income level capital gains corresponding to their average real estate portfolio. This corresponds to the average rent growth of neighborhoods where households of that income lived in the previous period, which is then scaled by the share of households who were homeowners according to the 2000 IPUMS data. Empirically, this share of home ownership increases systematically with labor income. We will use these empirical moments to discipline $\chi(w)$. To summarize, a household earning labor income $w$, receives a transfer of $\chi(w) = OS(w)\lambda_{1999,nj}(w)\sum_{nj}(p_{2014,nj}^h - p_{1990,nj}^h)$, where $OS(w)$ is the share of households with income $w$ who reported owning homes in the 2000 IPUMS data. This allows us to forgo taking a stance on the initial level of $\chi(w)$ and instead only focus on the changes in $\chi(w)$ over time that results from house price growth due to the income inequality shock that we study.

4.3 Second Stage: Method of Moments

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

Specifically, we exactly match one set of shares $S_{mk}^{nj}$ taken from the equilibrium that we directly read from the smartphone data. It is the share of amenity expenditures of households living in a neighborhood of type $(n,j)$ spent on amenities consumed in a neighborhood of type $(m,k)$.\(^40\) For our base model, we use our education definition to define neighborhood quality. Beyond these shares that the model exactly replicates, we target the following set of moments: (i) the whole distribution, by income level, of the share of workers living downtown in 1990 presented in the stylized facts section 2.2, and (ii) the median house price by neighborhood type, also in 1990, also employed in the demand elasticity estimation and described in section Appendix D.1. These two moments summarize the key economic concepts we aim to capture.

To accurately capture the location choices of higher-income households, we seek to match the

\(^{40}\)We proxy for these expenditure shares using trip shares from the smartphone data described earlier in this section.
downtown share of households at a finer income grid than the Census income brackets represented in the stylized facts section 2.2. To this end, we construct the same curves but for finer $5,000 income brackets (in 1999 dollars) using the micro IPUMS data. The additional detail in the income dimension comes at the expense of precision in the spatial dimension and, as a result, we are limited to studying 27 CBSAs of our original 100 in the calibration and counterfactual exercises.

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

\[
\tilde{q}_{n,j} = A_n Q_j \gamma N_{nj}^{\gamma} (P_{ar})^{-\alpha}, \tag{22}
\]

without separately identifying the individual terms and (ii) the price of housing in each location for each neighborhood type \(p_{n,j}^h\). Combined with the model elasticities, these variables pin down the calibrated value for location choice \(\lambda_{n,j}(w)\) in the model. Furthermore, using the equilibrium relationship (A.6), these composite variables also pin down \(h_{n,j}^h R_n\), the land prices of the model.

Importantly, we note that this calibration does not identify all of the deep parameters of the model (such as the exogenous quality of different neighborhoods \(A_n\) and \(Q_j\) or the fixed cost of building neighborhoods \(f_{nj}\)) separately. Rather, it identifies a set of composite variables \(\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{mk}^{nj}\}\) that is just sufficient, conditional on estimates for the model elasticities \(\{\rho, \gamma, \epsilon_n, \sigma, \alpha, \tau_n\}\), to compute any counterfactual equilibrium of the same model that relies on different primitives, using exact hat algebra following the method popularized by Dekle et al. (2007).

This step is described in more detail in section Appendix B.1.

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

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41Household income in the IPUMS data is sum of various components that are each top-coded at state-year-specific levels. We therefore interpolate incomes that are reported to be above the lowest of these component top-codes using the generalized Pareto method outlined in Piketty et al. (2018). See the data appendix for more details.

42The IPUMS data identifies the locations of respondents at the PUMA (Public Use Microdata Area), each of which contains approximately 100,000 individuals, relative to the 4,000 contained in each Census tract. To replicate the urban share for each fine income brackets, we first construct a crosswalk between PUMAs and our tract-based downtown areas. There are 27 CBSAs in which PUMAs are small enough relative to the downtown definition so as to allow for useful inference here. See the data appendix for more details.
set, for all income levels \( w \), of location choice equation:

\[
\frac{\lambda_D(w)}{\lambda_L(w)} = \frac{\sum_{j=L,H} \tilde{q}_{D,j} \rho \left( (1 - \tau_D)w - p_{D,j}^h \right)^\rho}{\sum_{j=L,H} \tilde{q}_{S,j} \rho \left( (1 - \tau_S)w - p_{S,j}^h \right)^\rho}
\]

Given \( \tau_n \) and \( w \), the calibration backs out the \( \tilde{q}_{n,j} \) and \( p_{n,j}^h \) that allow to match best the data distribution of location choices. The vectors \( \tilde{q}_{n,j} \) are pinned down up to a normalization level, whose value does not impact the counterfactuals done in the following section.

**Moment Fit.** The moment fit is presented in Figure 5. Despite a sparse specification, the calibrated model is able to match remarkably well the rich non-monotonic U-shape patterns of location choice by households of various incomes. Furthermore, we note that the model matches the relative housing prices in the suburbs quite well. In 1990, both the model and data have house prices in low quality downtown neighborhoods being roughly equal to low quality suburban neighborhoods. Likewise, both the model and data have high quality suburban neighborhoods having housing prices being about 40 percent higher than low quality neighborhoods. The model has a harder time matching the high quality housing prices downtown, and calls for prices in high quality downtown neighborhood that are much higher than those in the data. Although the magnitudes are off, both the model and the data have housing prices being the highest in downtown high quality neighborhoods.

Figure 5: Calibration to 1990 Urban Shares and Neighborhood Prices

To validate the model further, section 5.5 assesses the model’s performance in predicting two additional empirical facts, which respectively capture time series and cross-sectional variation of spatial sorting patterns. To explore these out of sample predictions, we have to compute model-based counterfactuals using the procedure detailed next.
5 Main Results

We describe how we use the structure of the model and its 1990 calibration to compute counterfactual equilibria, before turning to analyzing our counterfactual exercises of interest.

5.1 Computing Counterfactuals

Our main counterfactual exercise of interest isolates the impact of a change in the income distribution in the city on the within-city spatial equilibrium. We solve for a counterfactual equilibrium of the model that corresponds to an income distribution $L'(w)$ in the city that is different from the 1990 one. In the new equilibrium, price of housing and quality of urban amenities change endogenously in response to this change in demand, and households at all levels of the (new) income distribution choose where they want to live, given these new parameters. The model therefore predicts the counterfactual sorting patterns that would have prevailed in response to a given income distribution shock that we study in isolation. An approach similar to the one we describe here can be used for solving for counterfactual equilibria that correspond to other shocks to the economy, for instance one that implements a specific change in tax and transfer policy.

The information necessary to perform this step are (i) the model elasticities $\{\rho, \gamma, \epsilon_n, \sigma, \alpha, \tau_n\}$, and (ii) the calibrated values at the initial equilibrium for: for each neighborhood type, population, house prices, share of land, and share of amenities trips taken in different types of neighborhoods: $\{\lambda_{n,j}(w), L_{n,j}, p_{n,j}^h, S_{mk}^{nj}\}$. They were parametrized in the previous section. We denote with $L_{n,j}$ is the total population living in neighborhoods of type $\{n,j\}$, i.e., $L_{n,j} = \int L(w) \lambda_{n,j}(w) dw$. 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. Given the structure of the model, the counterfactual equilibrium is the solution to the set of equations (A.8)-(A.12) for $\{p_{n,j}^h, \lambda_{n,j}'(w), L_{n,j}'\}$ (or, equivalently, their “hat” values), which is fully determined conditional on the model elasticities and the calibrated values detailed above. Details of the procedure as well as the corresponding set of equations are given in Appendix B.

5.2 Computing Welfare Measures

Having solved for a counterfactual equilibrium of interest, we are interested in computing welfare measures at various levels of income. We measure changes in welfare using compensating variation, since it is more readily interpretable than the measure of utility from the model ($V(w)$, defined in (12)).

Let $i$ denote a percentile in the income distribution and $m_t(i)$ denote the corresponding income in equilibrium $t$, where $t = 2$ in the new equilibrium (e.g., a 2014 counterfactual), and $t = 1$ in the initial one (the 1990 calibration). Compensating variation (CV) for households at each percentile $i$ of the income distribution is:

$$CV(i) = e(p_2, V_2(i)) - e(p_2, V_1(i)) = m_2 (i) - m_2 \left(V_2^{-1}(V_1(m_1 (i)))\right),$$
where \( V_t(i) \) is the utility of households at percentile \( i \) of the income distribution in equilibrium \( t \) and \( e(\cdot) \) is the expenditure function. \( CV(i) \) measures the gain in well-being of a household at percentile \( i \) of the income distribution, in \( t = 2 \)-dollar equivalent prices. We refer to it as “welfare” or “well-being.” It reflects changes in well-being associated with not only changing income, but also changing housing costs, and changes in endogenous amenity quality. To measure welfare gains due to changing housing costs and amenity quality alone, we simply subtract the income growth of a given percentile \( i \) from their welfare (or CV) growth:\(^{43}\)

\[
\Delta W^c(i) = CV(i) - (m_2(i) - m_1(i)) / m_1(i)
\]

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

### 5.3 Baseline Counterfactual: Changing the Income Distribution

**Income Distribution Shock** Our main counterfactual isolates the impact of changes in the income distribution during the 1990 to 2014 period. This shock is summarized in Figure 6, which plots the percentage change in inflation-adjusted income earned within each income decile during the 1990 to 2014 period in our sample of large CBSAs. Similar to what has been documented extensively in the literature for the economy as a whole, income inequality has increased within the largest CBSAs over the last 25 years in the United States. For the bottom deciles of the income distribution for our sample, income actually fell slightly by approximately 1 percent. For the top decile, income increased by about 18 percent. Overall, there was a 19 percentage point increase in the income gap between the top and bottom decile in our sample.

\(^{43}\)We also compute a measure of equivalent variation (EV), measured as \( EV(i) = e(p_1, W_2(i)) - e(p_1, W_1(i)) \). This approach leads to similar insights.
Impact on Spatial Sorting  We compute the counterfactual spatial equilibrium that would have prevailed, through the lens of the model, if the only shock to the economy between 1990 and 2014 had been this change in the income distribution. Figure 7 shows that the 1990-2014 change in income distribution, in itself, results in a shift in location choices that has the same qualitative properties as the general trend we observe in the data. For each income decile, we show two statistics: the change in the propensity to live in downtown areas between 1990 and 2014 in the data ($\Delta \lambda_D(w)$), using clear wide bars, and the model-implied ones, in red skinnier bars. The clear bars summarize the shift in the U-shape shown in Figure 1.

In response to the observed shift in the income distribution top earners move into downtown, while households at lower income levels tend to move out. The predictive power of this shock alone on the change in spatial sorting patterns observed in the data is substantive. The shift in the income distribution explains about half of the out-migration from downtown areas of individuals in the bottom decile of the income distribution and about 40 percent of the in-migration into downtown areas of individuals in the top income decile. We note that the predicted urbanization of the highest income decile reflects both a shift along the calibrated U-shape of Figure 5 as well as an endogenous uptick in the U-shape, generated by the change in the income distribution. Figure A.5 in the appendix shows that the model also explains a significant portion of the uptick observed in the data. To quantify this, we can summarize the uptick observed in the data by the increase in the urban share of households earning more than $100,000. In 1990, 10 percent of downtown urban residents earned $100,000 dollars or more. By 2014, that number increased to 14 percent. Our baseline counterfactual analysis predicts 36 percent of this increase. From this we conclude that the shifting income distribution alone explains a substantial portion of the increasing propensity of high income individuals to live in downtown urban areas.

