Urban Revival in America*

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Abstract

This paper documents and explains the striking rise in the college share near city centers since 2000. We show that this urban revival is driven by younger college graduates in larger cities. A residential choice model reveals that the rising tendency of young college graduates to reside near non-tradable services accounts for more of their movement toward city centers than other commonly-cited hypotheses. We document corresponding changes in restaurant and nightlife consumption. We then link these changes in both consumption and urbanization to secular trends of top income growth and delayed family formation amongst young college graduates.

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This paper documents and seeks to explain the striking reversal in the fortunes of urban America since 2000. We show that, after decades of suburbanization, the college-educated population started urbanizing in most large U.S. cities between 2000 and 2010.[1] This reversal was entirely driven by rapid growth in the population of young college graduates near city centers. Contrary to claims of empty nesters urbanizing, we find that older college-educated cohorts continued to suburbanize up to 2010.

Various hypotheses could explain the distinct urbanization of young college graduates. Downtowns might be becoming more attractive to young college graduates with, for example, the centralization of high-skilled jobs, reduced urban crime rates, improved amenities, and new housing developments. Even without such changes in the environment, young college graduates might be increasingly attracted to stable features of downtowns, such as short commutes to existing jobs and proximity to consumption amenities, as their income and opportunity cost of time increase and family sizes decrease. In reality, many of these factors may be working simultaneously.

Our goal is to quantify the relative importance of these mechanisms in explaining the urbanization of the young and college-educated. To this end, we assemble a rich database at a fine spatial scale and estimate a residential choice model. This model is flexible enough to allow for the various competing hypotheses above and permits an intuitive linear decomposition of the predicted young-college urbanization rate into components associated with each factor.

Our analysis reveals that a high initial density of non-tradable service consumption amenities like restaurants and nightlife plays a more important role than other commonly-cited factors in explaining the urbanization of young college graduates. Recent changes in well-studied characteristics like job density and public amenities (school, crime, and transit) explain only a small portion of the urbanization of young college graduates, even though these characteristics are often important determinants of locational choices across all tracts and in the broader population.

The intuition behind these results is simple: an important explanatory factor for urban revival must 1) be highly prevalent near city centers relative to elsewhere, and 2) strongly attract young college graduates relative to other age-education groups. Our data reveal that high non-tradable service density is a persistent feature differentiating downtowns from the suburbs nationwide. Our regression estimates suggest that locations with a high initial density of non-tradable services have become increasingly attractive to young college graduates, but not so much to their older college-educated counterparts, or to the non-college educated. Overall, our

[1]This suburbanization has been extensively studied, such as in Glaeser et al. (2004), Baum-Snow (2007), and Boustan (2010). The reversal of this trend was already apparent in the 1990s and before in a handful of gateway cities like New York, Chicago, Boston and San Francisco. Carlino and Saiz (2019) also show that, while central cities do not experience a revival in the 1990s, some recreational districts were already seeing college-educated growth by the 1990s. Guerrieri et al. (2013) document gentrification near high-income neighborhoods in the early 2000s. Our finding is that urban revival emerges as a distinct widespread phenomenon in the 2000s, and is local to areas smaller than the central city.

analysis implies that the persistent urban density of non-tradable service amenities accounts for over 40 percent of young college-educated urbanization from 2000 to 2010, more than any other factor in our model.

One possible interpretation of our results is that the increasing attraction of young college graduates to locations with high initial densities of non-tradable services reflects rising preferences for non-tradable services. Complementary data on household expenditures and trips support this interpretation. Consistent with our regression estimates, the young and college-educated allocate a higher share of spending and trips to non-tradable service amenities like restaurants and nightlife than other age-education groups, and they increased those shares by the most since 2000. We caution against interpreting these changing allocations and the increasing taste for proximity to non-tradable services as reflecting shifts in deep underlying preference parameters. Instead, we posit that these changes are driven by external forces, such as delayed marriage and family formation, and top income growth amonst young college graduates.

In the final part of the paper, we document increasing shares of young college graduates in unmarried households without children and in higher income brackets, population segments that are historically more urbanized and spend more on and travel more to non-tradable services. All else constant, this changing composition of young college graduates across family types and income brackets mechanically predicts almost thirty percent of the observed growth of the young college-educated population downtown relative to the surburbs between 1990 and 2014.[2]

Overall, we make three main contributions. First, we document urban revival in space and time and identify the young and college-educated as the key population segment behind this trend. Second, we demonstrate the relevance of non-tradable services in explaining this trend using a number of complementary datasets on location choices, establishment locations, expenditures, and trips. Finally, we link both urban revival and changes in non-tradable service consumption to secular trends in household formation and top income growth.

Our analysis contrasts with existing work on residential choice in the U.S. in three important ways. First, our empirical approach incorporates a broad set of competing explanatory factors to quantify their relative importance. This comprehensive approach distinguishes our work from a concurrent set of papers on central city gentrification. Our results support work finding that the reduction in urban crime (Ellen et al., 2019) and rising distaste for commuting (Su, 2018; Edlund et al., 2016) each play a role in explaining the urbanization of young college graduates.[3] Like

[2]Our family formation results are similar using data from 2000 to 2010. We prefer to use the longer 1990-2014 time period for this part of our analysis because the recessions of 2001 and 2009 obscures any income trends between 2000 to 2010, and because unlike the tract level Census tables that we use in our regression analysis, the IPUMS micro-data allows us to look at the interaction of age and education in 1990.

[3]Edlund et al. (2016) and Su (2018) propose longer hours worked by college-educated workers after 1970 as an explanation for their centralization, providing evidence that these longer hours have increased the distaste for commuting. Our results indicate that this loss of leisure time may have had a larger impact on valuation for proximity to non-tradable service amenities useful in outsourcing home production, as in Murphy (2018), than on

Baum-Snow and Hartley (2017), however, we identify rising amenity values are the primary driver of downtown gentrification. Baum-Snow and Hartley (2017) show the importance of diverging amenity valuations across different racial groups in explaining urban gentrification since 2000. Our work, on the other hand, emphasizes diverging amenity valuations across different age and education groups. In addition, our work investigates which local consumption amenities matter for downtown gentrification, and demonstrates the distinct importance of non-tradable services relative to other types of residential amenities.[4]

Second, we document the important role of consumption amenities in residential choice within CBSAs. Following Glaeser et al. (2001) and Moretti (2012), academics have debated the relative importance of consumption versus production in explaining college-educated location choices. Diamond (2016) shows that local labor demand shocks matter more than amenities in the cross-city college-educated location choice. Our contribution is to establish the empirical relevance of consumption amenities for within-city sorting behavior, as posited in Brueckner et al. (1999). Glaeser et al. (2004) demonstrate that the share of college-educated individuals is a key determinant of economic success *across* cities since 1980. The new *within*-city trends that we study may have similarly far-reaching implications.

Existing empirical work on within-city residential choice in the U.S. has focused on measuring the willingness-to-pay for public amenities like schools and crime (see, e.g., Epple and Sieg, 1999 and Bayer et al., 2007). To study the distinct role of consumption amenities within CBSAs, we build tract-level density indexes capturing proximity to consumption amenities in various types of non-tradable services and tradable retail. The localized nature of these density indexes matters, as one may move to the Bay Area primarily for job opportunities, but choose to live in the center of San Francisco for the consumption amenities.

Finally, our empirical framework relates to but is methodologically distinct from existing work studying within-CBSA location choices. For instance, our model differs from Bayer et al. (2007)'s important application of McFadden (1973) and McFadden (1978)'s random utility model to neighborhood choice in the Bay Area in 1990. Relative to Bayer et al. (2007), we add a time dimension, a CBSA dimension, and many additional neighborhood characteristics. We obtain simpler first-difference linear regressions that control for time-invariant unobservables and permit the linear decomposition we use to assess the relative importance of different factors in explaining the urbanization of young college graduates.

valuation for proximity to jobs. Ellen et al. (2019) find that the 1990s crime drop predicts central city gentrification in the 2000s. We also find that reduced crime in the 1990s contributes to the urbanization of young college graduates after 2000.

[4] In Baum-Snow and Hartley (2017), amenities are an unobserved residual that compensate for differences in employment opportunities and house prices à la Rosen (1979) and Roback (1982). Behrens et al. (2018) also identify specific "pioneer" industries whose overrepresentation in a block predicts subsequent gentrification in New York City. These cultural, recreational, and creative industries tend to employ the same young, college-educated, single workers that we show to be driving urban revival.

Identifying preferences for many residential characteristics is inherently difficult, given the strong complementarity between these characteristics. Our identification strategy therefore relies on assembling a large array of neighborhood-level controls from new microdata sources. We also include strong controls for spatially correlated unobservables, like changes in the share of a given demographic group in nearby neighborhoods. In addition to these controls, we adapt standard instruments for house prices and wages to the neighborhood level. We are not aware of existing instruments for consumption amenities, so we develop one that draws on a recent IO literature on the determinants of entry and exit for various types of retail establishments (e.g., Igami and Yang, 2016).

The rest of the paper is divided as follows. Section 1 introduces our main data sources and establishes a number of stylized facts about changes in the within-city location choices of Americans between 1980 and 2010. Section 2 presents the residential choice model and our empirical application of this model to identifying the key drivers behind the distinct urbanization of the young and college-educated. Section 3 presents our main results. Section 4 provides external validity for the changing preferences for non-tradable service amenities that we find to drive urban revival and section 5 investigates the causes of these changing preferences. Section 6 concludes.

1 Data and Stylized Facts

The main geographical unit in our analysis is a census tract within a Core-Based Statistical Area (CBSA). We construct constant 2010-boundary CBSAs using constant 2010-boundary tracts from the Longitudinal Tract Data Base (LTDB). We define the city center of each CBSA using the definitions provided by Holian and Kahn (2012), obtained by entering the name of each CBSA's principal city into Google Earth and recording the returned coordinates. To establish the stylized facts on recent urban growth that motivate our empirical analysis, we assemble a database describing the residential locations of U.S. individuals at a decennial frequency. Tract-level population counts are from the decennial censuses of 1980 to 2000 and the American Community Survey (ACS) 2008-2012 aggregates, downloaded from the National Historical Geographic Information System (NHGIS). These local population counts are available by education in all years, and by age and education level from 2000 onwards.

1.1 Stylized Facts on Urban Revival

Figure 1 shows how tract population growth varies with distance from the city center in all CBSAs, for different population groups in different decades. In these plots, distance from the city center is weighted by aggregate population, and normalized to equal 1 at the outer edge of each CBSA. For example, a tract at a distance of 0.2 is further from its CBSA center than 20 percent of that CBSA's total population in the base year. The dashed horizontal line shows the average population growth across all tracts.

