

# Income Growth and the Distributional Effects of Urban Spatial Sorting\*

Victor Couture

Cecile Gaubert

Jessie Handbury

Erik Hurst

July 2019

## 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 nonhomothetic 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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\*We thank Hero Ashman and Allison Green for outstanding research assistance. We thank Treb Allen, David Atkin, Jonathan Dingel, Ingrid Ellen, Alessandra Fogli, Ed Glaeser, Gabriel Kreindler, Christopher Palmer, Andres Rodriguez-Clare, Jung Sakong, Yichen Su, Jacob Vigdor, and Jonathan Vogel for many helpful comments as well as seminar participants at Berkeley, UChicago, Edinburgh, Georgetown, HEC Montreal, LSE, Northwestern, Notre Dame, NYU, Oxford, Penn State, the Princeton IES Workshop, Stanford, UCLA, UToronto, Warwick, Wharton, UIUC, the 2017 Federal Reserve Bank of Richmond conference on “Understanding Urban Decline,” the 2018 European and U.S. Urban Economic Association meetings, the 2019 Barcelona GSE Summer Forum and various NBER programs. Victor Couture thanks the Fisher Center for Real Estate and Urban Economics at UC Berkeley for financial support. Cecile Gaubert thanks the Fisher Center for Real Estate and Urban Economics and the Clausen Center for International Business and Policy at UC Berkeley for financial support. Jessie Handbury thanks the Zell-Lurie Real Estate Center for financial support. Authors contact information: [couture@berkeley.edu](mailto:couture@berkeley.edu), [cecile.gaubert@berkeley.edu](mailto:cecile.gaubert@berkeley.edu), [handbury@wharton.upenn.edu](mailto:handbury@wharton.upenn.edu), and [erik.hurst@chicagobooth.edu](mailto:erik.hurst@chicagobooth.edu).

# 1 Introduction

Over the last three decades income inequality in the United States has grown sharply, with income growth 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 sparked a renewed discussion of neighborhood change within many U.S. cities.<sup>1</sup>

In this paper, we explore the impact of top income growth on within-city spatial sorting. We propose a novel mechanism that links changes in the income distribution to changes in residential location choices of different income groups within a city. At the heart of the mechanism are nonhomothetic preferences for residential locations. We develop a spatial equilibrium model of a city that features these preferences, along with endogenous housing costs and endogenous urban amenities. We use micro data to quantify the model and provide empirical evidence for the proposed nonhomothetic sorting mechanism. With the quantified model, we estimate the impact of top income growth on changes in within-city spatial sorting and the extent to which this mechanism amplifies welfare inequality across income groups. We also assess the effectiveness of policies aimed at mitigating the distributional effects of these changes in within-city spatial sorting.

We motivate our central mechanism with three stylized facts that characterize large U.S. cities. First, the propensity to live downtown is U-shaped in household income. As is well known, poorer households are over-represented downtown; a perhaps lesser known fact is that richer households are also systematically over-represented downtown.<sup>2</sup> Second, over time, the rich have become more likely to reside downtown and the poor less so, particularly in cities that have seen increasing incomes. Third, local urban amenities like restaurants or entertainment options are relative luxury goods.<sup>3</sup>

We posit that these facts are connected. As the incomes of the rich increase, their demand for neighborhoods with high quality urban amenities rises and more of them choose to reside downtown. In turn, as the income composition of downtown changes, the supply of high quality neighborhoods responds endogenously, which fuels further in-migration of the rich. Downtown rents are driven up, imposing a pecuniary externality on low income residents of downtown areas. Poorer residents, who are mostly renters, have a choice between paying higher rents for a bundle of amenities that they do not value as much and moving out of downtown. Because of these changes in neighborhood quality and prices driven by the in-migration of the rich to downtowns, welfare estimates of increased income inequality are *understated* when spatial sorting responses are ignored.

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<sup>1</sup>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.

<sup>2</sup>For New York, Philadelphia and Chicago, Glaeser et al. (2008) show a U-shaped average income gradient with respect to distance from the city center. In the 10 largest U.S. cities, Glaeser et al. (2001) find that average income within 1 mile of the city center is higher than the city average. We systematically document the propensity of each income group to live downtown in the 100 largest CBSAs in the U.S., and show that a U-shape relationship holds across years, across demographic groups, and for alternative measures of downtowns and incomes.

<sup>3</sup>For example, Aguiar and Bils (2015) estimate that restaurant meals and non-durable entertainment are among the goods with the highest income elasticities. Couture and Handbury (2017) document that downtown areas of major cities have a higher density of such amenities.

Our model formalizes the link between the rising incomes of the rich and neighborhood change. It features households with heterogeneous incomes who choose where to live among neighborhoods that offer different qualities of amenities and housing. Households trade off higher attractiveness of a neighborhood with higher cost of living there. This cost depends on housing prices, taxes, and the cost of commuting to work. Preferences for neighborhoods are nonhomothetic: households with higher incomes disproportionately choose to live in expensive high quality neighborhoods. Neighborhoods are built by private developers who compete for land within each area of the city. An influx of demand for high quality neighborhoods downtown leads to an increase in prices throughout downtown, including in low quality neighborhoods where the poor live. An increase in the supply of high quality neighborhoods amplifies this effect, by reducing the variety of low quality neighborhoods available to the poor. Through this base mechanism, an influx of richer households downtown unambiguously hurts the lower income renters residing there.

The model also builds in mitigating forces through which an influx of higher incomes downtown could benefit incumbent poor households. First, local governments build public amenities like parks or schools that benefit all households in a given location. The provision of public amenities increases as the tax base downtown increases. Second, households travel to consume amenities outside of their neighborhood of residence. An improvement in the quality of other neighborhoods in the city benefits all households who travel to consume these amenities, beyond its residents. Third, some low income downtown residents own their homes, and hence reap the benefits of house price appreciation. Given these mitigating forces, how an influx of richer households into downtown areas affects the well-being of lower income households on net is a quantitative question.

We use micro data to quantify the model and provide evidence for its sorting mechanism. We begin by estimating the key elasticity that governs the extent of nonhomotheticity in within-city location choices. Our estimation exploits changes in spatial sorting patterns in response to a CBSA-wide income shock, driven by plausibly exogenous variation in labor demand across cities. In particular, our instrumental variable estimation shows that a Bartik income shock raises house prices downtown more than in the suburbs, inducing the rich to re-sort into downtowns. These results suggest that income growth triggers within-city spatial sorting, consistent with our model of nonhomothetic location choices. A second key elasticity in the model governs the magnitude of the gains from accessing a variety of non-tradable amenities in the city. The model delivers a corresponding gravity equation for amenity consumption, which we estimate with a rich novel database of smartphone location data. This data traces the extent to which individuals from different neighborhoods travel to different venues. We use existing data sources to pin down other 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 U-shaped distribution of the propensity to reside downtown as a function of income, as well as relative housing prices between neighborhoods of different quality and location, for a representative U.S. city in 1990. We show that the calibrated model can replicate salient cross-sectional features of the data for large U.S. cities, including the fact that downtown areas are disproportionately populated by both very low and very high earn-

ers. Low income households minimize costs of housing and commuting by residing in low quality neighborhoods downtown. At the same time, higher income households are attracted downtown by the density of high quality, high amenity neighborhoods offered there.

We use the quantified model for welfare and counterfactual analysis. In our main counterfactual of interest, we compute the spatial equilibrium that results from the change in income distribution observed for large city residents between 1990 and 2014. We find that the increased incomes of the rich since 1990 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.<sup>4</sup> Under our base parameterization, the model predicts that shifts in the income distribution between 1990 and 2014 can explain roughly one-half of the increasing propensity of individuals in the top income decile to reside downtown. Using the structure of the model, we also compute the corresponding welfare effects at all levels of income. We find that the shifting income distribution between 1990 and 2014, mediated by change in neighborhood quality and spatial sorting, triggered an even larger increase in well-being inequality. Quantitatively, mitigating forces like public provision of amenities are not strong enough to overcome the base mechanism, which hurts the poor primarily through higher rents. Our estimates suggest that welfare differences between those in the top decile of the income distribution and those at the bottom decile increased by an additional 1.7 percentage points between 1990 to 2014, once accounting for spatial responses, compared to a nominal increase of 19 percentage points. Furthermore, we find that the neighborhood change downtown 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. The welfare losses to renters in the bottom income decile who remain downtown are even larger at 1.5 percent in consumption equivalent terms.

We present additional counterfactual analyses that serve to further validate the model. We compare the model predictions to two additional empirical facts. First, we repeat the procedure above, but for the 1970-1990 change in the income distribution. We find that our model predicts a more limited spatial sorting response compared to 1990-2014, 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. We then show that our model also performs quite well at explaining cross-CBSA variation in spatial sorting during the 1990 to 2014 period.

Finally, we end the paper by showing that our model can be used to inform the current policy debate, sparked by large neighborhood changes in U.S. cities. We simulate a policy that taxes

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<sup>4</sup>Throughout the paper, we often use “neighborhood change” of 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, nonhomothetic preferences for urban amenities, and endogenous spatial responses.

housing in high quality neighborhoods downtown to subsidize housing in low quality neighborhoods downtown, as well as a zoning policy that preserves the mix of high and low quality neighborhoods downtown. We find that these policies can be effective in maintaining a diverse income mix downtown. However, they do not overturn the increase in well-being inequality that we find for 1990-2014, which is instead fueled by upgrades in quality and prices in the suburbs. In contrast, a policy that relieves housing supply constraints mitigates the negative welfare impact of neighborhood change on the poor, but it does not curb the influx of the rich into downtowns.

This paper contributes to three main literatures. First, a growing literature studies how nominal income inequality growth can induce even stronger real income inequality growth in models with nonhomothetic preferences and endogenous supply responses.<sup>5</sup> We apply this logic to the endogenous development of neighborhoods within cities, building on the literature that studies changes in spatial sorting. In an early contribution, Gyourko et al. (2013) show that the increase in high incomes nationally can explain the upward co-movement of incomes and house prices observed in “superstar cities.” Diamond (2016) shows that, across cities, homophily among 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 neighborhoods over which households have nonhomothetic preferences. In this sense, our paper complements recent work by Tsivanidis (2019) who uses Stone-Geary preferences to study the distributional effects of infrastructure investment in Bogota across two skill groups. Contemporaneous work also studies welfare inequality within cities. Fogli and Guerrieri (2019) focus on the effect of income segregation on educational outcomes, while Su (2018b) emphasizes the role of rising value of time for high skilled workers as an engine for changes in spatial sorting. Our focus on urban amenities as an important dimension of neighborhood heterogeneity follows the early insights of Brueckner et al. (1999) and Glaeser et al. (2001): 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); Allen et al. (2015); Redding and Sturm (2016)). Different from our approach, these papers feature homogeneous workers, homothetic preferences, and model a specific city with no extensive margin of within-city locations. We propose a stylized model of a representative city that allows us to model the extensive margin: the number and quality of neighborhoods in a city is endogenous. Our approach also uniquely studies spatial sorting and well-being across the full distribution of incomes, with a common nonhomothetic preference structure across incomes.<sup>6</sup> The

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<sup>5</sup>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.

<sup>6</sup>In country-wide spatial equilibrium models, Peters et al. (2018) use PIGL preferences of a representative agent to study structural change across U.S. counties and Fajgelbaum and Gaubert (2018) study optimal spatial policies in models with heterogeneous workers who have heterogeneous but homothetic preferences over endogenous city amenities.

model’s core mechanisms are drawn from Fajgelbaum et al. (2011) and relate to the assignment model of Davis and Dingel (2019), where complementarity between location attractiveness and income drives the sorting of agents across locations. Our framework retains the tractability of quantitative spatial models, which allows us to take it to the data and quantify the impact of policies on neighborhood change and welfare.<sup>7</sup> Our paper therefore also complements recent work examining the welfare implications of urban policies by Diamond et al. (n.d.), Eriksen and Rosenthal (2010), Baum-Snow and Marion (2009), Diamond and McQuade (2019) and Hsieh and Moretti (2019).

Third, our approach complements a flourishing literature that highlights various causes and consequences of gentrification and neighborhood change.<sup>8</sup> Within this literature, our paper builds on a growing strand showing that demographic shifts downtown are not primarily driven by job location: Glaeser et al. (2001), Baum-Snow and Hartley (2018), and Couture and Handbury (2017) conclude that amenities play a major role in these changes. 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 among the rich, i.e., to live downtown but work in the suburbs.<sup>9</sup> These findings illustrate that changing job location or changing taste for commutes alone are unlikely to rationalize the rising propensity of high-skilled workers to live downtown. We contribute to this literature by documenting and quantifying a novel channel (rising top incomes, coupled with income effects on location choice), as well as methodologically, by providing a quantitative model that allows for policy assessment.

## 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 nonhomothetic preferences, in the next section. Our model and related counterfactuals are for a representative city. Given this, our stylized facts are calculated using a sample of the 100 largest U.S. Core Based Statistical Areas (CBSAs) in year 1990.

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<sup>7</sup>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 nonhomothetic preferences generates heterogeneous spatial sorting.

<sup>8</sup>See, for example, Guerrieri et al. (2013), Edlund et al. (2019), Ellen et al. (2019), 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 (2019), Meltzer and Ghorbani (2017), Lester and Hartley (2014), and Autor et al. (2017).

<sup>9</sup>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 (authors’ calculations).

## 2.1 Data

The stylized facts that 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 (Ruggles et al., 2018), adjusted for top-coding using the generalized Pareto method.<sup>10</sup> 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.<sup>11</sup> 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 (2018). Appendix C.4 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 propensity to live downtown as a function of income for 1970, 1990, and 2014. 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 so as to abstract from the suburbanization of the population as a whole over this period due to general population growth. The  $x$ -axis features the median family income for that bracket in the corresponding 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 data.

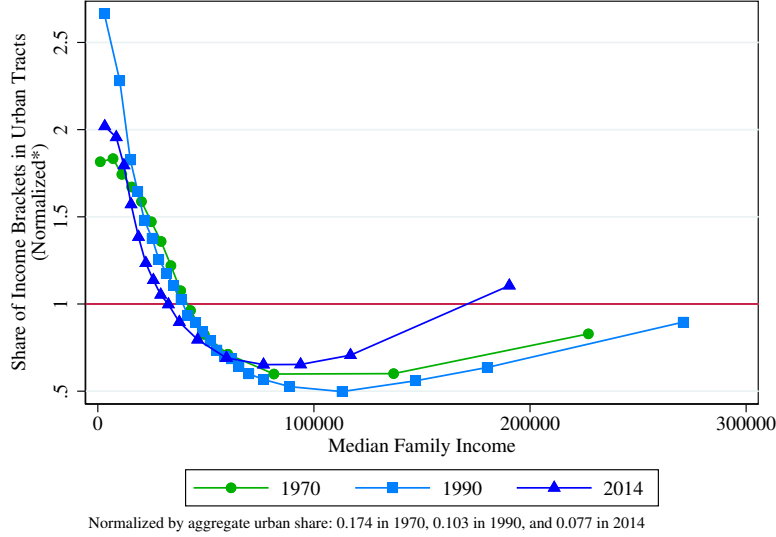
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<sup>10</sup>Household income in the IPUMS data is sum of various components that are each top-coded at state-year-specific levels. We therefore interpolate incomes that are reported to be above the lowest of these component top-codes using the generalized Pareto method outlined in Piketty et al. (2017). See the data appendix for more details.

<sup>11</sup>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.



Figure 1: Downtown Residential Income Propensity by Income



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

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 in 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, the choice of price deflator, 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 this U-shape pattern is even more pronounced at the top of the income distribution after controlling for socio-demographic characteristics such as age, race, native

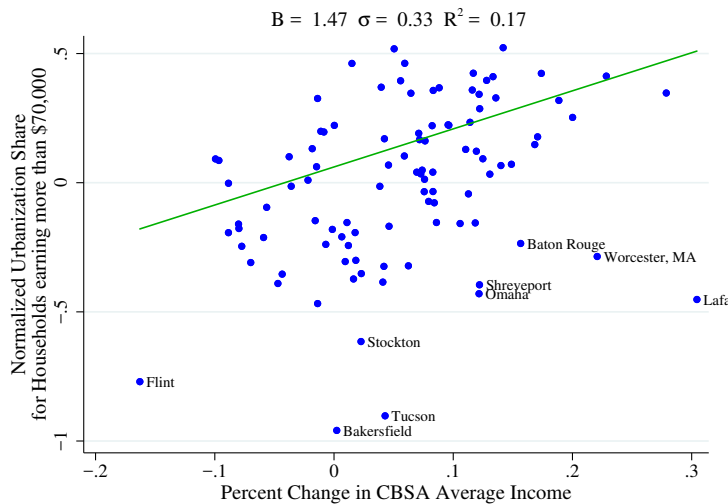


born status, and household composition. The change in the U-shape also persists after adding these controls and, in fact, we observe a U-shaped location pattern with an uptick between 1990 and 2014 within essentially all of the socio-demographic groups we looked at (e.g., 45-65 year olds, the foreign 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 evidence that this is the case using cross-city variation in the stylized fact presented above. We first 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: Richer Household Propensity to Live Downtown in Response to a CBSA Level Change in Income 1990-2014



Note: This figure shows each 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. The green line through the scatterplot depicts unweighted linear fit which has slope 1.47 with a standard error of 0.33. A weighted regression (where the weights are the CBSA 1990 population) yields a slope coefficient of 1.29 with a standard error of 0.34.

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

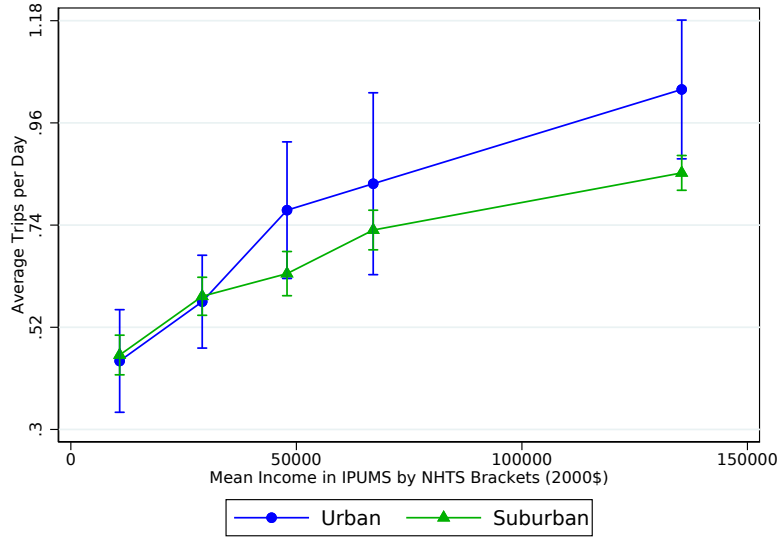
CBSA income during the 1990-2014 period was associated with a 13 percent increase in the over-representation of richer households downtown. This correlation suggests that shifts in the income distribution observed during the 1990-2014 period may be a quantitatively important factor in drawing higher 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 that income shocks trigger 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.

## 2.4 Urban Amenities as Relative Luxury Goods

At the heart of the model below are neighborhoods that offer different quality of urban amenities, and over which households have nonhomothetic preferences. This approach is motivated by 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, which 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 suggest, by revealed preference, that richer individuals consume more urban amenities. They motivate a key gentrification mechanism in the model: the increased provision of luxury amenities downtown.

Figure 3: Propensity to Travel to Non-Tradable Services by Income and Location.



Note: This figure shows the average number of daily trips to non-tradable services of individuals in different income brackets living downtown (in blue circles) and in the suburb (in green triangles). The data comes from the the 2009 NHTS survey and includes all members of participating households who are 25 to 65 year old and live in the 100 largest CBSAs. The downtown definition includes all tracts closest the the city center accounting for 10% of the population in 2000. Trips to non-tradable services include trips to restaurants, to go out/hang out (e.g., bars, entertainment), to gym/sports, to personal services, and to buy services (e.g., laundry, garage).

### 3 Model

We propose a model of the internal structure of a representative city. The model is designed to capture changing trends in the urban landscape of large U.S. cities documented above. The city is comprised of two areas, a central district, which we call Downtown, and the rest of the city, which we call the Suburbs. Each area is comprised of spatial units of heterogeneous quality that we call *neighborhoods*. Households with heterogeneous incomes choose a neighborhood where to live. Nonhomotheticities in preferences lead to the sorting of heterogeneous households into different types of neighborhoods. Housing costs, as well as the supply and quality of neighborhoods in the city, are endogenous. The model accommodates the empirical fact that downtown features an over-representation of both extremes of the income distribution.

We first lay out the setup of the model and solve for its equilibrium. Section 3.3 then discusses the main modeling assumptions and properties of the model, in particular how an income shock impacts the model equilibrium.

#### 3.1 Model setup

##### 3.1.1 City

The city is comprised of neighborhoods indexed by  $r$ . Space in the model is stylized. Neighborhoods are characterized by the area of the town where they are located, downtown or the suburbs, as

indexed by  $n \in \{D, S\}$ . Distance between two neighborhoods depends only on the location  $n$  and  $n'$  of these two neighborhoods. Within these two broad areas, neighborhoods are vertically differentiated by the quality of their housing stock and private amenities. This level of quality is indexed by  $j$ . We denote with  $\mathcal{B}(nj)$  the set of neighborhoods of quality  $j$  in area  $n$  of the city. Within each  $\mathcal{B}(nj)$ , neighborhoods  $r$  are differentiated horizontally, but are symmetric.