The shift in the aggregate income distribution does less well at explaining the changing location choices of individuals in the fourth to ninth deciles. This suggests that there are other factors that are important in determining the changing locational choice of residents into urban areas in addition to the changing income distribution.

Welfare Impact  Figure 8 reports our headline results, i.e. the welfare gains, above and beyond income change, accruing to different income deciles due to the spatial sorting response to rising incomes of the rich. The right hand panel shows results assuming that everyone is a renter, while the left hand panel instead allows for the fact that some households are homeowners. In this case, they reap the gains from the price appreciation of the housing stock between 1990 and 2014, which increases their total income. Specifically, as described in Section 5, we allocate the profits from increased house prices to each income decile based on their ownership shares by location type in 1990. This panel therefore accounts for the fact that homeowners are potentially made better off when neighborhoods gentrify.

A few results are striking in Figure 8. The spatial sorting response amplifies the differences in well-being between the rich and the poor during this time period. In the top decile of the income
distribution, well-being grew more than income, by 1.4 percentage points including the capital gains of the house price increase (left panel). As high earners move into downtown areas, the private amenities that they value endogenously respond, making them better off. House prices increase, but incumbents are compensated by the fact that they own. Even high-income renters, however, gain from gentrification. They see a 0.8 percentage point growth in welfare in spite of higher housing costs (right panel). The amenity effect dominates the price effect, at the top of the income distribution. At the bottom of the income distribution, on the other hand, households’ well-being grew less than what income suggests, by 0.5 percentage points. For these households, the price effect dominates the amenity effect, on net. Note that about 30 percent of individuals from the lowest income decile who resided downtown in 1990 owned their home. They are compensated for the housing cost increases by house price appreciation, so that their utility losses are smaller. On net, individuals from the bottom three income deciles are about 0.25 percentage points worse off from the rising incomes of the rich (left panel).

Before proceeding, it is worth commenting on the magnitudes of these findings. Figure 8 implies that a renter in the first decile of the income distributions - earning on average $30,000 per year - is made roughly $150 worse off per year in consumption equivalent terms.\textsuperscript{44} There are two reasons for this relatively small overall welfare impact. First, the largest welfare losses from an influx of rich households are concentrated on downtown residents who stay there. They represent only 15 percent of individuals earning $30,000 per year. If we focus only on low income renters who remain in low quality downtown areas, we find a welfare loss that is three times larger at $450.\textsuperscript{45} To put that number in perspective, it represents roughly one month’s rent for these households.

\textsuperscript{44}Recall that we restrict our analysis to households earning at least $25,000, so the first income decile includes households earning on average between $25,000 and $32,000.

\textsuperscript{45}We only take into account changes in amenities and prices for these households, holding constant their idiosyncratic preference shocks for location.
The second reason for the small magnitudes of our welfare results is that we solely input shifts in the income distribution into our model. In reality, not only did the relative share of rich people rise, but the absolute number of rich people rose as well through rapid population growth in our sample of CBSAs from 1990 to 2014. In our baseline results in Figures 7 and 8, we hold population growth fixed so as to explore solely the effects of the non-homothetic mechanism at the heart of our model. Below, we examine the welfare effects stemming from our model when allowing for both population growth and shifts in the income distribution. We find that this further amplifies the welfare losses of low income renters by a factor of six, a large magnitude commensurate with the current policy interest in alleviating the impact of downtown gentrification on this group.

To summarize, well-being inequality between the top and bottom deciles of the income distribution increased by an additional 1.7 percentage points - compared to income inequality growth (19 percentage points) – because of spatial sorting responses within cities. A key finding is that ignoring within city spatial sorting leads to understating the welfare differences between the rich and the poor of rising income inequality.

5.3.1 Mechanisms

There are four important components that drive these results.

**Price Effects** First, as the rich get richer, they move downtown to consume urban amenities. This puts upward pressure on housing prices downtown both for high and low quality neighborhoods. The left-hand panel of Figure 9 shows these house prices change, for different neighborhood types. The model predicts that the shift in the income distribution alone is resulting in a 6 percent increase in house prices in high quality downtown neighborhoods and a 3 percent increase in house prices in low quality downtown neighborhoods. These predicted increases in downtown house prices amount to
about 20 percent of the actual increases observed in the data for these neighborhoods. Again, these results suggest that other factors (like general CBSA population growth) are contributing housing price growth in these neighborhoods. However, we want to stress that the house price increases in the low-quality downtown neighborhoods predicted by our model contributes importantly to the welfare losses of the poor renters who remain downtown. Additionally, the model also predicts that house prices in low quality downtown areas increase more than the house prices in low quality suburban areas (3% vs 1%), where housing supply is elastic. This matches the data qualitatively, but not quantitatively, where the Zillow data (for the median price of 2-bedroom homes) show large decreases in house prices in low-quality suburban neighborhoods. Finally, following a relative increase of the number of high income households, our model also predicts that house prices in high quality suburban neighborhoods increase by about 5% (approximately one half of the increase observed in the data for this neighborhood type). Upper middle income households want to increase their consumption of private amenities. While they cannot afford to live in downtown high quality neighborhoods they do migrate into suburban high quality neighborhoods putting upward pressure on housing prices in those neighborhoods.

Figure 9: Mechanisms

Neighborhood Change Second, as the rich move downtown, and demand for high quality neighborhoods increases, the supply of high quality neighborhoods increases. Some of this entry is at the cost of exit of lower quality neighborhoods, so that gentrification takes place. Panel (b) of Figure 9 shows the growth in supply of neighborhoods in each area and quality level. The model predicts a large proportion of the downtown neighborhood change observed in the data (measured as the changing in number of constant geography Census tracts classified as low- and high-quality,

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46 The large decline in house prices in suburban low quality neighborhoods may be an artifact of the Zillow 2 bedroom price index. Using the broader Zillow price index does not display a large decline in house prices in SL areas.
respectively). Given love of variety preferences, the additional entry of high quality neighborhoods downtown makes high income households better off. Poorer households might benefit from it as well, to the extent that they consume some of these amenities themselves, but this effect is quantitatively limited in the data (low quality neighborhood residents make 81% of their amenity trips in low quality neighborhoods). Our model also predicts gentrification in that the number of low quality neighborhoods downtown contract. This is also consistent with the data. Overall, the associated gentrification makes low income households worse off. Finally, we note that the predicted supply of high quality neighborhoods also expands in the suburbs but at a rate much smaller than the expansion downtown. The gap between the observed and predicted increase in the number of high-quality neighborhoods in the suburbs (i.e., neighborhoods with college shares above 40%) might reflect both the aggregate increase in the college-share over this period and the increase in population of high income individuals into our sample of CBSAs during this period.

To tease out the respective roles played by endogenous neighborhood entry and price changes we compute a counterfactual that shuts down love of variety effects across neighborhoods by setting the two between-neighborhood substitution elasticities, $\gamma$ and $\sigma$, to infinity. We do this for the specification where we account for homeownership. Results are shown in Figure 10 (red bars). For ease of comparison, we re-display our base welfare results inclusive of homeownership (clear bars) in the background. In this counterfactual, prices respond to changes in the income distribution, but there is no increase in neighborhood (or associated amenity) variety. The welfare gap across income groups is mitigated substantially when the love of variety effects are shut down. Specifically, the well-being growth gap between households in the top vs. the bottom decile of the income distribution in 1990, is 0.55 percentage points without love of variety effects, vs. 1.7 percentage point in the baseline suggesting that about two-thirds of the welfare gap in our base results stems from the endogenous private amenities response. Interestingly, the absolute welfare losses for the bottom decile increased from -0.25 to -0.5 percentage points, since they benefit less from the positive amenities that accompany the influx of the wealthy (both public and private). The welfare gains for the rich are almost completely gone when the love of variety effects are shut down.

**Public amenities** Third, as downtown gets richer, taxes collected are higher and public amenities respond. This increases amenities for all households downtown, including the poorest ones. Absent price responses, this would make both richer and poorer households better off downtown, but housing price responses to this amenity increase tend to hurt poorer households. Therefore, it is unclear a priori whether, on net, the public amenity channel mitigates the well-being inequality that accompanies gentrification. We turn to the model to quantify this net effect. Figure 11 reports a counterfactual with no endogeneous response in public amenities (red bars), and compares it to the baseline welfare results (clear results). We see that the public amenities channel in itself tends to mitigate slightly the welfare differential between richer and poorer households. The welfare effect for richer households (top five income brackets) are close to unchanged when endogenizing public amenities. Endogenous public amenities increase when households get richer but so does the tax
burden on higher income households. The endogenous public amenities do, however, make lower income households slightly better off. These results suggest that endogenous public amenities do mitigate the effect of gentrification, but are far from overturning the general tendency of spatial sorting responses to increase well-being inequality.

Movers and stayers Finally, some of the low income households choose to relocate to lower quality neighborhoods in the suburbs. In doing so, they move to a location that, by revealed
preference in the initial equilibrium, they enjoy less. This decreases their welfare. This mechanism is captured in the model by idiosyncratic utility shocks. These are reduced-form shocks that can capture attachment to a place as well as proximity to family and social networks and the access to social insurance they provide. These all matter strongly in location decisions and are arguably important in analyzing the well-being consequences of gentrification. For households that are just indifferent between moving out of downtown and staying, the welfare loss is quantitatively identical to the one incurred by stayers, coming from a change in price and quality downtown. Now, for households who prefer to move, this welfare loss is less strong. Moving mitigates welfare losses from gentrification.

5.3.2 Robustness

Which elasticities are important in driving the magnitudes of our distributional welfare results? To explore this question, we examine the sensitivity of our welfare results and changing location choice predictions to alternate parameter values, as summarized in Table 4. The first three columns report the sensitivity of the absolute change in welfare of the top and bottom decile of the income distribution (columns 1 and 2) and the relative change in welfare between these deciles (column 3) to values of the key parameters, while feeding in the same income shock. The next three columns show the same welfare statistics for renters (i.e., households not receiving any share of the house price appreciation mutual fund). The final two columns summarize the uptick that the model predicts in the urbanization of households earning over $100,000, first in absolute percentage point terms and then as a share of the 3.3 percentage point increase observed in the data. Collectively, the results in this table highlight the key mechanisms that are driving our welfare estimates.

Table 4 shows the sensitivity of our results to \( \rho \), the parameter that governs the strength of non-homotheticity in location choices. We set \( \rho = 2 \) and \( \rho = 4 \), which encompass a two-standard deviation band around our baseline estimates (\( \rho = 3 \)). As individuals get richer, they are more likely to move downtown when \( \rho \) is higher. Additionally, the poor are more likely to migrate out in response to the price increase associated with rich moving downtown as \( \rho \) is higher. In other words, gentrification forces increase as \( \rho \) increases. Therefore, higher values of \( \rho \) amplify our welfare results. However, it is interesting to note that even when \( \rho = 2 \) accounting for spatial sorting responses increases the inequality between the top and bottom income deciles by 1.46 percentage points (compared to 1.68 percentage points in our baseline specification).