The first row of Figure 1 tells an unequivocal story of continuing suburbanization of the general population. In all three decades since 1980, population growth is slower than average in the innermost tracts containing approximately half of the initial population and faster than average in tracts further out. These plots also reveal the remarkable stability of the urban population over recent decades: the near-zero intercept of each plot implies that there was, on average, no population growth in tracts nearest to the center of CBSAs in all decades between 1980 and 2010.

The second row of Figure 1 tells a different story for the college-educated population. While the aggregate population growth curve slopes upwards from the city center, the college-educated curve slopes downwards. Between 2000 and 2010, in particular, the college-educated population grew 15 percentage points faster than in the near suburbs, at distance 0.2. The downward slope was more subtle in the 1980s and 1990s. Over these decades, the college-educated population grew around 5 percentage points faster at the city center than at distance 0.2. It was only after 2000 that the city center saw higher college-educated population growth than the average observed across all tracts. Together with the stable center city population documented in the first row of the figure, this downtown college-educated population growth – though small in absolute terms – is sufficient to generate meaningful change in the composition of downtown tracts.[5]

The third row of Figure 1 breaks down college-educated growth by age group since 2000, the earliest time period for which tract-level age-by-education group population tables are available from the Census. The plot shows that the urbanization of the college-educated in U.S. cities is explained almost entirely by growth in the two younger age groups: "young" 25-34 year-olds and, to a lesser extent, "middle-aged" 35-44 year-olds. Contrary to claims by the popular press that retiring baby boomers are urbanizing, the older 45-64 and 65+ year-old (not shown) college-educated groups are still rapidly suburbanizing.[6] The young age group exhibits the sharpest gradient with nearly 40 percent growth near city centers relative to around 15 percent growth outside of distance 0.2. The young college-educated curve is also different in that it does

[5]In 2000, the college-educated are less likely to live downtown than the average person, so the percentage growth in the number of college graduates residing downtown amounts to a small change in absolute terms. The young college graduates who drive this growth, however, are more likely to live downtown than the average person in 2000, and their growth in absolute terms is substantial.

[6]The popular press also emphasizes the urbanization of "millennials," those born from 1980 to the late 1990s, but this generation is too young to drive urban revival, which shows even in 2005-2009 ACS data. The oldest millennials, born in 1980, are only 30 in 2010. Rappaport (2015) suggests that aging baby boomers will support strong demand for multi-family units, but that these downsizing households will remain close to their original suburban locations. This is consistent with our finding that baby boomers do not contribute to urban revival.

not have a significant uptick in the suburbs: the young are the only group of college graduates that do not exhibit faster than average population growth in the suburbs.

In section 5, we use IPUMS data to investigate location choices by age-education group over a longer time period from 1990 to 2014. This micro-data helps illustrate how sharply age- and skill-biased urban revival has been. Figure 2 plots changes in the share of college graduates and non-college graduates living downtown by age. For the college-educated, the change in the share living downtown is highest for the young, with over 40 percent growth in the late 20s, and declines sharply for older cohorts, with zero growth in the urban share at age 40 and an approximate 20 percent decline in the urban share for all ages from 50 upwards. By contrast, the urban share of the non-college educated decreased by approximately 20 percentage points over the same period for all age groups. These facts align with our conclusion that urban revival is led by the young and college-educated.[7]

The urbanization of the young and college-educated is explained by changes in their locations in large CBSAs, in particular. In fact, the urbanization of the college-educated is not occuring in small cities (outside of the largest 50 in 2000), where the center city growth of even the 25-34 year-old college-educated population is below its average rate across all locations in these cities. To further characterize college-educated growth across large cities, we define a downtown in each CBSA as the set of tracts closest to the city center accounting for 5 percent of a CBSA's population. For each CBSA, we compare population growth in these "downtown" areas with population growth in the surrounding suburbs. In the 1980s and 1990s, fewer than 10 of the largest 50 CBSAs saw their college-educated population grow faster downtown than elsewhere in the CBSA. In the 2000s, this number almost tripled, to 28 of the 50 largest CBSAs. The acceleration in the urbanization of the college-educated from the 1990s to the 2000s occurred as the set of CBSAs experiencing downtown college-educated growth spread from a handful of gateway cities in the 1990s, like New York, Chicago and San Francisco, to almost every other large cities in the 2000s. Strikingly, in the 2000s young college graduates grew faster downtown than elsewhere in the CBSA in 23 of the 25 largest CBSAs. The exceptions are Riverside, CA, whose downtown is small, and Detroit.[8] These patterns are robust to a number of downtown definitions, but are too localized to show up in a simple comparison of central

[7]IPUMS data allows us to define age-education group prior to 2000, but forces us to restrict our sample to 27 CBSAs in which we can define constant geography downtowns out of Public Use Micro Areas with enough confidence in both 1990 and 2014. These downtowns are defined such that they contain 10% of each CBSAs population closest to the city center in 2000.

[8]Rust-belt cities like Cleveland and Detroit provide interesting case studies. Cleveland experienced "urban revival" despite a declining downtown population (a 12 percent drop from 2000 to 2010), thanks to changes in downtown composition (78 percent growth in young-college graduates from 2000 to 2010). Detroit also has a downtown population that declines as it shifts towards the young and college-educated. However, Detroit's downtown had the sharpest population drop and the smallest young college-educated growth of any large city. Detroit's downtown still shows promise of future revival: its youngest college-educated group - 18-24 year-olds, a very small group - urbanized quickly from 2000 to 2010.

cities with surrounding areas.[9]

Despite being localized and concentrated in larger CBSAs, these urbanization trends are strong enough to have an aggregate impact. About 150 million Americans live in the 50 largest CBSAs. In these large cities, downtowns accounting for five percent of the population experienced 24 percent of the total increase in the young college-educated population between 2000 and 2010. Our stylized facts are also robust to using a different city center definition (i.e., defined as Central Business Districts from the 1982 census of retail trade), age-income groups instead of age-education groups, and alternative datasets, such as the LODES data of commute by wage groups. We see the same patterns from 2000 to 2007 (using the earliest ACS data available, 2005-2009), showing that urban revival starts before the Great Recession. Finally, we note that other current work on central city gentrification corroborates our findings. Baum-Snow and Hartley (2017) show that downtowns are becoming richer, more educated and more white and also pin down the beginning of widespread and rapid downtown gentrification in year 2000.

The objective of the rest of this paper is to find the factors driving the 2000-2010 population growth gradients by age-education groups documented in Figure 1, with a sharp focus on explaining the remarkable growth of the young and college-educated near city centers. Data constraints force us to use 2000 as a base period for most of our model analysis. Fortunately, this is early enough to capture the period of widespread urban revival that we observe in almost all large US cities since 2000. To investigate the secular trends driving urban revival in section 5, we can consider a longer time period starting in 1990. The same external forces driving urban revival since 2000 may also explain some of the shoots of urban revival observed in the largest CBSAs in the 1990s.

1.2 Other data sources

In what follows we complement the residential location data used in the stylized facts section above with other datasets described herein. To estimate our residential choice model, we pair the age-education-tract level population counts with datasets describing access to jobs, consumption amenities, and house prices in the vicinity of each census tract in 2000 and 2010. To measure job density by wage group, we use the LEHD Origin-Destination Employment Statistics (LODES) datasets for 2002 and 2011. The LODES data provide counts of people who live and work in a given census block pair by three different nominal wage groups: high-wage workers earning more than \$3,333 per month, middle-wage workers earning \$1,251 to \$3,333

[9]Online Appendix Figure A.1 replicates Figure 1 separately for two sets of cities: the 50 largest by population in 2000 and those remaining. Online Appendix C proposes different ways of tabulating the data shown in Figure 1. It compares downtown growth - using various downtown definitions - to that in the rest of the CBSA to document the scope of urban revival across cities.

per month, and low-wage workers earning less than $1,250 per month.[10]

To measure consumption amenity density, we pair a geo-coded census of establishments in 2000 and 2010 from the National Establishment Time-Series (NETS) with a dataset containing travel times between these establishments and census tract centroids by foot from Google Maps.[11] We calculate indexes measuring four types of consumption amenities: two non-tradable services (restaurants and nightlife) and two types of tradable retail (food and apparel). We also measure consumption amenity diversity as an inverse-Herfindahl index using the most refined industry classification available in the NETS (at the SIC8 level, e.g., Korean restaurants). Finally, we use the smartphone visit data, described further in Couture et al. (2019), to calculate an amenity quality index that captures the presence of restaurant chains preferred by a given age and education group.

Our primary measure of housing costs for 2000 and 2010 is the Zillow House Value Index for two-bedroom homes, which measures median house prices at the zip code level. In robustness checks, we use alternative house price indices, rental prices using HUD's Fair Market Rent Series for one-, two-, and three-bedroom homes (available at the county level), and the median age of the housing stock from the 2000 census and the 2008-2012 ACS, to measure one aspect of housing quality and new housing developments.[12]

We complement these three main tract-characteristic datasets with information on public amenities (transit times, violent crime per capita, school district rankings) and natural amenities. Our measure of transit performance at the tract-level comes from Google Maps in 2014, and is the average travel time of a five-mile trip from a tract centroid to a random set of NETS establishments. We measure violent crime (murder, rape, robbery, and aggravated assault) at the police district-level using the Uniform Crime Reporting Program (UCR) data for 2000 and 2010. We measure school quality using within-state rankings of school districts in 2004 and 2010 from SchoolDigger.com.[13] There are typically multiple tracts within a particular police

[10] In 2002 and 2011, 27 and 37 percent of workers were considered high-wage, respectively. To address confidentiality issues, the LODES data are partially synthetic. We describe the generation of synthetic data in Appendix A, and show how aggregation of census block data at the tract level ensures that 90 percent of the LODES data are unaffected by this procedure.

[11] The popularity of the Walk Score, which rates neighborhoods by how walkable they are, hints at the importance of such highly localized indexes in location decisions.

[12] We match zip codes to 2010 tract geography using a crosswalk from the U.S. Department of Housing and Urban Development (HUD). Our alternative price indices include Zillow's per square foot index; the FHFA house price index, a weighted, repeat-sales index calculated by using Fannie Mae and Freddie Mac mortgage securitizations as described in Bogin et al. (2018); and finally a hedonic price index calculated using DataQuick data and the model from Ferreira and Gyourko (2011).

[13] While we believe that SchoolDigger.com is the most comprehensive database available, we have school ranking data for less than half of our CBSAs' sample of tracts. SchoolDigger.com compiles test scores and provides a ranking of each school district within each U.S. state. The ranking averages over test scores in different fields for schools from grades 1 through 12. We use the inverse of that ranking in percentile for 2004 - the earliest year available - and for 2010 in the school district that a tract falls into as our measure of school quality in 2000 and 2010.

and school district. We match these areas to 2010 tract boundaries using Census shapefiles.[14] Data on natural amenities, like the precipitation, hilliness, and coastal proximity of each census tract, are from Lee and Lin (2018).