### 3.1.2 Households

Households, indexed by  $\omega$ , supply labor inelastically and are heterogeneous in incomes  $w(\omega)$ . We take the aggregate distribution of incomes in the city  $L(w)$  as a primitive of the model.<sup>12</sup> Households who live in neighborhood  $r \in \mathcal{B}(nj)$  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  $r \in \mathcal{B}(nj)$  is:

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

The shifter  $A_n$  summarizes quality of life in downtown relative to the suburbs (e.g., their differences in public amenities such as parks and schools) while  $Q_j$  summarizes the quality level of a neighborhood (intrinsic to, for example, its housing stock and private urban amenities). The shock  $b_r(\omega)$  captures the idiosyncratic preferences of household  $\omega$  for living in neighborhood  $r$ . It is drawn from a Generalized Extreme Value distribution:

$$F(\{b_r\}) = \exp \left( - \left[ \sum_{n,j} \left( \sum_{r \in \mathcal{B}(nj)} b_r^{-\gamma} \right)^{-\frac{\rho}{\gamma}} \right] \right). \quad (2)$$

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*  $\{n, j\}$  pairs, and  $\gamma$  governs the variance of idiosyncratic preference draws *within*  $\{n, j\}$  pairs. Consistency with utility maximization requires  $\gamma > \rho > 1$ .

Households consume a CES aggregate of private amenities – e.g., restaurants and entertainment

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<sup>12</sup>We make the implicit assumption that, in a first step that is not modeled, workers find jobs with income  $w$  in the city. In a second step, they choose where to live within the city. 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.

options – in different neighborhoods of the city:

$$a_r = \left( \sum_{r'} (\beta_{j(r)j'(r')})^{\frac{1}{\sigma}} (a_{rr'})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad (3)$$

where  $a_{rr'}$  is consumption of amenities in  $r'$  for a household living in  $r$ ,  $\sigma > 1$  is the elasticity of substitution between amenities in different neighborhoods, and the disutility term  $\beta_{j(r)j'(r')}$  depends on the dissimilarity in quality between a household's own neighborhood and the destination neighborhood.<sup>13</sup> Commuting to amenities is costly, with a cost that increases with distance. The cost of consuming amenities in neighborhood  $r'$  for a household living in  $r$  is  $d_{rr'}^\delta p_{r'}^a$ , where  $\delta$  governs how the cost of commuting to consume amenities in  $r'$  varies with the distance  $d_{rr'}$  between  $r$  and  $r'$ , and  $p_{r'}^a$  is the price of amenities in  $r'$ . Let  $N_{nj}$  denote the number of neighborhoods in  $\mathcal{B}(nj)$ . Given our symmetry assumptions, neighborhoods in  $\mathcal{B}(nj)$  offer the same price index for amenity consumption:<sup>14</sup>

$$P_{nj}^a = \left( \sum_{n',j'} N_{n'j'} \beta_{jj'} \left( d_{nn'}^\delta p_{n'j'}^a \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \quad (4)$$

Finally, the net income  $m$  of a household  $w$  depends on its area of residence  $n$ , as follows:

$$m_n(w) = (1 - \tau_n)w + \chi_n(w) - T_n(w). \quad (5)$$

The parameter  $\tau_n$  captures commuting cost to work while  $\chi_n(w)$  captures returns to the household's real estate portfolio, which we allow to depend on household type  $w$  and location  $n$ , to capture the corresponding heterogeneity in homeownership rates in the data. Finally,  $T_n(w)$  are net taxes levied by the local government of area  $n$ . Note that commuting costs to work  $\tau_n w$  depend on place of residence  $n$  and on household wage  $w$ , which captures the opportunity cost of time spent commuting. We assume that  $\tau_D < \tau_S$ : households living downtown have an easier access to jobs compared to those living in the suburbs.

Households choose their neighborhood of residence  $r$  by maximizing (1) subject to the budget constraint  $p_r^h + P_r^a a + c = m_r(w)$ . The price of the freely traded good is taken as the numeraire, while  $p_r^h$  is the price of the unit of housing in neighborhood  $r$  that one must rent to live there. To summarize, the indirect utility of a household  $\omega$  with wage  $w$  is:

$$\max_r v_r(\omega) = (P_r^a)^{-\alpha} A_n Q_j \left( m_n(w) - p_r^h \right) b_r(\omega) \quad (6)$$

<sup>13</sup>We normalize  $\beta_{jj} = 1$  while typically  $\beta_{jj'} \leq 1$  if  $j \neq j'$ , so that households value horizontal differentiation within their preferred quality level and value to a lesser degree amenity options of a different quality.

<sup>14</sup>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  $j$ , where  $j = j(r)$  and  $n = n(r)$ , whenever it is clear to do so.

### 3.1.3 Neighborhood Development

Monopolistically competitive private developers use land to develop neighborhoods that feature housing units and retail amenities. Developers rent out housing units. They operate retail stores and restaurants that are marketed to households living in the neighborhood as well as to those living in other parts of the city.

Land is provided competitively by atomistic absentee landowners.<sup>15</sup> There are two land markets, segmented by location ( $n = D$  or  $S$ ). 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:

$$K_n = K_n^0 (R_n)^{\epsilon_n}, \quad (7)$$

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 total land supply of downtown relative to the suburbs. Developers use  $K_{nj}^h$  and  $K_{nj}^a$  units of land in location  $n$  to build  $H_{nj}^h$  housing units of quality  $j$  and  $H_{nj}^a$  retail areas of quality  $j$ , respectively. We allow for the unit land requirement,  $k_{nj}^i = \frac{K_{nj}^i}{H_{nj}^i}$  to increase with quality (i.e.,  $k_{nj}^i > k_{nj'}^i$  for  $i \in \{h, a\}$  when  $j > j'$ ) to reflect that higher quality space is more expensive to build.<sup>16</sup> The land market clearing equation pins down the rental price in location  $n$ :

$$K_n = \sum_j \left( k_{nj}^h H_{nj}^h + k_{nj}^a H_{nj}^a \right). \quad (8)$$

There is free entry of developers into each segment  $(n, j)$ . Developers pay a fixed cost  $f_{nj}$  to develop a differentiated neighborhood  $r$  of type  $(n, j)$ . The number  $N_{nj}$  of neighborhoods of type  $(n, j)$  adjusts so that:

$$\pi_{nj}^h + \pi_{nj}^a - f_{nj} = 0, \quad (9)$$

where  $\pi_{nj}^i$  for  $i = h, a$  is the operating profit of a developer in neighborhood type  $(n, j)$  and activity  $i$ .

### 3.1.4 Provision of Public Amenities

Public amenities in location  $n$  – like parks, schools, or fighting crime – are in part exogeneous, and in part financed by local governments. Specifically, they respond to taxes according to:

$$A_n = A_n^o (G_n)^\Omega, \quad (10)$$

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<sup>15</sup>We allow for rents made in this economy to be distributed to local inhabitants ex post, through a portfolio with ownership shares  $\chi(w)$  that may depend on income  $w$ , as mentioned above.

<sup>16</sup>Land is understood here to be equipped land. The model can be easily extended to feature a production function for housing that relies on land and capital. Given that the calibration relies on matching the resulting housing supply elasticities between downtown and the suburbs, this extension does not affect our results.

where  $A_n^o$  is the exogenous part of amenities,  $G_n$  is local government spending, and  $\Omega$  is the supply elasticity of public amenities. Government spending is equal to taxes levied in the location  $n$ :

$$G_n = \int L(w) \left( \sum_j \lambda_{nj}(w) \right) T_n(w) dw. \quad (11)$$

## 3.2 Equilibrium

### 3.2.1 Households

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  $\lambda_{nj}$  is the probability that the neighborhood chosen is of type  $(n, j)$  and  $\lambda_{r|nj}$  indicates the conditional probability of choosing  $r$  among other  $(n, j)$  choices. In equilibrium, all neighborhoods are symmetric within type, so that  $\lambda_{r|nj}(w) = \frac{1}{N_{nj}}$ . Given the structure of the idiosyncratic preference shocks, these shares are:

$$\lambda_{r|nj}(w) = \frac{V_r(w)^\gamma}{\sum_{r' \in \mathcal{B}(nj)} V_{r'}(w)^\gamma} \quad \text{and} \quad \lambda_{nj}(w) = \frac{V_{nj}^\rho(w)}{\sum_{n', j'} V_{n', j'}^\rho(w)}, \quad (12)$$

where  $V_r(w)$  is the inclusive value of neighborhood  $r$  and  $V_{nj}$  is the inclusive value of all neighborhoods of type  $(n, j)$ :

$$V_r(w) = (m_n(w) - p_r^h) (P_r^a)^{-\alpha} A_{n(r)} Q_{j(r)}, \quad (13)$$

$$V_{nj}(w) = \left( \sum_{r' \in \mathcal{B}(nj)} V_{r'}(w)^\gamma \right)^{\frac{1}{\gamma}} = A_n Q_j N_{nj}^{\frac{1}{\gamma}} (P_{nj}^a)^{-\alpha} (m_n(w) - p_{nj}^h). \quad (14)$$

In turn, the average welfare of households with wage  $w$  is given by:

$$V(w) = \left( \sum_{n', j'} V_{n', j'}^\rho(w) \right)^{1/\rho}. \quad (15)$$

### 3.2.2 Developers

The pricing and entry behaviors of developers are provided in detail in Appendix B.1. Given CES demand for amenities, developers price amenities at a constant markup over marginal costs, i.e.:

$$p_{nj}^a = \frac{\sigma}{\sigma - 1} k_{nj}^a R_n. \quad (16)$$

They also price housing by maximizing their profits on the residential market. Given the unit housing demand assumption, using (6) and (12) leads to the following housing pricing formula:

$$p_{nj}^h = \frac{\gamma}{\gamma + 1} k_{nj}^h R_n + \frac{1}{\gamma + 1} \mathcal{I}_{nj}(p_{nj}^h), \quad (17)$$



where  $\mathcal{I}_{nj}(\cdot)$  is a measure of demand for a neighborhood of type  $(n, j)$ .<sup>17</sup> These prices and land rents pin down developers' operating profits. Under free entry, the number of developers entering location  $n$  at quality  $j$  is:

$$N_{nj} = \frac{1}{f_{nj}} \left[ \int_w \lambda_{nj}(w) \left( p_{nj}^h - k_{nj}^h R_n + \frac{\alpha}{\sigma} (w - p_{nj}^h) \right) dL(w) \right]. \quad (18)$$

An equilibrium of the model is a distribution of location choices by income  $\lambda_{nj}(w)$ , housing and amenity prices  $p_{nj}^h$ , land rents  $R_{nj}$ , and number of neighborhoods  $N_{nj}$  such that (i) households maximize their utility; (ii) developers and landowners maximize profits; (iii) developers make zero profits; (iv) local government budget is balanced; and (v) the markets for land, private amenities, and housing clear. Given the structure of the model, it is straightforward to show that an equilibrium of the model can be expressed in terms of changes relative to another reference equilibrium, with different primitives (e.g., with a different city-level distribution of income or different exogenous levels of amenities). We detail this approach and leverage it in section 5.1.<sup>18</sup>

This concludes the description of the framework. We now turn to discussing the key assumptions and properties of the model.

### 3.3 Discussion

Our key object of interest is the heterogeneous choice of residence, within a city, made by households with different incomes. In the model, all relevant heterogeneity in within-city locations occurs at the level of what we call a *neighborhood*. The setup of the model implies that different neighborhoods are characterized by two composite elements that are sufficient to pin down sorting patterns and welfare (see summary equations (12)-(14)):<sup>19</sup>

1. heterogeneous levels of amenities summarized by:  $B_{nj} \equiv (1 - \tau_n) A_{nj} Q_{nj} N_{nj}^{1/\gamma} (P_{nj}^a)^{-\alpha}$ ;
2. heterogeneous cost of living, driven both by commuting costs and housing prices:  $p_{nj} \equiv \frac{p_{nj}^h}{1 - \tau_{nj}}$ .

We first describe consumption and sorting patterns of heterogeneous households conditional on  $\{B_{nj}, p_{nj}\}$ . We then turn to discussing how neighborhood characteristics  $\{B_{nj}, p_{nj}\}$  are impacted by shocks to the city.

#### 3.3.1 Patterns of Consumption and Sorting by Income

**Housing consumption** Neighborhoods differ in the size and quality of their housing units, driven by the quality shifter  $k_{nj}^h$  that in turn impacts housing prices  $p_{nj}^h$  (see equation (17)), but housing is

<sup>17</sup>Specifically,  $\mathcal{I}_{nj}(p) = \frac{\int_w \Lambda_{nj}(p, w) [(1 - \tau_n)w + \chi_n(w)] dL(w)}{\int_w \Lambda_{nj}(p, w) dL(w)}$  with  $\Lambda_{nj}(p, w) = \frac{\lambda_{nj,r}(w) L(w)}{[(1 - \tau_n)w + \chi_n(w) - p]}$ .

<sup>18</sup>The model may give rise to multiple equilibria if the agglomeration effects at play are too strong compared to the dispersion forces, driven by the housing supply (in-)elasticity  $\epsilon_n$  and the idiosyncratic preference for locations-quality types driven by  $\rho$ . Around our estimated 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.

<sup>19</sup>For ease of exposition, we ignore local taxes and transfers.

homogeneous within a neighborhood. In the model, variation in housing spending patterns across income groups arises solely from variation in the fraction of households who choose neighborhoods of various types. This is seen from reformulating equation (12) in terms of the quality shifter  $B_{nj}$  and cost of living  $p_{nj}$  terms defined above:

$$\lambda_{nj}(w) = \frac{B_{nj}(w - p_{nj})^\rho}{V(w)^\rho}. \quad (19)$$

Denoting with  $\bar{p}(w) \equiv \sum_{n,j} \lambda_{nj}(w) p_{nj}$  expenditure on housing for households of income  $w$ , the income elasticity of housing consumption in the model is:

$$\frac{\partial \log \bar{p}(w)}{\partial \log w} = \rho \frac{w}{\bar{p}(w)} \sum_{n,j} \left( p_{nj}^h - \bar{p}(w) \right) \lambda_{nj}(w) \nu_{nj}(w), \quad (20)$$

where  $\nu_{nj}(w) = (w - p_{nj})^{-1}$  is a measure of cost of living relative to income, which increases with cost of living in  $(n, j)$  and decreases with income  $w$ . We show in Appendix B that this income elasticity is strictly positive as soon as the city has more than one type of neighborhoods to choose from, and would be trivially 0 otherwise. Meanwhile, the housing expenditure share decreases with income, as in the data. We show in Figure 6 that our quantified model captures the empirical fact that, within cities, the expenditure share on housing decreases, as a function of income.<sup>20</sup>

**Amenity Consumption** To capture the empirically relevant feature that households of different incomes consume a systematically different bundles of urban amenities, we embed frictions to traveling to amenities that depend on (i) where household live, as controlled by  $n$ , and (ii) the quality of the neighborhood where they live, as controlled by  $j$  (see equations (3) and (4)). This modeling tool reflects the fact that amenity consumption may depend on income not only quantitatively – as captured by that our preference function, through which amenity consumption is a luxury good – but also qualitatively: conditional on expenditure on amenities, poorer households tend to consume lower quality urban amenities.

**Spatial Sorting** Next, we explore spatial sorting patterns by income. Expressing the relative propensity to live in various neighborhood types by income as:

$$\frac{\lambda_{nj}(w)/\lambda_{nj}(w')}{\lambda_{n'j'}(w)/\lambda_{n'j'}(w')} = \left[ \frac{(w - p_{nj}) / (w' - p_{nj})}{(w - p_{n'j'}) / (w' - p_{n'j'})} \right]^\rho, \quad (21)$$

---

<sup>20</sup>In contrast to what we do here, the literature in economic geography frequently models housing consumption assuming Cobb-Douglas preferences, which deliver a constant expenditure share of housing. This assumption is well suited for models of location choice across cities with homogeneous workers, as shown by Davis and Ortalo-Magne (2011). They compute, city by city, the distribution across households of expenditure on housing divided by income, and show that the *median* of this distribution is stable *across* cities. In contrast, our model focuses on within-city sorting and on heterogeneous incomes. We show that our model assumption is better suited to capture the empirical fact that the expenditure share on housing decreases with income.

we see that  $\frac{\partial^2 \log \lambda_{nj}(w)}{\partial w \partial p_{nj}} = \rho / (w - p_{nj})^2 > 0$ . This derivation implies, first, that higher incomes sort more into high cost-of-living neighborhoods. Higher income households have a higher willingness to pay the high equilibrium price to live in high quality neighborhoods. Second,  $\rho$  governs the strength of nonhomotheticity in location choice. The higher is  $\rho$ , the more richer households are over-represented in expensive neighborhoods, all else equal. This makes  $\rho$  an important parameter to estimate in our quantitative exercise, as it governs the extent of spatial sorting by income in the model.

A key stylized fact our framework aims to capture is the U-shaped propensity to live downtown, by income. To see how this property can arise from our model, note that the share of households living in each type of neighborhood  $\lambda_{nj}(w)$  varies with income as follows:

$$\frac{\partial \log \lambda_{nj}(w)}{\partial w} = \rho [\nu_{nj}(w) - \bar{\nu}(w)], \quad (22)$$

where  $\nu_{nj}(w)$  was defined above and  $\bar{\nu}(w) = \sum_{n,j} \lambda_{nj}(w) \nu_{nj}(w)$  is the average cost of living over all neighborhoods chosen by income  $w$ . Equation (22) implies that the share of households living in a neighborhood  $(n, j)$  rises with income if and only if neighborhoods  $(n, j)$  are costlier than the average neighborhood where households with income  $w$  live. In particular, it implies that the share of households living in the most expensive neighborhood in the city increases with income, and the share of households living in the least costly neighborhood of the city decreases with income.

Our object of focus is not directly  $\lambda_{nj}(w)$ , but rather the share of households who live downtown at each level of income,  $\lambda_D(w) = \sum_j \lambda_{Dj}(w)$ . We focus on the specification that we retain in quantification, with two quality tiers  $j = \{L, H\}$  – hence 4 quality neighborhood options in the city – where  $L$  and  $H$  indicate low and high quality neighborhoods, respectively. In this case, we have:

$$\frac{d \log \lambda_D(w)}{dw} = \lambda_{L|D}(w) \frac{d \log \lambda_{DL}(w)}{dw} + \lambda_{H|D}(w) \frac{d \log \lambda_{DH}(w)}{dw}, \quad (23)$$

where  $\lambda_{j|D}(w)$  is the probability a household at income  $w$  lives in quality  $j$  conditional on residing downtown. Equations (22) and (23) imply that when the following condition holds:

$$\frac{p_{DL}}{1 - \tau_D} < \frac{p_{SL}}{1 - \tau_S} < \frac{p_{SH}}{1 - \tau_S} < \frac{p_{DH}}{1 - \tau_D}, \quad (24)$$

the patterns of spatial sorting downtown are a U-shaped function of income. To see this, note that  $\frac{d \log \lambda_{DL}(w)}{dw} < 0$  while  $\frac{d \log \lambda_{DH}(w)}{dw} > 0$ , by the argument made above. Similar derivations show that, given the ordering of cost of living in equation (24),  $\lambda_{L|D}(w)$  decreases with income while  $\lambda_{H|D}(w)$  increases with income. Taken together, these comparative statics deliver the result that the very rich and the very poor are both overrepresented downtown.

Taking stock, the model is able to match the U-shape location choice patterns downtown if low quality downtown neighborhoods offer the lowest cost option while high quality neighborhoods downtown are the most expensive option, in a model with two quality tiers. Costs of living in low quality neighborhoods downtown will be low if housing prices are relatively low in  $DL$  and/or

commuting costs are lower downtown than in the suburbs ( $\tau_D < \tau_S$ ). Housing prices (defined in equation (17)) will be low if land rents ( $R_D$ ) are low or equipped land requirements ( $k_{DL}^h$ ) are low, reflecting small and low quality housing units. In contrast, costs of living in high quality neighborhoods downtown will tend to be high, in spite of low commuting costs and land rents ( $R_D$ ), if equipped land requirements ( $k_{DH}^h$ ) are high, reflecting large and high quality housing units.

### 3.3.2 Impact of a shock to the income distribution

We next discuss how a given shock to the city leads to changes in neighborhood characteristics  $\{B_{nj}, p_{nj}\}$  that govern sorting and welfare. To fix ideas, we focus on our main shock of interest: an increase in the relative number of high-income households.

**Main Mechanism** The key sorting mechanism in the model in response to a shift in the income distribution acts through changes in housing prices, themselves driven by changes in land prices (equation (17)). Land markets are segmented by location  $n$ . Within each location  $n$  all neighborhood qualities  $j$  compete for scarce land. Given the land market clearing condition in  $n$  (equations (7) and (8)), a demand shock for housing in high quality neighborhoods transmits to the entire downtown area – including in low quality neighborhoods – through changes in land prices. The intensity of the price increase is driven in particular by the housing supply elasticities  $\epsilon_n$ , with a more inelastic supply downtown leading to steeper price increases there. Given the impact of neighborhood prices on sorting, higher prices downtown tend to increase the share of high income residents and decrease the share of low income residents there.