The elasticities of substitution between neighborhoods for housing and non-tradable amenity consumption, \( \gamma \) and \( \sigma \), were studied above (Figure 10). In Table 4, we show the sensitivity of our results to different values of \( \gamma \) and \( \sigma \) pairs. For lower value of \( \gamma \) or \( \sigma \), endogenous amplification of amenities downtown is stronger, which amplify the welfare results as is intuitive. As the endogenous amplification of amenities increases, more high income individuals move downtown putting further upward pressure on downtown land prices in both high and low quality neighborhoods. We note that changing \( \delta \) has very little effect on our welfare estimates. This is because the share of household spending on non-tradable amenities is relatively small (\( \alpha = 0.15 \) in our base case).
Table 4: Robustness of Welfare Estimates to Key Parameters

<table>
<thead>
<tr>
<th>Decile:</th>
<th>(ΔCV - ∆Inc)/Inc&lt;sub&gt;1990&lt;/sub&gt;</th>
<th>Δ Urban Share of HHs Earning $100K</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Households</td>
<td>Renters Only</td>
</tr>
<tr>
<td>Base Specification</td>
<td>1.40</td>
<td>-0.25</td>
</tr>
<tr>
<td>Elasticity of Substitution between Neighborhood Types (base: ρ = 3)</td>
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<td></td>
</tr>
<tr>
<td>ρ = 2</td>
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<td>-0.27</td>
</tr>
<tr>
<td>ρ = 4</td>
<td>1.64</td>
<td>-0.23</td>
</tr>
<tr>
<td>Elasticity of Substitution between Same-Type Neighborhoods (base: γ = 6.5)</td>
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<td></td>
</tr>
<tr>
<td>γ = 5</td>
<td>1.82</td>
<td>-0.14</td>
</tr>
<tr>
<td>γ = 8</td>
<td>1.17</td>
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</tr>
<tr>
<td>γ = ∞</td>
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<tr>
<td>Elasticity of Substitution between Private Amenities (base: σ = 6.5)</td>
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<td></td>
</tr>
<tr>
<td>σ = 5</td>
<td>1.55</td>
<td>-0.22</td>
</tr>
<tr>
<td>σ = 8</td>
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<td>-0.27</td>
</tr>
<tr>
<td>σ = ∞</td>
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</tr>
<tr>
<td>Distance Elasticity of Amenity Consumption (base: δ = 0.2)</td>
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<td></td>
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<tr>
<td>δ = 0.1</td>
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<td>-0.25</td>
</tr>
<tr>
<td>δ = 0.3</td>
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<td>-0.25</td>
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<tr>
<td>Amenity Expenditure Share (base: α = 0.15)</td>
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<td>α = 0.05</td>
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<td>α = 0.5</td>
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<td>Housing/Land Supply Elasticities (base: ε&lt;sub&gt;D&lt;/sub&gt; = 0.6, ε&lt;sub&gt;S&lt;/sub&gt; = 1.33)</td>
<td></td>
<td></td>
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<tr>
<td>ε&lt;sub&gt;D&lt;/sub&gt; = 0.1, ε&lt;sub&gt;S&lt;/sub&gt; = 1.33</td>
<td>1.40</td>
<td>-0.26</td>
</tr>
<tr>
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<td>1.41</td>
<td>-0.23</td>
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<td>Public Amenity Elasticity (base: Ω = 0.05)</td>
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<tr>
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<td>Ω = 0.08</td>
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<td>-0.23</td>
</tr>
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<td></td>
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<tr>
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<td>-0.25</td>
</tr>
<tr>
<td>T&lt;sub&gt;D&lt;/sub&gt; = 0.25, T&lt;sub&gt;S&lt;/sub&gt; = 0.25</td>
<td>1.41</td>
<td>-0.28</td>
</tr>
</tbody>
</table>
corresponding channel is therefore quantitatively limited in the model. The higher the value of $\alpha$, the larger the well-being inequality increase and the higher the endogenous amenity creation, and the more $\sigma$ and $\delta$ matter for our welfare results. In our base calibration, the main love of variety effect at play quantitatively is the on the choice of a neighborhood where to live (governed by $\gamma$), rather than on the choice of a neighborhood where to go consume amenities (governed by $\sigma$).

The elasticity of housing supply downtown versus the suburbs play an important role in the welfare effects for poor renters. This is not surprising. Much of the welfare effect on the poor stems from them paying higher rents downtown as the rich move in. The more inelastic is the downtown housing supply (in both absolute level and relative to the suburbs), the more house prices move and the larger the additional welfare differences between high and low income households. However, when price growth is higher, poor owners are made better off. Changing the land supply elasticity does not affect the welfare gaps between the poor and the rich on average. However, the land supply elasticity is crucial for understanding the welfare losses to lower income renters. If we simultaneously set $\epsilon_D = \epsilon_S$ to high levels while also setting $\gamma = \sigma = \infty$, there are essentially no welfare changes for any income group stemming from the shifting income distribution over time. As noted above, setting $\gamma = \sigma = \infty$ shuts down the love of variety effects which generates zero welfare gains for high income households while setting the $\epsilon$’s to high values shuts down the housing price effects which leaves welfare unchanged for low income households.

Finally, the response of our welfare estimates to the elasticity of the endogenous component of public amenities confirms that low-income households benefit from the increases in local tax revenues that accompany gentrification. However, as we highlighted in our discussion of Figure 11 the effects of changing the parameters governing endogenous public amenities on welfare is quantitatively small.

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

5.4 Welfare Impact of Alternative Income and Population Change

In the analysis above, we have studied the effects of changes in the observed income distribution holding everything else, including population, constant. We complement this analysis by studying the implication of total population change itself. Furthermore, to tease out what characteristic of the 1990-2014 income shock are important in driving our result, we explore alternative changes in income distribution.

Table 5 reports the results. Row 1 re-displays our baseline results. In the second row, we feed in both the actual population change and the change in the income distribution between 1990 and 2014. The third row isolates the effects of population growth separately from income growth,
by feeding in only the observed change in population, holding the underlying income distribution constant. Accounting for growth in population results in a larger increase in welfare inequality between rich and poor households compared to our baseline. The larger increase stems from two forces. First, population growth amplifies the love of variety effects. As there are more people, developers provide more neighborhoods of differing varieties. Just as above, these variety effects enhance the welfare of the rich relative to the poor. In addition, the increases in population drives up rents everywhere but more so in the downtown areas where land is more constrained. Given our unit housing assumption, this impacts poorer households disproportionately. Changing both population and income increases the well-being gap between high and low income residents by over 5.7 percentage points (on a base of 19 percentage points). Additionally, poorer renters are made worse off in absolute terms by an amount equal to 3.2 percent of their income.

In the fourth row of the table, we return to holding population fixed, and we now assume that all households experience the same income growth equal to the 1990-2014 per capita average. Interestingly, under this alternative income change, the welfare of the poor are made much more worse off in absolute terms relative to our base specification. The reason for this is that when making the increase in income broad based, many middle class individuals in the suburbs also want to move up their residential Engel curves. This causes even more individuals to want to live downtown putting further upward pressure on house prices. In our baseline counterfactual very few households are treated with the income increase given the gains are concentrated at the top of the income distribution. The more broad based the treatment of income growth, the larger the spatial sorting response. As a result, the increase in welfare inequality due to spatial responses is higher than in the baseline case, at about 2.7 percent (instead of 1.7 percent).

In the final rows (5 through 7) of the table we explore crude predictions about the potential future of neighborhood change. Specifically, we hold population growth fixed and ask what happens through the lens of our model when income growth increases by an additional 10, 20 and 30 percent for everyone, respectively, starting from the actual 2014 income distribution. These counterfactuals shed some light on the potential effects of future economic growth on the spatial distribution of residents within cities. Holding population fixed, the quantified model suggests that the spatial sorting response from a rise in income of 10 percent for all individuals (which does not impact income inequality) increases well-being inequality. The mechanisms are the same as what we highlight above. Our model predicts that if income growth in the U.S. continues, even without further increase in income inequality, additional gentrification and within city neighborhood change will be an enduring feature of the urban landscape. These results suggest that is not income inequality per se that driving our results but instead an increase in the absolute number of high income households regardless of what is happening to the rest of the income distribution.
Table 5: Welfare Estimates under Different Counterfactual Income Distributions

<table>
<thead>
<tr>
<th>Decile:</th>
<th>All Households</th>
<th>Renters Only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Top</td>
<td>Bottom</td>
</tr>
<tr>
<td>[1] Base Specification (aggregate population fixed)</td>
<td>1.40</td>
<td>-0.25</td>
</tr>
<tr>
<td>Alternative Driving Forces (1990-2014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[2] Allowing for population growth</td>
<td>4.52</td>
<td>-1.20</td>
</tr>
<tr>
<td>[3] Only population growth, no change to income distribution</td>
<td>2.69</td>
<td>-0.96</td>
</tr>
<tr>
<td>[4] No population growth, 1990 income distribution +10%</td>
<td>2.08</td>
<td>-0.66</td>
</tr>
<tr>
<td>Projected Further Welfare Changes from Further Income Growth from 2014 Onward</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[5] 2014 income distribution +10%</td>
<td>2.98</td>
<td>-1.04</td>
</tr>
</tbody>
</table>

5.5 Additional Out of Sample Tests

We now use counterfactual analysis to conduct two out of sample tests as further validation exercises of the model. We compare the model prediction to two additional empirical facts.

1970 Counterfactual In our benchmark analysis, we calibrated the model using 1990 data and ask how far can the 1990-2014 shift in the income distribution go in explaining changes in spatial sorting over the period. Alternatively, we now look backwards and ask the same question, for the 1970 to 1990 period.

Figure 1 showed that the U-shape pattern between 1970 and 1990 was essentially stable. Does our model predict a stable U-shape pattern between the two years if we feed in the change in the income distribution going backwards from 1990 to 1970? The answer is yes. The top panel of Figure 12 shows the income distribution change from 1990 to 1970 while the lower panel shows the results of our baseline model feeding in the 1970 income distribution. Notice, like the data, our model does not predict a large shift in the U-shape between 1970 and 1990.\(^{47}\) If anything, the model, like the data, predicts the reverse of what we observed between 1990 and 2014: relative to the average household, those at the very right tail of the income distribution urbanized between 1970 and 1990, while those at the left tail urbanized.

According to the quantified model, a rightward shift in the income distribution per se does not necessarily cause high income households to disproportionally move downtown. This only happens with sufficient numbers of households with really high incomes - to the right of our U-shape. In contrast, when households are getting richer through income increase in the middle

\(^{47}\)In the lower panel of Figure 12, we display normalized U-shape patterns - the propensity of a given income group to reside downtown relative to the average person. Between 1970 and 1990, all income groups became more suburbanized meaning there was a level shift up in the non-normalized U-shape in 1970. While our model misses the general suburbanization trend, it matches very well the differences across income groups.
of the distribution, households move up their Engel curve by shifting from low quality suburban neighborhoods to high quality suburban neighborhoods. The relative share of households downtown is barely impacted by this within-suburbs shift. Income growth between 1990 and 2014 has much more growth of very high incomes (incomes above $100,000) compared to the 1970 to 1990 income growth.

Figure 12: 1970 Counterfactual

Cross-CBSA Predictions  In our benchmark exercise, we assumed a representative CBSA by pooling data over large CBSAs. To assess the extent to which our model can match the heterogeneous change in spatial sorting across CBSAs during the 1990-2014 period, we re-calibrate the model separately for each CBSA, targeting in each case the 1990 CBSA-specific U-shape in locational choice by income. We assume that all of the key parameters in Table 1 are identical across CBSAs, except for the land supply elasticities ($\epsilon_D$ and $\epsilon_S$). To do so, we use our estimated equation (21) and feed in actual data on density for each pair of CBSA, Downtown or Suburbs. We then
feed in CBSA-specific changes in the income distribution between 1990 and 2014 and compute the corresponding counterfactual equilibrium for each CBSA. Our goal is then to assess whether our model can reproduce some of the cross-CBSA variation in changes in spatial sorting patterns, given cross-CBSA variation in the change in income distribution. We compare those predictions to actual CBSA level data.