To investigate recent trends in family formation, income growth, expenditures, and travel that can explain the changing preferences of young college graduates, we use counts of individuals by family type and income bracket within each age-education group. These counts come from the 5% Integrated Public Use Micro-data Series (IPUMS) sample of the 1990 and 2000 censuses and the 5% IPUMS sample from 2012-2016 ACS surveys, as well as micro-data from the 1996 to 2016 Consumer Expenditure Survey (CEX) and the 2001 and 2009 National Household Transportation Survey (NHTS). We design a procedure for allocating individuals in IPUMS to constant geography urban and suburban areas. See Appendix A for further detail on all data sources and spatial concordance procedures.

2 Empirical Strategy

2.1 Deriving an Estimating Equation

To explain the changing residential location choices of different age-education groups, we specify a discrete choice model. The model delivers a simple log-linear estimating equation capturing how changes in the environment (jobs, amenities, and house prices) from 2000 to 2010, as well as initial 2000 levels in these variables, relate to changes in the share of an age-education group living in a given tract.

Each individual i in group d chooses a tract j in CBSA c in which to reside in year t to maximize the following indirect utility:

$$(1) \quad V^i_{jct} = \beta^{d(i)}_{wt} \ln w^{d(i)}_{jct} - \beta^{d(i)}_{Ht} \ln p_{Hjct} - \beta^{d(i)}_{At} \ln p_{Ajct} + \beta^{d(i)}_{at} \ln a_{jct} + \mu^{d(i)}_{jc} + \xi^{d(i)}_{jct} + \varepsilon^i_{jct},$$

where w^d_{jct} is the wage net of commute costs, which we assume to be common to all individuals in group d residing in tract j, p_{Hjct} is the price of housing, p_{Ajct} is a price index for consumption amenities that varies with transport costs to these amenities, and a_{jct} is the level of public amenities. The group-specific tastes for each tract are represented by the sum of two group-specific terms: a time-invariant component μ^d_{jc}, and a time-varying component, ξ^d_{jct}. The

[14]This mapping projects 11,044 police districts to 57,095 census tracts, and 12,956 school districts to 24,283 census tracts. Police districts are mostly cities and, while CBSAs consist of many cities, the central city in most CBSAs is larger than the downtown experiencing urban revival. In some cases like Houston and Atlanta, police districts are at the county level, so the parts of the respective central city in different counties report different numbers. Our results are robust to using a sub-sample containing only those CBSAs where the largest police district contains less than 30 percent of the CBSA population.

individual-specific tastes, ε^i_{jct}, take a nested-logit structure with tracts nested by CBSA with a within-group correlation parameter σ^d.[15]

This utility maximization problem, outlined in Berry (1994), yields a linear equation for the share $\tilde{s}^d_{jct}$ of individuals in group d who choose tract j relative to a base tract $\bar{j}$:

$$(2) \qquad \ln \tilde{s}^d_{jct} = \beta^d_{wt} \ln \tilde{\mathbf{w}}_{\mathbf{jct}} + \beta^d_{At} \ln \tilde{\mathbf{A}}_{\mathbf{jct}} - \beta^d_{Ht} \ln \tilde{p}_{Hjct} + \mu^d_{jc} + \tilde{\xi}^d_{jct} + \tilde{\xi}^d_{w,jct} + \sigma^d \ln \tilde{s}^d_{j|ct},$$

where $\tilde{X}_j = X_j - X_{\bar{j}}$, we normalize $\mu_{\bar{j}c}$ to equal zero, and the final term $\ln \tilde{s}^d_{j|ct}$ is a "nested-logit" term equal to the share of group d choosing tract j within CBSA c in year t. The steps of this derivation are standard and can be found in online Appendix F. To simplify the presentation, we use the vector $\tilde{\mathbf{A}}_{\mathbf{jct}}$ to denote the sum of the public and consumption amenity terms, $\beta^d_{At} \ln (1/p_{Ajct}) + \beta^d_{at} \ln a_{jct}$. $\mathbf{w_{jct}}$ denotes a vector of time-varying accessibility to jobs in three different wage brackets, which we use to proxy for w^d_{jct}, the group's wage net of commute costs. $\xi^d_{w,jct}$ reflects the residual variation in the wages earned by group d individuals residing in location j.[16]

Differencing this equation between 2000 and 2010, the two years in our data, we obtain our estimating equation:

$$\begin{aligned}(3) \quad \Delta \ln \tilde{s}^d_{jc} \quad = \quad & \beta^d_{w,2010} \Delta \ln \tilde{\mathbf{w}}_{\mathbf{jc}} + \Delta\beta^d_w \ln \tilde{\mathbf{w}}_{\mathbf{jc,2000}} + \beta^d_{A,2010} \Delta \ln \tilde{\mathbf{A}}_{\mathbf{jc}} + \Delta\beta^d_A \ln \tilde{\mathbf{A}}_{\mathbf{jc,2000}} \\ & + \beta^d_{p_H,2010} \Delta \ln \tilde{p}_{Hjc} + \Delta\beta^d_{p_H} \ln \tilde{p}_{Hjc,2000} + \sigma^d \Delta \ln \tilde{s}^d_{j|c} + \Delta\tilde{\xi}^d_{jc} + \Delta\tilde{\xi}^d_{w,jc} + \epsilon^d_{jc},\end{aligned}$$

where $\Delta X = X_{2010} - X_{2000}$ for both variables and coefficients. Note that fixed tastes for unobserved time-invariant tract characteristics like nice weather or historical architecture cancel out in first-difference. The error term is the sum of any unobserved changes in the perceived residential quality of tract j for group d (i.e., labor supply shocks $\Delta\tilde{\xi}^d_{jc}$), unobserved changes in the wages earned by group d individuals residing in tract j (i.e., labor demand shocks $\Delta\tilde{\xi}^d_{w,jc}$) , and an additional term ϵ^d_{jc} capturing any remaining measurement error.

We derived equation 3 from an indirect utility function, so it is possible to interpret our regression coefficient as reduced-form preference parameters. In this interpretation, coefficients on changes in characteristics from 2000 to 2010 (e.g., $\Delta\tilde{\mathbf{A}}_{\mathbf{j}}$) capture the preference levels of demographic group d in 2010 (i.e., $\beta^d_{A,2010}$), while coefficients on initial levels of characteristics (e.g., $\tilde{\mathbf{A}}_{\mathbf{j,2000}}$) capture changes in the preferences of demographic group d from 2000 to 2010

[15]This implies that individual-specific taste shocks, ε^i_{jct}, are themselves the weighted sum of two shocks, $\varepsilon^i_{jct} = \psi^i_{ct}(\sigma^{d(i)}) + (1 - \sigma^{d(i)})\nu^i_{jct}$. Tract-specific taste shocks, ν^i_{jct}, are independent draws from the extreme value distribution, while CBSA taste shocks, ψ^i_{ct}, are independent draws from the unique distribution such that $\psi^i_{ct}(\sigma^{d(i)}) + (1 - \sigma^{d(i)})\nu^i_{jct}$ is also an extreme value random variable. The parameter $0 \leq \sigma^d < 1$ governs the within-group correlation in the error term $\psi^i_{ct}(\sigma^{d(i)}) + (1 - \sigma^{d(i)})\nu^i_{jct}$. As σ^d approaches zero, the model collapses to a standard logit model.

[16]Note that this indirect utility function can be derived from a Cobb-Douglas utility maximization problem.

(i.e., $\Delta\beta^d_{A,2010}$). Note that the $\sigma^d \Delta \ln \tilde{s}^d_{j|c}$ term captures within-CBSA variation in shares, which implies that preferences in equation 3 are identified by cross-CBSA variation in location choice. If we replaced this term with a CBSA fixed-effect, preferences would be instead identified from within-CBSA location choice, and all coefficients in equation 3 would be scaled up by a factor $1/(1-\sigma^d)$. We show results for both a nested-logit and CBSA fixed-effect specifications, but retain the nested-logit as our main specification, because it allows us to compare preference parameters across age-education groups net of the group specific scaling factor $1/(1-\sigma^d)$.

In this empirical framework, changes in residential location decisions are driven by either changes in location characteristics (including prices), $\Delta\tilde{X}_{jc}$, or changes in the preferences of the relevant demographic group for these characteristics, $\Delta\beta^d_X$. The young and college-educated might be moving downtown either because characteristics of downtown tracts changed in ways correlated with their preferences (i.e., $Corr(\Delta\tilde{X}_{jc}, \beta^d_{X,2010}) > 0$) or because their preferences tilted towards characteristics in which downtown tracts were already advantaged (i.e., $Corr(\Delta\beta^d_X, \tilde{X}_{jc,2000}) > 0$).

Our analysis therefore relies on two key ingredients: 1) data on the initial levels and changes in the characteristics of tracts at different distance from the city center, and 2) estimates of the parameters reflecting both the levels and change in the preferences of the young and college-educated for these characteristics. We now present data summarizing the initial levels and changes in tract characteristics. We then outline our estimation procedure, identification strategy, and baseline parameter estimates. Finally, we bring these two ingredients together to quantify the contribution of each factor in explaining the urbanization of young college graduates.

2.2 Recent Spatial Trends in Jobs, House Prices, and Amenities

Figures 3 and 4 show how key tract characteristics vary with distance to the city center. Panel A of each figure shows the kernel density plot of the 2000 logged level of a variable and Panel B shows a kernel density plot of the log change from 2000 to 2010, with kernel weights based on the 2000 tract share of young and college-educated individuals. The data presented include all tracts in our estimation sample of 355 CBSAs for which a variable is available. We provide details on the construction of all variables in Appendix B.

Figure 3 presents gradients from the city center for job density, house prices, and public amenities (school quality and crime). Job density is an inverse distance-weighted average of the number of jobs in tracts surrounding each residential tract in 2002 and 2011, computed using the three wage groups in the LODES data. The leftmost plots show gradients from the city center for the initial level and change in the high-wage job density (>$3,333 per month, the dashed line) and the low-wage job density ($1,250/month or less per month, the solid line). The density of both job types is highest near the city center, but only high-wage jobs have grown faster near the city center over the last decade.

The middle panel shows similar gradients for house prices, plotting our main two-bedroom price index (dashed) as well as the Zillow per square foot price index (solid). Houses are more expensive away from the city center in 2000, but less so when prices are measured on a per-square-foot basis. House price growth from 2000 to 2010 displays a strongly negative gradient from the city center, especially on a per square foot basis.

The rightmost panel shows that public amenity levels are lower near the city center, with lower-ranked schools (dashed, not logged) and more violent crime per capita (solid). Schools near the city center have dropped even further in state district rankings from 2004 to 2010. Violent crime rates are decreasing everywhere from 2000 to 2010 as expected, but particularly towards the city center and in the "middle-distance" suburbs.