**Amplification** This sorting effect is reinforced by an intuitive amplification mechanism: increased demand for high quality neighborhoods downtown drives entry of new high quality developers, increasing their supply  $N_{DH}$  (equation (18)). Our model thus provides a theoretical mechanism for the gentrification of downtowns: the extensive margin of neighborhoods of various qualities in the city is endogenous. This change in supply naturally feeds back into sorting patterns, as follows. Households have idiosyncratic preferences for horizontally differentiated neighborhood within a  $(n, j)$  type (see equations (1), (2), and (6)), which embeds a love of variety effect. The more options to choose from, the better the quality of the match between households and the neighborhood they choose. Through this love of variety effect, an increase in the supply of neighborhoods demanded downtown by higher incomes increases the perceived quality of this type of neighborhoods, further fueling the sorting of higher incomes downtown, and reinforcing the price mechanism described above. The intensity of this feedback loop depends on the elasticity of substitution between neighborhoods where to live,  $\gamma$ . A parallel feedback loop operates through the love of variety in the consumption of amenities offered in same type of neighborhood where a household resides and is governed by the elasticity of substitution between neighborhoods in which to consume,  $\sigma$  (see equation (A.3)).

**Mitigators** On the other hand, it is arguably the case that richer households moving into downtown benefit households of all incomes. The model contains three intuitive mechanisms through which we think this may happen. These mechanisms mitigate the main force we just described. First, we assume that public amenities  $A_n$  are determined by location  $n$  but are common across neighborhoods of varying quality  $j$  (equation (6)). As the tax base downtown increases, government revenues  $G_n$  increases, which raises  $A_n$  for all households downtown (equations (10) and (11)).

Second, we allow households to travel to amenities (e.g., restaurants and entertainment options) outside of one’s own neighborhood type in the model, as we observe in the data. Through this channel, households benefit from an increased supply of urban amenities outside of their own type of neighborhood, mitigating our main sorting mechanism. The extent of this effect, relative to the amplification effect from the love of variety in consumption of amenities in one’s own neighborhood type, will be disciplined in Section 4 with data on trips taken between home and amenities throughout the city.

Finally, we allow residents to own part of the housing stock. As land prices in downtown neighborhoods increase, incumbent homeowners receive a capital gain on their housing stock making them better off compared to renters. The extent of this mitigating force is governed by  $\chi_n(\omega)$  which we discipline empirically by matching homeownership rates by income in different locations.

These three mechanisms mitigate the adverse effect of an increase in income inequality on welfare inequality, while endogenous neighborhood supply amplify the baseline price effect. The net effect of increased incomes of the rich on welfare inequality through spatial sorting is therefore ambiguous. We turn to its quantification next.

## 4 Quantification of the Model

In this section, we explain how we take the model to the data (section 4.1). We also provide empirical evidence in support of the sorting mechanism in the model and estimate our key sorting parameter  $\rho$  (section 4.2). Finally, we estimate and calibrate the remaining key model elasticities and quantify the model (section 4.3). Additional details on all data sources and variable construction used in this section can be found in online Appendix A, respectively.

### 4.1 Mapping Model to Data

To take our model to the data, we must characterize neighborhoods empirically. Throughout, 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.

We also specify the number of quality layers that characterize neighborhoods in the model. We retain a parsimonious specification with two layers, *High* and *Low* quality ( $j \in \{H, L\}$ ), leading to four neighborhood types in the city. We show in section 4.3.5 that this level of heterogeneity is sufficient to capture salient features of the data, such as the U-shape pattern of spatial sorting

by income, and patterns of housing expenditure by income. We pursue two different 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 top 100 CBSAs are respectively classified as high quality in 1990, 2000 and 2014.

For robustness, we alternatively define high quality neighborhoods based on the quality of amenities that they provide. We measure the quality of local amenities – specifically, restaurants – leveraging novel smartphone movement data (Couture et al., Work in Progress). The smartphone data aggregates GPS geolocations from the locational services of multiple applications used by smartphone devices. It allows us to identify 600 million visits to the 100 largest restaurant chains from 2016 to 2018. For each of these chains, 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, only considering trips that start from a person’s home and controlling for their proximity to chain establishments. A given chain receives a quality index larger than 1 if, all else equal, people in high income block groups are more likely to visit that chain than the average person.<sup>21</sup> To measure neighborhood-level restaurant quality, we combine this index with the geocoded location of establishments from these chains in 2000 and 2012 from the National Establishment Time-Series (NETS). We define a census tract as high quality (H) if average chain restaurant has quality higher than 1.1. We choose this cut-off to match the high quality tract share in 2014 under our main college share definition above. Under this cut-off, 13 and 34 percent of census tracts with non-missing quality in the top 100 CBSAs are classified as high quality in 2000 and 2012, respectively.

Despite these two methods being conceptually different and having different strengths and weaknesses, we find similar estimates of many of our key results across them. In what follows, we present all our results for the college share quality measure. In Appendix C.3, we replicate our main estimation and counterfactual welfare results for the restaurant quality measure.

In what follows, we study the share of households at each income level  $w$  that reside in each area-quality ( $n \in \{D, S\}; j \in \{H, L\}$ ) pair within each CBSA  $c$ :  $\lambda(w_m)_{nj,c}$ . We drop all households with income smaller than \$25,000 per year. Given the presence of public housing, such households are not well represented by the model.<sup>22</sup> We measure house prices using Zillow’s 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

<sup>21</sup>We define high income blocks as those blocks with median resident income higher than \$100,000. 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).

<sup>22</sup>For instance, data from the department of Housing and Urban Development shows that in our downtowns in 2014, about 30 percent of households earning between \$5,000 and \$14,000 in 1999 dollars lived in subsidized housing.

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 to minimize the impact of transitory fluctuations on our results.<sup>23</sup> Specifically, we compute  $p_{nj,c}^h$  as the annual user cost of a median priced 2 bedroom house in area-quality pair  $(n, j)$  within CBSA  $c$ .<sup>24</sup> We convert housing prices and income to 1999 dollars using the urban CPI.<sup>25</sup>

## 4.2 Evidence on Income-based Sorting and $\rho$ Estimation

In this section, we validate the key sorting mechanism in the model. Specifically, we show how CBSA-level income shocks generate different spatial sorting responses for the rich and the poor. This same cross-CBSA variation allows us to identify  $\rho$ , the elasticity of substitution between neighborhoods of different types. Given the functional form assumption of the model,  $\rho$  also governs the strength of nonhomotheticity in neighborhood choice, and it is the key parameter linking shifts in the income distribution to changes in urban spatial sorting.

**Model Prediction on Sorting** To guide our empirical work on spatial sorting by income, we start with equation (19). This equation provides a mapping between location choices and household income. In what follows, our reduced form empirical work and our formal estimation of  $\rho$  exploits variation in sorting patterns over time and across CBSAs. Interpreting different time periods as different equilibria of the model, we take log differences of (19) across two time periods and add a CBSA-subscript  $c$ :

$$\Delta \ln \lambda_{nj,c}(w) = \Delta \ln Z_c(w) + \Delta \ln B_{nj,c} + \Delta \ln(w - p_{nj,c}^h)^\rho, \quad (25)$$

where  $Z_c = -V_c^\rho$ . Given that  $\Delta \ln B_{nj,c}$  and  $\Delta \ln Z_c(w)$  are unobservable, we difference (25) in two additional ways. First, we difference the change in the log share of households with income  $w$  living downtown in quality  $j$  ( $\Delta \ln \lambda_{Dj,c}(w)$ ) from that same change in the suburbs ( $\Delta \ln \lambda_{Sj,c}(w)$ ). Doing so differences out, for each income group, any common factors at the CBSA level (i.e.,  $\Delta \ln Z_c(w)$ ). Second, we take differences across pairs of households earning different incomes,  $w_m$  and  $w_{m'}$ , in their downtown-vs.-suburbs change in location choices within each quality  $j$  in a CBSA. Doing so differences out any common CBSA-specific area quality fixed effects (i.e.,  $\Delta \ln B_{nj,c}$ ). The resulting triple-difference estimating equation is:

<sup>23</sup>Given the data limitations, we match 1990 to 2014 changes in residential location with 1996-98 to 2012-16 changes in house prices. House prices were relatively flat over the 1990 to 1995 period suggesting that this measurement issue unlikely to bias our results in any meaningful way.

<sup>24</sup>The annual user cost of housing is 4.7 percent of house prices in 2000, and 4.6 percent in 2014 according to data from the Lincoln Institute of Land Policy.

<sup>25</sup>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.



$$\Delta \ln \left( \frac{\lambda_{Dj,c}(w_m)}{\lambda_{Sj,c}(w_m)} \right) - \Delta \ln \left( \frac{\lambda_{Dj,c}(w_{m'})}{\lambda_{Sj,c}(w_{m'})} \right) = \rho \left[ \Delta \ln \left( \frac{w_m - p_{Dj,c}^h}{w_m - p_{Sj,c}^h} \right) - \Delta \ln \left( \frac{w_{m'} - p_{Dj,c}^h}{w_{m'} - p_{Sj,c}^h} \right) \right] + \epsilon_{j,c}(w_m, w_{m'}). \quad (26)$$

Equation (26) serves three purposes. First, it motivates a reduced-form test of the key sorting mechanism in the model. In the model, non-homothetic spatial sorting comes from the unit housing requirement. All households have the same perception of the relative quality of residential neighborhoods, but if  $\rho > 0$ , higher income household demand is less elastic with respect to house prices, so they are more likely to live in expensive neighborhoods. Below, we estimate equation (26) in a two stage IV procedure to provide reduced-form evidence for that sorting mechanism. In particular, we show that a large CBSA income shock raises house prices downtown more than in the suburbs (first-stage), and this shock to relative house prices causes high income households to re-sort downtown. Second, equation (26) allows us to estimate  $\rho$ . We discuss our identification strategy below. Third, estimating the differential responses to CBSA shocks across income pairs allows us to test the strong functional form implications of our model. Specifically, we can also estimate equation (26) pair-by-pair and show that  $\rho$  does not vary systematically with  $w_m$  and  $w_{m'}$ .

**Identification Strategy** We lack micro panel data, so we cannot observe how the location choice of a given household changes as their income  $w$  changes. Instead, we identify our key sorting mechanism using repeated cross sectional variation, exploiting changes in *net disposable income* – wage income net of housing costs – stemming exclusively from changes in  $p_{nj,c}^h$ , the cost of housing in a given area. We measure  $\lambda(w_m)_{nj,c}$  with the change in share of census households at each income-bracket  $m$  that reside in each area-quality ( $n \in D, S; j \in H, L$ ) pair within each CBSA  $c$ , measured in 1990 and 2014, as in section 2. For each constant CPI-adjusted census bracket,  $w_m$  is the median household income within that bracket. We calculate this median using 2000 IPUMS micro data from the 100 largest CBSAs, and hold it fixed over time and across CBSAs. After dropping households with incomes below \$25,000, we are left with 10 income brackets.

Taking the model literally, there is no error term in equation (26). In the empirical exercise, however, both data mismeasurement and model misspecification can bias our OLS estimates. There is likely attenuation bias from classical measurement error in our measure of 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 commute time to high-skilled jobs, or to access amenities above and beyond what is already captured by the model’s quality bins. 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 (26) 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 identification strategy comes

from the model: as CBSA residents are hit with a plausibly 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.<sup>26</sup>

**Reduced Form Evidence of Sorting Mechanism** The first-stage and reduced-form of equation (26) provide evidence for the key sorting mechanism of the model. The first stage of our IV estimation comes from the Bartik income shock raising house prices more in downtown areas relative to suburban areas within a given quality level. This relative house price variation is what drives the variation in the independent variable in equation (26). 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. Consistent with the model, within each quality tier a more positive income shock raises housing prices downtown relative to the suburbs.

The structural equation (26) has a useful reduced-form representation, showing how individuals in different income brackets change their residential choices in response to a CBSA level Bartik shock pooling over quality tiers:

$$\Delta \ln \left( \frac{\lambda_{D,c}(w)/\lambda_{D,c}}{\lambda_{S,c}(w)/\lambda_{S,c}} \right) = \mu_w^0 + \mu_w^1 \widehat{\Delta \text{Income}_c}^{\text{Bartik}} + \epsilon_c(w). \quad (27)$$

To build intuition, we estimate equation (27) separately for each of our 10 bracketed income groups.  $\mu_w^1 < 0$  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. The right panel of Figure 4 reports estimates from equation (27), along with their 95 percent confidence bounds, where all changes in residential choice are defined over the 1990 to 2014 period. We find that a CBSA income shock causes differential spatial sorting responses from the rich vs. the poor that are consistent with the model predictions. Recall that the model predicts that rich households are more likely than poor households to move downtown in response to relative price increase downtown. This is indeed what we find. For all the top five income groups,  $\mu_w > 0$  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 were unrelated to income,  $\mu_w^1$  would be zero for all income groups, and our IV estimate of  $\rho$  would be zero. To summarize, Figure 4 provides reduced form evidence consistent with the key sorting

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<sup>26</sup>With respect to our estimation of (26), we have 45 distinct potential pairs of  $w_m$  and  $w_{m'}$  for each quality tier  $j$ . We pool our estimation across income group pairs and 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. We also remove any observation with  $w - p_{cnj}^h < 0$  (1.4% of our sample). We then censor the top and bottom 1 percent of  $\ln \left( \frac{w - p_{cDj}^h}{w - p_{cSj}^h} \right)$  in each year.

Table 1: Estimation of elasticity  $\rho$ 

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\rho}$	2.34 (0.27)	3.07 (0.63)	2.69 (0.69)	2.47 (0.75)	3.21 (0.75)	3.96 (0.65)
Instrument	None	Base	Omit Top Urban Industries	Omit FIRE Industries	Omit Hi-Tech Industries	Omit Manufacturing Industries
$R^2$	0.24					
KP F-Stat		23.1	16.7	14.8	16.5	14.9
Obs	5,586	5,586	5,586	5,586	5,586	5,586

Notes: This table shows estimates from equation (26). Data from 100 largest CBSAs in 1990 and 2014, neighborhood quality defined from education mix of residents. 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.

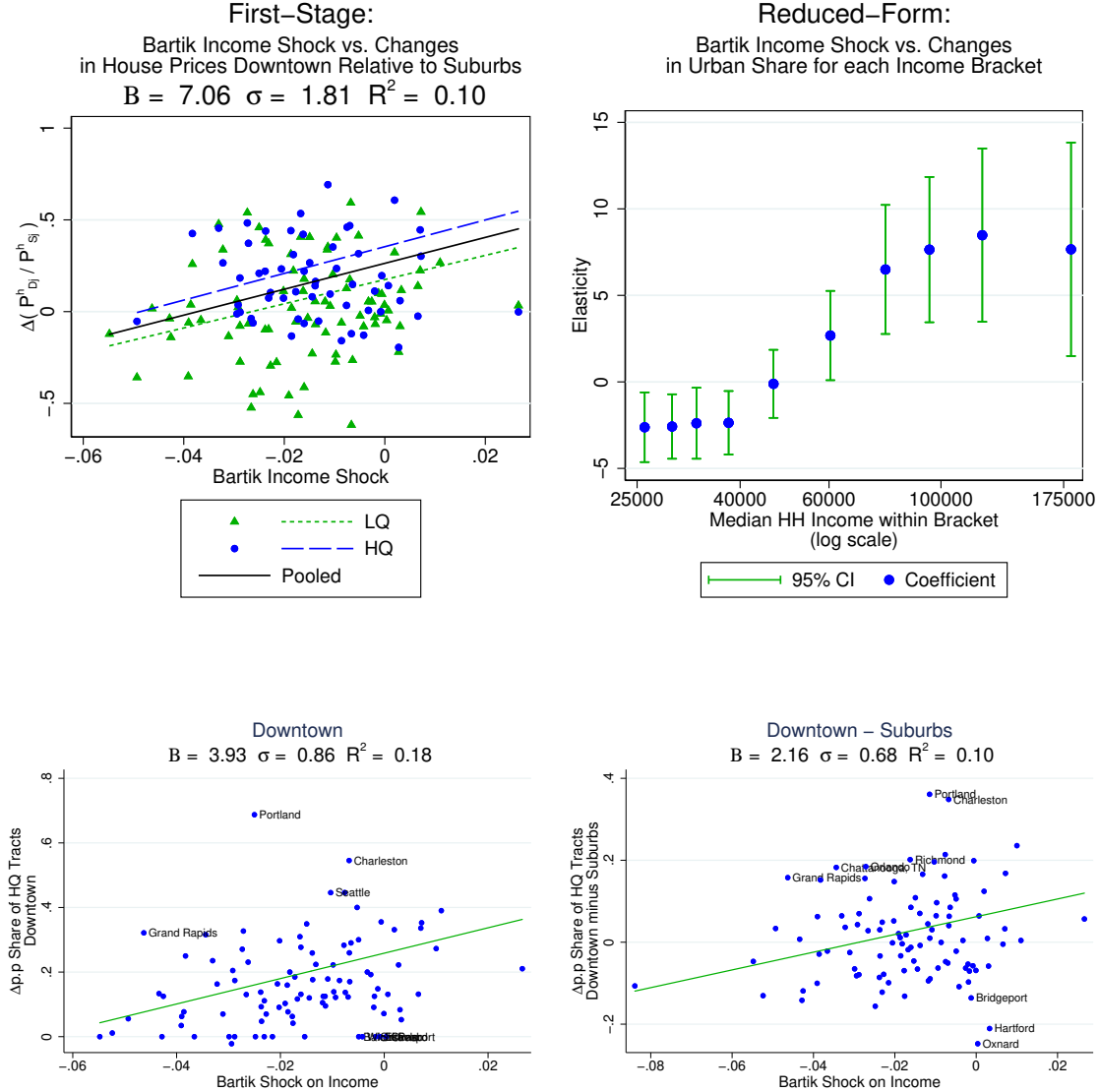
mechanism in our paper. As CBSA income increases, richer households are more likely to resort downtown relative to poorer households.

Before turning to our estimation of  $\rho$ , we highlight one additional reduced form relationship consistent with the predictions of our model. As highlighted in Section 3.3.2, a positive shock to the income distribution should raise the supply of high quality neighborhoods downtown. The bottom two panels of Figure 4 show evidence consistent with this prediction. Again exploiting cross-CBSA variation, we find that a large Bartik shock to CBSA-level income raises the share of high quality census tracts downtown, both in absolute terms (lower left panel) and *relative* to the suburbs (lower right panel). CBSAs with more income growth experienced more gentrification, and this gentrification occurred disproportionately downtown. The results in the bottom panels of Figure 4 use the education mix of residents to define high quality neighborhoods. The same relationships hold using our restaurant quality index to measure high quality neighborhoods. More generally, we find that restaurant quality rose faster downtown than in the suburbs during the 2000s, with the increase being significantly larger in CBSAs that experienced larger Bartik shocks.

**Estimation of  $\rho$**  Our base estimation results of  $\rho$  from equation (26) are reported in the first two columns of Table 1. 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 downweights 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 somewhat lower than our IV estimates (2.34 vs. 3.07). As noted above, measurement error in our house

Figure 4: Bartik Income Shock vs House Prices, Urban Shares, and Neighborhood Quality.



Note: On the top left, we plot changes in downtown relative to suburban house prices within each quality tier on the y-axis, against the Bartik income shock between 1990 and 2014 on the x-axis for each of the largest 100 CBSAs. The house price data is from the Zillow 2 Bedroom Index in 1996-1998 and 2012-2016. We drop the top and bottom 1% of  $\Delta(p_{Dj}^h / p_{Sj}^h)$  from the plot. On the top right, we show income bracket-specific coefficients, along with 95 percent confidence intervals, from equation (27) on the y-axis (regression of Bartik income shock on changes in normalized urban share from 1990 to 2014), against median income within each income bracket on the x-axis. In the lower panels, each observation is the one of the largest 100 CBSAs in 1990. On the x-axis is the Bartik income shock from 1990 to 2014. In the lower left panel, the y-axis shows change in the share of downtown tracts that are high quality. In the lower right panel, it shows change in the share of downtown tracts that are high quality minus the change in the share of suburban tracts that are high quality. A high quality tract is defined as having a college share of at least 40%. All panels show CBSA population weighted regression coefficients.

price measure could attenuate our OLS estimates of  $\rho$ . Second, our instrument has a strong first stage predictive power with a F-stat of 23. Finally, as a robustness exercise, we also estimated the regression 90 separate times—once for each possible  $w_m - w_{m'}$  income pair and for each quality level—instead of running the pooled regression (26). There, we find that our weighted median OLS and IV estimate of  $\rho$  in these 90 regressions are 2.09 and 4.05. Importantly, we find that these  $m - m'$ -pair specific  $\rho$  estimates are essentially uncorrelated with the difference in gross income between the  $w_m - w_{m'}$  pairs in the regression. This invariance is a 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.<sup>27</sup> 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 roughly the two standard deviation bands of our estimate in column 2.