Results are shown in Figure 13. We summarize changes in the U-shape of location choice by income by computing for each CBSA and each period the share of residents earning more than $100K of income living downtown, relative to the average propensity to live downtown. The right hand panel of Figure 13 compares this share for 1990 in the model and in the data. Each point is a different CBSA.\textsuperscript{48} We segment CBSAs into two groups: those with downtown land supply elasticity $< 0.6$ (orange x’s) and those with downtown land supply elasticity $> 0.6$ (blue circle’s). Given that we target the U-shape in 1990, it is not surprising that our model matches the data so well. In the middle panel, we make the comparison for 2014. The model variables correspond to counterfactual predictions for 2014, feeding in solely the income distribution shock CBSA by CBSA. Of course, there are many additional forces at the CBSA level, beyond the change in income distribution on which we focus, that could be changing in a way that affects residential spatial sorting by income. We note that in spite of this, our model predicts 2014 spatial sorting patterns that match the data quite well.

Figure 13: CBSA-by-CBSA Results

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure13.png}
\caption{CBSA-by-CBSA Results}
\end{figure}

Much of the fit in the middle panel may simply result from persistent differences across CBSAs that are well captured in the initial calibration. Our key finding from this analysis, therefore, is shown in the right panel of Figure 13. In this panel, we ask how well our model explains the change\textsuperscript{48} For this analysis, we can only use 18 of 27 CBSAs. These are the CBSAs for which there is sufficient coverage above the state-specific IPUMS income top codes to implement the generalized Pareto interpolation procedure that we use to measure CBSA-level income distributions and U-shapes, as described in the data appendix.
in spatial sorting of high income individuals resulting from the changing income distribution. This panel is similar in spirit to Figure 2 where we show that CBSAs with higher average income growth had more high income individuals moving downtown, but we now perform model counterfactuals feeding in the full change in the CBSA income distributions (as opposed to just mean income growth). Here, we see that the CBSAs our model predicts should have had a large relative increase in high income individuals residing downtown are actually the CBSAs where we observe such an increase empirically. The growth in the population share earning over $100,000 and the increase in the share of households earning over $100,000 that reside downtown (relative aggregate increase in the share downtown) are correlated with a coefficient of 0.77 in the data and 0.59 using in the model’s prediction for the increase in the urban share. The extent to which our model fits less well is for CBSAs that have relatively elastic land supply elasticities.

We conclude from this out of sample analysis that the model does quite well at matching time series changes for a representative CBSA as well as cross-CBSA heterogeneity. Many aggregate stories that could be confounding our baseline results get differenced out in this cross-CBSA analysis. Given the model’s success at matching the cross CBSA patterns, we view this as a strong test of the model’s implications linking the growth in income at the top of the income distribution with the influx of the rich into downtown neighborhoods within a CBSA.

5.6 Gentrification Curbing Policy

Finally, we turn to analyzing the impact of policies that aim to shape the spatial sorting of heterogeneous households within the city.

**Taxing developments**  As an example, we use the model to study the impact of systematically taxing the high-quality housing developments downtown, while subsidizing rents for poorer households downtown. This is a stylized “anti-gentrification” policy. It aims to limit the development of high-quality neighborhoods downtown while helping poorer households to remain located in the city. We assume that the local government imposes a tax $t$ on housing prices downtown, for housing units in high-quality neighborhoods. The tax levied is then fully redistributed as a place-quality-specific subsidy for households who choose to locate downtown, but in low-quality neighborhoods.\(^49\)

We recompute the spatial equilibrium of the city, implementing the policy with a tax of 5%. We focus on the environment of our benchmark 1990 to 2014 counterfactual: we measure how much such a policy would have curbed gentrification triggered by the 1990-2014 income inequality shock.

The left panel of Figure 14 shows that the policy has the effect of stemming part of the gentrification of downtown neighborhoods. Compared to the case without policy, we find that there is less increase in population of high quality neighborhoods, and less decrease in low quality neigh-

\(^{49}\)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:

$$
\delta = \frac{\int L(w)\lambda_D(w)\lambda_{DH}(w)t_p DHdF(w)}{\int L(w)\lambda_D(w)\lambda_D L(w)dF(w)}.
$$
borhoods, and that the policy is effective at stemming part of the land price increase in low income neighborhoods downtown. Overall, the inflow of high income households downtown is curbed, as is the outflow of low income families. Turning to the well-being effect of this policy, in the right panel of Figure 14, we find that it is much more muted. It reverses some of the gains for higher income households, but it has only marginal benefits for low-income households: the benefits are spread out over a broad base of households, so that the per capita positive impact is quantitatively limited. Put differently, the increase in well-being inequality could arguably be targeted more efficiently by direct redistribution. On the other hand though, we note that the policy does contributes to limiting neighborhood change and spatial resorting. To the extent that governments intrinsically value social diversity within their downtowns, this suggest that these policies can help achieve some of these targets.

Figure 14: Location Choices and Well-Being under “Anti-Gentrification” Policy

Zoning restrictions Next we study the effect of an alternative anti-gentrification policy, which is closer to a zoning policy. It imposes that the relative number of high to low quality neighborhoods remains constant over time, despite a rise in incomes. The effect of this policy turns out to be very similar to the effect of the direct tax policy, as can be seen from Figure 15. The impact on social mixing downtown is significant, but the welfare effects are very small.

Regulatory constraints on housing supply Finally, we consider a policy that has been widely-proposed by economists for addressing the regressive welfare impacts associated of housing inflation: relieving regulatory housing supply constraints. Housing regulations do not feature directly into our model but, rather, are reflected indirectly through the housing supply elasticities that we employ in

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50 In addition, mechanically, effective housing costs increase by less than the price increase for low quality housing residents downtown, who receive the redistribution of the tax revenues, and increase by more for high-quality housing residents downtown, who bear the incidence of the tax.
In section 5.3.2 and Table 4, we saw that doubling the elasticity of housing supply both downtown and in the suburbs has little impact on the distribution of welfare growth. Figure 16 shows that it also does little to stem neighborhood change downtown (in the left panel) but it does mitigate the associated welfare losses on the poor (in the right panel). These welfare gains arise because doubling the housing supply elasticity lowers inflation-adjusted house price growth by approximately 1 percentage point in all neighborhoods, effectively shutting it down in the suburbs.

Recall that we calibrate the housing supply elasticities to the estimates from (Saiz, 2010), where housing supply is driven by both physical geography and land-use regulation.
6 Conclusion

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

In the model, as the rich get richer, their increased demand for urban amenities drives up housing prices in downtown areas, where the development of these amenities is fueled by economies of density. The poor are either displaced or end up paying higher rents, making them worse off. Our estimates suggest that increases in the incomes of high income individuals was a substantive contributor to increased urban neighborhood change during the last 25 years within the U.S. Furthermore, our analysis suggests that the neighborhood change resulting from the increased incomes of the rich did, in fact, make poorer residents worse off. Our estimates imply that accounting for the spatial sorting response resulting from the changing in the income distribution between 1990 and 2014 increased the growing inequality between the top and bottom income decile by an additional 1.7 percentage points. We explore possible policy responses to the rise in gentrification, and find that policies that contain gentrification seem to only lead to a very modest mitigation of the increase in well-being inequality, which could arguably be targeted more efficiently by direct redistribution. On the other hand, it is effective in maintaining social diversity in urban neighborhoods, arguably one of the goals of such a policy. While the process of gentrification is complex and has many underlying root causes, we show that the rising incomes of the rich coupled with nonhomothetic demand for urban amenities is one important factor contributing to the changing composition of urban centers. Future work can use our framework to study other underlying potential causes of neighborhood change.
References


Appendix A  Data Appendix

Appendix A.1  Census Data and ACS Data

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

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

IPUMS Data  PUMA geography is also not constant from 1990 to 2014, so we use a crosswalk between PUMAs (Public-Use Microdata Areas) and CBSAs in each year to link each PUMA to a CBSA. To construct constant downtowns from PUMAs across years, we follow the methodology in (Couture and Handbury, 2017). We first intersect PUMA geographies in 1990 and 2014 with our constant downtown geography described in the main text, defined out of tracts closest to the city center accounting for 10 percent of a CBSA’s population in 2000. PUMAs generally intersect with both the urban and suburban area of a CBSA, so we assign an urban weight to each PUMA equal to the percentage of that PUMA’s population falling within the urban area (i.e., downtown) of that CBSA. We compute the urban and suburban population of each PUMA using the population of all census blocks whose centroid falls in a given area.

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

Topcoding in IPUMS Data  IPUMS data is topcoded by income component. Household and family income is sum of total individual income for all members of the household or family. Total individual income is the sum of income components where each component has a unique topcode. Table A.1 shows the all income components contributing to total individual income and their respective topcodes for 1990 and 2014.
Table A.1: Topcoded Income Components Contributing to Total Individual Income

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Topcode (nominal)</th>
<th>Variable</th>
<th>Description</th>
<th>Topcode (nominal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>INCWAGE</td>
<td>Pre-tax wage and salary income</td>
<td>$140,000</td>
<td>INCWAGE</td>
<td>Pre-tax wage and salary income</td>
<td>99.5th Percentile</td>
</tr>
<tr>
<td>INCBUS</td>
<td>Non-farm business and/or professional practice income</td>
<td>$90,000</td>
<td>INCBUS00*</td>
<td>Business and farm income and/or professional practice income</td>
<td>99.5th Percentile</td>
</tr>
<tr>
<td>INCFARM</td>
<td>Farm</td>
<td>$54,000</td>
<td>INCSS</td>
<td>Social security and disability</td>
<td>Not Topcoded</td>
</tr>
<tr>
<td>INCWELFR**</td>
<td>Other government assistance</td>
<td>$17,000</td>
<td>INCWELFR</td>
<td>Other government assistance</td>
<td>Not Topcoded</td>
</tr>
<tr>
<td>INCINVST</td>
<td>Rents, interests, dividends, etc.</td>
<td>$40,000</td>
<td>INCSUPP</td>
<td>Supplementary Security Income</td>
<td>Not Topcoded</td>
</tr>
<tr>
<td>INCRETIR</td>
<td>Retirement income other than social security</td>
<td>$30,000</td>
<td>INCRETIR</td>
<td>Retirement income other than social security</td>
<td>99.5th Percentile</td>
</tr>
<tr>
<td>INCOOTHER</td>
<td>Income not included above</td>
<td>$20,000</td>
<td>INCOOTHER</td>
<td>Income not included above</td>
<td>99.5th Percentile</td>
</tr>
</tbody>
</table>

* 1990 equivalent is INCBUS + INCFARM
** 2014 equivalent is INCWELFR + INCSUPP

In 1990, component topcodes are the same across all states. Table A.2 shows the percent of all units impacted by topcoding for each component for individuals, households, and families. For households and families, we apply the person-level topcode for each component. The last row of the table shows the percent of total aggregate income impacted where we apply the individual-level topcode for wages.

In the 2012-2016 ACS, component topcodes vary both across states and each year of the ACS. State-specific topcodes for wages range from $105,000 to $280,000 in 1999 dollars. Because of this high variance, we allow each state to retain a state-specific topcode, that is the minimum topcode in 1999 dollars across the 5 years of ACS. Table A.3 shows the percent of income impacted by topcodes for different components and units of observation. The last row of the table shows the percent of total aggregate income impacted where we apply the state specific individual-level topcode for wages.