Figure 4 presents similar gradients for two representative consumption amenities: restaurants (dashed) and food stores (solid). From left to right, the plots show measures of amenity density, diversity, and quality, respectively. The density and diversity indexes are the travel-cost weighted average number and diversity of restaurants in the vicinity of a census tract calculated using the CES price index methodology from Couture (2016). The quality variable is only available for restaurants in 2012 (instead of 2010), and uses the methodology and smartphone visit data used in Couture et al. (2019). This quality index is high if restaurants in a tract belong to chains that young college graduates favor with high visit probabilities, after controlling for spatial variation in their choice sets.

The density of restaurants and food stores is highest near the city center, but has grown faster in the suburbs from 2000 to 2010. *Rising* consumption amenity density is therefore unlikely to explain urban revival. Unlike density, restaurant diversity in 2000 is relatively low downtown and highest in the near suburbs, while restaurant quality follows a distinct non-monotonic pattern, being highest downtown and in the city outskirts. Between 2000 and 2010, restaurant quality, and diversity of both restaurants and food stores increased faster near city centers.

Finally, it is worth noting that the strong centrality of consumption amenity density is not a recent phenomenon. A comparison of the amenity density gradients for restaurants and food stores in 1992 (the earliest year NETS data is available), 2000, and 2010 reveals that the urbanized nature of restaurant and food store density did not emerge in recent history. If anything, amenity density growth was even faster in the suburbs relative to downtown in the 1990s than it was in the 2000s (see online Appendix Figure A.2).

2.3 Identification

Our base specification of the estimating equation (3):

$$\begin{aligned}\Delta \ln \tilde{s}^d_{jc} \;&=\; \beta^d_{w,2010}\Delta \ln \mathbf{\tilde{w}_{jc}} + \Delta\beta^d_w \ln \mathbf{\tilde{w}_{jc,2000}} + \beta^d_{A,2010}\Delta \ln \mathbf{\tilde{A}_{jc}} + \Delta\beta^d_A \ln \mathbf{\tilde{A}_{jc,2000}} \\ &\quad + \beta^d_{p_H,2010}\Delta \ln \tilde{p}_{Hjc} + \Delta\beta^d_{p_H} \ln \tilde{p}_{Hjc,2000} + \sigma^d \Delta \ln \tilde{s}^d_{j|c} + \Delta\tilde{\xi}^d_{jc} + \Delta\tilde{\xi}^d_{w,jc} + \epsilon^d_{jc}\end{aligned}$$

includes job densities, consumption amenity densities, and the "two-bedroom" house price index to reflect $\mathbf{w_{jc}}$, $\mathbf{A_{jc}}$, and p_{Hjc}, respectively. The dependent variable is the 2000 to 2010 log change in the share of age-education group d that lives in tract j of CBSA c relative to a base tract. We also include in $\mathbf{A_{jc}}$ variables measuring natural amenities, distance to the city center, local demographics, and population density to control for unobserved endogenous amenities as described below. In robustness checks below, we further add to $\mathbf{A_{jc}}$ explanatory variables for specific observable public amenities, such as school quality, crime, and transit times, and other dimensions of the spatial distribution of consumption amenities, such as diversity and quality of establishments.[17]

Identifying the effect of neighborhood characteristics on residential choice is inherently challenging. The first-difference regression controls for time-invariant tract characteristics that could be correlated with our regressors. However, our regressors, both in initial levels and in changes, could still be correlated with unobserved changes in perceived tract quality ($\Delta\tilde{\xi}^d_{jc}$) or local wage premia ($\Delta\tilde{\xi}^d_{w,jc}$). Our identification strategy therefore also relies on the inclusion of a wide array of controls for levels and changes in neighborhood characteristics, described below. We address remaining reverse causality concerns with instruments and alternatively, in the case of house prices, by relying on the structure of the model. To instrument changes in house prices and jobs, we adapt standard instruments to our context at the neighborhood level. To instrument consumption amenities, we draw on a recent IO literature on the determinants of entry and exit for various types of retail establishments (e.g., Igami and Yang, 2016). We do not have instruments for the initial levels of consumption amenities, jobs, and house prices. So conditional on all the controls in our regressions, we take these variables in levels as exogenous.

Controls We include a series of controls to help pick up changes in, or changing tastes for, unobserved tract characteristics. First, we control for the change and level of the share of one's own type in nearby tracts (homophily and spatially correlated unobservables) and the change and the level of population density in nearby tracts. We exclude the same tract (j) from each of these measures since it would mechanically co-vary with our dependent variable, but we do include the 2000 levels of the share of one's own type and population density in

[17]These variables are excluded from our base specification because we either have no instrument for them or only limited spatial coverage.

the same tract as independent controls.[18] We also control for natural amenities (precipitation, hilliness, coastal proximity) within 1 mile of the tract centroid. Finally, given the urbanization of young college graduates, one might worry that their location choice correlate with initial levels of variables that are urbanized, non-tradable service amenities in particular. We include a control for the distance to the city center to alleviate concerns that coefficient on amenity levels are simply picking up the increasing taste of the young and college-educated for another centralized unobserved amenity. With this control, our coefficients are identified by location choices conditional on distance to the city center. Further controls – e.g., for crime, school, transit, and amenity diversity and quality – are included in robustness checks.

Instruments Unobserved shocks subject our change variable coefficients to reverse causality concerns. For instance, an influx of young college graduates in response to unobserved shocks to tract quality or nearby wages may attract amenities and jobs and raise house prices. We address such concerns with instruments described herein.

Employment Density by Wage Level The simultaneous determination of work and residential locations is a key identification concern in residential choice model estimation. This problem is straightforward: young and college-educated workers can reduce their commute costs by moving to areas experiencing an influx of firms hiring them. At the same time, firms may move closer to a young, educated talent pool, which is often cited as justification for new downtown offices by employers like Amazon, Twitter or Google (Johnson and Wingfield, 2013). We follow Diamond (2016), amongst others, and instrument for changes in our job amenity indexes with standard Bartik instruments. The LODES data include jobs in our three wage groups by 20 North American Industry Classification System (2-digit NAICS) sectors. This industry breakdown allows us to obtain Bartik predictions of wage group-specific employment growth that depend on the industrial composition of each tract, and on national industry growth.

In our context, a particular challenge to the exclusion restriction is that some high skill sectors that drive growth in high wage jobs, such as finance and insurance, or technology, also choose to collocate with unobserved amenities that young college graduates like. We therefore verify that our IV coefficients and results are robust to dropping any of the 20 industries that we use to compute our instruments.[19]

[18] We measure proximity to one's own type as the inverse distance-weighted average of the population share of demographic group d in all tracts excluding tract j in year t, and nearby population density as the inverse distance-weighted average population density in all tracts excluding tract j in year j.

[19] Recent work on Bartik instruments (Borusyak et al., 2018; Goldsmith-Pinkham et al., 2019) recommend exploring which industries drive variation in the instrument.

Housing Prices To overcome the endogeneity of house price changes, we exploit the correlation between housing prices and exogenous natural amenities identified by Lee and Lin (2018). We expect geographic features like oceans and mountains to act like anchors imposing supply constraints on land, thereby driving up relative house price levels, as described in Gyourko et al. (2013). These supply constraints may also amplify the reaction of house prices to demand shocks, so we also use these natural amenities as instruments for changes in house prices. Our vector of geographic features includes the log Euclidean distances (in km) of the centroid of tract j from the coast of an ocean or Great Lake, from a lake, and from a river, the log elevation of the census tract centroid, the census tract's average slope, an indicator for whether the tract is at high risk of flooding, the log of the annual precipitation, and the log July maximum and January minimum temperatures in the tract averaged over 1971 and 2000.[20] As in Bayer et al. (2007), our instrument for tract j uses geographic features of tracts one to three miles away, controlling for the average geographic features of tracts within one mile. The key exclusion restriction is that geographic features further than one mile away from a tract do not impact demand for living in that tract, conditional on the geographic features within one mile. As an additional instrument for changes in housing prices (and for the levels of local demographic shares), we include historical tract-level 1970 population shares, by age and by education group.

In a robustness check, we assume a Cobb-Douglas preference structure to simply difference out the CEX housing expenditure share of each age-education group from the utility function. Endogeneity of housing is then no longer an issue because housing variables are used to adjust the left-hand side variable and are excluded from the right-hand side regressors. This approach, taken in Baum-Snow and Hartley (2017), replaces a reliance on assumptions related to instruments with a reliance on assumptions about the demand structure.

Consumption Amenity Density The key challenge to identifying coefficients on changes in amenity density is that they may correlate with changes in unobserved demand factors that we do not control for, such as the entry of amenities not in our model. We therefore design an instrumental variable that predicts amenity firm entry using supply side drivers.

The main idea is that firms consider local supply factors when deciding where to open new establishments. Different firms put different weights on these supply factors. For instance, Subway may be less likely to open new stores near existing ones than, say, McDonalds, because it has stronger concerns about cannibalizing existing store sales. We exploit such differences in firm's national business expansion strategies within finely-categorized industries to predict

[20] Such instruments have been criticized by Davidoff (2016) in the context of cross-CBSA regressions. Davidoff (2016) shows that geographical supply constraints are correlated with demand factors and that constrained cities like New York and San Francisco also have more productive workers. Our within-CBSA instrument is less vulnerable to this criticism.

differences in aggregate amenity entry in each tract, in a way that is plausibly orthogonal to the determinants of people's location choice modeled in equation 3.

The supply factors that we try to capture are those highlighted by an existing literature. Igami and Yang (2016), for example, show that firms do not want to open establishments too close to their own preexisting outlets or their direct competitors. In addition to such cannibalization and competition concerns, firms also consider positive spillovers. Establishments from complementary product types in close proximity provide foot traffic (Shoag and Veuger, 2018), while proximity to upstream suppliers and a firm's own establishments, at a wider margin, can help reduce distribution and marketing costs (Holmes, 2011). To capture each of these factors, we estimate the following reduced-form model of establishment entry and exit at the tract-level for each SIC8 category in our amenity data:

(4)

$$n^{sic8}_{j10} - n^{sic8}_{j00} = \alpha^{sic8} + \sum_{dist\in\{[0,1],[1,2],[2,4],[4,8]\}} \left(\beta^{sic8}_{dist} n^{sic8}_{j00,dist} + \beta^{sic6|8}_{dist} n^{sic6|8}_{j00,dist} + \beta^{sic4|6}_{dist} n^{sic4|6}_{j00,dist}\right) + \varepsilon^{sic8}_{j}.$$

The dependent variable is the change in the number of establishments within a given SIC8 code in tract j. The regressors characterize the business environment in the vicinity of tract j in 2000. Specifically, $n^{sic8}_{j00,dist}$, $n^{sic6|8}_{j00,dist}$ and $n^{sic4|6}_{j00,dist}$ denote the number of establishments within distance interval $dist$ from the centroid of tract j that fall in the same SIC8, in the same SIC6 but not the same SIC8, and in the same SIC4 but not the same SIC6. For instance, $n^{sic8}_{j00,[0,1]}$ captures the number of direct competitors an $sic8$ firm faces in tract j, i.e., the number of establishments that are very close both geographically and in the same finely-defined industry space (e.g., other Korean restaurants located within 1 mile). $\beta^{sic8}_{[0,1]}$ reflects the marginal effect of such direct competitors on net entry.