We now discuss potential violations 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 1.<sup>28</sup> First, we define our Bartik shock excluding the top quartile of urbanized industries. Specifically, we remove industries in which residents of urban areas are most likely to work. We find little impact on our IV estimates (column 3). Second, we recompute our Bartik instrument leaving out technology (column 4), or finance, insurance, and real estate (FIRE) industries (column 5). These industries disproportionately employ higher skilled workers. We also recompute our Bartik instrument excluding manufacturing which disproportionately employs lower skilled workers (column 6). Our estimates of  $\rho$  using these alternate Bartiks as instruments are similar to our base results, ranging from 2.47 to 3.96. 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 (2018), and Su (2018b) who all find evidence that spatial resorting of jobs plays little role in explaining the recent movement of high income individuals downtown.

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<sup>27</sup>Appendix C.2 shows further robustness of our estimates of  $\rho$  to many different specifications, including different time periods, different house price measures, and different quality cut-offs. These robustness estimates are all within two standard error bands of our preferred estimate.

<sup>28</sup>Many of our robustness exercises are similar in spirit to those suggested by Goldsmith-Pinkham et al. (2018) and Borusyak et al. (2018). They suggest exploring the underlying industry variation that is driving the Bartik shock variation across regions.

Table 2: Key Model Parameters

Parameter	Description	Value	Source
<u>Non-homothecity</u>			
$\rho$	Between-type neighborhood substitution elasticity	3.0	Estimation
<u>Amplification</u>			
$\gamma$	Within-type neighborhood substitution elasticity	6.5	Assumption = $\sigma$
$\alpha$	Amenity share	0.15	CEX
$\sigma$	Substitution elasticity across neighborhoods	6.5	Estimation+literature
$\delta$	Distance elasticity across neighborhoods	0.2	Estimation+literature
<u>Land Price Responses</u>			
$\epsilon_D$	Downtown land supply elasticity	0.6	Calibrated to Saiz (2010)
$\epsilon_S$	Suburban land supply elasticity	1.3	Calibrated to Saiz (2010)
<u>Other</u>			
$T_D$	Downtown local property tax	0.2	IPUMS 2000
$T_S$	Suburban local property tax	0.3	IPUMS 2000
$\Omega$	Public amenity supply elasticity	0.05	Literature
$\tau_D^C$	Commute costs as share of labor income downtown	0.044	Authors' calculation
$\tau_S^C$	Commute costs as share of labor income suburbs	0.059	Authors' calculation

### 4.3 Additional Model Parametrization

We now detail how we parameterize and calibrate the remaining model parameters. We do this in two stages. In a first stage, we estimate key model elasticities and detail how we calibrate the other ones. In a second stage, we use method of moments to fully calibrate the remaining parameters of the model. The twelve parameters that we estimate or calibrate directly are listed in Table 2. The first is  $\rho$ , whose estimation we discussed above. The role played by these parameters in driving sorting patterns and welfare results are discussed in detail in Section 5.1.

#### 4.3.1 Estimation and Parametrization of Demand Parameters ( $\alpha$ , $\delta$ , $\sigma$ , and $\gamma$ )

We first discuss the estimation of the demand system for consumption of non-traded amenities. Specifically, we focus on estimating  $\delta$  and  $\sigma$  (defined in Equation (4)) using a model-implied gravity equation. We then parameterize  $\alpha$ , the share of net disposable income spent on urban amenities using expenditure data (see Equation (1)). Finally, we discuss our parametrizations of  $\gamma$ , the Frechet shape parameter that governs love of variety for neighborhoods of a given type (see Equation (2)). 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 neighborhood amenities that are luxurious, endogenous, locally-provided, and

subject to strong economies of density.

The model delivers the following gravity equation for amenity demand:

$$\ln \left( \frac{a_{rr'}}{a_{rr}} \right) = \overbrace{\ln \left( \frac{\beta_{rr'}^q}{\beta_{rr}^q} \right)}^{\beta_{j(r) \neq j(r')}} - \sigma \delta \ln \left( \frac{d_{rr'}}{d_{rr}} \right) - \overbrace{\sigma \ln \left( \frac{p_{r'}^a}{p_r^a} \right)}^{\theta_r + \theta_{r'}}. \quad (28)$$

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

$$\ln \left( \frac{a_{rr'}}{a_{rr}} \right) = \beta_{j(r) \neq j(r')} - \sigma \delta \ln \left( \frac{d_{rr'}}{d_{rr}} \right) + \theta_r + \theta_{r'} + \epsilon_{rr'}. \quad (29)$$

Estimating equation (29) 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 of 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 million devices for which we can identify a permanent home location. 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 individual to tracts available within their 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 specifications. 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. (2018).<sup>29</sup> The

<sup>29</sup>There is limited evidence on the strength of gravity in travel to consumption amenities. Agarwal et al. (2019) find much smaller distance elasticities of around -0.4 for different consumption sectors using credit card transaction data at the census place level. Davis et al. (Forthcoming) use Yelp restaurant reviews in New York City to find



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, in our data, high quality tract residents take over 80 percent of their amenity trips to other high quality tracts, and low quality tract residents also take over 80 percent of their amenity 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.

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

	All (1)	Home (2)	Weekend (3)	Home-Home (4)
$\hat{\delta}\sigma$	1.57 (0.00)	1.42 (0.00)	1.20 (0.00)	1.18 (0.00)
$\beta_{j(r) \neq j(r')}$	-0.14 (0.00)	-0.12 (0.00)	-0.10 (0.00)	-0.09 (0.00)
$R^2$	0.91	0.87	0.88	0.85
Obs	22,791,347	6,403,153	11,924,874	3,050,752

Notes: This table shows estimates from equation (29). From smartphone data on trips to non-tradable services in 100 largest CBSAs in 2016-2018, and neighborhood quality defined based on education mix of residents. 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.

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  $\delta$  that map into our model's parameter. As discussed in Appendix A.3, we find a  $\delta$  around 0.2 using data from Couture (2016). Given our estimate of  $\sigma\delta = 1.3$  from Table 3, we recover  $\sigma = 6.5$ , which reassuringly stands midway in the range of values from the existing literature. Atkin et al. (2018) find an elasticity of substitution of 3.9 for retail stores in Mexico, Einav et al. (2019) find 6.1 for offline stores in the U.S., Su (2018a) and Couture (2016) find 7.5 and 8.8 respectively for restaurants in the U.S. So we pick  $\delta = 0.2$  and  $\sigma = 6.5$  as our baseline parameters and explore robustness over the range of values above. Finally, because the land area of downtown and the suburbs change endogenously between equilibria in the model, the representative distance between two neighborhoods also changes. We make the geometric assumption that the representative distance  $d_{nn}$  changes with the square root of the area of  $n$ ,  $K_n$ , while  $d_{nn'}$  changes with the square root of  $K_n + K_{n'}$ .

review elasticity between -1.1 to -1.5 with respect to travel time from home, and Athey et al. (2018) find a distance elasticity of -1.4 using smartphone visits to restaurants in San Francisco. Our estimates here confirm the values in the latter two papers, using a much larger sample in individual, product, and geographic space, and solving an important identification problem by selecting trips whose sole purpose is amenity consumption.

We now parametrize  $\alpha$ , the share of expenditures on local amenities such as restaurants, bars, entertainment venues, gym memberships, and other personal services, net of housing costs and transportation to work. In the 2013 Consumer Expenditure Survey (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, in the model, the higher the value of  $\alpha$ , the larger the amplification in welfare differences between the rich and the poor due to the spatial sorting response following a rise in income inequality.

Finally, we parametrize  $\gamma$ , the elasticity of demand between neighborhoods.  $\gamma$  determines the size of gains from variety as the number of neighborhoods within an  $nj$  pair expands. Given the assumptions on idiosyncratic preference shocks,  $\rho$  must be lower than  $\gamma$ . This bounds  $\gamma$  from below. Existing research, on the other hand, suggests that there is less socio-economic diversity within census tracts than there is within retail establishments such as grocery stores and restaurants.<sup>30</sup> In the context of our model, this suggests that the substitution elasticity for residential amenities ( $\sigma$ ) is an upper bound for  $\gamma$ . Given the estimation above,  $\gamma$  lies between 3.0 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.

#### 4.3.2 Parametrization of Land Market Transmission Mechanism ( $\epsilon_S$ and $\epsilon_D$ )

In the model, the area-specific elasticity of land supply  $\epsilon_n$  is equivalent to an elasticity of housing supply. This elasticity determines the strength of an important welfare transmission mechanism through land markets. When housing supply is inelastic, an influx of rich households in high quality neighborhoods downtown raises rents for poor incumbent households in low quality neighborhoods. 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 MSAs to our CBSA 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 vary systematically, in equi-

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<sup>30</sup>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.

librium, with average household density ( $density_c$ ), and estimate the following log-linear regression of  $\epsilon_c$  on  $density_c$ :

$$\ln(\epsilon_c) = 1.97 - \frac{0.30}{(0.07)} \ln(density_c) + \xi_c^\epsilon, R^2 = 0.21 \quad (30)$$

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 (30) computed at typical density of  $D$  and  $S$  neighborhoods in the 100 largest CBSAs. We find  $\hat{\epsilon}_D = 0.60$  and  $\hat{\epsilon}_S = 1.33$ .<sup>31</sup> We use these values in our baseline calibration and test the sensitivity of our results to alternative parameter values.

#### 4.3.3 Parametrization of Commuting Costs ( $\tau_S$ and $\tau_D$ )

To estimate an area-specific commuting cost  $\tau_n$ , we use data on trip time to work by car from the geo-coded 2009 National Household Travel Survey. Specifically, the average daily commute time for drivers living in the suburbs of the top 100 CBSAs is 64 minutes, while for those living downtown it is 47 minutes. 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  $\tau_n = 0.5 \times \text{CommuteTime}_n / 9$ , or  $\tau_D = 0.044$  and  $\tau_S = 0.059$ .

#### 4.3.4 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 30% in the suburbs and 20% 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 households who own their home to reap the benefits of 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 transfer equals the average house price growth in the 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 (reported for each income decile in Table A.11). Empirically, this share of home ownership increases systematically with labor income. We 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

<sup>31</sup>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).

Table 4: Non-tradable Trip Shares

		Destination			
		DL	DH	SL	SH
Origin	DL	0.61	0.20	0.12	0.07
	DH	0.07	0.82	0.03	0.08
	SL	0.02	0.03	0.78	0.17
	SH	0.01	0.03	0.19	0.77

Notes: This table shows the share of trips observed in the smartphone data to non-tradable services in neighborhoods of each quality-area type. Each row shows the allocation of trips for individuals that live in neighborhoods of each quality-area type. Section 4.3.1 defines the non-tradable services included. Appendix A provides further details on this data source.

$OS(w)$  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.

#### 4.3.5 Second Stage: Method of Moments

**Calibration.** Armed with estimates for the key elasticities of the model, we conclude the calibration of the model using a method of moments. We set the remaining parameters to levels that, conditional on the model elasticities, 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 are targeted without being fully matched.

We exactly match the share of amenity expenditures of households living in a neighborhood of type  $(n, j)$  spent on amenities consumed in a neighborhood of type  $(m, k)$ ,  $S_{nj}^{mk}$ , predicted in equilibrium to levels that we directly read from the same smartphone data used in Section 4.3.1 above. We proxy for expenditure shares with trip shares reported in Table 4.

We target two further sets of moments that summarize key economic concepts we aim to capture: (i) the 1990 distribution, by income level, of the share of workers living downtown (i.e., the U-shape presented in stylized facts section 2.2), and (ii) the median 1990 house price by neighborhood type (as employed in the demand elasticity estimation and described in section 4.1). To accurately capture the location choices of higher-income households, we target the 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.<sup>32</sup>

<sup>32</sup>The IPUMS data identifies the locations of respondents at the PUMA (Public Use Microdata Area), each of

The method of moments allows us to back out two key composite model variables: (i) the price of housing in each location for each neighborhood type ( $p_{n,j}^h$ ), and (ii) the relative values of neighborhood amenities in each location for each neighborhood type ( $B_{n,j}$  defined in section 3.3) in the baseline equilibrium without separately identifying their individual components. Combined with the model elasticities, these two variables pin down the calibrated values for location choices  $\lambda_{n,j}(w)$ . 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  $\{\lambda_{n,j}(w), p_{n,j}^h, S_{nj}^{mk}\}$  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).

The identification of the model in this second stage is quite straightforward. First, it is clear how the house price moments directly inform the calibration of  $p_{n,j}^h$ . 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,  $B_{n,j}$ ). This is a quite intuitive revealed preference approach, applied to our nonhomothetic 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 set of location choice equations for all income levels  $w$ :

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

Given  $\tau_n$  and  $w$ , the calibration backs out the  $B_{n,j}$  and  $p_{n,j}^h$  that allow to match best the data distribution of location choices. The vectors  $B_{n,j}$  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. 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. Despite a sparse specification, the calibrated model is able to match the rich non-monotonic U-shape patterns of location choice by households of various incomes remarkably well. The model also 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,

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which contains approximately 100,000 individuals, relative to the 4,000 contained in each Census tract. To replicate the urban share for each fine income brackets, we first construct a cross-walk between PUMAs and our tract-based 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.

and calls for prices in high quality downtown neighborhood that are much higher than those in the data. Both in the model and the data though, the highest price option is downtown high quality neighborhoods.<sup>33</sup>

Figure 5: Calibration to 1990 Urban Shares and Neighborhood Prices

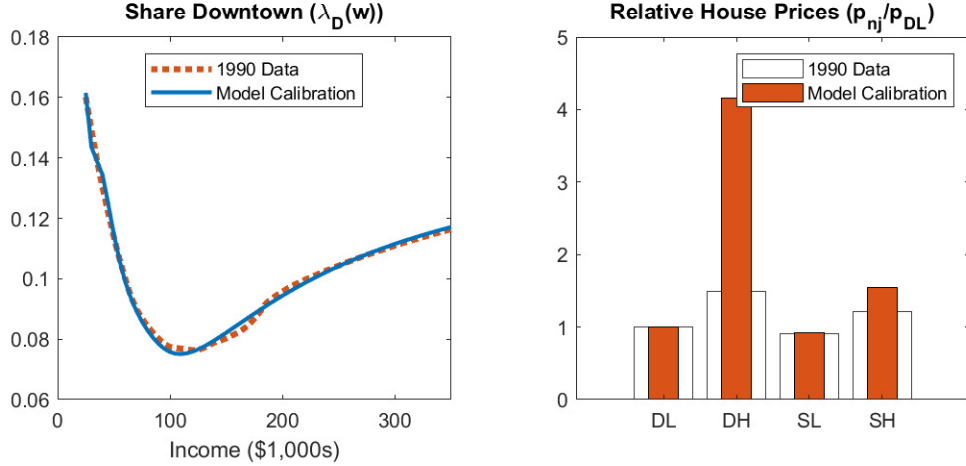


Figure 6 shows that the Engel curve in housing implied by the calibrated model does quite well at matching the relationship between housing expenditure and income in the 2014 CEX. In the model, the downward slope is driven by a strong declining pattern coming from the within-neighborhood effect, by which all households pay the same amount on housing irrespective of income, and an across-neighborhood sorting effect that mitigates it, as higher incomes sort into more expensive neighborhoods. At the limit, a model with a fully flexible range of neighborhood prices to choose from would be able to perfectly replicate the data patterns. We note that although the quantified model features only four neighborhood types, this heterogeneity goes a long way in replicating the downward sloping housing expenditure share from the data.

## 5 Quantitative Results

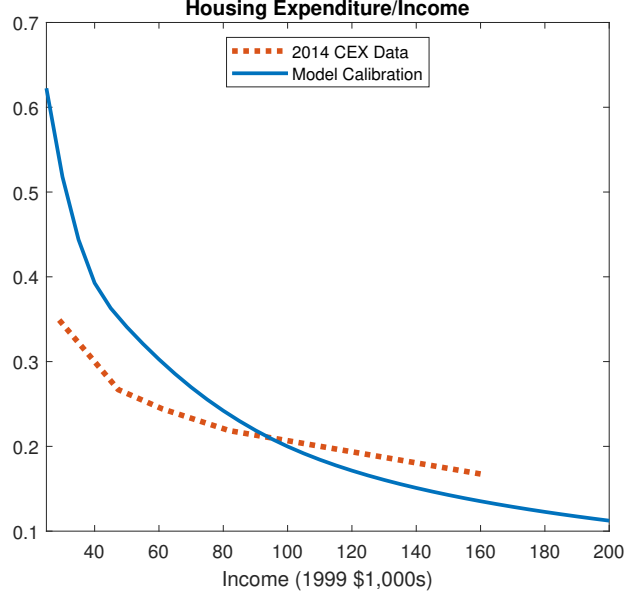
We now describe how we use the structure of the model and its 1990 calibration to compute counterfactual equilibria, before turning to analyzing our counterfactual exercises of interest.

### 5.1 Computing Counterfactuals

**Counterfactual Equilibria** To compute a counterfactual equilibrium of the model, we follow a logic similar to Dekle et al. (2007). Given the structure of the model, any counterfactual equilibrium – in particular one that relies on a different distribution of incomes  $L(w)$  in the city – can be computed with the following parameters on hand: (i) the model elasticities  $\{\rho, \gamma, \epsilon_n, \sigma, \delta, \alpha, \tau_n\}$ , as

<sup>33</sup>A calibration of the model with three quality layers, for example, produces similar welfare effects, without significant improvements in the fit of either the U-shape or relative price moments.

Figure 6: Housing Expenditure Share by Income



Notes: This figure shows both the model implied relationship between share of income allocated to housing (solid line) and the corresponding data from the Consumer Expenditure Survey in 2014 (dashed line). In published tables, the CEX reports average household income and average expenditure on shelter for each household income decile. The earliest year that the CEX reported average expenditures by income decile was 2014. The CEX line includes only eight data points, one for each decile where decile income exceeded \$25,000.

parameterized in section 4.3 and (ii) the calibrated values at the initial equilibrium for population in each neighborhood type, house prices, and amenity trip shares:  $\{\lambda_{n,j}(w), p_{n,j}^h, S_{nj}^{mk}\}$ . Details of the procedure as well as the corresponding set of equations are given in Appendix B.

**Welfare Measures** We measure changes in welfare between equilibria, at various levels of income, using compensating variation to get a dollar-denominated measure of change in well-being. It is related to the measure of utility from the model  $V(w)$ , defined in (15), as follows. Let  $i$  index percentiles in the income distribution. Let the subscript  $t$  index variables in the two equilibria that we compare:  $t = 2$  denotes the counterfactual equilibrium, and  $t = 1$  is the initial one. Then, compensating variation (CV) for households at percentile  $i$  of the income distribution is:

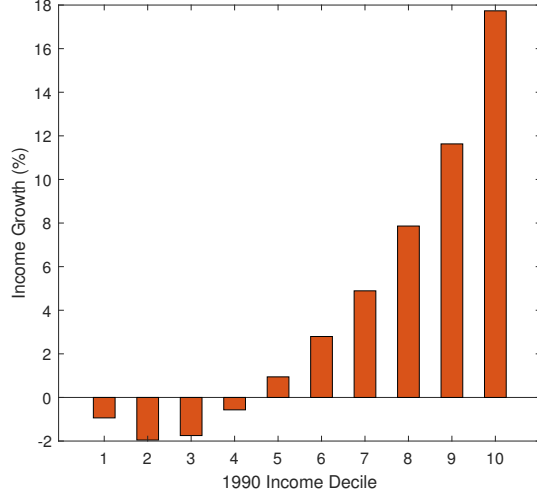
$$CV(i) = e(p_2, V_2(i)) - e(p_2, V_1(i)) = m_2(i) - m_2(V_2^{-1}(V_1(m_1(i)))) ,$$

where  $e(\cdot)$  is the expenditure function and  $m_t(i)$  is income of percentile  $i$  in equilibrium  $t$ .  $CV(i)$  is a measure of the gain in well-being of a household at percentile  $i$  of the income distribution, in  $t = 2$ -dollar equivalent prices.<sup>34</sup> It reflects changes in well-being associated with not only changing income, but also changing housing costs, and changes in endogenous amenity quality. We refer

<sup>34</sup>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 results.



Figure 7: Income Changes from 1990 to 2014



to CV as “welfare” or “well-being.” 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:

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

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

## 5.2 Baseline Counterfactual: Changing the Income Distribution

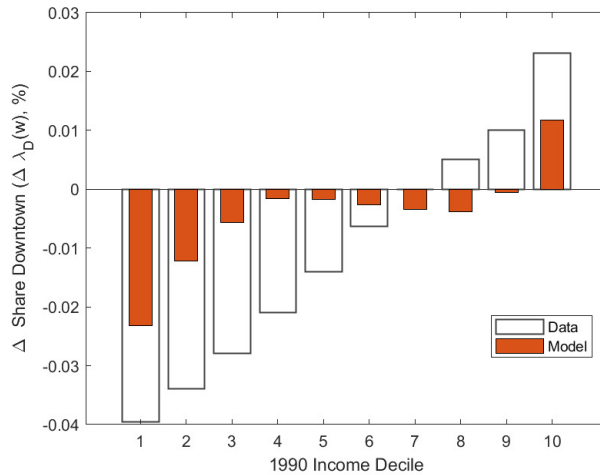
**Income Distribution Shock** Our main counterfactual isolates the impact of changes in the income distribution during the 1990 to 2014 period. This shock is summarized in Figure 7, which plots the percentage change in inflation-adjusted income earned within each income decile during the 1990 to 2014 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.