Armour et al. (2016) apply a type I Pareto distribution to estimate the tail of topcoded income in survey data. Equation A.1 shows their formula for estimating the pareto shape parameter $\alpha_{tsn}$ for time period $t$, state $s$, and area $n$.\(^{52}\)

\[
\tilde{\alpha}_{tsn} = \frac{M_{tsn}}{T_{tsn} \ln(X_{Ts}) + \sum x_{m_{tsn}} \leq x_{i} < x_{T_{tsn}} \ln(x_{i}) - (M_{tsn} + T_{tsn}) \ln(x_{m_{tsn}})}
\]

$M_{tsn}$ is the number of households or families with earnings between the lower cutoff $x_{m_{tsn}}$ and

\(^{52}\)Since we are only able to define urban cores for the set of 27 CBSAs with sufficiently small PUMAs in 1990 and 2014, we find $\alpha_{tsn}$ only for the portion of state $s$ that is covered by a CBSA in that sample.
Table A.2: Percent of Income Impacted by Topcoded Components in 1990

<table>
<thead>
<tr>
<th>Variable</th>
<th>Person</th>
<th>Household</th>
<th>Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>incwage</td>
<td>0.60%</td>
<td>1.39%</td>
<td>1.66%</td>
</tr>
<tr>
<td>incbus</td>
<td>3.70%</td>
<td>4.25%</td>
<td>4.62%</td>
</tr>
<tr>
<td>incfarm</td>
<td>2.79%</td>
<td>3.28%</td>
<td>3.48%</td>
</tr>
<tr>
<td>incss</td>
<td>0.73%</td>
<td>3.67%</td>
<td>5.60%</td>
</tr>
<tr>
<td>incwelfr</td>
<td>3.18%</td>
<td>5.80%</td>
<td>6.83%</td>
</tr>
<tr>
<td>incinvest</td>
<td>2.11%</td>
<td>2.98%</td>
<td>3.18%</td>
</tr>
<tr>
<td>incretir</td>
<td>3.20%</td>
<td>4.15%</td>
<td>5.08%</td>
</tr>
<tr>
<td>incother</td>
<td>2.28%</td>
<td>2.51%</td>
<td>2.43%</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td>0.62%</td>
<td>1.78%</td>
<td>2.28%</td>
</tr>
</tbody>
</table>

Note: The table shows the percent of income at or above the topcode value in 1990 among the set of observations where income is non-missing and greater than $0.

Table A.3: Percent of Income Impacted by Topcoded Components in 2014

<table>
<thead>
<tr>
<th>Variable</th>
<th>Person</th>
<th>Household</th>
<th>Family</th>
</tr>
</thead>
<tbody>
<tr>
<td>incwage</td>
<td>1.2%</td>
<td>3.5%</td>
<td>4.5%</td>
</tr>
<tr>
<td>incbus</td>
<td>3.7%</td>
<td>4.4%</td>
<td>5.1%</td>
</tr>
<tr>
<td>incinvest</td>
<td>3.6%</td>
<td>4.6%</td>
<td>5.2%</td>
</tr>
<tr>
<td>incretir</td>
<td>3.5%</td>
<td>5.6%</td>
<td>7.2%</td>
</tr>
<tr>
<td>incother</td>
<td>3.4%</td>
<td>4.0%</td>
<td>4.0%</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td>1.5%</td>
<td>4.1%</td>
<td>5.8%</td>
</tr>
</tbody>
</table>

Note: The table shows the percent of income at or above the topcode value in 2014 among the set of observations where income is non-missing and greater than $0. The topcode value is set at the minimum topcode in each state across the five years of ACS (2012-2016).
censoring point \( x_{T_{tsn}} \). In 1990, we assign the censoring point as the topcode for a single-wage household adjusted to 1999 dollars ($188,160). In 2014, for state \( s \) we choose censoring point as the topcode for a single-wage household for the year with the lowest topcode of the 5 years surveyed. \( T_{tsn} \) is the number of households with income at or above censoring point \( x_{T_{tsn}} \). We choose the lower cutoff \( x_{m_{tsn}} \) as the 95% income in state \( s \) for period \( t \) and area \( n \). This is consistent with Armour et al. (2016). \(^{53}\)

Piketty et al. (2018) further improve upon the constant parameter estimate. They find using individual tax data that a single Pareto distribution cannot sufficiently explain the tail of an income distribution. In the US context, the relationship between the Pareto parameter and income has become increasingly U-shaped over time. This would suggest that the simple Pareto as outlined in Armour et al. (2016) not only underestimates the fatness of the right tail of the income distributions but does so especially in 2014 relative to 1990. Piketty et al. (2018) develop a methodology to construct generalized Pareto curves that allow the pareto coefficient to vary across income. However, the generalized pareto methodology requires an unbiased estimate of average income for some top quantile of income. We use our estimates of \( \hat{\alpha}_{tsn} \) from the simple Pareto distribution to approximate the average income above the topcode. Using the R package gpinter that Piketty et al. (2018) developed to implement the procedure we estimate the generalized Pareto curves for each state \( s \), area \( n \), and period \( t \).\(^{54}\)

We then combine the income distribution using actual IPUMS data below the topcode with the approximated distribution above the topcode. To do this, we construct a kernel-smoothed CDF using the IPUMS data below the topcode. We then join the below-topcode CDF with the above-topcode CDF from the generalized Pareto distribution. To avoid any kinks around the join point we first adjust the above-topcode CDF such that it matches the CDF at the topcode for the below-topcode. We use numerical differentiation of this CDF to derive the full distribution for PDF adjusting for topcoding. To further avoid any kinks around the topcode, we then cut income $1,500 around the topcode and interpolate through the PDF. Using the total population in area \( n \), state \( s \), and period \( t \) we use this smoothed PDF to get a population estimate at each $5,000 interval. Finally, we can aggregate across states to get the urban, suburban, and total distribution for the 27-CBSA sample in 1990 and 2014.

\(^{53}\)We add the additional restriction that at least 1.5% of the total income distribution falls between \( x_{m_{tsn}} \) and \( x_{m_{tsn}} \) to ensure we have a sufficient amount of data to estimate the shape parameter. If less than 1.5% of the total income distribution falls between those two points we lower the percentile cutoff by 1% percentage point until that condition is met.

\(^{54}\)The gpinter package approximates the income distribution using a set of income percentiles and the average income between each percentile. For each state, area, and period we use the same set for the first 6 percentiles: \([10,30,45,60,75,85]\). Then based on where the topcode falls for that particular distribution we allow the set of top percentiles to vary. If the topcode percentile \( p_t \) falls between the 85th and 92nd percentile, we include no additional moments between the 85th and \( p_t \). If \( p_t \) falls between the 92nd and 93rd percentile, our top two percentiles are \( [85 + \frac{2(p_t - 85)}{3}, p_t] \). If \( p_t \) falls between the 93rd and 96th percentile are top three percentiles are \( [85 + \frac{2(p_t - 85)}{3}, 85 + \frac{2(p_t - 85)}{3}, p_t] \). If \( p_t \) falls above the 9th percentile the top 4 percentiles are \( [85 + \frac{2(p_t - 85)}{4}, 85 + \frac{2(p_t - 85)}{4}, 85 + \frac{3(p_t - 85)}{4}, p_t] \).
Appendix A.2 Smartphone movement data

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

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

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

Table A.4 shows the number of establishment in the smartphone data basemap for the ten largest restaurant chains, compared with recent estimates of the actual number that we found online. This comparison shows that the smartphone basemap is nearly complete, with one exception, Starbucks, where almost half of the establishments are missing from the smartphone basemap.

Appendix A.3 NETS Data

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

Neumark et al. (2007) assess the NETS reliability by comparing it to other establishment datasets (i.e., QCEW, CES, SOB and BED data). Their conclusions support our use of the NETS data.

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55 We do not observe all travel by devices, so visit duration is a lower bound and missing in some cases. This explains why we are only able to ascertain 10 percent of trips as staring from home, whereas for instance about 30 percent of trips to restaurants in the NHTS start from home.
Table A.4: Ten Largest Restaurant Chains in NHTS vs Smartphone Data

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

Notes: The data source from the most recent actual count obtained on 19 December 2018 from the following websites:
McDonald: https://news.mcdonalds.com/our-company/restaurant-map
Starbucks: https://www.loxcel.com/sbux-faq.html
Pizza Hut: https://locations.pizzahut.com/
Burger King: https://locations.bk.com/index.html
Wendys: https://locations.wendys.com/united-states
Dunkin Donuts: https://www.dunkindonuts.com/en/about/about-us
KFC http://www.yum.com/company/our-brands/kfc/
Taco Bell: http://www.yum.com/company/our-brands/taco-bell/
Dairy Queen: https://www.qsrmagazine.com/content/23-biggest-fast-food-chains-america
data to compute a long 12-year difference from 2000 to 2012. They report that NETS has better coverage than other data sources for very small establishments (1-4 persons), which is often the size of consumption amenity establishments.

Table A.4 suggests that the NETS database is less complete than the smarpnace basemap, but some of this difference is due to the earlier count. The NETS contains a majority of establishments for eight of the ten largest chains, with the exceptions of McDonalds and Starbucks where the NETS misses more than half the actual number of establishments. We further assess the precision of the NETS by considering aggregate growth of chain establishments. For instance, Chipotle had nearly 100 stores in 2000 and grew to about 1000 stores in 2010. The NETS reports 21 Chipotle stores in 2000 and around 840 in 2012. Together, these numbers show that the NETS data captures general growth patterns, but we struggle to identify all chains due to merging on inconsistent establishment names and lags in D&B recording new locations.

Appendix A.4 Zillow House Price Indexes

Our main house price index comes from Zillow.com. Our two-bedroom home index is the Zillow House Value Index (ZHVI) for all two-bedroom homes (i.e., single family, condominium, and cooperative), which is available monthly for 8,030 zip codes in 1996, 8,031 zip codes in 2000, 8,575 zip codes in 2012, and 8,898 zip codes in 2016. In robustness checks, we use the per square foot Zillow House Value Index for All Homes, which is available monthly for 14,417 zip codes in 1996, 14,421 zip codes in 2000, and 15,500 zip codes in 2014. For each zip code in the Zillow data, we compute a yearly index by averaging over all months of the year. We map zip codes to tracts with a crosswalk from HUD. We compute the tract-level index as the weighted average of the home value index across all zip codes overlapping with the tract, using as weights the share of residential address in the tract falling into each each zip code. For tracts falling partly into missing zip codes, we normalize the residential share in zip codes with available data to one. The final data set contains home value indexes for 34,989 tracts in 1996, 34,999 tracts in 2000, 36,744 tracts in 2012, and 38,628 tracts in 2016.

Appendix A.5 National Household Transportation Survey (NHTS)

The National Household Travel Survey (NHTS) conducted by the Federal Highway Administration (and local partners) provides travel diary data on daily trips taken in a 24-hour period for each individual in participating households. We use the 2009 NHTS survey. Each trip has a WHYTO (trip purpose) code that we match to non-tradable service purposes to produce Figure 3, and to work purposes to compute commute cost $\tau_D$ and $\tau_S$. Non-tradable service trip purposes are:

1. Restaurants (WHYTO 80, 82, 83, Meals, get/eat meal, coffee/ice cream/snacks)

2. Nightlife (WHYTO 54, Go out/hang out: entertainment/theater/sports event/go to bar)

We collected the data in February 2019. The index and methodology are available at: http://www.zillow.com/research/data/.
3. Personal Services (WHYTO 63, ”Use personal services: grooming/haircut/nails”)

4. Gym/sports (WHYTO 51, ”Go to gym/exercise/play sports”)

5. Buy services (WHYTO 42, ”Buy services: video rentals/dry cleaner/post office/car”)

Work trip purposes are:

1. Work (WHYTO 10)

2. Go to work (WHYTO 11)

3. Return to work (WHYTO 12)

4. Attend business meeting/trip (WHYTO 13)

5. Other work related (WHYTO 14)

We use weights at the person level to compute population estimates of mean trip shares.

Appendix A.6 Subsidized and Public Housing

We use tract-level data from HUD on the total number of households living in federal subsidized or public housing in 2014 and 2000. HUD reports the total number of available and available units by program. They also report the share of households in each tract living in subsidized or public housing across different income brackets. We standardized income brackets between 2000 and 2014 by assuming that households are uniformly distributed within a bounded bracket. For any tracts with missing data or no units reported, we assume that no households within that tract were living in public or subsidized housing. We observe 57,502 tracts in 2000 and 42,467 tracts in 2014 with occupying subsidized or public housing.