The estimation results summarized in Table 1 indicate that competition and cannibalization concerns are strong predictors of establishment entry and exit in the vast majority of the 350 SIC8 codes used to define our four consumption amenity indexes. In 92 percent of SIC8 codes, the presence of establishments in the same SIC8 within 0-1 miles significantly reduces entry in a tract. Our estimated coefficients are larger for some establishment types that have stronger cannibalization concerns: this cross-industry heterogeneity will work alongside spatial heterogeneity in the pre-existing business landscape to provide variation in our instrument, once we condition for the aggregate initial level of amenity density in our second stage.

We also see heterogeneity in the strength of agglomeration forces across SIC8 categories. Proximity to establishments in related but less similar product spaces tends to yield positive agglomeration externalities, but not in all SIC8 categories: the coefficient on the number of establishments within 1 mile in the same SIC6 but not SIC8 ($\beta^{sic6|8}_{[0,1]}$) and in the same SIC4 but not SIC6 ($\beta^{sic4|6}_{[0,1]}$) are positive and significant in about 50 percent of cases and negative and significant in about 10 percent of cases.

Our instruments for the change in the amenity density index are built analogously to the original variable, but replacing the actual tract-level establishment counts for each amenity category in 2010 with their predicted values. The 2010 predicted tract-level establishment count for an amenity category (i.e., restaurants, food stores, etc.) is the observed tract-level establishment count in 2000 adjusted by the sum of the fitted values of the net entry regression above across all of the SIC8 categories within the broader amenity category.

First stage statistics presented in Table 4 indicate that these instruments are relevant. A valid instrument must also be exogenous, i.e., uncorrelated with the error terms in equation 3 conditional on other regressors. The exclusion restriction could be violated if the instrument correlates with supply shocks that affect the unobserved group-specific wage premia $\Delta\tilde{\xi}^d_{w,jc}$, but it is hard to find a story such that this would be true, especially for the college-educated groups who are unlikely to work in restaurants and food stores.

The instrument is robust to changes in local demand because the cross-tract variation in the instrument is determined by tract-invariant, national coefficient estimates interacted with the local, but predetermined, business mix. A violation of the conditional exclusion restriction would require that demand factors not controlled for in equation 3 drive differences across firms in their estimated business expansion strategies. For instance, the same unobserved demand factors could drive both the difference in cannibalization concerns between Greek and Korean restaurant firms, and the difference in the propensity of some age-education groups to enter areas with initally more Greek than Korean restaurants. There is no particular reason to expect this, but we cannot entirely exclude these stories. To alleviate these concerns, equation 3 includes a large array of demographic and amenity level controls, similar to what retailers would consider in their demand-side market analysis.

Homophily and Population Density Controls We instrument for the change in population density in nearby tracts using the 1970 population density in the same tract and its inverse distance-weighted average across nearby tracts. Similarly, we instrument for the change in the share of the same demographic group in nearby tracts using tract-level 1970 population shares, by age and by education group, in the same tract as well as in nearby tracts (using an inverse-distance weighted average). Such historical instruments to predict population density have been used since the pioneering work of Ciccone and Hall (1996), see Combes et al. (2010) for a recent discussion.

Nested-Logit Within-CBSA Share Instrumenting the change in the nested-logit share of type d individuals within CBSA c who live in tract j, $\Delta s^d_{j|c}$, requires exogenous factors affecting the attractiveness of tract j relative to all other tracts in its CBSA c. For each instrument described above, we compute $instr(\Delta s^d_{j|c})$ as the average difference between the instrument in tract j and that in all other tracts k in CBSA c:

$$instr(\Delta s^d_{j|c}) = \frac{\sum_{k \in c_j \, and \, k \neq j}(instr_j - instr_k)}{N_{c_j}},$$

where N_{c_j} is the number of tracts in the same CBSA c as tract j.[21]

3 Results

3.1 Regression Results

Table 2 presents regression results for the nested-logit model (equation 3) for the three college-educated age groups shown in Figure 1: 25-34, 35-44, and 45-64 years of age. Panel A presents coefficient estimates for a specification where we instrument only for the nested-logit within-CBSA share variable, which might otherwise cause collinearity issues. We refer to these estimates as our "OLS" estimates.[22] In Panel B, we instrument for all change variables, as described above. Table 4 provides first-stage statistics for all instrumented variables. The reduced-form and conditional Sanderson and Windmeijer (2016) first-stage statistics all reject that the instruments are irrelevant.

Each panel shows coefficient estimates for three broad sets of location characteristics: house prices, job density, and consumption amenities. For the sake of parsimony, this base specification includes two representative consumption amenity density indexes for restaurants and food stores (the non-tradable service and the tradable retail amenity with the largest CEX expenditure and NHTS trip shares). All specifications also include the controls described in Section 2 above. To facilitate comparisons of coefficients across variables and specifications, the presented coefficients are standardized. For example, the positive IV coefficient of 0.265 on the change in high-income jobs means that moving up one standard deviation in the tract-level distribution of this change induces a 0.265 standard deviation increase in the share of young college-educated individuals living in a tract.

For each age group, the first column shows coefficients on the 2000 to 2010 first-difference in each variable (i.e., the $\beta^d_{X,2010}$ coefficient on a variable $\Delta\tilde{X}_{jc}$) and the second column shows coefficients on the 2000 value of the corresponding variables (i.e., the $\Delta\beta^d_X$ coefficient on a variable $\tilde{X}_{jc,2000}$). We first compare the OLS coefficients (panel A) with their IV counterparts

[21] In the discrete product choice case, Berry (1994) suggests instrumenting for the within-nest shares with characteristics of firms producing other products in the nest. Our instruments are the analog of these competitor characteristics where, in our setting, products are tracts and nests are CBSAs.

[22] Our main results hold without taking this precaution.

(panel B). The OLS coefficients on the change in the house price index, the density of food stores, and the nearby young college share (our homophily control) are shifted downward in the instrumented specification, likely due to classic endogeneity bias (unobserved amenities and reverse causality). The OLS coefficients for jobs and restaurant density are of the same sign as their IV counterparts but smaller in magnitude, likely as a result of attenuation bias.[23] Below we demonstrate that these differences in magnitude do not impact our main results on the relative importance of various factors in explaining urban revival, which are robust to whether we use the OLS or IV coefficient estimates. With this in mind, we turn the focus of our discussion to the instrumented coefficient estimates.

The IV coefficients (panel B) generally have the expected sign. The coefficients on the variables in changes imply that the young and college educated have a distaste for high house prices and proximity to low- and middle-wage jobs (i.e., those paying less than $3,333 a month), conditional on proximity to other amenities. These positive amenities include proximity to high-wage jobs, restaurants, nearby population density, and nearby concentration of their peers. The relatively large standardized coefficient on the change in high-wage job density is consistent with the important role that job location plays in the household location decisions of the young and college-educated. The relative magnitudes of these coefficient estimates across age and education groups also make sense. All three college-educated age groups have a similar estimated distaste for high house prices, though they tend to be less sensitive to house prices than households without a college degree (Table 3 replicates Table 2 for the non-college educated). College-educated 25-34 year olds have the strongest preferences for proximity to high-wage jobs of any age-education group in both OLS and IV. They also have the strongest taste for restaurant density in both OLS and IV.[24]

Coefficients on variables in initial levels are harder to interpret. As explained in section 2, one possible interpretation is that a positive coefficient on a variable in initial level denotes a positive change in preference for that variable. This interpretation is consistent with the discrete choice model underlying the regression. In that case, the coefficients in column 2 of panel B provide evidence of statistical and economically relevant increases in the preference of the young and college-educated for proximity to restaurants between 2000 and 2010 and, to a lesser extent, evidence of their declining preference for proximity to food stores. The coefficient

[23]Though measurement error has been shown to generate bias of the magnitude suggested here in, for example, crime data (Chalfin and McCrary, 2018), we also check to make sure that our IV coefficients are not being driven by outlier observations. Online Appendix Figure A.3 presents our key coefficient of interest on the 2000 level of restaurant density re-estimated dropping one CBSA at a time from our main sample. While the IV coefficients vary when dropping Boston and Las Vegas, in particular, the estimates never drop below 0.12 with t-statistics of at least 6.

[24]The mild distaste for proximity to food stores may not be that surprising. The fact that most jurisdictions have zoning regulations preventing commercial use near residential areas supports the notion that built amenities that one rarely visits are indeed dis-amenities.

estimate on the level of high-wage job density indicate that young college graduate preferences for proximity to high-wage jobs also increased over this period, albeit to a much smaller degree.

3.2 Decomposition Analysis

An important objective of our paper is to compare the relative power of various factors in explaining the changing location choices of the young and college-educated. To this end, we combine the coefficients estimated above with the spatial distribution of each variable in urban relative to suburban areas from section 2.2. Intuitively, a variable contributes to urban revival if: 1) young college graduates like it, and 2) it is highly prevalent downtown. In terms of our empirical framework, such a variable has: 1) a positive regression coefficient for young college graduates in Table 2, and 2) a negative gradient from the city center in Figure 3 or 4.

3.2.1 Does the Model Predict Urban Revival?

Before studying the estimated contribution of each variable individually, we first look at their collective performance fitting the particular urbanization of young college graduates relative to other age-education groups. Our regression equation 3 predicts the log change in the share of a given demographic group d living in a given tract j relative to a fixed base tract:

$$\widehat{\Delta \ln \tilde{s}^d_{jc}} = \sum_k \widehat{\beta^d_k} \tilde{X}_{jc,k} \tag{5}$$

where $\tilde{X}_{jc,k}$ is the value a characteristic k takes in tract j relative to the base tract and $\widehat{\beta^d_k}$ is the estimated coefficient on that regressor for group d. The dashed curves in Figure 5 plot this fitted value of predicted growth against distance to the city center for each age-education group, while the solid curves plot the corresponding population growth gradient observed in the data. To make a fair comparison, the predicted curve is based on the aggregate contribution of all regressors in our base IV specification (Table 2), except for the distance to city center and the within-CBSA share controls, which would provide a good fit mechanically (i.e., $\sum_k \widehat{\beta^d_k} \tilde{X}_{jc,k}$ for all k except $dist_{jc}$ and $\Delta s^d_{j|c}$). Each curve is normalized to zero at the outer edge of CBSAs to facilitate comparisons across age-education groups.[25]

Figure 5 shows that our model successfully matches the overall shape and ordering of the population growth gradients for all six age-education groups, i.e., 25-34 year old college graduates and, to a lesser extent, 35-44 year old college graduates are moving downtown, while older college graduates and all three age groups of non-college-graduates are moving to the suburbs.