**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 8 shows that the 1990-2014 change in the 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.

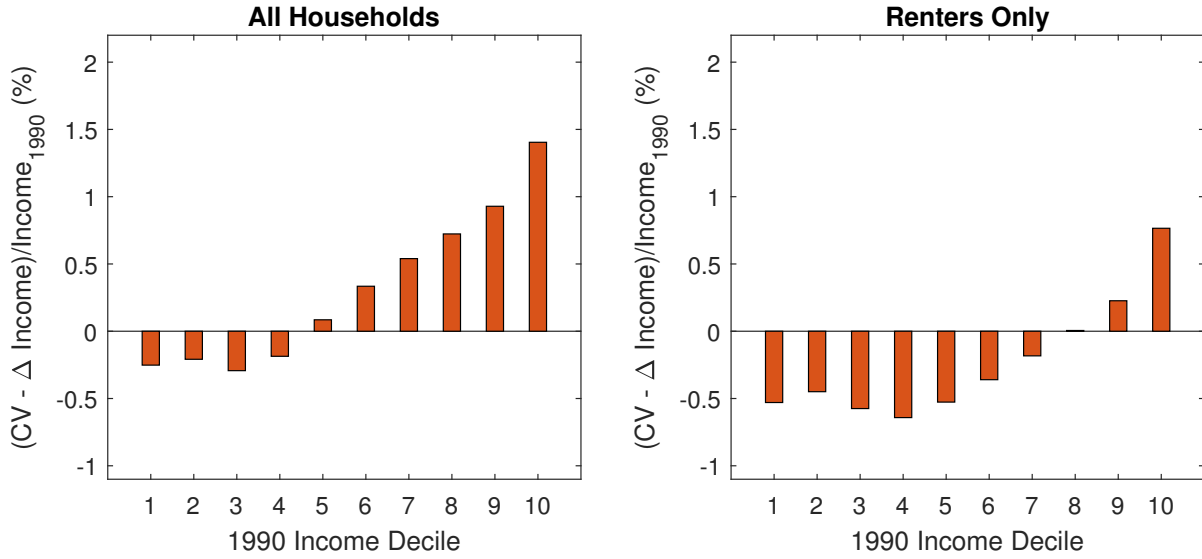
In response to the observed shift in the income distribution, top earners move into downtown, while households at lower income levels tend to move out. The predictive power of this shock alone on the change in spatial sorting patterns observed in the data is substantive. The shift in the income distribution explains about 60 percent of the out-migration from downtown areas of individuals in the bottom decile of the income distribution and about half 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. Overall, the shift in the income distribution alone explains a substantial portion of the increasing propensity of high income households to live in downtown urban areas and the outward migration of low income households. However, it does less well at explaining the changing location choices of individuals in the fourth to ninth deciles. Given this, Figure 8 highlights that other factors, in addition to the changing income distribution, are important in determining the changing location choices of residents of large cities.

Figure 8: Counterfactual impact of shift in income distribution



**Welfare Impact** Figure 9 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

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



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 9. 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). At the top of the income distribution, the amenity effect dominates the price effect. 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 9 implies that a renter in the first decile of the income distribution - earning on average \$30,000 per year - is made roughly \$150 worse off per year in consumption equivalent terms.<sup>35</sup> 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

<sup>35</sup>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.

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.<sup>36</sup> To put that number in perspective, it represents roughly one month’s rent for these households.

The second reason for the relatively 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 8 and 9, we hold population growth fixed so as to explore solely the effects of the nonhomothetic 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 from rising income inequality.

### 5.2.1 Mechanisms

There are four important factors that drive these results.

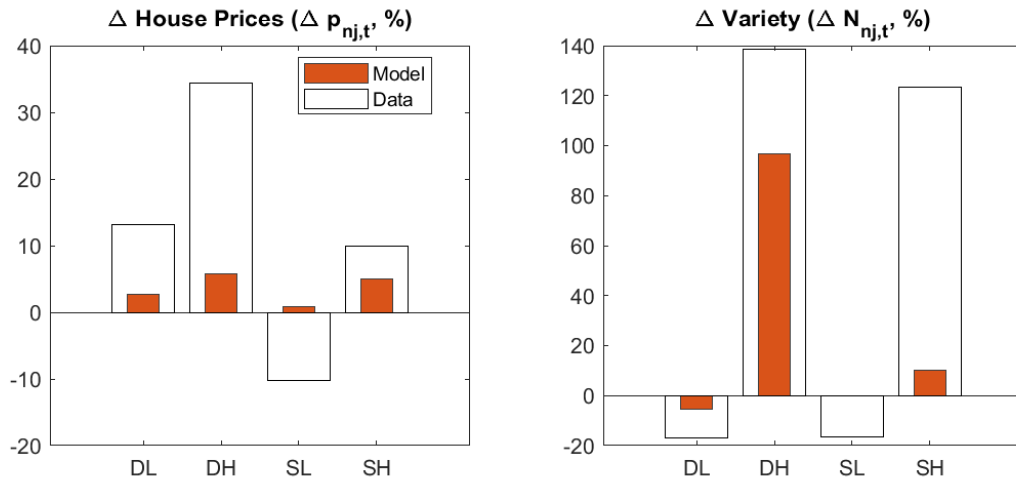
**Price Effects** First, as the rich get richer, they move downtown to consume urban amenities. This puts upward pressure on housing prices downtown both for high and low quality neighborhoods. The left-hand panel of Figure 10 shows these house prices change, for different neighborhood types. The model 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 to housing price growth in these neighborhoods. In any case, 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. The model predicts that house prices increase more in low quality areas downtown than in low quality areas in the suburbs (3% vs 1%), where the housing supply is more elastic. This matches the data qualitatively where house price growth between 1990 and 2014 was higher in low quality downtown neighborhoods relative to low quality suburban neighborhoods. Finally, the model predicts that house prices in high quality suburban neighborhoods increase by about 5%, approximately half of the increase

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<sup>36</sup>We only take into account changes in amenities and prices for these households, holding constant their idiosyncratic preference shocks for location.

observed in the data. While upper middle income households want to increase their consumption of private amenities, they cannot afford to live in downtown high quality neighborhoods, so they migrate into suburban high quality neighborhoods. This migration puts upward pressure on housing prices in those neighborhoods.

Figure 10: Mechanisms

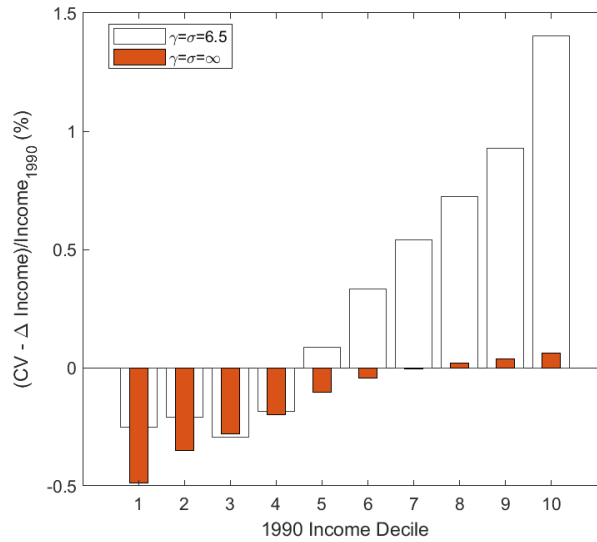


**Neighborhood Change** Second, as the rich move downtown and demand for high quality neighborhoods increases, the supply of high quality neighborhoods increases. Some of this entry is at the cost of exit of lower quality neighborhoods, so that gentrification takes place. The right-hand panel of Figure 10 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, 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, where restaurant trips are heavily skewed to neighborhoods of the same type as a person's residence (see Table 4). After their own neighborhood type, residents of low quality neighborhood residents take the second highest share trips to high quality neighborhoods in the same area. Growth in the variety of high quality neighborhoods downtown does benefit them, but not enough to reverse the negative effect of the crowding out of low quality neighborhoods downtown that account for most of their trips. Our model also predicts gentrification in that the number of low quality neighborhoods downtown contracts, consistent with the data. Overall, this gentrification makes low income households worse off. Finally, we note that the predicted supply of high quality neighborhoods also expands in the suburbs but a rate much smaller than the expansion

downtown.<sup>37</sup>

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 11 (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, from 1.7 percentage point in the baseline to 0.55 percentage points without love of variety effects. 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 gets worse, from -0.25 to -0.5 percentage points, as price increases are not compensated by the positive amenities that accompany the influx of the wealthy. The welfare gains for the rich are almost completely gone when the love of variety effects are shut down.

Figure 11: Shutting Down Amplification

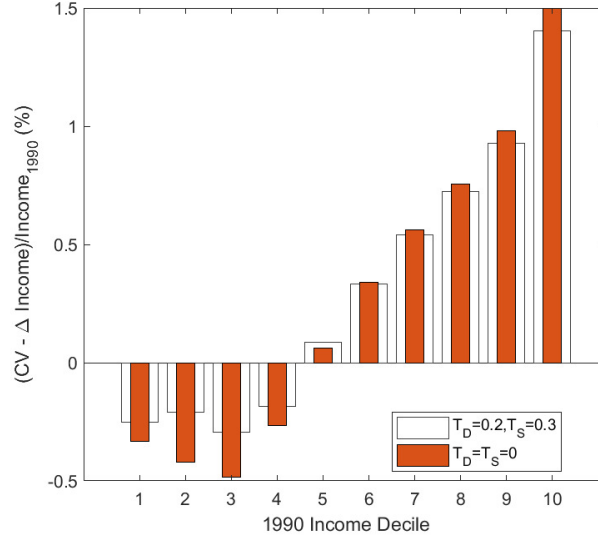


**Public amenities** Third, as downtown gets richer, taxes collected are higher and public amenities respond for all households downtown. This effect makes both richer and poorer households better off downtown, but housing prices respond to this amenity increase which tends to hurt poorer households. To quantify the net effect, we compute a 1990-2014 counterfactual with no endogenous response in public amenities. Figure 12 reports the results (red bars), and compares it to the baseline

<sup>37</sup>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 the aggregate increase in the college share in our sample of CBSAs over this period.

(clear bars). We see that endogenous public amenities tend to mitigate the welfare differential between richer and poorer households somewhat, but are far from strong enough to overturn the general tendency of spatial sorting responses to increase well-being inequality.

Figure 12: Shutting Down Public Amenities



**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 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. For households who prefer to move, this welfare loss is less strong. Moving mitigates welfare losses from gentrification.

### 5.2.2 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 5. 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 columns summarize the model predictions for the urbanization of top income decile households and the suburbanization of bottom income deciles, first in absolute percentage point terms and then as a share of the respective 2.3 percentage point inflow and 4 percentage point outflow observed in the data. Collectively, the results in this table highlight the key mechanisms that are driving our welfare estimates.

Below our baseline results, Table 5 first shows the sensitivity of these results to  $\rho$ , the parameter that governs the strength of nonhomotheticity in location choices. We set  $\rho = 2$  and  $\rho = 4$ , which is roughly 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).

Next in Table 5, we show the sensitivity of our results to different values of  $\gamma$  and  $\sigma$  pairs. For lower values of  $\gamma$  or  $\sigma$ , endogenous amplification of amenities downtown is stronger, amplifying 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. Table 5 then shows 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). The 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 one 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  $\sigma$ ).

Table 5 then shows that land supply elasticities downtown and in the suburbs are a crucial determinant of the welfare losses to 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 the downtown housing supply (in both absolute terms and relative to the suburbs), the more house prices move, generating modest additional growth in the welfare gap between the poor and the rich. The growth in the welfare gap masks heterogeneity between owners and renters. Additional price growth mitigates welfare losses for poor owners downtown, but exacerbates losses to poor 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

Table 5: Robustness of Welfare Estimates to Key Parameters

Decile:	$(\Delta CV - \Delta Inc)/Inc_{1990}$						$\Delta$ Urban Share			
	All Households			Renters Only			Predicted (p.p.)		Share of Actual	
	Top	Bottom	Diff.	Top	Bottom	Diff.	Top	Bottom	Top	Bottom
Base Specification	1.40	-0.25	1.66	0.77	-0.53	1.30	1.17	-2.32	50%	59%
Elasticity of Substitution between Neighborhood Types (base: $\rho = 3$ )										
$\rho = 2$	1.18	-0.27	1.45	0.58	-0.56	1.14	0.87	-2.02	38%	51%
$\rho = 4$	1.64	-0.23	1.87	0.96	-0.49	1.45	1.94	-2.99	84%	76%
Elasticity of Substitution between Same-Type Neighborhoods (base: $\gamma = 6.5$ )										
$\gamma = 5$	1.82	-0.14	1.97	1.04	-0.39	1.43	1.87	-3.53	81%	89%
$\gamma = 8$	1.17	-0.30	1.47	0.61	-0.61	1.22	0.95	-1.89	41%	48%
$\gamma = \infty$	0.35	-0.44	0.79	0.03	-0.96	0.99	0.57	-1.03	24%	26%
Elasticity of Substitution between Private Amenities (base: $\sigma = 6.5$ )										
$\sigma = 5$	1.55	-0.22	1.77	0.91	-0.50	1.41	1.27	-2.51	55%	63%
$\sigma = 8$	1.32	-0.27	1.59	0.68	-0.55	1.23	1.12	-2.21	48%	56%
$\sigma = \infty$	1.00	-0.35	1.35	0.37	-0.62	0.99	0.97	-1.93	42%	49%
Distance Elasticity of Amenity Consumption (base: $\delta = 0.2$ )										
$\delta = 0.1$	1.41	-0.25	1.66	0.77	-0.53	1.30	1.17	-2.31	50%	58%
$\delta = 0.3$	1.40	-0.25	1.65	0.76	-0.53	1.29	1.17	-2.32	51%	59%
Amenity Expenditure Share (base: $\alpha = 0.15$ )										
$\alpha = 0.1$	1.39	-0.20	1.58	0.79	-0.41	1.20	1.13	-2.20	49%	56%
$\alpha = 0.3$	1.35	-0.37	1.72	0.64	-0.75	1.39	1.35	-2.72	58%	69%
Housing/Land Supply Elasticities (base: $\epsilon_D = 0.6, \epsilon_S = 1.33$ )										
$\epsilon_D = 0.1, \epsilon_S = 1.33$	1.40	-0.26	1.66	0.75	-0.55	1.31	1.07	-2.69	46%	68%
$\epsilon_D = \epsilon_S = 1.33$	1.41	-0.23	1.64	0.80	-0.47	1.27	1.30	-1.86	56%	47%
$\epsilon_D = 1.2, \epsilon_S = 2.66$	1.48	-0.08	1.56	0.96	-0.20	1.15	1.27	-2.24	55%	57%
Public Amenity Elasticity (base: $\Omega = 0.05$ )										
$\Omega = 0$	1.28	-0.29	1.57	0.64	-0.56	1.21	1.15	-2.26	50%	57%
$\Omega = 0.03$	1.35	-0.27	1.62	0.72	-0.54	1.26	1.16	-2.29	50%	58%
$\Omega = 0.08$	1.48	-0.23	1.71	0.84	-0.51	1.35	1.18	-2.35	51%	59%
Property Tax Rates (base: $T_D = 0.2, T_S = 0.3$ )										
$T_D = T_S = 0$	1.50	-0.33	1.84	0.90	-0.67	1.58	1.13	-1.79	49%	45%
$T_D = 0.15, T_S = 0.25$	1.46	-0.25	1.71	0.83	-0.53	1.36	1.18	-2.24	51%	56%
$T_D = 0.25; T_S = 0.25$	1.41	-0.28	1.69	0.79	-0.55	1.34	1.12	-2.25	48%	57%

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 12 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. But 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.

### 5.3 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. Further, to tease out what characteristic of the 1990-2014 income shock are important in driving our result, we explore alternative changes in the income distribution.

Table 6 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 compared to our baseline. The larger increase stems from two forces. First, population growth amplifies the love of variety effects described above. Second, the increase 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 3.3 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 poor are much more worse off in absolute terms relative to our base specification. This happens because a broad based increase in income generates a stronger spatial sorting response, with many middle class individuals in the suburbs moving up their residential Engel curves. This rising demand for downtown living puts more upward pressure on house prices than in our baseline counterfactual, where incomes rise for only a few households at the top of the distribution. As a result, the increase in welfare inequality due to spatial responses is higher with broad based income growth than in our 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

Table 6: Welfare Estimates under Different Counterfactual Income Distributions

		$(\Delta CV - \Delta Inc)/Inc_{1990}$					
		All Households			Renters Only		
	Decile:	Top	Bottom	Diff.	Top	Bottom	Diff.
[1] Base Specification (aggregate population fixed)							
		1.40	-0.25	1.66	0.77	-0.53	1.30
Alternative Driving Forces (1990-2014)							
[2]	Allowing for population growth	4.52	-1.20	5.71	2.49	-3.33	5.82
[3]	Only population growth, no change to income distribution	2.69	-0.96	3.65	1.43	-2.83	4.26
[4]	No population growth, income distribution shifts rightwards	2.08	-0.66	2.74	1.87	-1.41	3.28
Projected Further Welfare Changes from Further Income Growth from 2014 Onward							
[5]	$HHInc_i = HHInc_{i,2014} \times 110\%$	2.98	-1.04	4.02	2.60	-1.98	4.58
[6]	$HHInc_i = HHInc_{i,2014} \times 120\%$	7.80	-2.72	10.52	6.26	-4.83	11.08
[7]	$HHInc_i = HHInc_{i,2014} \times 130\%$	11.39	-4.84	16.22	8.39	-8.93	17.32

future welfare impact 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, 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 an additional 10 percent income growth for all individuals (which does not impact income inequality) further 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. This suggests that it is not income inequality per se that drives 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.

Before turning to counterfactual policy analysis, we now analyze two counterfactuals that provide additional model validation.

#### 5.4 Additional Out of Sample Tests

To validate the model further, we compare the prediction of the model to two additional empirical facts.

**1970 Counterfactual** In our benchmark analysis, we calibrate the model using 1990 data and ask how far the 1990-2014 shift in the income distribution can go in explaining changes in spatial sorting over that period. We now instead look backwards, asking the same question for the 1970 to 1990 period. To that end, we feed in to the model the 1970-1990 change in the income distribution, represented in the top panel of Figure 13.

Figure 1 showed that the U-shape pattern between 1970 and 1990 was essentially stable. The lower panel of Figure 13 shows the results of the 1970-1990 counterfactual, where the model correctly predicts only small changes in the U-shape between 1970 and 1990.<sup>38</sup> 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 suburbanized between 1970 and 1990, while those at the left tail urbanized.

According to the quantified model, a positive shift in the income distribution per se does not necessarily cause high income households to disproportionately move downtown. This only happens for a sufficient increase in the number of households with very high income, far to the right of the bottom of our U-shape. The shift in the income distribution from 1970 to 1990 was much less skewed towards the very rich than the shift between 1990 and 2014. From 1970 to 1990, the largest shift in the income distribution happened around the bottom of the U-shape (around \$100,000). In this income range, households move along their residential Engel curve by moving from low to high quality neighborhoods within the suburbs. The relative share of households downtown is barely impacted by this within-suburbs shift.

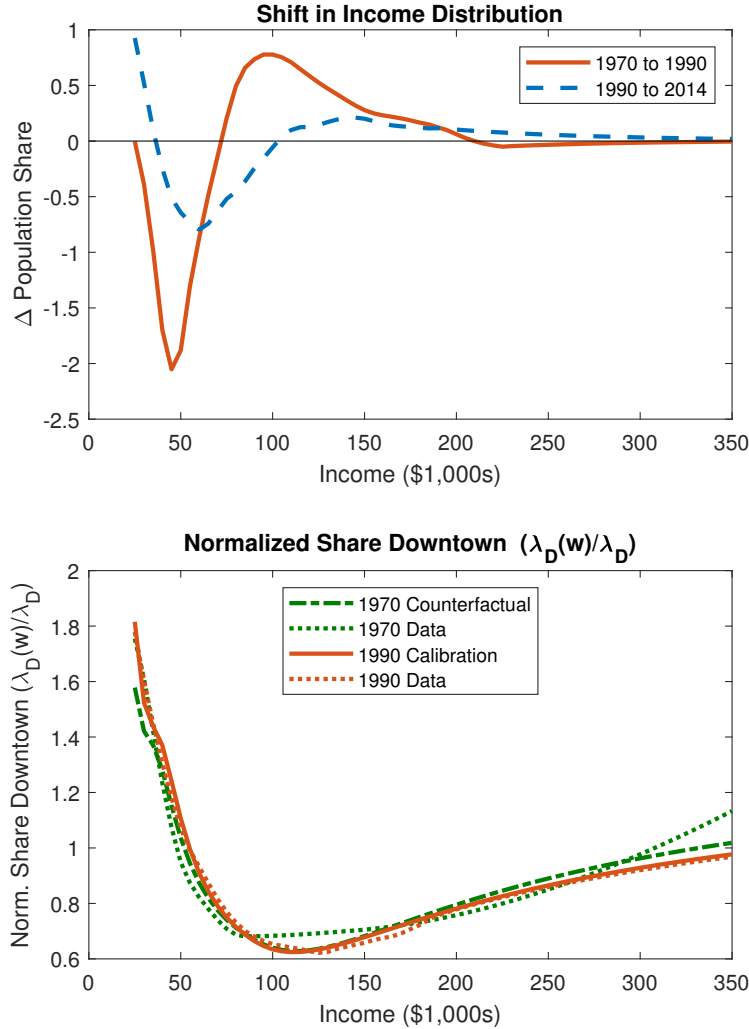
**Cross-CBSA Predictions** As a last validation exercise, we now assess the model predictive power across cities. To that end, we re-calibrate the model separately for each CBSA (rather than for a representative city in the baseline). For each CBSA, we target the 1990 distribution of location choice by income. The income distribution in 1990 and land supply elasticities ( $\epsilon_D$  and  $\epsilon_S$ ) are CBSA-specific. To calibrate the land supply elasticities, we use our estimated equation (30), feeding in actual data on density for the Downtown and Suburban area of each CBSA. The other parameters in Table 2 are taken as identical across CBSAs. Armed with these calibrations, we feed in the 1990 to 2014 change in the income distribution for each CBSA, and compute the corresponding counterfactual equilibrium in each city. 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 changes in the income distribution.