Appendix B Model Appendix

Appendix B.0.1 Entry of Developers

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

\[ p^a_r = \frac{\sigma}{\sigma - 1} h^a_{n(r),j(r)} R_{n(r)}, \]  

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

\[ \pi^a_{n,j} = \frac{\alpha^a}{\sigma} \int_w \frac{\lambda_{n,j}(w) \left( w - p^h_{n,j} \right)}{N_{nj}} dL(w) \]
and the land used by amenities of type \((n,j)\) is:

\[
R_nK^a_{n,j} = \frac{\sigma - 1}{\sigma} \alpha^a \int_w \lambda_{n,j}(w) \left( w - p^h_{n,j} \right) dL(w)
\]  \hspace{1cm} (A.3)

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

\[
R_nK^h_{n,j} = \int_w \lambda_{n,j}(w) h^h_{n,j} R_n dL(w)
\]  \hspace{1cm} (A.4)

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

\[
\pi^h_r = \int_w \lambda_r(w) dL(w) \left( p^h_r - h^h_{n,j} R_n \right)
\]  \hspace{1cm} (A.5)

Using (9), (8) and (10) leads to the following pricing formula:

\[
p^h_r = \frac{\gamma}{\gamma + 1} h^h_{n,j} R_n + \frac{1}{\gamma + 1} \mathcal{I}_{n,j}(p^h_r),
\]  \hspace{1cm} (A.6)

where the term \(\mathcal{I}_{n,j}(p^h_r)\) is a measure of demand for neighborhood \(r\).\(^{57}\) By symmetry, all neighborhoods of type \((n,j)\) have the same price in equilibrium, which we denote as \(p^h_{n,j}\).

This leads to:

\[
N_{n,j} = \frac{1}{f_{n,j}} \left[ \int_w \lambda_{n,j}(w) \left( p^h_{n,j} - h^h_{n,j} R_n + \frac{\alpha^a}{\sigma} \left( w - p^h_{n,j} \right) \right) dL(w) \right]
\]  \hspace{1cm} (A.7)

Appendix B.1 Computing Counterfactuals

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

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

and where \(S^m_{nk}\) is the share of amenity expenditures of households living in a neighborhood of type \(nj\) spent on amenities consumed in a neighborhood \((m,k)\). These shares are taken from the smartphone data.

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 \(\{p^h_{n,j}', \lambda_{n,j}'(w), L'_{n,j}\}\) (or, equivalently, their “hat” values).

\(^{57}\) Specifically, \(\mathcal{I}_{n,j}(p) = \int_w \Lambda_{n,j}(p,w)[(1-r_n)w + \chi(w)]dP(w)\) with \(\Lambda_{n,j}(p,w) = \frac{\lambda_{n,j}(w)L(w)}{[(1-r_n)w + \chi(w) - p]}\).
First, given (6), changes in housing costs are given by:

$$
\hat{R}_n = \left( \sum_j s_{n,j}^h \hat{R}_n L_{n,j} + s_{n,j}^a \hat{R}_n \hat{K}_{n,j}^a \right) \frac{1}{1+s_{n,j}^h}, \quad (A.8)
$$

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

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

which we compute from the calibrated values of $R_n K_{n,j}^h$ using equation A.3, as well as the calibrated values of $R_n K_{n,j}^h$ using equation A.4.\(^{58}\) Note that $\hat{L}_{n,j} = \int \lambda'_{n,j}(w) dL'(w)$ while $\hat{R}_n \hat{K}_{n,j}^a = \frac{\int \lambda_{n,j}(w)(w-p^h_{n,j})' dL'(w)}{\int \lambda_{n,j}(w)(w-p^h_{n,j}) dL'(w)}$, where $\lambda'_{n,j}(w)$ is unknown and a solution of the system of equations described here, while the counterfactual distribution of income $L'(w)$ is taken as given.

Second, the housing prices in the new equilibrium are defined by:\(^{59}\)

$$
(p_{n,j}^h)' = \frac{\gamma}{\gamma + 1} h_{n,j}^h \hat{R}_n + \frac{1}{\gamma + 1} T'_{n,j} \left( (p_{n,j}^h)' \right), \quad (A.9)
$$

where the function $T_{n,j}'(p)$ is defined by:

$$
T'_{n,j}(p) = \int_w \lambda'_{n,j}(p, w) \left( (1 - \tau_n) w + \chi(w)' \right) L'(w) dw \int_w \lambda_{n,j}(p, w) L'(w) dw, \quad (A.10)
$$

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

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

$$
\tilde{q}_{n,j} = \tilde{N}_{n,j}^{\frac{1}{\alpha}} \left( \hat{P}_{n,j}^a \right)^{-\alpha} \quad (A.11)
$$

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

$$
\tilde{N}_{n,j} = \pi_{n,j}^h L_{n,j} \left( (p_{n,j}^h)' - h_{n,j}^h R_n' \right) p_{n,j}^h - h_{n,j}^h R_n \left( X'_{n,j} - \left( p_{n,j}^h \right)' L'_{n,j} \right),
$$

\(^{58}\) We have $\sum_{i,j} s_{i,j}^i = 1$ for $n = D$ or $S$ and $\sum_{m,k} s_{m,j}^{nk} = 1$, for $n = D, S$ and $j = H, M, L$.

\(^{59}\) Note that $h_{n,j}^h R_n$ is known in the initial equilibrium using equation A.6 and the known variables $p_{n,j}^h, \lambda_{n,j,\ell}(w), L(w)$.
where we define $X_{n,j}$ to be total income in $n,j$:

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

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

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

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

$$\left( \hat{P}^a_{nj} \right)^{1-\sigma} = \sum_{j' n'} S^{n' j'}_{n_j} \hat{N}_{n' j'}^{\delta} \hat{K}_{n'}^{\delta} \left( \hat{R}'_{n'} \right)^{1-\sigma},$$

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

$$S^{m k}_{n j} = \frac{N_{m,k} K_m^\delta (R_m)^{1-\sigma}}{\sum_{n' j' n} S^{n' j'}_{n_j} \hat{N}_{n' j'}^{\delta} \hat{K}_{n'}^{\delta} (\hat{R}'_{n'})^{1-\sigma}}.$$

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

$$\hat{\lambda}_{n,j}(w) = \frac{\hat{q}_{n,j}^\rho}{\hat{V}^\rho (w)} \frac{w(1 - \tau_n) + \chi'(w) - p'_{r}}{w(1 - \tau_n) + \chi'(w) - p'_{r}} \lambda_{n,j}(w), \quad \text{(A.12)}$$

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

$$\hat{V}^\rho (w) = \sum_{n_j} \frac{\hat{q}_{n,j}^\rho \rho}{\hat{V}^\rho (w)} \frac{(1 - \tau_n)w + \chi'(w) - p'_{r}}{(1 - \tau_n)w + \chi(w) - p_{r}} \lambda_{n,j}(w), \quad \text{(A.13)}$$

Values for $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}\}$ are the solutions of equations (A.8)-(A.12) that define a counterfactual equilibrium of the economy corresponding to an alternative distribution of income $L'(w)$ in the city.

**Appendix C  Variable definition**

This appendix details the computation of variables used in our analysis.
Appendix C.1 CBSA level wage Bartik shock


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

For both the Bartik shock from 1990-2014 and 2000-2014, we fix the share of people working in each 3-digit census industry for each CBSA in 1990. We then compute the Bartik predicted wage growth as average industry leave-out wage growth weighted by initial 1990 industry shares in each CBSA. For our robustness specifications, we compute Bartik shocks leaving out three major industry categories for some robustness specifications: Finance, Real Estate and Insurance (1990 industry codes 700-712), Manufacturing (1990 industry codes 100-399), and Technology. We also compute Bartik shocks leaving out the top quartile of most urbanized industries. To do so, we first rank 3-digit industries by the share of their workers who live downtown. Then, starting from the most urbanized industry, we remove industries entirely from our Bartik computation until we 25 percent of all workers have been removed. Table A.6 shows the 10 most and 10 least urbanized industries in 1990.

Appendix C.2 Median income within Census table brackets

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

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

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60 181 = Pharmaceuticals; 342 = Electronic component and product manufacturing; 352 = Aircraft and Parts; 362 = Aerospace products and parts manufacturing; 891 = Scientific research and development services; 732 = Computer systems design and related services + Software Publishing + Data processing, hosting, and related services; 882 = Architectural, engineering, and related services.
determine median income using 2000 IPUMS microdata.

Appendix C.3  Yearly user cost of housing by quality, location and CBSA \((p_{njc})\).

Computing \(p_{nj}\) We first compute a population weighted-median house price over all tracts in a
given area quality pair in a given CBSA. To obtain \(p_{njc}\) that we use in estimation and calibration,
we multiply this median house value by a user cost of housing equal to 5.0 percent of house value
in 1996, 4.7 percent in 2000 and 4.6 percent in 2014. These rent-price ratios come from the Lincoln
Institute of Land Policy.\(^{61}\)

Property Taxes as a share of \(p_{njc}\) Using CPI-adjusted tract-level ACS and Census estimates
of the median property taxes for owner-occupied units, we find the population-weighted median
amount paid in property taxes in 1990, 2000, and 2014 for each area quality pair. We then divide
this amount by \(p_{njc}\).

Appendix C.4  Share of expenditures on amenities \(\alpha\)

Table 2 in Aguiar and Bils (2015) reports Engle curve estimates for 20 expenditure categories using
1994-1996 CEX data. Both "entertainment" and "restaurants" have expenditure elasticities higher
than 1. Entertainment has the second highest elasticity at 1.74 (the highest is cash contributions,
such as charitable donation), and restaurants has the seventh highest elasticiticy at 1.32. Based on
CEX 2013 tables, entertainment fees and admission have a mean expenditure share of 1.1 percent,
and food away from home has a mean share of 5.1 percent, excluding alcohol away from home.\(^{62}\) In
the model, \(\alpha\) is net of expenditures on transportation to work and housing costs. The CEX share
of expenditure on direct shelter is 19.7 percent with an additional 7.3 percent in utilities. This
gives a combined housing share of 27 percent. The share on transportation is 17.6 percent, and if
we assume that 40 percent of it is for work, we find 0.5*17.6=8.8 percent of expenditure on work
transportation.\(^{63}\) Putting this together we obtain \((0.051 + 0.011)/(1 – 0.088 – 0.270) = \alpha = 0.10,\)
which is our lower bound for \(\alpha\) in the text.

Appendix C.5  Tract level quality index.