[25] Under this normalization, the log change in the population share of a tract relative to a base tract is equal to the tract population growth depicted in Figure 1. The role that the regression coefficients and characteristic gradients play in shifting the population growth curves shown in Figure 1 is derived in online Appendix F.

The predicted growth at the city center (relative to growth at the edge) captures approximately one third of the relative urban population growth (or decline) observed in the data for each age-education group. We emphasize that the moments used to generate these predictions are not targeted by our model.

3.2.2 Which Variables Explain Urban Revival?

The contribution of each individual regressor k to the predicted shift of a demographic group d towards tract j in CBSA c in expression (5) is $\widehat{\beta_k^d}\tilde{X}_{jc,k}$. Figure 6 presents a kernel plot splitting out the contribution of each explanatory variable k in pulling young-college graduates towards tracts at different population-weighted distances from the city center, again using coefficients from our base IV specification in Table 2. The left-hand plot shows the contribution of the change variables, and the right-hand plot shows that of initial level variables. Again, to make comparisons of contribution across variables easier, we normalize the contribution of each variable at the outer edge of a CBSA to zero. As a result, the intercept of each plot with the city center provides a ranking of each variable according to the importance of its contribution to urbanizing a given group.

As an example of how to interpret these plots, consider the urbanizing contribution of change in high-wage job density. The change in high-wage job density has a large positive standardized coefficient, so it is an important determinant of location choice for young college graduates. However, changes in high-wage job density contribute little to urbanizing young college graduates, because of their relatively flat gradient shown in Figure 3. That is, young college graduates value proximity to high-wage jobs, but these have not been growing much faster in urban relative to suburban areas.

Figure 6 shows the key result of the paper: the initial density of restaurants, a non-tradable service, is the most important contributor to the urbanization of the young and college-educated. Restaurants are representative of non-tradable services more generally: when we replicate this exercise including additional consumption amenities, we find that the level of our other non-tradable amenity, nightlife, is similarly identified as a top contributor to urban revival. Interpreting the regression coefficients as preference parameters, the model suggests that the main contributing factor to the rising share of young college graduates near city centers is an increasing preference for urbanized non-tradable service amenities.

Table 5 quantifies these results. The table summarizes the contribution of the initial levels of non-tradable services density in urbanizing young college graduates (see online Appendix Figure A.6 for the y-axis intercepts of each of the variables in Figure 6). The first row of column 1 shows that, in our baseline specification, the initial level of restaurant density ranks first amongst all of the variables included in the model, with the highest and most positive intercept in Figure 6. The initial level of restaurant density accounts for 45 percent of the total contribution of all variables that make a positive contribution to the predicted urbanization of young college graduates.[26] In the base OLS specification, the level of non-tradable (restaurant) service ranks fourth with a 17 percent contribution. This contribution rises to 48 percent (ranked first) if we ignore the contributions of the highly endogenous variables for share of young college graduates in nearby tracts and population density in nearby tracts, as shown in columns 3 and 4. Other rows of Table 5 show the robustness of these conclusions for different specifications discussed later in the paper.

One way to characterize this analysis is as an attempt at distinguishing the role of changes in characteristics from the role of changes in the willingness to pay for those characteristics in explaining the difference in the spatial distribution of the young and college-educated between 2000 and 2010. This can be thought of as an application of the Oaxaca (1973) decomposition commonly employed in the labor literature attempting to understand wage differentials between two worker types (see, for example, Card and Krueger, 1992). Fortin et al. (2011) highlights that this decomposition is sequential, in the sense that the order of the decomposition matters for the conclusion. In our case, this implies that the use of the 2000 level variables, rather than 2010 level variables, could matter. For the purposes of estimation, we use the 2000 level variables since they are less subject to reverse causality biases than the 2010 level variables, which are mechanically correlated with the 2000-2010 change variables. Using the parameter estimates obtained from this base specification, our contribution plots are almost invariant to whether we decompose the log share using 2000 shares as in $\widehat{\Delta \ln \tilde{s}_{jc}^d} = \sum_{k \in K_1} \left(\widehat{\beta_{k,2010}^d} - \widehat{\Delta\beta_k^d} \right) \Delta \tilde{X}_{jc,k} + \sum_{k \in K_2} \widehat{\Delta\beta_k^d} \tilde{X}_{jc,k,2000}$ or using 2010 shares as in $\widehat{\Delta \ln \tilde{s}_{jc}^d} = \sum_{k \in K_1} \left(\widehat{\beta_{k,2010}^d} \right) \Delta \tilde{X}_{jc,k} + \sum_{k \in K_2} \widehat{\Delta\beta_k^d} \tilde{X}_{jc,k,2010}$.

3.2.3 Why Did Urban Revival Happen Primarily in Larger Cities?

In the urbanizing contribution plots above, the spatial distribution of each variable comes from our estimation sample of all tracts in all CBSAs. However, our stylized facts document that the urbanization of the young and college-educated is primarily a large city phenomenon. Figure 7 shows that non-tradable service levels can explain this as well. The plot on the left shows the contribution of initial level of restaurant density to urbanizing young college graduates for four groups of CBSAs ranked by population: top 10, top 11 to 50, top 50 to 100, and all other CBSAs. We find that the initial level of restaurant density indeed provides a stronger urbanizing

[26]The denominator in this share is the sum of the positive y-axis intercepts in Figure 6 that are used to generate our model fit in Figure 5 (recall that this excludes the nested-logit within-CBSA share term and the distance to city center control). In absolute magnitude, the contribution of non-tradable service initial levels to young college graduate growth near city centers is 1.3 times *larger* than the actual growth documented in Figure 1. However, other factors are also pushing against the urbanization of young college graduates.

push in larger CBSAs, which have a higher relative density of restaurants (as well as nightlife) near their city centers relative to surrounding areas than smaller cities.

3.3 Robustness

We now present various robustness exercises. First, we demonstrate the robustness of our results to alternative specifications and additional controls. Then we explore the role of other factors for which our data is more limited, and therefore choose not to include in our main analysis.[27]

3.3.1 Alternative Specifications

Table 6 presents the robustness of our base specification for our key demographic of interest (college-educated 25-34 year olds) to alternative specifications. Specifically, between columns 1 through 4 and columns 5 through 8, we switch from a standard nested-logit specification to a multinominal logit specification that permits the use of CBSA fixed effects. As mentioned before, in this case preferences are identified from within- rather that across-CBSA variation in location choices. The first two columns in each set show the specifications in IV and the second two columns in each set show the specifications in OLS. Notably, the qualitative patterns in the coefficients estimated in the CBSA fixed-effect specification are broadly consistent with those estimated in the baseline nested specification.[28] Table 5 shows that, as in the nested specification, the initial level of non-tradable services is one of the top contributors to the urbanization of young college graduates in both the OLS and IV non-nested CBSA fixed-effect specifications, ranking second amongst all variables in both cases.[29]

Omitted Consumption Amenities It is important to establish that our amenity density coefficients are measuring preferences for proximity to restaurants and food stores, rather than to other amenities not controlled for in our base specification. To that end, Table 7 adds a series of controls for other amenities to our base specification.

First, we confirm that the estimated preference patterns of young college graduates for non-tradable services and tradable retail generalize to consumption amenities other than restaurants and food stores. Columns 3 and 4 add nightlife and apparel stores to the set of amenities in our base IV specification (replicated in columns 1 and 2 for convenience). We choose these

[27]Online Appendix D demonstrates the robustness of our results to alternative measures of housing costs.

[28]The magnitudes of all of the standardized coefficients increase, since their relative explanatory power is not dampened by the presence of the within-CBSA share that plays no role in the non-nested specification.

[29]The CBSA fixed-effect specification fails to deliver a clear top contributor to the urbanization of young college graduates. The most important contributor in OLS is change in share of same type nearby, while the most positive contributor in IV is the high wage job density, which makes almost no contribution in OLS. Unlike other competing variables, non-tradable service levels show up as either the most, or one of the most important contributors to urban revival across a broad range of specifications and identifying variation.

two amenities because, like restaurants and food stores, they have reasonable counterparts in the expenditure and travel data that we use to study external validity. The coefficients suggest that the growing attraction of young college graduates towards restaurants and their weakening attraction to food stores is indicative of a general trend towards non-tradable services and away from tradable retail.[30]

Columns 5 and 6 demonstrate the robustness of our estimates to tract-level endogenous controls for the level and change in the diversity of food stores and restaurants, described above in section 2.2. The coefficients on the diversity controls are positive and statistically significant, but adding them has little impact on the coefficient estimates from our baseline specification. Columns 7 and 8 add controls for our restaurant quality index, which takes a high value if a tract contains restaurant chains preferred by the young and college-educated. The coefficients on the level and change of the quality index are not statistically different from zero. This result may not be surprising, given that we already include direct controls capturing the number of other young college graduates nearby. As expected, the quality variables become positive and significant once we remove these nearby population density and share of same type controls in Columns 9 and 10. This provides some reassurance that our homophily and density controls indeed capture unobservable factors, like the quality of amenities, that could otherwise confound our estimates.

Panel B in Table 5 shows the contribution of the level of non-tradable (restaurant) density to the urbanization of the young and college-educated remains high when we add controls for amenity quality and diversity. The young and college-educated are attracted to the increasing quality and diversity of restaurants downtown but this mechanism does not drive our main result. Instead, increases in the relative diversity and quality of downtown restaurants work alongside the changing taste for non-tradable density to attract young college graduates downtown. It is worth noting that we see much faster increases in restaurant diversity and quality near their city centers relative to their suburbs in larger cities, where we have also seen the strongest urbanization of young college graduates.

We also address the concern that our 2000 amenity index levels reflect recent establishment entry and exit caused by expectations of future demographic shifts. To this end, columns 11 and 12 of Table 7 substitute the 2000 levels and 2000-2010 changes in our restaurant and food store density indexes with 1992 levels and 1992-2010 changes, respectively. Our coefficients are very similar. This is not surprising given the stability of the amenity density gradients shown in Appendix Figure A.2.

Finally, as mentioned in Section 2.3, omitted amenities may correlate with sectors that have experienced rapid growth in high wage jobs, thus violating the exclusion restriction for our Bartik IV. We verified that coefficients are robust to dropping each of the 20 industries that we

[30]The growing taste for non-tradable services is not limited to food and beverage-related establishments. We estimate similar preference patterns for density in personal service establishments and gyms.

use to compute our instrument. In particular, the coefficient on changes in high wage jobs never rises above 0.270, from a baseline of 0.265 in Table 2.