The results are shown in Figure 14. We summarize location choice patterns by income, in each city and period, by computing the relative propensity of households with incomes higher than \$70,000 of living downtown. The left hand panel of Figure 14 compares these shares for 1990 in the model and in the data. Each point is a different CBSA.<sup>39</sup> Given that we target the U-shape in 1990, it is not surprising that our model matches the 1990 data. 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. Despite the fact that there are

<sup>38</sup>In the lower panel of Figure 13, 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 the differences across income groups very well.

<sup>39</sup>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.

Figure 13: 1970 Counterfactual

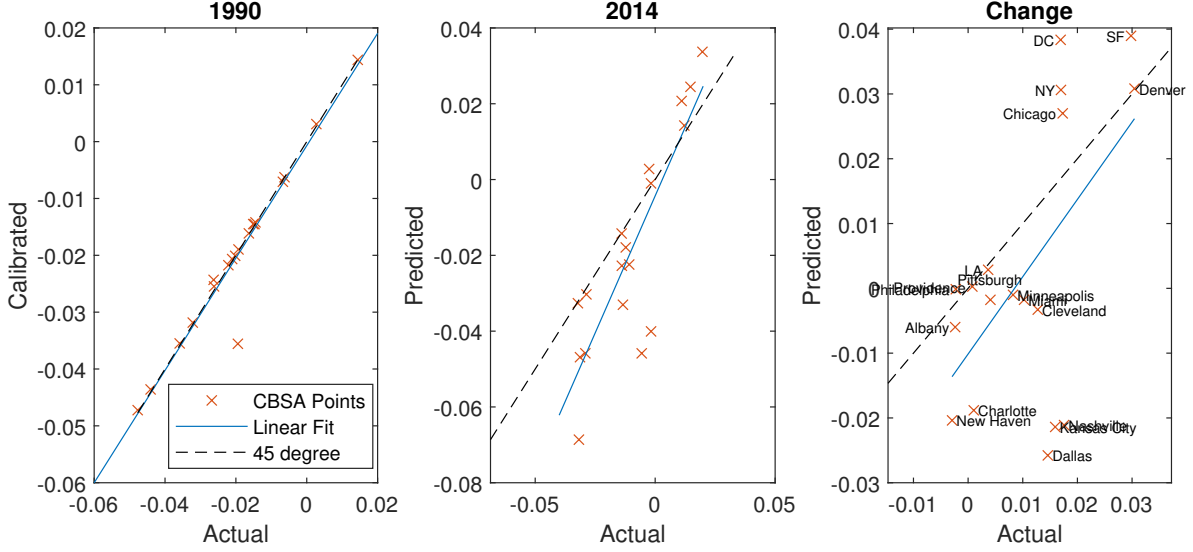


many other forces, beyond the change in income distribution, that could be affecting changes in residential spatial sorting by income across cities, our model predicts 2014 spatial sorting patterns that match the data quite well.

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 14. In this panel, we ask how well CBSA-level changes in the income distribution, filtered through the lens of our model, explain CBSA-level *changes* in spatial sorting of high income individuals. 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. We see that the CBSAs predicted by the model to have a large relative increase in high income individuals residing downtown are actually the ones for which we observe such an increase empirically.

We conclude from this out of sample analysis that the model does quite well at matching time

Figure 14: Urban Share of Households Earning Above \$70,000 Less the Average Urban Share



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.

## 5.5 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** We use the model to study the impact of a stylized “anti-gentrification” policy, which systematically taxes the high-quality housing developments downtown and uses the proceeds to subsidize rents in low-quality neighborhoods downtown. It aims to limit the development of high-quality neighborhoods downtown while helping poorer households to remain located downtown. We recompute the 2014 income distribution spatial equilibrium, implementing the policy with a tax on high quality housing downtown of  $t = 5\%$ .<sup>40</sup> Figure 15 reports the results and contrasts them with our baseline 1990-2014 counterfactual, in order to evaluate how much such a policy would have curbed the gentrification triggered by changes in the income distribution from 1990 to 2014. The left panel of Figure 15 shows that the policy has the effect of stemming part of the gentrification of downtown neighborhoods: the inflow of high income households downtown is curbed, as is the outflow of low income families, compared to baseline. The policy is effective

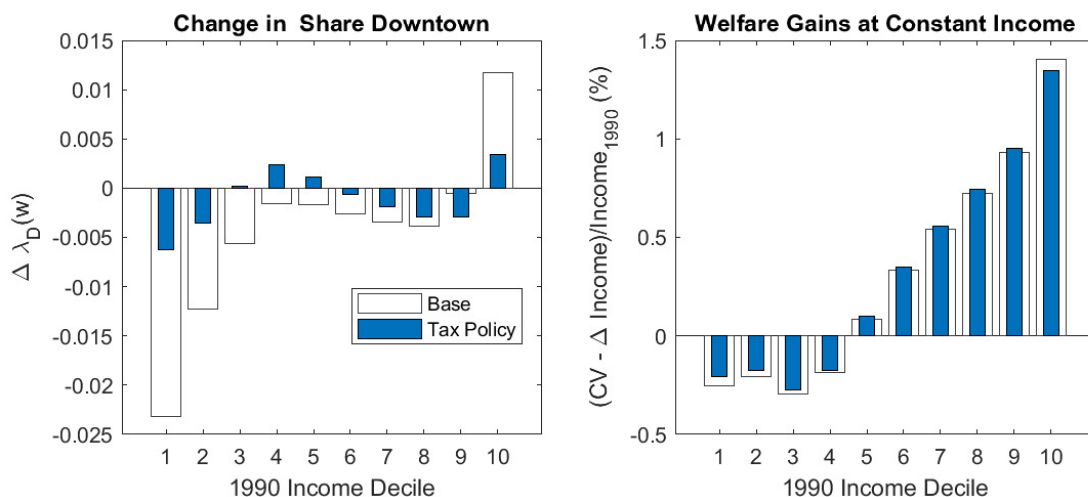
<sup>40</sup>Specifically, the price including taxes paid by household for D,H houses is  $p_{DH}(1 + t)$  while the one paid for D,L houses is  $p_{DL} - \delta$ , where  $\delta = \frac{\int L(w)\lambda_D(w)\lambda_{DH}(w)tp_{DH}dF(w)}{\int L(w)\lambda_D(w)\lambda_{DL}(w)dF(w)}$ .



at stemming part of the land price increase downtown, and limiting quality changes.<sup>41</sup> To the extent that governments intrinsically value social diversity within their downtowns, this simulation suggests that such an anti-gentrification policy can help achieve such target.

On the other hand, turning to the well-being effect of this policy, we find that it is much more muted (see right panel of Figure 15). The policy reverses some of the gains for highest incomes and benefits lower income households, but both effects are marginal. This is in part because subsidies only accrue to a small share of lower income households (recall that even in the lowest income decile, only 15 percent of households resided downtown in 1990). More importantly, low income households living in the suburbs see greater welfare losses compared to baseline: the policy shifts gentrification – i.e. neighborhood quality and price growth – from downtown to the suburbs where land is more, but not perfectly, elastic. On net, therefore, the per capita positive impact of the policy on lower incomes within the entire city is quite limited. The welfare losses are simply transferred from residents living in low quality downtown neighborhoods to residents living in low quality suburban neighborhoods.

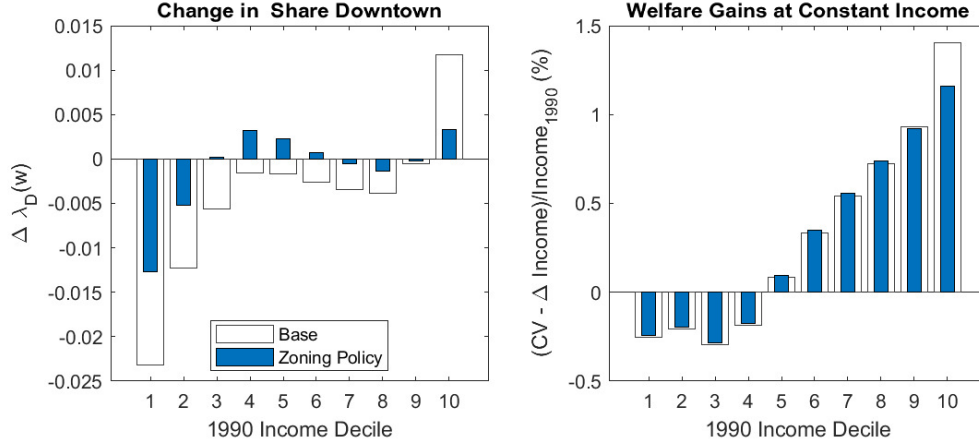
Figure 15: Location Choices and Well-Being under “Anti-Gentrification” Policy



**Zoning restrictions** We also study the effect of an alternative anti-gentrification policy, which models zoning restrictions. It imposes that the relative number of high to low quality neighborhoods remains constant over time, despite the rise in incomes. Figure 16 reports the results. The effect of this policy turns out to be very similar to the effect of the direct tax policy. The impact on social mixing downtown is significant, but the welfare effects are again very small, as quality and price growth are pushed to the suburbs.

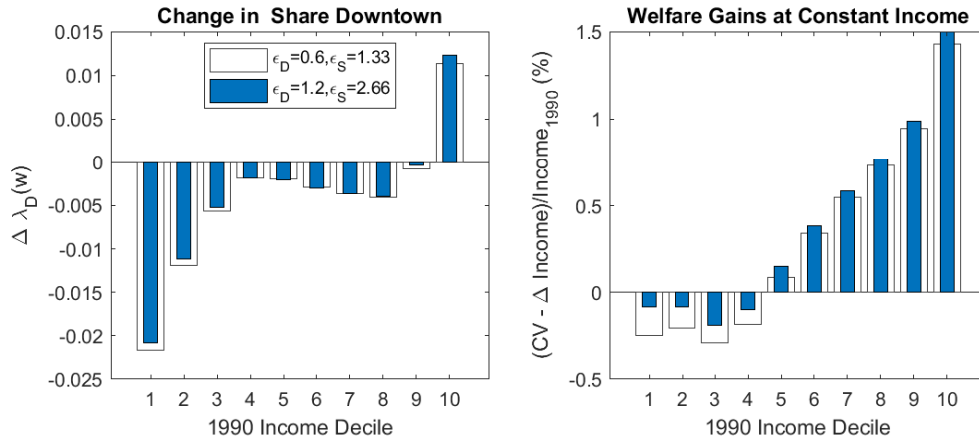
<sup>41</sup>In addition, mechanically, the tax and subsidy scheme leads to lower effective housing costs for low quality housing residents downtown, and higher effective costs for high-quality housing residents downtown.

Figure 16: Location Choices and Well-Being under Zoning Policy



**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 our calibration. In section 5.2.2 and Table 5, 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 17 shows that it also does little to stem neighborhood change downtown (in the left panel) but it does mitigate the 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.

Figure 17: Effects of Increasing Supply Elasticity



## 6 Conclusion

We set out to explore the link between rising incomes at the top of the income distribution and changes in the urban landscape of U.S. cities in the past few decades: high income households have been moving into downtowns, where housing prices have gone up and neighborhoods have been changing dramatically. These changes have lead to anti-gentrification protests and a renewed interest in policy circles for 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 nonhomothetic preferences. We quantify the model and use it 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.

Our estimates suggest that rising incomes at the top of the distribution was a substantive contributor to increased urban neighborhood change during the last 25 years within the U.S. The analysis also suggests that neighborhood change resulting from the increased incomes of the rich did make poorer residents worse off. Accounting for the spatial sorting response resulting from the change in income distribution between 1990 and 2014 exacerbates the growing inequality between the top and bottom income decile by an additional 1.7 percentage points.

We explore possible policy responses to mitigate these distributional impacts of neighborhood change. We 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, these policies are effective at maintaining social diversity in urban neighborhoods, arguably one of the goals of such policies.

In this paper, we have focused on the within-city consequences of a rise in top incomes. By doing so, we have highlighted one mechanism that has contributed to shape neighborhood change in the past twenty five years: the rising incomes of the rich coupled with non-homothetic preferences for location across income groups. In order to conduct this analysis, we have developed a model that is stylized in some dimensions, but is very flexible. It is in particular amenable to study other sources of changes in within-city spatial sorting that are potentially empirically relevant. Using our framework to study other potential causes of neighborhood change is a natural avenue for future research.

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# Online Appendix:

## “Income Growth and the Distributional Effects of Urban Spatial Sorting” (Not for Publication)

### Appendix A Data Appendix

In this appendix, we discuss our data sources, we provide additional detail on variable construction, we describe our calibration of  $\delta$ , and we illustrate the downtown areas of some CBSAs.

#### Appendix A.1 Data Sources and Sample Descriptions

This subsection details the data sources used in our various empirical analyses. We also discuss how we adjust our income data for topcoding in the IPUMS data.

##### Appendix A.1.1 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 the 100 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 reported in the IPUMS data 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 each of the income components that contribute to total individual income and their respective topcodes for 1990 and 2014.

Table A.1: Topcoded Income Components Contributing to Total Individual Income

1990			2000+		
Variable	Description	Topcode (nominal)	Variable	Description	Topcode (nominal)
INCWAGE	Pre-tax wage and salary income	\$140,000	INCWAGE	Pre-tax wage and salary income	99.5th Percentile in State
INCBUS	Non-farm business and/or professional practice income	\$90,000	INCBUS00*	Business and farm income and/or professional practice income	99.5th Percentile in State
INCFARM	Farm	\$54,000	INCSS	Social security and disability	Not Topcoded
INCSS	Social security and disability	\$17,000	INCWELFR	Other government assistance	Not Topcoded
INCWELFR**	Other government assistance	10,000	INCSUPP	Supplementary Security Income	Not Topcoded
INCINVST	Rents, interests, dividends, etc.	\$40,000	INCINVST	Rents, interests, dividends, etc.	99.5th Percentile in State
INCRETIR	Retirement income other than social security	\$30,000	INCRETIR	Retirement income other than social security	99.5th Percentile in State
INCOTHER	Income not included above	\$20,000	INCOTHER	Income not included above	99.5th Percentile in State

\* 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 conservatively assume that any household or family whose reported component level income is above the person-level topcode is subject to topcoding for that 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 year. State-specific topcodes for wages range from \$105,000 to \$280,000 in 1999 dollars. Because of this high variance,

Table A.2: Percent of Income Impacted by Topcoded Components in 1990

Variable	Person	Household	Family
incwage	0.60%	1.39%	1.66%
incbus	3.70%	4.25%	4.62%
incfarm	2.79%	3.28%	3.48%
incss	0.73%	3.67%	5.60%
incwelfr	3.18%	5.80%	6.83%
incinvest	2.11%	2.98%	3.18%
incretir	3.20%	4.15%	5.08%
incother	2.28%	2.51%	2.43%
TOTAL	0.62%	1.78%	2.28%

Note: This 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

Variable	Person	Household	Family
incwage	1.2%	3.5%	4.5%
incbus	3.7%	4.4%	5.1%
incinvest	3.6%	4.6%	5.2%
incretir	3.5%	5.6%	7.2%
incother	3.4%	4.0%	4.0%
TOTAL	1.5%	4.1%	5.8%

Note: This 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).

we allow each state to retain a state-specific topcode: 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  $\hat{\alpha}_{tsn}$  for time period  $t$ , state  $s$ , and area  $n$ .<sup>42</sup>

$$\hat{\alpha}_{tsn} = \frac{M_{tsn}}{T_{tsn} \ln(X_{Ts}) + \sum_{x_{m_{tsn}} \leq x_i < x_{T_{tsn}}} \ln(x_i) - (M_{tsn} + T_{tsn}) \ln(x_{m_{tsn}})} \quad (\text{A.1})$$

$M_{tsn}$  is the number of households or families with earnings between the lower cutoff  $x_{m_{tsn}}$  and the censoring point  $x_{T_{tsn}}$ . In 1990, we assign the censoring point as the topcode for a single-wage

<sup>42</sup>Since we are only able to define urban cores for the set of 27 CBSAs with sufficiently small PUMAs in 1990 and 2014, we estimate  $\hat{\alpha}_{tsn}$  only for the portion of state  $s$  that is covered by a CBSA in that sample.

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).<sup>43</sup>

Piketty et al. (2017) further improve upon the constant parameter estimate. Using individual tax data, they find that a single Pareto distribution cannot sufficiently explain the tail of an income distribution. In the U.S. 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. (2017) develop a methodology to construct generalized Pareto curves that allow the pareto coefficient to vary with income. We use the R package *gpinter* that Piketty et al. (2017) developed to estimate the generalized Pareto curves for each state  $s$ , area  $n$ , and period  $t$ .<sup>44,45</sup>

We combine the income distribution observed in the IPUMS data below the topcode with the approximated distribution above the topcode. To do this, we first 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 cut incomes within \$1,500 of 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 each of the 27 CBSAs in our calibration sample in 1990 and 2014 and across samples to get the urban, suburban, and total distribution for our pooled “representative city” sample.

<sup>43</sup>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 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.

<sup>44</sup>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  $[85 + \frac{p_t-85}{2}, p_t]$ . If  $p_t$  falls between 93rd and 96th percentile are top 3 percentiles are  $[85 + \frac{(p_t-85)}{3}, 85 + \frac{2(p_t-85)}{3}, p_t]$ . If  $p_t$  falls above the 9th percentile the top 4 percentiles are  $[85 + \frac{(p_t-85)}{4}, 85 + \frac{2(p_t-85)}{4}, 85 + \frac{3(p_t-85)}{4}, p_t]$ .

<sup>45</sup>The generalized pareto methodology requires an unbiased estimate of average income for some top quantile of income. We use our estimates of  $\widehat{\alpha_{tsn}}$  from the simple Pareto distribution to approximate the average income above the topcode.

### Appendix A.1.2 Smartphone Movement Data

The smartphone movement data is from October 2016 to August 2018. Our data provider aggregates data from multiple apps’ location services.<sup>46</sup> Each visit comes from raw movement data intersected with a basemap of polygons (usually buildings). Each visit receives a unique location, device, and time stamp.

We define the permanent home location of each device as in Couture et al. (Work in Progress), using 90 billion visits to residential establishments. We first identify a individual’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 individuals between 2016 and 2018. We refer to this location as the person’s home location.

We have 9.6 billion visits to commercial establishments in our sample. Of these, our amenity demand estimation uses 2.3 billion that are to non-tradable amenities, defined as restaurants, gyms, movie theaters, and outdoor amenities (we exclude all retail locations.) To identify visits starting from home, we use the time stamp and duration of each visit. We define a trip as from home if the previous visit was to home and ended less than 60 minutes earlier. That procedure identifies 220 million trips to non-tradable services that start from home.<sup>47</sup> 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.1.3 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

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<sup>46</sup>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 the mapping of commercial establishments visited by smartphone users to the business registry is relatively complete.

<sup>47</sup>We do not observe all travel by individuals, so visit duration is a lower bound and missing in some cases. This explains why we are only able to ascertain 10 percent of trips as starting from home, whereas for instance about 30 percent of trips to restaurants in the NHTS start from home.

Table A.4: Ten Largest Restaurant Chains in NHTS vs Smartphone Data

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

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

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

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

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

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

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

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

Dunkin Donuts: <https://www.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>



records the exact address for about 75 percent of establishments. In the remaining cases, we observe the establishments zip code and assign it's location to the zip code centroid.

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

Table A.4 suggests that the NETS database is less complete than the smartphone basemap, but some of this difference is due to the earlier count. The NETS contains a majority of establishments for nine of the ten largest chains, with the exceptions of Subway 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.1.4 Zillow House Price Indexes**

Our main house price index comes from Zillow.com.<sup>48</sup> Our 2 bedroom 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 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 the 2 bedroom index for around 35,000 tracts in each year, and the all home index for around 53,000 tracts in each year.