Appendix C.5.1  Estimating chain quality

We define quality for the 100 largest restaurant chains, with the most establishments in the smart-
phone data basemap. We index block groups by \(i\), venues by \(j\), and chains by \(c\). We denote by \(N_{ic}\)
the total number of visits by devices living in block \(i\) that start from home and end in venues in
chain \(c\) within its CBSA. Our main specification has two controls for proximity of block \(i\) to venues

\(^{61}\)Data collected in October 2018 from \url{https://datatoolkits.lincolninst.edu/subcenters/land-values/rent-price-ratio.asp}


\(^{63}\)In the NHTS 2009, travel to work represents only about 30 percent of trips, and 50 percent of total distance
traveled for 25 to 65 year olds.
in chain c: first the normalized straightline distance between the centroid of block i and the closest venue j in chain c, denoted by \( \text{dist}_{ic(\text{closest})} \), and second the normalized number of establishments in chain c within 5 miles of block i, denoted by \( \text{num}_{5\text{mil}ic} \). Our estimation sample consists of 2.3 million block*chain pairs with at least one within-CBSA visit from home. In a first step, we purge the number of visits from the impact of proximity to chains by running:

\[
\ln N_{ic} = \beta_1 + \beta_2 \ln(\text{dist}_{ic(\text{closest})}) + \beta_3 \ln(\text{num}_{5\text{mil}ic}) + \epsilon_{ic}.
\]

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

\[
\hat{N}_{ic} = \exp\left(\ln N_{ic} - \hat{\beta}_2 \ln(\text{dist}_{ic(\text{closest})}) - \hat{\beta}_3 \ln(\text{num}_{5\text{mil}ic})\right)
\]

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

\[
S_{c}^{\text{High}} = \frac{\sum_{i \in I_c} \hat{N}_{ic}^{\text{High}}}{\sum_{c=1}^{100} \sum_{i \in I_c} \hat{N}_{ic}^{\text{High}}},
\]

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

\[
\text{Quality}_c = \frac{S_{c}^{\text{High}}}{S_c},
\]

where \( \text{Quality}_c = 1 \) means that high income devices are as likely to visit chain c as the average device, controlling for differences in proximity to venues in chains c.

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

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

\[\text{In that case, } N_{ic} = 0 \text{ gets adjusted upward if the closest venue to block } i \text{ is farther than median distance, and therefore included as a positive number of visits in the index computation, possibly creating the opposite bias as in our preferred specification. We use the invert hyperbolic sine transform to allow for log of zeros.}\]
than 5 miles, and for demographic similarity between block \(i\) and the block in which the closest venue in chain \(c\) is located (median income difference, age difference, share college difference, EDD measure of racial dissimilarity in Davis et al. Forthcoming). The correlation of these indices with our preferred chain quality index is above 0.98.

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

In the NETS data, we can find all of the 100 largest chains in the smartphone data in 2012, accounting for 64,000 establishments, and 96 chains in 2000, accounting for 49,000 establishments.\(^{66}\)

We compute quality at the tract level as the average quality of all chains within the tract. If a tract contains fewer than 3 chains, we take the average over all tracts with centroid within 0.25 mile from the tract, and so on in further 0.25 mile increment until there are at least 3 chains. We set a limit of 1.5 miles in urban areas, and 3 miles in suburban areas, below which we set quality to missing if there are still fewer than 3 chains within that limit. This procedure generates 4 percent missing tracts in urban areas, and 15 percent in suburban areas.\(^{67}\)

**Appendix D  Robustness estimation**

**Appendix D.1  Elasticity of Demand Between Neighborhood Types (\(\rho\))**

Our preferred estimate of \(\rho\) from equation (17) is shown in column 2 of Table 2. Here, we show variants of this estimation in Table A.5. In column 1, we change the time period from 1990-2014 to 2000-2014. In column 2 and 3, we change the house price index from Zillow 2 Bedroom to Zillow All Home in column 2, and to the Census median house price in column 3. These IV estimates are noisier than our base estimate, but they range from 1.91 to 3.84, which is about two standard deviation away from our preferred estimate of \(\rho=3\).

We also explored the robustness of our estimate to changes in our quality definition (not shown). First, we changed our high quality cut-off from a 40 percent college share, to a 30, 50, or 60 percent college share. Estimates with more restrictive cut-offs are noisier, but IV estimates remain between 2.6 and 4.1. Second, we changed our quality definition to that based on restaurant chains. We used high quality cut-offs ranging from average chain quality of 100 to average chain quality of 140. We obtain somewhat lower \(\rho\) estimates using this restaurant quality definition, with larger standard errors and IV estimates ranging from 1.4 to 2.6.\(^{68}\)

Finally, Table A.6 provides additional detail on the robustness exercise in the main text where we drop industries from our Bartik instrument. The table shows the 10 most urbanized and 10 least

---

\(^{66}\)The earliest NETS data is in 1992, but we cannot reliably define tract quality so far back in the past, because too many of the largest chains in our 2016-2018 smartphone data only experienced national growth after 1992.

\(^{67}\)For urban tract, there are at least three chains within tract for 15 percent of tracts, within 0.5 miles for 29 percent of tracts, and within 1 mile for 73 percent of tracts. For suburban tracts, there are at least three chains within tracts for 20 percent of tracts, within 0.5 miles for 25 percent of tracts, within 1 mile for 55 percent of tracts, and within 2 miles for 86 percent of tracts.

\(^{68}\)Our measure of restaurant quality is not available in 1990, so we impute 2000 tract quality to 1990 tracts.
Table A.5: Robustness exercise for $\rho$ estimation.

<table>
<thead>
<tr>
<th></th>
<th>2000-2014 Zillow All Price</th>
<th>Census Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\hat{\rho}$</td>
<td>1.91</td>
<td>2.94</td>
</tr>
<tr>
<td></td>
<td>(0.57)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>Instrument</td>
<td>Base</td>
<td>Base</td>
</tr>
<tr>
<td>KP F-Stat</td>
<td>14.4</td>
<td>7.9</td>
</tr>
<tr>
<td>Obs</td>
<td>6193</td>
<td>7000</td>
</tr>
</tbody>
</table>

Notes: Data from 100 largest CBSAs. Observations are weighted by their cell size. Standard errors clustered at the CBSA-quality level are in parentheses. KP F-Stat = Kleinberger-Papp Wald F statistic. Column (1) based on 2000 to 2014 data and other columns based on 1990-2014 data. We define neighborhood quality based on the education mix of residents.

urbanized industries, along with the share of urban workers in that industry. The table highlights that even for the most urbanized industry (Museum, Art Galleries, Historical Sites, and Similar Institutions) the share of urban workers is only 24 percent, and most of the Bartik variation comes from the suburbs. This is because our urban areas, by construction, are small relative to the suburbs.
Table A.6: Most and Least Urbanized Industries

<table>
<thead>
<tr>
<th>Code</th>
<th>Industry</th>
<th>Urban Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>872</td>
<td>Museums, art galleries, historical sites, and similar institutions</td>
<td>24.8%</td>
</tr>
<tr>
<td>762</td>
<td>Traveler accommodation</td>
<td>20.6%</td>
</tr>
<tr>
<td>151</td>
<td>Cut and sew apparel manufacturing</td>
<td>20.5%</td>
</tr>
<tr>
<td>800</td>
<td>Motion pictures and video industries</td>
<td>20.2%</td>
</tr>
<tr>
<td>750</td>
<td>Car Washes</td>
<td>19.5%</td>
</tr>
<tr>
<td>900</td>
<td>Executive offices and legislative bodies</td>
<td>19.2%</td>
</tr>
<tr>
<td>761</td>
<td>Private households</td>
<td>18.9%</td>
</tr>
<tr>
<td>721</td>
<td>Advertising and related services</td>
<td>18.4%</td>
</tr>
<tr>
<td>951</td>
<td>U. S. Coast Guard</td>
<td>18.4%</td>
</tr>
<tr>
<td>542</td>
<td>Apparel, fabrics, and notions wholesalers</td>
<td>17.6%</td>
</tr>
<tr>
<td>352</td>
<td>Aircraft and Parts</td>
<td>4.0%</td>
</tr>
<tr>
<td>622</td>
<td>Other motor vehicle dealers</td>
<td>3.8%</td>
</tr>
<tr>
<td>311</td>
<td>Agricultural implement manufacturing</td>
<td>3.6%</td>
</tr>
<tr>
<td>950</td>
<td>U. S. Marines</td>
<td>3.4%</td>
</tr>
<tr>
<td>561</td>
<td>Farm supplies wholesalers</td>
<td>3.2%</td>
</tr>
<tr>
<td>41</td>
<td>Coal Mining</td>
<td>2.8%</td>
</tr>
<tr>
<td>362</td>
<td>Guided Missles, Space Vehicles, and Parts</td>
<td>2.7%</td>
</tr>
<tr>
<td>821</td>
<td>Office of chiropractors</td>
<td>2.5%</td>
</tr>
<tr>
<td>590</td>
<td>Miscellaneous retail stores</td>
<td>2.3%</td>
</tr>
<tr>
<td>11</td>
<td>Animal production</td>
<td>1.2%</td>
</tr>
</tbody>
</table>

Notes: The Table shows the 3-digit industries with the highest share of workers who live in urban areas in row 1 to 10, and industries with the lowest share in row 11 to 20. IPUMS data from the 27 CBSAs with constant geography urban area in 1990 and 2014. These urban areas contain 10 percent of each CBSA’s population in 2000.
Appendix E  Urbanization by income controlling for demographic characteristics

In this section, we replicate Figure 1 showing normalized urban shares by income bracket, but controlling for demographic characteristics.

Appendix E.1 Data Construction

Unlike Figure 1 that uses Census tables from the 100 largest CBSAs, here we use our calibration IPUMS data in 27 CBSAs with constant urban geography, which allows us to control for demographic characteristics of households. We create demographic control dummies for race, age, family type, and nationality of birth.\textsuperscript{69} For age, we construct 5-year age buckets. For family type, we define four categories: Unmarried - No Children, Married - No Children, Youngest Child \textlessthan 5, and Youngest Child \textgreater 5. For race, we use the IPUMS definitions.\textsuperscript{70,71} For nationality of birth, we define two categories: native born and foreign born.

Appendix E.2 Estimating Equation

To compute urban shares within each income bracket without demographic controls, we estimate the following equation, separately in 1990 and in 2014:

\[
\text{UrbanWeight}_i = c + \sum_{k \in K} \beta_k \text{IncomeDummy}_{ki}, \tag{A.14}
\]

where UrbanWeight\textsubscript{i} is the urban weight of household \textit{i}, which equals 1 if the household is assigned entirely to the urban area of its CBSA.\textsuperscript{72} IncomeDummy\textsubscript{ki} is a dummy equal to 1 if household \textit{i} is in income bracket \textit{k}.\textsuperscript{73} The fitted values from this regression are urban shares within each income bracket. To normalize these shares relative to the average household, we divide the fitted value for each income bracket, \( c + \hat{\beta}_k \), by a weighted average of all fitted values, where each fitted value is weighted by the total number of households in that income bracket. Plotting these normalized fitted values against median income within each dummy replicates Figure 1 in the paper, but using IPUMS data for our 27 constant geography CBSAs instead of Census tables.

\textsuperscript{69}The age, race, and nationality at birth are that of the head of household. The youngest age for a head of household with nonzero income is 15.

\textsuperscript{70}We have to merge three categories in 2014 so the definitions are consistent across both periods. These three categories are ‘Other race’, ‘Two major races’ and ‘Three or more major races’. We correspond all of these to the 1990 definition ‘Other race’.

\textsuperscript{71}Hispanic is a separate variable in IPUMS. For this analysis, we do not distinguish whether a person is hispanic or not.

\textsuperscript{72}We use a weight instead of a 0/1 dummy because we only know the PUMA location of an individual, and some PUMAs span both the urban and suburban areas.

\textsuperscript{73}We assign each household into 100 evenly log-spaced total household income brackets. We adopt this methodology so brackets are directly comparable between 1990 and 2014, and to ensure large enough population counts in higher income brackets. We merge the bottom 61 brackets with income below $10,000, and then we drop all income between $200,000 and $400,000 that is heavily impacted by topcoding in IPUMS. See topcoding appendix here for further discussion. Our results are robust to different methods of adjusting for topcodes.
To compute urban shares that control for demographic characteristics, first denote each group of controls (age, household type, race, birth status) by \( g \), and each category within a group by \( d \) (e.g., 30-34 year olds). The estimating equation becomes:

\[
\text{UrbanWeight}_i = c + \sum_{k \in K} \beta_k \text{IncomeDummy}_{ki} + \sum_{g \in G} \sum_{d \in D} \gamma_{gd} \text{DemoDummy}_{igd}, \tag{A.15}
\]

where \( \text{DemoDummy}_{igd} \) is equal to 1 if household \( i \) is in category \( d \) within group of controls \( g \). To obtain urban shares within each income bracket \( k \) that control for demographic characteristics, we compute fitted values of equation A.15 under the assumption that demographic shares within each income brackets are exactly representative of the demographic shares within the total population. Under this assumption, fitted urban shares are equal to:

\[
c + \hat{\beta}_k + \sum_{g \in G} \sum_{d \in D} \text{SharePop}_{gd} \times \hat{\gamma}_{gd},
\]

where \( \text{SharePop}_{gd} \) is the share of total population in each category \( d \) (e.g., share of 30-34 year olds).