Crime, School, and Transit Public amenities like school quality, crime rates, and transit availability are important determinants of residential location choices. The well-documented decline in central city violent crime since 1990 (e.g., Levitt, 2004) is also a potential explanation for urban revival. Anecdotal evidence suggests that school quality drives the suburban location choice of families with children. Transit availability is, on the other hand, a prominent characteristic of city centers.

Table 5 documents that the initial level of non-tradable services is still the most important determinant of urbanization for the young and college-educated even after including controls for each of these public amenities to our base IV specification. The same is true in the corresponding OLS regression and if we add the public amenities together, although we run into power issues since the sample in which all three public amenity variables is available is limited.

Together these results indicate that our baseline results are not biased by the omission of these public amenity variables. Nevertheless, the role of public amenities implied by the coefficients on these variables and the changes in their urban-suburban gradients documented in Section 2.2 are worth noting.

Table 8 reports coefficients on controls for the changes and initial levels in local school district rankings and per capita violent crime, and for 2014 level of the transit time of a five-mile trip, when added to our base IV specification for each of the six age-education groups we study. Adding these public amenities variables reduces our sample size, yet we can still identify meaningful differences in the attraction of each age-education group towards (or away from) these neighborhood characteristics.

The sign of the coefficient on change in violent crime per capita is negative and significant for all college-educated age groups. Others (e.g., Kneebone and Raphael, 2011) have documented that the decline in urban crime was faster in the 1990s, the decade preceding the widespread urban revival that we document. To test the Ellen et al. (2019) hypothesis that college-educated individuals move to central cities that experienced a *prior* decline in crime, we also use 1990 crime levels and 1990-2010 changes in crime in place of our 2000 and 2000-2010 variables. There too we find a negative coefficient on the longer-run change in crime that, combined with the relative reductions in urban crime over the longer period, contributes to urbanizing the young and college-educated. However, this contribution is still negligible compared to that of non-tradable service levels, explaining 1 percent of the urbanization of young college graduates. Even if we allowed for as much as the five-fold downward attenuation bias that Chalfin and McCrary (2018) find when using the same UCR data, the contribution of the crime variables would still be less than one fifth of the contribution of non-tradable amenities.[31,32] One could also think that reductions in crime make having a large number of non-tradable amenities, like restaurants and bars, within walking distance more attractive for the young and college-educated. We do not find any evidence that this is the case, however (the estimated coefficient on a control interacting the 1990s reduction in crime with the 2000 level of restaurant density is a statistical zero). Finally, as noted in Edlund et al. (2016), there is anecdotal evidence that central locations in large European cities are also experiencing rising demand from the young and college-educated, despite not having had the high rates and subsequent decline in crime that U.S. central cities experienced. Combined, these pieces of evidence do not preclude a significant role of crime decline in generating favorable conditions for urban revival, but they suggest that the root of the widespread, recent urbanization of young college graduates lies elsewhere.

We also find that improvements in school quality are unlikely to be a major factor in urban revival. Figure 3 showed that the relative ranking of schools near city centers worsened from 2004 to 2010. The young and college-educated show no preference for highly ranked school districts in Table 8, unlike the middle-aged and older college-educated. While these preferences and trends in relative school quality might anchor the older college graduates to the suburbs, they do not help to explain why the young started moving downtown.

Finally, our transit performance index in 2014 (the only year for which we have tract-level transit travel times) is correlated with a positive influx of the young and college-educated, though less so than for older college graduates and the non-college educated. This accords with evidence that transit accessibility plays a role in the urbanization of low-income households (LeRoy and Sonstelie, 1983; Glaeser et al., 2008). The implied increasing taste for short public transit commutes to downtown, meanwhile, only contributes 3% of the urbanization of the college-educated, compared with the 46% contribution of the change in taste for proximity to non-tradable services.

[31] The direction of the endogeneity bias is in theory ambiguous, but Autor et al. (2017) show that gentrification reduces crime. This suggests that the endogeneity bias works in the opposite direction to the attenuation bais, pushing our coefficient on crime change in the direction of finding a larger negative impact on the location choice of college-educated groups. Our positive coefficient estimates on change in crime for non-college-educated groups is also consistent with this direction of bias.

[32] We note two differences between our approach and that in Ellen et al. (2019) that help to reconcile our results. First, we focus on the younger college-educated group in particular and on areas smaller than central cities, motivated by the stylized facts in section 1.1. Second, our empirical approach infers a general aversion to violent crime regardless of the area, rather than assigning specific aversion to "central city" crime to different groups.

4 External Validity

In this section, we corroborate our regression results with complementary data documenting patterns in travel to amenities, expenditures on amenities, and commutes to work.

Travel and Expenditure Data

NHTS trip data and CEX expenditure data on restaurants and nightlife support our key regression finding that non-tradable service amenities play a special and increasingly important role in the location choices of young college graduates relative to other age-education groups.

Figure 9 shows CEX expenditure shares and NHTS trip shares separately for all six age-education groups, in 2010 levels and in 2000 to 2010 changes, along with 95 percent confidence bands.[33] Expenditure and trip allocations to restaurants are shown in Panel A, while allocations to nightlife are shown in Panel B.[34] The top row of bar charts in each panel show the 2010 level of expenditure and trip shares for each age-education group and the bottom row of bar charts in each panel show how these gaps developed over the preceding decade. For instance, the top left chart in Panel A shows that young college graduates spent 25 percent more of their expenditure on restaurants than old college graduates. The lower left chart in Panel A shows that more than half of this gap emerged between 1998 and 2014, over which time the restaurant expenditure share of the young increased almost three times as much as that of the old.

More broadly, in 2010, the young and college-educated allocated more of their expenditures and trips to restaurants and nightlife than any of the other five age-education groups. The young and college-educated also increased their expenditures on and trip shares to both restaurants and nightlife over the preceding decade. In fact, the young and college-educated increased their restaurant trip and nightlife expenditure shares by more than any other age-education group, and these differential trends are statistically significant. Notably, the young and college-educated increased their spending on nightlife by over 50%, and they were the only group to increase their trip share to restaurants, in a period when all groups were taking relatively fewer such

[33] The NHTS takes place roughly every 7 years, so we use the 2001 and 2009 NHTS, which are two consecutive surveys with exactly the same trip definitions (trip definitions are different in the previous and subsequent NHTS surveys in 1995 and 2017). We show CEX data for 1998 and 2014 instead of 2000 and 2010 to avoid measuring expenditures right before and right after recessions, which cause temporary declines in expenditures on luxury goods like non-tradable services. Importantly, the ranking of young college graduates across groups discussed below is exactly the same if we use the 2000-2010 instead of 1998-2014 CEX. To maximize sample size, we aggregate quarterly CEX data over 5 years (i.e., 1996-2000 and 2012-2016). 1996 is the earliest year available on the CEX website (`https://www.bls.gov/cex/pumd_data.htm`, accessed 1 April 2019).

[34] CEX expenditures on "restaurants" include all food away from home, except alcohol. The CEX reports expenditures at the household ("consumption unit") level, so we attribute the expenditure shares of the household to its individual members by age and education status. The NHTS records all trips on a single survey day separately for all members of participating households. We define as "nightlife" trips to "Go out/Hang out: entertainment/theater/sports event/go to bar" and expenditures on "alcohol away from home". All details appear in Appendix A.

trips. Young college graduates raised their restaurant expenditure share and nightlife trip share by more than all but one age-education group, with similar increases in restaurant expenditures to the middle-aged college graduates and in nightlife trips to young non-college graduates.

These patterns do not replicate for tradable retail like food and apparel stores (see Figure A.4). For instance, the young and college-educated have the lowest expenditure share on food stores of any age-education group, and the second lowest trip share to buy goods (groceries, clothing, and hardware).

Of course, expenditure and trips shares may not capture preferences if travel costs decline with proximity to consumption amenities, and if the young and college-educated live closer to these amenities in 2010. Using confidential geo-coded NHTS trip data, we verify that the patterns documented above persist after controlling for the amenity density in a traveler's residential tract.

This increase in young college graduates' CEX expenditure and NHTS trip shares to non-tradable services, in absolute value and relative to other groups, lend credence to our conclusion from the regressions in Section 3 that young college graduates experienced a change in their preferences for non-tradable services that is positive and larger than that of other groups. The importance of residential amenities in location choice should not come as a surprise. In the 2009 NHTS travel data, high-income individuals in the urban areas of large cities on average take more trips to non-tradable service amenities than commute trips to work.

Commute Data

We now use LODES commute data by wage groups between 2002 and 2011 to corroborate our regression results that residential amenities play a role in urban revival, which we observe even after conditioning on changing job locations and changing tastes towards short work commutes.

Figure 8 shows recent changes in commute patterns - the percent change in the number of workers living and working at different distances from the city center - from the LODES data by wage groups between 2002 and 2011.[35] Consistent with Figure 1, Panel A shows that the aggregate workforce has been suburbanizing. In particular, residential suburbanization has outpaced workplace suburbanization, with faster worker population growth in the suburbs than downtown holding fixed workplace distance from the city center. Panel B, meanwhile, shows that high-wage workers in large cities have instead centralized both their workplaces and residences. Here too, the residential shift has outpaced the workplace shift, but in the opposite direction: holding fixed distance from workplace to city centers, high-wage employees are

[35] Residential distance from the city center is fixed within each row of the matrix and workplace distance from the city center is fixed within each column. The row/column distance bins are: 0-1, 1-2, 2-4, 4-8, 8-16, 16-32, and 32+ miles from the city center. The bars to the left of each cell depict the relative magnitude of the population growth.

moving their residences closer to city centers in large CBSAs.

Overall, average commute length increased slightly for high-wage workers from 2002 to 2011, with the largest increase for those living near the city center, due in part to the rising share of reverse commuters (workers living close to the city centers of large CBSAs but working in the outskirts). The longer commutes that high-wage workers are willing to incur to live near city centers are consistent with our main finding in this paper on the increasing attractiveness of downtown residential amenities. Though based on the location patterns of a different set of people than our main census results (LODES high-wage workers are a much larger group than the young and college-educated), these commuting results support our conclusion that residential amenities contribute to urban revival.

5 Explaining Changing Tastes for Non-Tradable Services

Our model estimates suggest that young college graduates's rising propensity to locate near non-tradable service amenities plays an important role in America's recent urban revival. In this section, we use shift-share analyses to show that the changing socioeconomic characteristics of young college graduates can explain their rising collective tastes for non-tradable services and, in turn, their urbanization.