#### **Appendix A.1.5 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

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<sup>48</sup>We collected the data in February 2019. The index and methodology are available at: <http://www.zillow.com/research/data/>.

(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)
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.1.6 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 2000 and 2014. HUD reports the total number of available units by housing 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 subsidized or public housing.

### **Appendix A.2 Variable Definition**

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

### Appendix A.2.1 CBSA Level Wage Bartik shock

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

To calculate national wage growth for each industry between 1990-2014 or 2000-2014, we use person-level IPUMS data in 1990, 2000, and 2014. We keep the sample of people between 21 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. As in Diamond (2016), we compute wage growth in each industry as the (leave out) difference in average log wage across years. Our Bartik income shock is then 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: Finance, Real Estate and Insurance (1990 industry codes 700-712), Manufacturing (1990 industry codes 100-399), and Technology.<sup>49</sup> 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 25 percent of all workers have been removed. Table A.7 shows the 10 most and 10 least urbanized industries in 1990.

### Appendix A.2.2 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 95<sup>th</sup> 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 distributed within each bracket, except for the top bracket. We can then map each CPI-adjusted census brackets in 1990 and 2000 onto 2014 bracket definitions, setting median income  $w$  as the mid-point of these constant brackets. For the top bracket (above \$140,600 in 1999 dollars), we determine median income using 2000 IPUMS microdata.

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<sup>49</sup>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.

### Appendix A.2.3 Yearly User Cost of Housing ( $p_{nj,c}^h$ ).

**Computing  $p_{nj,c}^h$**  We first compute a population weighted-median house price over all tracts in a given area quality pair in a given CBSA. To obtain  $p_{nj,c}^h$  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.<sup>50</sup>

**Property Taxes as a Share of  $p_{nj,c}^h$**  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  $p_{nj,c}^h$ .

### Appendix A.2.4 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 elasticity at 1.32. Based on CEX 2013 tables, entertainment fees and admission have a mean expenditure share of 1.1 percent, and food away from home has a mean share of 5.1 percent, excluding alcohol away from home.<sup>51</sup> 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  $0.5 \times 17.6 = 8.8$  percent of expenditure on work transportation.<sup>52</sup> 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 A.2.5 Tract Level Quality Index.

**Estimating Chain Quality** We define quality for the 100 largest restaurant chains, with the most establishments in the smartphone data basemap. We index block groups by  $i$ , venues by  $j$ , and chains by  $c$ . We denote by  $N_{ic}$  the total number of visits by individuals living in block  $i$  that start from home and end in venues in chain  $c$  within its CBSA. Restricting our sample of chain visits to those that start from a person's home isolates the choice of visiting a chain from other considerations of travelers (e.g., eating during lunch at work).

We further control for proximity to venues within that chain to isolate chains that high income people like from chains that simply co-locate with them. Our main specification has two controls

<sup>50</sup>Data collected in October 2018 from <https://datatoolkits.lincolninst.edu/subcenters/land-values/rent-price-ratio.asp>.

<sup>51</sup><https://www.bls.gov/ce/2013/combined/income.pdf> Accessed on 6 January 2019.

<sup>52</sup>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.

for proximity of block  $i$  to venues in chain  $c$ : first the normalized straightline distance between the centroid of block  $i$  and the closest venue  $j$  in chain  $c$ , denoted by  $dist_{ic(closest)}$ , and second the normalized number of establishments in chain  $c$  within 5 miles of block  $i$ , denoted by  $num5mil_{ic}$ .<sup>53</sup> Our estimation sample consists of 2.3 million block\*chain pairs with at least one within-CBSA visit from home. In a first step, we purge the number of visits from the impact of proximity to chains by running:

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

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

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

In the next step, we compute the relative propensity of high income individuals 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 individuals living in high income block groups, is:

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

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

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

where  $Quality_c = 1$  means that high income individuals 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.<sup>54</sup> 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

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<sup>53</sup>We normalize  $dist_{ic(closest)}$  to equal 1 at the median distance of the closest venue for that chain, computed across all blocks with at least one visit to that chain. The variable  $dist_{ic(closest)}$  is then in multiples of that median distance. We do this to ensure that our distance-adjusted number of visits remains unchanged for a block at median distance from chain  $c$ .

<sup>54</sup>In that case,  $N_{ic} = 0$  gets adjusted upward if the closest venue to block  $i$  is farther than median distance, and therefore included as a positive number of visits in the index computation, possibly creating the opposite bias as in our preferred specification. We use the invert hyperbolic sine transform to allow for log of zeros.

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

**From Chain Quality to Tract Quality** 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.<sup>55</sup> 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.<sup>56</sup>

### Appendix A.3 Calibrating $\delta$

In this subsection, we discuss how we calibrate the parameter  $\delta$ . Combining data on restaurant trips, prices, and expenditures with existing empirical estimates of value of travel time, Couture (2016) finds that a significant majority (59%) of trips to a restaurant from home take between 5 and 15 minutes, and that over this range of travel times, the total price of amenity rises by 27% due to travel costs. If we similarly calibrate  $\delta$  such that tripling distance increases travel cost by 27% percent, we obtain:<sup>57</sup>

$$\frac{d_{rr'}^\delta p^a}{d_{rr''}^\delta p^a} = \left(\frac{15}{5}\right)^\delta = 1.27 \quad (\text{A.2})$$

and recover  $\delta = 0.22$ .

### Appendix A.4 Downtown Census Tracts for Some CBSAs

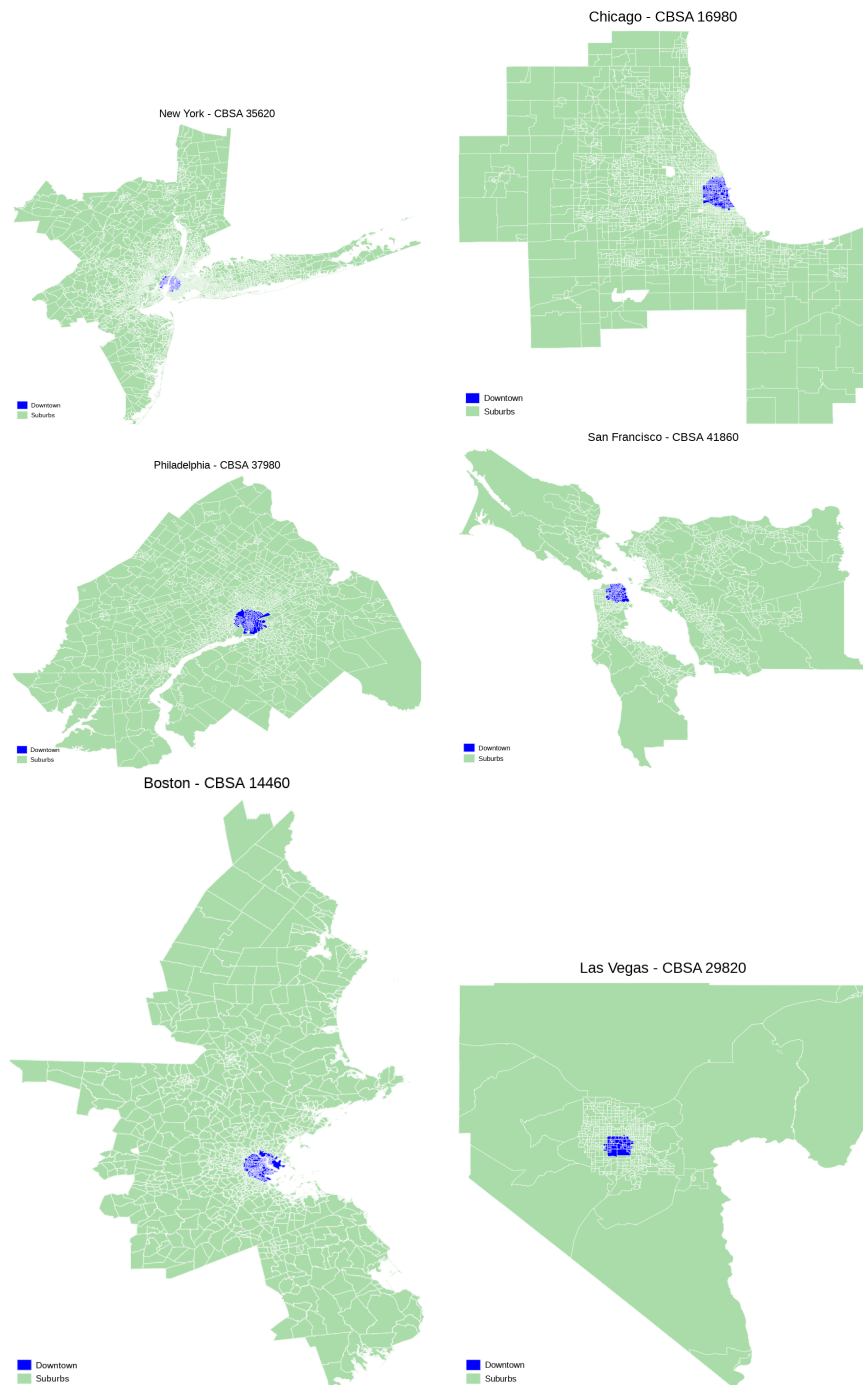
Figure A.1 shows the downtown and suburban tracts for the CBSAs of New York, Chicago, Philadelphia, San Francisco, Boston, and Las Vegas. Figure A.2 shows income growth in downtown and selected suburban tracts within the central county of each of these CBSAs.

<sup>55</sup>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.

<sup>56</sup>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.

<sup>57</sup>This result is not reported by Couture (2016), who uses a different parametrization of distance than that in our paper, but it can be computed with the data reported in that paper.

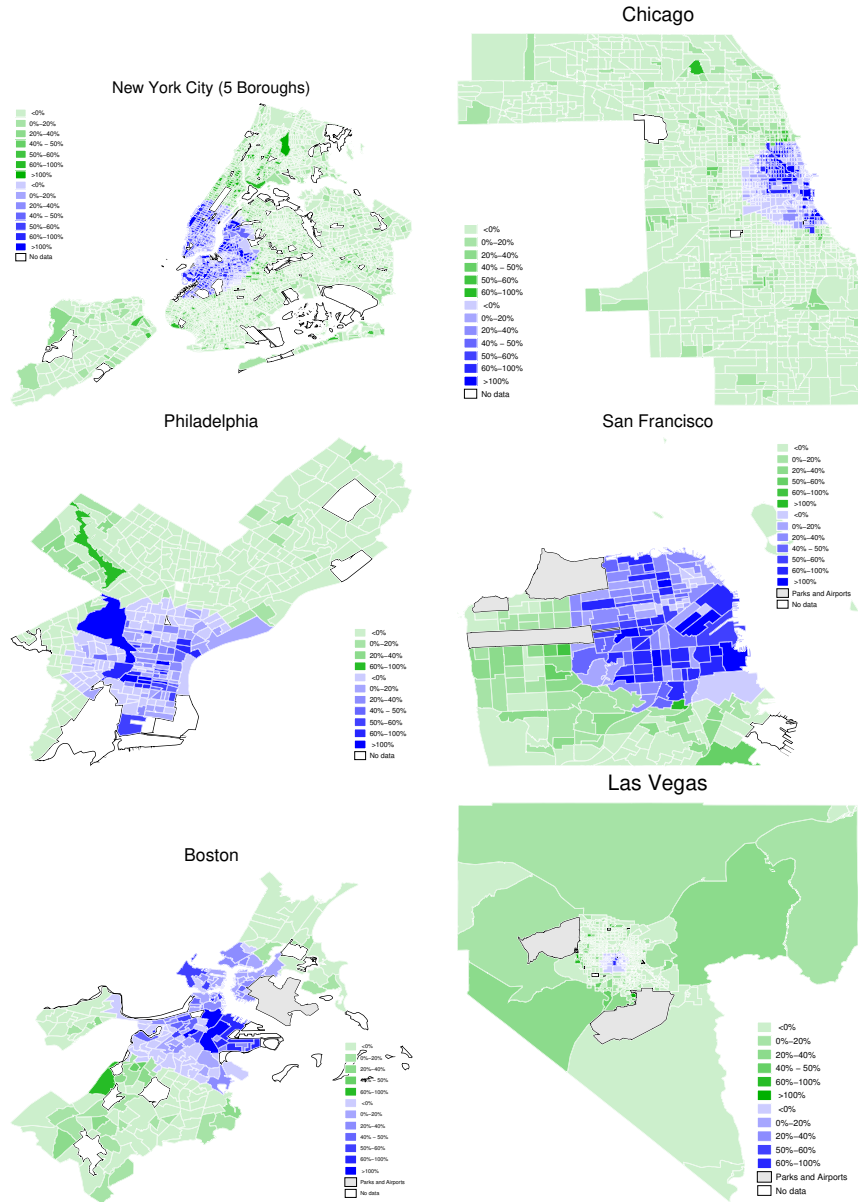
Figure A.1: Downtown and Suburban Tracts in Selected CBSAs.



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.2: Income Growth in 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.



## Appendix B Model Appendix

### Appendix B.1 Entry of Developers

Denote with  $K_{n,j}^a$  land used by amenities in neighborhood  $n, j$  and with  $K_{n,j}^h$  land used by housing. Given CES demand for amenities, developers price amenities at a constant markup over marginal costs, that is:

$$p_r^a = \frac{\sigma}{\sigma - 1} k_{n(r),j(r)}^a R_{n(r)}, \quad (\text{A.3})$$

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

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

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

$$R_n K_{n,j}^a = \frac{\sigma - 1}{\sigma} \alpha^a \int_w \lambda_{n,j}(w) (w - p_{n,j}^h) dL(w) \quad (\text{A.4})$$

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

$$R_n K_{n,j}^h = \int_w \lambda_{n,j}(w) k_{n,j}^h R_n dL(w) \quad (\text{A.5})$$

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

$$\pi_r^h = \left[ \int_w \lambda_r(w) dL(w) \right] (p_r^h - k_{n,j}^h R_n) \quad (\text{A.6})$$

Using (6) and (12) leads to the following pricing formula:

$$p_r^h = \frac{\gamma}{\gamma + 1} k_{n,j}^h R_n + \frac{1}{\gamma + 1} \mathcal{I}_{n,j}(p_r^h), \quad (\text{A.7})$$

By symmetry, all neighborhoods of type  $(n, j)$  have the same price in equilibrium, which we denote as  $p_{n,j}^h$ .

This leads to:

$$N_{n,j} = \frac{1}{f_{n,j}} \left[ \int_w \lambda_{n,j}(w) \left( p_{n,j}^h - k_{n,j}^h R_n + \frac{\alpha^a}{\sigma} (w - p_{n,j}^h) \right) dL(w) \right] \quad (\text{A.8})$$

### Appendix B.2 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  $\{\lambda_{n,j}(w), p_{n,j}^h, S_{n,j}^{mk}\}$ , 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  $S_{n,j}^{mk}$  is the share of amenity expenditures of households living in a neighborhood of type  $nj$  spent on amenities consumed in a neighborhood  $(m, k)$ . 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  $\{(p_{n,j}^h)'\}$ ,  $\lambda'_{n,j}(w)$ ,  $L'_{n,j}$  (or, equivalently, their “hat” values).

First, given (8), changes in housing costs are given by:

$$\hat{R}_n = \left( \sum_j s_{n,j}^h \hat{R}_n \hat{L}_{n,j} + s_{n,j}^a \hat{R}_n \hat{K}_{n,j}^a \right)^{\frac{1}{1+\epsilon_n}}, \quad (\text{A.9})$$

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

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

which we compute from the calibrated values of  $R_n K_{n,j}^a$  using equation A.4, as well as the calibrated values of  $R_n K_{n,j}^k$  using equation A.5.<sup>58</sup> Note that  $\hat{L}_{n,j} = \frac{\int \lambda'_{n,j}(w) dL'(w)}{\int \lambda_{n,j}(w) dL(w)}$  while  $\hat{R}_n \hat{K}_{n,j}^a = \frac{\int \lambda'_{n,j}(w) (w - (p_{n,j}^h)') dL'(w)}{\int \lambda_{n,j}(w) (w - p_{n,j}^h) dL(w)}$ , where  $\lambda'_{n,j}(w)$  is unknown and a solution of the system of equations described here, while the counterfactual distribution of income  $L'(w)$  is taken as given.

Second, the housing prices in the new equilibrium are defined by<sup>59</sup>:

$$(p_{n,j}^h)' = \frac{\gamma}{\gamma+1} k_{n,j}^h R_n \hat{R}_n + \frac{1}{\gamma+1} \mathcal{I}'_{n,j} \left( (p_{n,j}^h)' \right), \quad (\text{A.10})$$

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

$$\mathcal{I}'_{n,j}(p) = \frac{\int_w \Lambda'_{n,j}(p, w) [(1 - \tau_n)w + \chi(w)'] L'(w) dw}{\int_w \Lambda'_{n,j}(p, w) L'(w) dw}, \quad (\text{A.11})$$

<sup>58</sup>We have  $\sum_{i,j} s_{n,j}^i = 1$  for  $n = D$  or  $S$  and  $\sum_{m,k} S_{n,j}^{mk} = 1$ , for  $n = D, S$  and  $j = H, L$ .

<sup>59</sup>Note that  $k_{n,j}^h R_n$  is known in the initial equilibrium using equation A.7 and the known variables  $p_{n,j}^h, \lambda_{n,j,r}(w), L(w)$

with  $\Lambda'_{n,j}(p, w) = \frac{\lambda'_{n,j,r}(w)}{[(1-\tau_n)w + \chi(w) - p]}$ . 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  $\hat{N}_{n,j}$  and the change in density  $\hat{K}_n$ . Starting from the definition of  $B_n$ , simple algebraic manipulations lead to:

$$\hat{B}_{n,j} = \hat{N}_{n,j}^{\frac{1}{\gamma}} \left( \hat{P}_{n,j}^a \right)^{-\alpha} \quad (\text{A.12})$$

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

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

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

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

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

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

Furthermore, given Equation 4, the change in the price index for amenities in a neighborhood of type  $n, j$  is:

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

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

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

To solve for  $\hat{d}_{nn'}$ , we make use of the geometric assumption that representative distance  $d_{nn'}$  changes like the square root of the corresponding area.

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

$$\widehat{\lambda}_{n,j}(w) = \frac{\widehat{B}_{n,j}^\rho}{\widehat{V}^\rho(w)} \frac{[w(1 - \tau_n) + \chi'(w) - p'_r]^\rho}{[w(1 - \tau_n) + \chi'(w) - p_r]^\rho}, \quad (\text{A.13})$$

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

$$\widehat{V}^\rho(w) = \sum_{n,j} \widehat{B}_{n,j}^\rho \frac{[(1 - \tau_n)w + \chi'(w) - p'_r]^\rho}{[(1 - \tau_n)w + \chi(w) - p_r]^\rho} \lambda_{n,j}(w), \quad (\text{A.14})$$

Values for  $\{p'_{n,j}, \lambda'_{n,j}(w), L'_{n,j}, R'_{n,j}\}$  are the solutions of equations (A.9)-(A.13) that define a counterfactual equilibrium of the economy corresponding to an alternative distribution of income  $L'(w)$  in the city.

### Appendix B.3 Income elasticity of housing consumption

Proof that  $\frac{\partial \log \bar{p}(w)}{\partial \log w} > 0$ : Recall that  $\nu_{nj}(w) = (w - p_{nj})^{-1}$ . If there is only one type of neighborhood, one can factorize  $\nu(w)$  and get that  $\frac{\partial \log \bar{p}(w)}{\partial \log w} = \rho \nu(w) \frac{w}{\bar{p}(w)} \sum_{nj} (p_{nj}^h - \bar{p}(w)) \lambda_{nj}(w) = 0$ , by definition of  $\bar{p}$ . If there are several types of neighborhoods, note that  $\nu_{nj}(w)$  increases with  $p_{nj}$ . Therefore,  $\text{cov}(p_{nj}^h \lambda_{nj}(w) - \bar{p}(w) \lambda_{nj}(w), \nu_{nj}(w)) > 0$  for any  $w$ . The result follows.

## Appendix C Robustness and Additional Results

In this section, we show various additional results and robustness exercises that are referenced in the text. We begin by discussing the robustness of the U-shape patterns highlighted in Section 2 to controlling for demographics. We then show various robustness specifications for our estimate of  $\rho$ . Next, we discuss how all of our key findings change if we define neighborhood quality based on our restaurant index (as opposed to the educational mix of residents). Finally, we show additional moments of interest referenced in the text.

### Appendix C.1 U-Shape with Demographic Controls

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

#### Appendix C.1.1 Data Construction

Unlike Figure 1 that uses Census tables from the 100 largest CBSAs, here we use our calibration IPUMS data in our 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.<sup>60</sup> For age, we construct 5-year age buckets. For family type,

<sup>60</sup>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.

we define four categories: Unmarried - No Children, Married - No Children, Youngest Child < 5, and Youngest Child > 5. For race, we use the IPUMS definitions.<sup>61,62</sup> For nationality of birth, we define two categories: native born and foreign born.