**Appendix E.3 Results**

Figure A.1 shows normalized urban shares for each income bracket in 1990 and 2014. The left-hand plots shows estimates from equation A.14 (without control) and the right-hand plot shows estimates from equation A.15 (with demographic controls.)

Our key finding is that controlling for demographics makes the U-shape even more pronounced at the top of the income distribution, in both 1990 and 2014. The regression results from equation A.15 show what drives this finding. In Table A.7, column 1 and 2 show the coefficient on each demographic group dummy in 1990 and 2014, column 3 and 4 show the correlation of each demographic group dummy with household income in 1990 and 2014, and column 5 and 6 show the share of the population within each demographic group. The table shows that there is almost an exact correspondence between the demographic groups that are most suburbanized, wealthiest, and largest. This explains why the urban share of high income households is larger once we control for demographics; high income households would be even more urbanized if they weren’t also white, middle-aged, and with older children, all of which are suburbanized demographic categories. These first order correlations hold in both 1990 and 2014, so the uptick in the U-shape from 1990 to 2014 largely persists after adding demographic controls.

To further assess whether the U-shape patterns that we document are specific to certain demographic categories, in Figure A.2 we plot normalized urban share separately by demographic category within each group. To get large enough samples, we further aggregate some our age and race categories, into four age categories (25-34, 35-44, 45-64, 65+) and three race categories (we keep "white" and "black". The "other" category is comprised mostly of Asian, Indigenous, or multiethnic households.) Remarkably, we find a U-shape pattern, and an urbanization of high income household from 1990 to 2014 in all categories within all demographic groups.
Table A.7: Coefficient on Demographic Control Dummies in 1990 and 2014

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Age ≥24 (omitted)</td>
<td>.</td>
<td>.</td>
<td>-0.114</td>
<td>-0.091</td>
<td>0.047</td>
<td>0.032</td>
</tr>
<tr>
<td>Age 25-29</td>
<td>-0.001</td>
<td>0.021</td>
<td>-0.051</td>
<td>-0.051</td>
<td>0.101</td>
<td>0.071</td>
</tr>
<tr>
<td>Age 30-34</td>
<td>-0.008</td>
<td>0.004</td>
<td>0.066</td>
<td>-0.005</td>
<td>0.123</td>
<td>0.091</td>
</tr>
<tr>
<td>Age 35-39</td>
<td>-0.011</td>
<td>-0.026</td>
<td>0.049</td>
<td>0.030</td>
<td>0.118</td>
<td>0.092</td>
</tr>
<tr>
<td>Age 40-44</td>
<td>-0.019</td>
<td>-0.046</td>
<td>0.098</td>
<td>0.051</td>
<td>0.109</td>
<td>0.098</td>
</tr>
<tr>
<td>Age 45-49</td>
<td>-0.020</td>
<td>-0.059</td>
<td>0.118</td>
<td>0.063</td>
<td>0.088</td>
<td>0.102</td>
</tr>
<tr>
<td>Age 50-54</td>
<td>-0.021</td>
<td>-0.069</td>
<td>0.099</td>
<td>0.062</td>
<td>0.071</td>
<td>0.106</td>
</tr>
<tr>
<td>Age 55-59</td>
<td>-0.019</td>
<td>-0.072</td>
<td>0.067</td>
<td>0.049</td>
<td>0.066</td>
<td>0.100</td>
</tr>
<tr>
<td>Age 60-64</td>
<td>-0.018</td>
<td>-0.071</td>
<td>0.010</td>
<td>0.014</td>
<td>0.068</td>
<td>0.087</td>
</tr>
<tr>
<td>Age 65-69</td>
<td>-0.024</td>
<td>-0.076</td>
<td>-0.063</td>
<td>-0.014</td>
<td>0.067</td>
<td>0.072</td>
</tr>
<tr>
<td>Age 70-74</td>
<td>-0.029</td>
<td>-0.078</td>
<td>-0.096</td>
<td>-0.044</td>
<td>0.055</td>
<td>0.052</td>
</tr>
<tr>
<td>Age 75-99</td>
<td>-0.032</td>
<td>-0.083</td>
<td>-0.109</td>
<td>-0.061</td>
<td>0.044</td>
<td>0.038</td>
</tr>
<tr>
<td>Age 80-84</td>
<td>-0.037</td>
<td>-0.087</td>
<td>-0.098</td>
<td>-0.066</td>
<td>0.027</td>
<td>0.029</td>
</tr>
<tr>
<td>Age 85+</td>
<td>-0.034</td>
<td>-0.094</td>
<td>-0.087</td>
<td>-0.081</td>
<td>0.017</td>
<td>0.030</td>
</tr>
<tr>
<td>Native Born (omitted)</td>
<td>.</td>
<td>.</td>
<td>0.041</td>
<td>0.048</td>
<td>0.847</td>
<td>0.752</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>0.038</td>
<td>0.027</td>
<td>-0.041</td>
<td>-0.048</td>
<td>0.149</td>
<td>0.248</td>
</tr>
<tr>
<td>Unmarried (no children) (o)</td>
<td>.</td>
<td>.</td>
<td>-0.288</td>
<td>-0.244</td>
<td>0.343</td>
<td>0.380</td>
</tr>
<tr>
<td>Married (no children)</td>
<td>-0.056</td>
<td>-0.058</td>
<td>0.111</td>
<td>0.128</td>
<td>0.209</td>
<td>0.200</td>
</tr>
<tr>
<td>Youngest Child ≤ 5</td>
<td>-0.073</td>
<td>-0.104</td>
<td>0.012</td>
<td>0.031</td>
<td>0.138</td>
<td>0.105</td>
</tr>
<tr>
<td>Youngest Child &gt; 5</td>
<td>-0.062</td>
<td>-0.076</td>
<td>0.189</td>
<td>0.125</td>
<td>0.310</td>
<td>0.315</td>
</tr>
<tr>
<td>White (omitted)</td>
<td>.</td>
<td>.</td>
<td>0.150</td>
<td>0.113</td>
<td>0.780</td>
<td>0.690</td>
</tr>
<tr>
<td>Black</td>
<td>0.147</td>
<td>0.058</td>
<td>-0.148</td>
<td>-0.132</td>
<td>0.141</td>
<td>0.158</td>
</tr>
<tr>
<td>Native American</td>
<td>0.048</td>
<td>0.037</td>
<td>-0.014</td>
<td>-0.017</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Chinese</td>
<td>0.089</td>
<td>0.042</td>
<td>0.011</td>
<td>0.023</td>
<td>0.010</td>
<td>0.021</td>
</tr>
<tr>
<td>Japanese</td>
<td>0.034</td>
<td>0.034</td>
<td>0.016</td>
<td>0.010</td>
<td>0.004</td>
<td>0.003</td>
</tr>
<tr>
<td>Other Asian</td>
<td>0.014</td>
<td>-0.001</td>
<td>0.019</td>
<td>0.053</td>
<td>0.020</td>
<td>0.049</td>
</tr>
<tr>
<td>Other Race (including mixed raced)</td>
<td>0.121</td>
<td>0.038</td>
<td>-0.073</td>
<td>-0.070</td>
<td>0.041</td>
<td>0.074</td>
</tr>
</tbody>
</table>

Note: Columns 1 and 2 report the coefficients for years 1990 and 2014 of Equation A.15 with all demographic controls included. The standard errors are very small and not shown. Columns 3 and 4 show the pairwise correlation of each demographic control dummy and household income. Columns 5 and 6 report the total share of population falling into each demographic category across the set of included groups.
Figure A.1: Demographic Controls on Relative Urbanization

Normalized IPUMS Urban Share

No Controls

Demographic Controls

Note: This figure shows the urban share curves normalized by the aggregate urban share in each year with and without demographic controls. The left plot shows the coefficients from Equation A.14. The right plot shows the coefficients from A.15. All Income Brackets with mean Household Income below $10,000 are dropped from the plot. All income between $200,000 and $400,000 is dropped, which is the income most severely impacted by topcoding.
Figure A.2: Normalized Urban Shares by Demographic Categories in 1990 and 2014

Panel A: Age

Panel B: Race

Panel C: Family Type

Panel D: Foreign Status

Note: This figure shows the normalized urban share curves plotted separately for each major demographic group. All income brackets with mean Household Income below $10,000 are dropped from the plot. All income between $200,000 and $400,000 is dropped, which is the income most severely impacted by topcoding.
Appendix F  Robustness of Counterfactual Results to Restaurant Quality Cutoff

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

To illustrate this, Table A.8 redisplay Table 4 from the main text using our chain restaurant index to segment neighborhoods. As seen from this table, our results are very similar in all specifications using this alternate procedure to define high quality neighborhoods.
Table A.8: Robustness of Welfare Estimates to Key Parameters using Restaurant Quality Cutoff

<table>
<thead>
<tr>
<th>Decile:</th>
<th>All Households</th>
<th>Renters Only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top</td>
<td>Bottom</td>
<td>Diff.</td>
</tr>
<tr>
<td>Base Specification</td>
<td>1.23</td>
<td>-0.23</td>
</tr>
<tr>
<td>$\rho = 2$</td>
<td>1.11</td>
<td>-0.25</td>
</tr>
<tr>
<td>$\rho = 4$</td>
<td>1.41</td>
<td>-0.17</td>
</tr>
<tr>
<td>$\gamma = 5$</td>
<td>1.68</td>
<td>-0.03</td>
</tr>
<tr>
<td>$\gamma = 8$</td>
<td>1.02</td>
<td>-0.28</td>
</tr>
<tr>
<td>$\gamma = \infty$</td>
<td>0.31</td>
<td>-0.45</td>
</tr>
<tr>
<td>$\sigma = 5$</td>
<td>1.38</td>
<td>-0.19</td>
</tr>
<tr>
<td>$\sigma = 8$</td>
<td>1.14</td>
<td>-0.25</td>
</tr>
<tr>
<td>$\sigma = \infty$</td>
<td>0.82</td>
<td>-0.34</td>
</tr>
<tr>
<td>$\delta = 0.1$</td>
<td>1.24</td>
<td>-0.23</td>
</tr>
<tr>
<td>$\delta = 0.3$</td>
<td>1.22</td>
<td>-0.23</td>
</tr>
<tr>
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</tr>
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<td>-0.30</td>
</tr>
<tr>
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<tr>
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<td>-0.23</td>
</tr>
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<td>-0.21</td>
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<td>-0.26</td>
</tr>
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$\Delta CV = \Delta Inc/Inc_{1990}$
Appendix G  Additional Figures and Tables
Figure A.3: 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 A.4: Gentrifying Tracts in Central County of Selected CBSA

Note: Each map shows the central county of a given CBSA, except for New York which shows the five counties (boroughs) of New York City. Downtown tracts in blue consist of all tracts closest to the city center and accounting for 10% of total CBSA population in 2000. The shading of each tract shows its percent growth in median household income between 1990 and 2014.
Figure A.5: Counterfactual impact of shift in income distribution on the U-shape