### Appendix C.1.2 Estimating Equation

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

$$\text{UrbanWeight}_i = c + \sum_{k \in K} \beta_k \text{IncomeDummy}_{ki}, \quad (\text{A.15})$$

where  $\text{UrbanWeight}_i$  is the urban weight of household  $i$ , which equals 1 if the household is assigned entirely to the urban area of its CBSA.<sup>63</sup>  $\text{IncomeDummy}_{ki}$  is a dummy equal to 1 if household  $i$  is in income bracket  $k$ .<sup>64</sup> 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,  $\hat{c} + \hat{\beta}_k$ , 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 income bracket replicates Figure 1 in the paper, but using IPUMS data for our 27 constant geography CBSAs instead of Census tables.

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:

$$\text{UrbanWeight}_i = c + \sum_{k \in K} \beta_k \text{IncomeDummy}_{ki} + \sum_{g \in G} \sum_{d \in D} \gamma_{gd} \text{DemoDummy}_{igd}, \quad (\text{A.16})$$

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.16 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:

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<sup>61</sup>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’.

<sup>62</sup>Hispanic is a separate variable in IPUMS. For this analysis, we do not distinguish whether a person is hispanic or not.

<sup>63</sup>We use a weight instead of a 0/1 dummy because we only know household location at the PUMA level, and some PUMAs span both the urban and suburban areas.

<sup>64</sup>We assign each household into 100 evenly log-spaced 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 Appendix A for further discussion. Our results are robust to different methods of adjusting for topcodes.

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

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

### Appendix C.1.3 Results

Figure A.3 shows normalized urban shares for each income bracket in 1990 and 2014. The left-hand plots shows estimates from equation (A.15) (without demographic controls) and the right-hand plot shows estimates from equation (A.16) (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.16 show what drives this finding. In Table A.5, 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.4 we plot normalized urban shares separately by demographic category within each group. To get large enough samples, we further aggregate age (25-34, 35-44, 45-64, 65+), and race (we keep "white" and "black". The "other" category is comprised mostly of Asian, Indigeneous, or multiethnic households.) Remarkably, we find a U-shape pattern, and an urbanization of the richest households from 1990 to 2014 in each category within each group of demographic characteristics.

### Appendix C.2 Robustness of Estimation of $\rho$

Our preferred estimate of  $\rho$  from equation (26) is shown in column 2 of Table 1. Here, we show variants of this estimation in Table A.6. 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 1.94 to 3.10, which is within two standard deviations from our preferred estimate of  $\rho = 3.0$ .

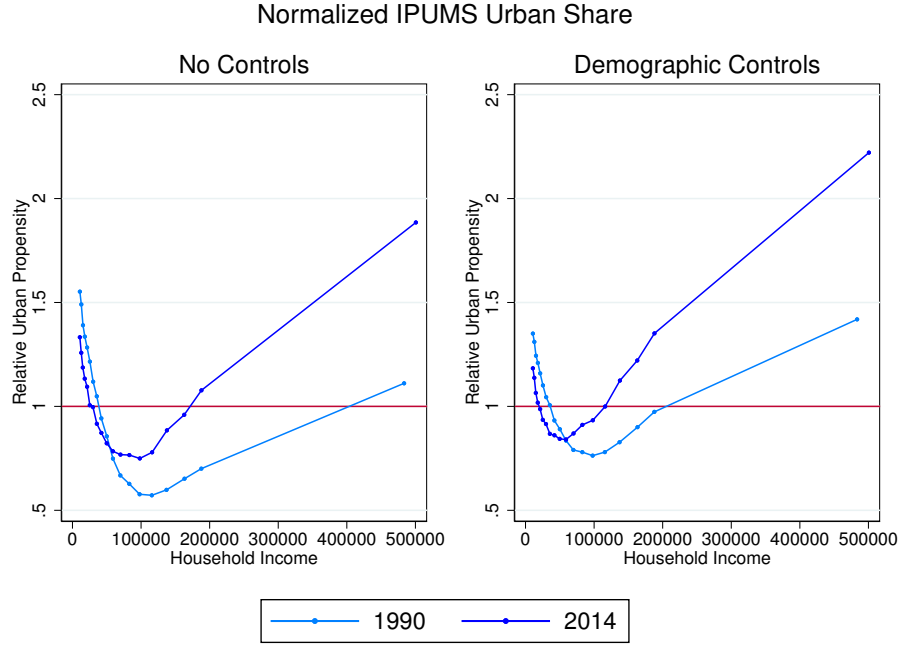
We also explored the robustness of our estimate to changes in our high quality cut-off from at least 40 percent college share, to at least 30, 50, or 60 percent college share. Estimates are noisier

Table A.5: Coefficients on Demographic Control Dummies in 1990 and 2014

Variable	Coefficient		Correlation with HH Income		Share of Pop Within Group	
	1990	2014	1990	2014	1990	2014
Age < 24 (omitted)	.	.	-0.114	-0.091	0.047	0.032
Age 25-29	-0.001	0.021	-0.051	-0.051	0.101	0.071
Age 30-34	-0.008	0.004	0.006	-0.005	0.123	0.091
Age 35-39	-0.011	-0.026	0.049	0.030	0.118	0.092
Age 40-44	-0.019	-0.046	0.098	0.051	0.109	0.098
Age 45-49	-0.020	-0.059	0.118	0.063	0.088	0.102
Age 50-54	-0.021	-0.069	0.099	0.062	0.071	0.106
Age 55-59	-0.019	-0.072	0.067	0.049	0.066	0.100
Age 60-64	-0.018	-0.071	0.010	0.014	0.068	0.087
Age 65-69	-0.024	-0.076	-0.063	-0.014	0.067	0.072
Age 70-74	-0.029	-0.078	-0.096	-0.044	0.055	0.052
Age 75-99	-0.032	-0.083	-0.109	-0.061	0.044	0.038
Age 80-84	-0.037	-0.087	-0.098	-0.066	0.027	0.029
Age 85+	-0.034	-0.094	-0.087	-0.081	0.017	0.030
Native Born (omitted)	.	.	0.041	0.048	0.847	0.752
Foreign Born	0.038	0.027	-0.041	-0.048	0.149	0.248
Unmarried-No children (omitted)	.	.	-0.288	-0.244	0.343	0.380
Married-No children	-0.056	-0.058	0.111	0.128	0.209	0.200
Youngest Child $\leq 5$	-0.073	-0.104	0.012	0.031	0.138	0.105
Youngest Child $> 5$	-0.062	-0.076	0.189	0.125	0.310	0.315
White (omitted)	.	.	0.150	0.113	0.780	0.690
Black	0.147	0.058	-0.148	-0.132	0.141	0.158
Native American	0.048	0.037	-0.014	-0.017	0.004	0.004
Chinese	0.089	0.042	0.011	0.023	0.010	0.021
Japanese	0.034	0.034	0.016	0.010	0.004	0.003
Other Asian	0.014	-0.001	0.019	0.053	0.020	0.049
Other Race (including mixed raced)	0.121	0.038	-0.073	-0.070	0.041	0.074

Note: Columns 1 and 2 report the coefficients from equation (A.16) for years 1990 and 2014 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.

Figure A.3: Impact of Demographic Controls on Relative Urbanization by Income



Note: This figure shows urban shares normalized by the aggregate urban share in each year with and without demographic controls. The left plot shows the coefficients from equation (A.15). The right plot shows the coefficients from equation (A.16). We drop household with income below \$10,000 and between \$200,000 and \$400,000. IPUMS data from 1990 and 2014 in 27 CBSAs with constant urban areas.

for the highest cut-offs which contain a very small share of high quality tracts, but IV estimates remain between 2.10 and 4.52.

Finally, Table A.7 provides additional detail on the robustness exercise in the main text where we drop the most urbanized industries from our Bartik instrument. The table shows the 10 most urbanized and 10 least 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, so that most of the Bartik variation comes from the suburbs. This is because our urban areas, by construction, are small relative to the suburbs.

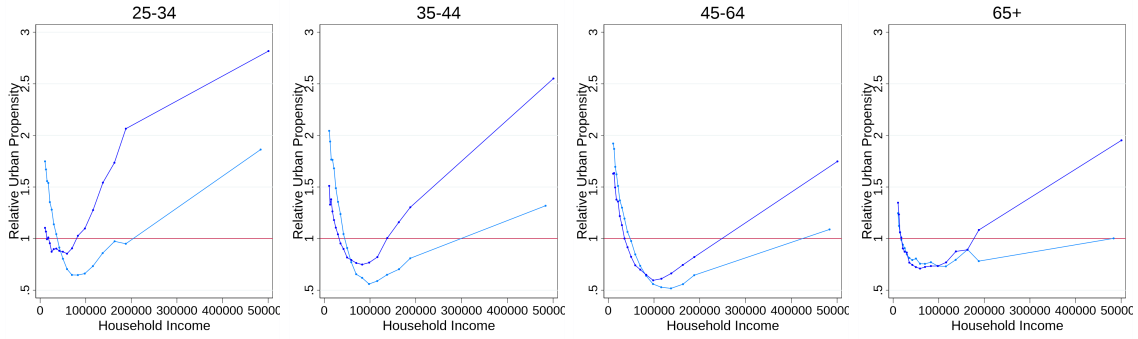
### Appendix C.3 Robustness to Alternate Neighborhood Quality Definition

In section 4.1, we define 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. In the main text, we show our estimation and counterfactual results using this baseline college share definition. Second, we define high quality neighborhoods as those that have a chain restaurant index greater than 1.1. Here we show that relative to using the college share quality definition, the restaurant chain quality definition delivers somewhat lower  $\rho$  estimates, very similar

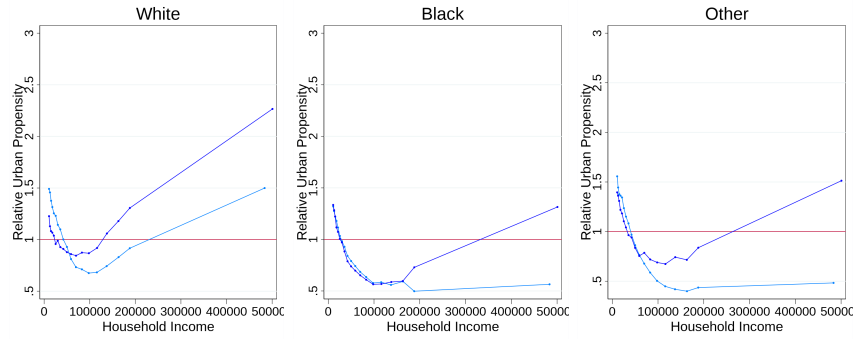


Figure A.4: Normalized Urban Shares by Demographic Categories in 1990 and 2014

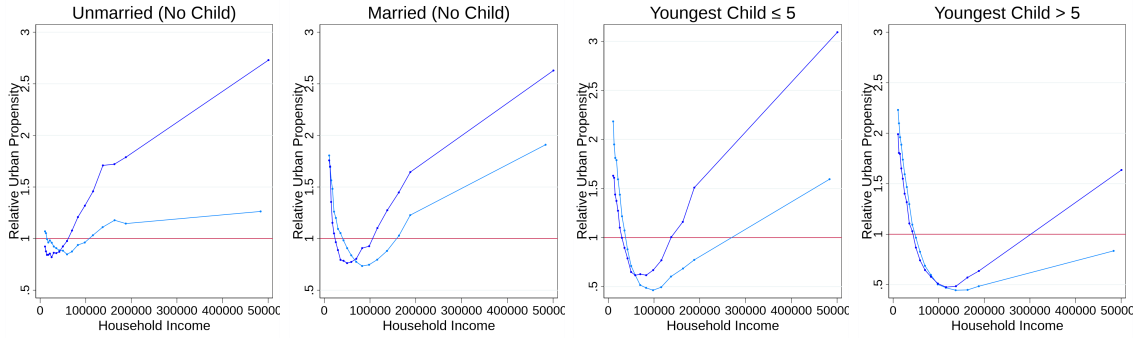
Panel A: Age



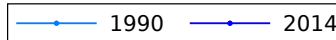
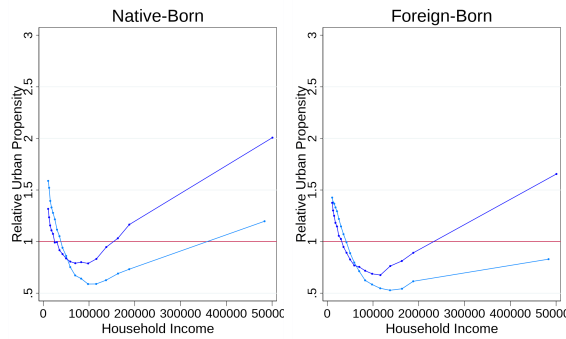
Panel B: Race



Panel C: Family Type



Panel D: Foreign Status



Note: This figure shows normalized urban shares from equation (A.15), plotted separately for each demographic category. The right plot shows the coefficients from equation (A.16). We drop household with income below \$10,000 and between \$200,000 and \$400,000. IPUMS data from 1990 and 2014 in 27 CBSAs with constant urban areas.

Table A.6: Robustness exercise for  $\rho$  estimation.

	2000-2014 (1)	Zillow All Price (2)	Census Price (3)
$\hat{\rho}$	3.10 (1.01)	1.94 (0.56)	2.67 (1.00)
Instrument	Base	Base	Base
KP F-Stat	8.4	5.3	3.7
Obs	5,901	6,632	7,031

Notes: This table shows estimates from equation (26). Data from 100 largest CBSAs, from 2000 and 2014 in column 1 and from 1990 and 2014 in column 2 and 3, neighborhood quality defined from education mix of residents. 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.

$\sigma\delta$  estimates, and very similar counterfactual and welfare results.

Table A.8 shows OLS and IV estimates of  $\rho$  for our base specification in column 1 and 2 of Table 1. We show these estimates for different high quality cut-off of our restaurant chain index ranging from 1 to 1.3.<sup>65</sup> We find OLS coefficients ranging from 1.64 to 1.83 that are somewhat smaller than the 2.34 that we obtained for the college share definition. IV estimates are also smaller, ranging from 1.2 to 2.6, but they have weaker first stage and larger standard errors. Table A.9 shows estimates of the amenity demand gravity parameter  $\sigma\delta$  using the restaurant quality definition. These estimates are almost identical to those from Table 3 using the college share quality definition. Finally, Table A.10 redisplay our welfare results for our main counterfactual exercise from Table 5, but using the restaurant quality definition. In all specifications, our welfare results are very similar to those obtained from the college share definition.

<sup>65</sup>Our measure of restaurant quality is not available in 1990, so we impute 2000 tract quality to 1990 tracts.

Table A.7: Most and Least Urbanized Industries

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

Notes: This 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.

Table A.8:  $\rho$  Restaurant Cutoff Robustness

	1.0		1.1		1.2		1.3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\rho$	1.73 (0.16)	1.21 (0.64)	1.64 (0.23)	1.62 (1.41)	1.78 (0.24)	2.64 (2.37)	1.83 (0.26)	2.55 (2.20)
Instrument	None	Base	None	Base	None	Base	None	Base
$R^2$	0.25		0.19		0.18		0.20	
KP F-stat		5.52		3.20		2.43		3.09
Obs	5284	5284	4782	4782	4383	4383	4085	4085

Notes: This table shows estimates from equation (26). Data from 100 largest CBSAs in 1990 and 2014, neighborhood quality defined based on chain restaurant quality. 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. Columns 1-2 define high quality tracts with an average restaurant index of at least 1.0.

Table A.9: Gravity Parameter  $\sigma\delta$  Restaurant Robustness

	All (1)	Home (2)	Weekend (3)	Home-Home (4)
$\hat{\delta}\sigma$	1.56 (0.00)	1.40 (0.00)	1.18 (0.00)	1.17 (0.00)
$\beta_{j(r) \neq j(r')}$	-0.04 (0.00)	-0.03 (0.00)	-0.03 (0.00)	-0.03 (0.00)
$R^2$	0.91	0.87	0.88	0.85
Obs	9,858,033	5,645,813	10,419,101	2,696,680

Notes: This table shows estimates from equation (29). From smartphone data on trips to non-tradable services in 100 largest CBSAs in 2016-2018, and neighborhood quality defined based on chain restaurant quality. 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.

Table A.10: Robustness of Welfare Estimates to Key Parameters using Restaurant Quality Cutoff

Decile:	$(\Delta CV - \Delta Inc)/Inc_{1990}$						$\Delta$ Urban Share			
	All Households			Renters Only			Predicted (p.p.)		Share of Actual	
	Top	Bottom	Diff.	Top	Bottom	Diff.	Top	Bottom	Top	Bottom
Base Specification	1.23	-0.23	1.46	0.66	-0.53	1.18	1.28	-3.00	55%	76%
Elasticity of Substitution between Neighborhood Types (base: $\rho = 3$ )										
$\rho = 2$	1.11	-0.25	1.36	0.54	-0.55	1.09	0.90	-2.30	39%	58%
$\rho = 4$	1.41	-0.17	1.57	0.82	-0.48	1.30	2.39	-4.70	103%	119%
Elasticity of Substitution between Same-Type Neighborhoods (base: $\gamma = 6.5$ )										
$\gamma = 5$	1.67	-0.03	1.71	1.01	-0.36	1.36	2.53	-6.28	109%	159%
$\gamma = 8$	1.02	-0.28	1.31	0.52	-0.61	1.13	1.00	-2.29	43%	58%
$\gamma = \infty$	0.31	-0.45	0.77	0.01	-0.98	0.99	0.56	-1.10	24%	28%
Elasticity of Substitution between Private Amenities (base: $\sigma = 6.5$ )										
$\sigma = 5$	1.38	-0.19	1.57	0.80	-0.50	1.30	1.41	-3.32	61%	84%
$\sigma = 8$	1.14	-0.25	1.39	0.57	-0.54	1.12	1.21	-2.83	52%	72%
$\sigma = \infty$	0.82	-0.34	1.15	0.25	-0.62	0.87	1.01	-2.32	43%	59%
Distance Elasticity of Amenity Consumption (base: $\delta = 0.2$ )										
$\delta = 0.1$	1.24	-0.23	1.46	0.66	-0.52	1.19	1.28	-3.00	55%	76%
$\delta = 0.3$	1.22	-0.23	1.45	0.65	-0.53	1.18	1.28	-3.00	55%	76%
Amenity Expenditure Share (base: $\alpha = 0.15$ )										
$\alpha = 0.1$	1.21	-0.18	1.39	0.68	-0.40	1.08	1.22	-2.71	53%	68%
$\alpha = 0.3$	1.19	-0.32	1.51	0.55	-0.75	1.29	1.54	-4.09	67%	103%
Housing/Land Supply Elasticities (base: $\epsilon_D = 0.6, \epsilon_S = 1.33$ )										
$\epsilon_D = 0.1, \epsilon_S = 1.33$	1.23	-0.23	1.46	0.65	-0.54	1.19	1.22	-3.38	53%	85%
$\epsilon_D = \epsilon_S = 1.33$	1.24	-0.21	1.45	0.68	-0.48	1.16	1.36	-2.52	59%	64%
$\epsilon_D = 1.2, \epsilon_S = 2.66$	1.31	-0.05	1.36	0.85	-0.18	1.03	1.35	-2.98	58%	75%
Public Amenity Elasticity (base: $\Omega = 0.05$ )										
$\Omega = 0$	1.11	-0.26	1.37	0.54	-0.55	1.09	1.27	-2.98	55%	75%
$\Omega = 0.03$	1.18	-0.24	1.42	0.61	-0.54	1.15	1.28	-2.99	55%	76%
$\Omega = 0.08$	1.30	-0.21	1.51	0.73	-0.51	1.24	1.28	-3.01	55%	76%
Property Tax Rates (base: $T_D = 0.2, T_S = 0.3$ )										
$T_D = T_S = 0$	1.24	-0.30	1.54	0.71	-0.65	1.35	1.18	-2.07	51%	52%
$T_D = 0.15, T_S = 0.25$	1.28	-0.22	1.50	0.71	-0.52	1.23	1.27	-2.84	55%	72%
$T_D = 0.25; T_S = 0.25$	1.23	-0.26	1.49	0.68	-0.55	1.23	1.24	-2.99	53%	76%

## Appendix C.4 Additional Tables and Figures

In this subsection, we show a variety of additional results referenced in the main text. In particular, we show the average income and homeownership share for all income deciles. We also show the shift in the U-shape for our baseline counterfactual (change in the income distribution from 1990 to 2014).

Table A.11: Income and Homeownership Rates by Income Decile

Decile	Income (\$1,000s)		% Growth	2000 Homeowner Share	
	1990	2014		Downtown	Suburbs
1	28.3	28.0	-0.94	32%	49%
2	34.7	34.1	-1.95	35%	53%
3	41.4	40.7	-1.75	39%	57%
4	48.5	48.2	-0.57	43%	62%
5	56.2	56.7	0.94	48%	68%
6	64.9	66.7	2.80	51%	73%
7	75.3	79.0	4.89	55%	77%
8	89.0	96.0	7.86	60%	82%
9	110.7	123.6	11.63	65%	87%
10	168.6	198.5	17.73	71%	91%

Notes: This table shows the average income in 1990 and 2014 and 2000 homeownership rate of households by income decile in 2000, using data from IPUMS. See Appendix A for details on this data source.

Figure A.5: Counterfactual impact of shift in income distribution on the U-shape