Figure 10 shows a shift-share analysis by family type on the left, and by income type on the right. The shifts in family and income types are in Panel A and the initial urban and suburban shares of each type are in Panel B. Panel A shows that between 1990 and 2014, the young and college-educated were delaying childbirth and marriage, and experiencing top income growth.[36] The population share of unmarried and childless individuals grew by 10 percentage points, from 44 to 54 percent of young college graduates, while the population share earning more than $150,000 (in 1999 dollars) almost doubled from 2.3 to 3.8 percent. Panel B shows that in 1990, the unmarried/childless and higher income types were the most urbanized segments of the young college-educated population.[37] Together, Panels A and B of Figure 10

[36]For this analysis, we use IPUMS microdata, where we can decompose the population into age-education-family types and age-education-income brackets not available in tract-level census tables used in our analysis above. We limit our attention to the 27 large CBSAs whose PUMAs (IPUMS geographic units) are small enough for us to construct constant geography downtowns in 1990 and 2014, as outlined in Appendix A. We study changes from 1990 to 2014, rather than from 2000 to 2010, since the recessions of the early and late 2000s obscure income trends. Our main family type results hold using 2000 to 2010 data. Figure A.5 in online Appendix C provides similar family type shares for additional years (1990, 2000, 2010, and 2014), and demonstrates that delayed family formation accelerates after 2000.

[37]One may worry that unmarried/childless and richer individuals patronize non-tradable services only because they live close to such amenities. Using confidential geo-coded NHTS data, we find that the higher propensity of unmarried/childless, and rich indivisuals to travel to non-tradable services relative to that of individuals living in other types of households persists almost entirely after controlling for the non-tradable service density near a traveler's residence.

show young college graduates shifting from suburbanized family types, such as families with children, towards the only urbanized type, the unmarried with no children. Between 1990 and 2014, young college graduates also moved to the ends of the income distribution, both of which disproportionately reside downtown.

These shifts in the composition of young college graduates across family types and income brackets mechanically explain their urbanization over this period. If the propensity of each group to reside downtown remained fixed at its 1990 level and only the composition of young college graduates across family types changed between 1990 and 2014, the resulting difference between the urban and suburban growth of young college graduates would account for 20 percent of the observed difference. The changes in the incomes of young college graduates predict an additional 10 percent of their outsized urban growth. Together, these two forces together mechanically predict a large 19 percentage point gap between urban and suburban young-college growth over the last 25 years (30 percent of the actual 64 percentage point urban-suburban gap in young-college growth over the same period).[38]

Figure 11 shows data for a similar shift-share analysis, this time to see if changes in the family and income composition of young college graduates explain changes in their non-tradable service consumption. The "shift" in Panel A is the same as in Figure 10 and shows delayed family formation and top income growth between 1990 and 2014. Panel B shows the initial trip and expenditure shares on non-tradable services in 2000, the earliest year we have NHTS data.[39] Once again, the fastest growing types also have the largest expenditure (CEX) and travel (NHTS) shares on restaurants and nightlife. For instance, unmarried and childless households spend almost twice as much on restaurants as households with young children, and four times as much on nightlife. While young college-educated family types with the highest propensity to spend on and travel to restaurants and nightlife (unmarried and childless) are growing, the types with the lowest propensity (families with children) are shrinking. As a result, a family type shift-share analysis correctly predicts the upward shift in travel and expenditures to restaurant and nightlife documented in Figure 9. Magnitudes of the predicted growth range between 15 and 56 percent of actual growth.

Replicating this analysis for all age-education groups, we find that in all cases, either the young college or young non-college-educated have the fastest predicted growth in non-tradable

[38]We note that our income measure is adjusted for family size, so these family formation and income change are separate trends by construction. As a result, considering changes in the interaction of family type and income group predicts 27 percent of the actual urbanization.

[39]Ideally we would also produce results with 1990 level of travel and expenditure share, but these are not available so we use 2000 levels. We cannot directly use the NHTS and CEX to measure changes in family and income types across surveys, because these samples are much too small in size and not stratified for this purpose. We compute this percentage change as $\sum(s_{n,14} - s_{n,90})x_{n,00})/x_{00}$, where $s_{n,14}$ is the share of families of type n in 2014 and $x_{n,00}$ is the expenditure (or travel) share for type n in 2000. We compute change in family types and income brackets for all households in IPUMS (to match our NHTS and CEX samples), but results are similar using our sample of 27 CBSAs with constant geography.

service consumption. Delayed family formation pushed the young, both college and non-college educated, towards non-tradable services. Shifts in the income distribution, however, make different predictions for college and non-college educated. For the non-college educated groups, skilled biased income growth from 1990 to 2014 predicts a large decline in trip and expenditure shares to luxury non-tradable services like restaurant and nightlife. The young and middle-age college educated, meanwhile, have much higher predicted growth from shifts in the income distribution (though it is still close to zero because the share of both rich and poor college-educated households is rising).

To summarize, we find that, due to delayed family formation and top income growth, young college graduates increasingly live in households with a high propensity for co-locating with, spending on, and traveling to non-tradable services. This shift-share analysis is unlikely to entirely explain the entire shift of this demographic towards non-tradable services or downtown areas. Simultaneous endogenous neighborhood change, such as the rise in the quality and diversity of downtown restaurants that we document above, likely play an important coincident role. To fully capture the impact of rising income inequality on location choices given that both rich and poor households are initially urbanized, one needs to model how shifts in the income distribution impact urban house prices and endogenous luxury amenities.[40] Couture et al. (2019) pursue this structural approach to specifically investigate the impact of top income growth on the urbanization of high income households. In that model, non-tradable service amenities, which we identify here as the most important driver of urban revival, play the key role in driving the rich downtown as their incomes rise.

In online Appendix G, we review and find limited support for alternative explanations for changing tastes for non-tradable services, such as changes in the technology available to access information on these amenities.

6 Discussion

Urban revival currently attracts considerable media attention and interest from the general public. Using census data, we show that this revival is indeed happening in almost all large U.S. cities, and is driven by the location decisions of the young and college-educated. While the rest of the country continues to suburbanize, the young and college-educated flock downtown.

We evaluate the importance of various explanations for this trend. We find that diverging preferences for non-tradable services like restaurants and nightlife explain the diverging loca-

[40]For instance, a shift share analysis can make counterfactual urbanization predictions for other groups, and changes in the income distribution predicts the urbanization of the non-college-educated, but because the share of poor non-college-educated households is growing, and the poor are also overrepresented in urban areas (Glaeser et al., 2008).

tion decisions of the young and college-educated relative to other groups. Travel and expenditure shares of the young and college-educated also diverge from that of other groups, lending further credence to our model's results.

It is, of course, important to identify the source of such changing preference parameters. Our investigation highlights the role of delayed family formation and top income growth. The young and college-educated are increasingly likely to be unmarried and childless, and to earn income in the highest bracket, which are the two segments with the strongest demand for urban living and non-tradable service amenities.

It is striking that the classic factors used to explain residential location decisions (e.g., jobs, housing, and schooling) struggle to explain urban revival. If the key factor at play is indeed a changing preference for urban non-tradable consumption amenities, then there are important consequences for the sustainability and welfare implications of urban revival. Consumption amenities are endogenous, and diverging preferences mean that while high-quality non-tradable services may compensate the young and college-educated for high housing prices near city centers, these amenities fail to compensate the poorer households already living there. These poorer households may either be displaced or incur high housing costs for downtowns offering fewer of the amenities that suit their less luxurious tastes. We are exploring these welfare implications in complementary work (Couture et al., 2019).

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Tables and Figures

Table 1: Tract-level Predicted Establishment Entry at the SIC8 Level

	Percentage of SIC8-Specific Coefficients		
	Negative and Significant	Positive and Significant	Not Significant at 10% Level
Same SIC8			
Within 0-1 miles	92%	1%	7%
Within 1-2 miles	53%	9%	39%
Within 2-4 miles	23%	25%	42%
Within 4-8 miles	17%	41%	42%
Same SIC6, Different SIC8			
Within 0-1 miles	6%	53%	41%
Within 1-2 miles	14%	26%	61%
Within 2-4 miles	16%	19%	65%
Within 4-8 miles	23%	22%	55%
Same SIC4, Different SIC6			
Within 0-1 miles	17%	52%	32%
Within 1-2 miles	20%	23%	57%
Within 2-4 miles	19%	15%	66%
Within 4-8 miles	29%	21%	49%

Notes: This table provides the percentage of the 350 SIC8-level regressions in which each of the listed explanatory variables in the net entry regression (Equation 4) was either negative and significant at the 10 percent level, positive and significant at the 10 percent level, or neither.

Table 2: Nested-Logit Residential Location Choice Regression Results for All College-Educated Age Groups

Panel A: OLS

	25-34 Year-Olds		35-44 Year-Olds		45-65 Year-Olds	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]
House Price Index	0.026***	-0.024***	-0.002	0.007***	-0.005***	0.005***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Low Wage Job Density	-0.031***	-0.014**	-0.034***	-0.069***	0.002	-0.080***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)
Med. Wage Job Density	-0.006	0.047***	0.040***	0.097***	0.046***	0.142***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)
High Wage Job Density	0.051***	-0.040***	0.000	-0.030***	-0.025***	-0.040***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Restaurant Density	0.023***	0.044***	0.010***	0.009**	0.004***	-0.001
	(0.003)	(0.006)	(0.002)	(0.004)	(0.002)	(0.003)
Food Store Density	0.009***	0.008	0.014***	0.013**	0.013***	-0.008**
	(0.003)	(0.007)	(0.002)	(0.005)	(0.002)	(0.004)
(Nearby) Population Density	0.066***	0.042***	0.050***	0.067***	0.046***	0.039***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.004)
(Nearby) Share of Same Type	0.090***	0.161***	0.070***	0.164***	0.033***	0.089***
	(0.003)	(0.008)	(0.002)	(0.007)	(0.001)	(0.004)
Population Density		-0.091***		-0.116***		-0.095***
		(0.006)		(0.006)		(0.005)
Share of Same Type		-0.113***		-0.104***		-0.071***
		(0.005)		(0.005)		(0.003)
Distance to City Center		-0.008***		-0.017***		-0.015***
		(0.002)		(0.002)		(0.001)
Within-CBSA Share	0.652***		0.732***		0.801***	
	(0.013)		(0.011)		(0.007)	
Observations	22,911		22,789		23,386	

Panel B: IV

	25-34 Year-Olds		35-44 Year-Olds		45-65 Year-Olds	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]
House Price Index	-0.038***	-0.028***	-0.044***	-0.005**	-0.038***	0.004***
	(0.005)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
Low Wage Job Density	-0.063***	0.040***	-0.028**	-0.029***	-0.016**	-0.071***
	(0.012)	(0.007)	(0.012)	(0.007)	(0.007)	(0.004)
Med. Wage Job Density	-0.167***	-0.045***	-0.018	0.056***	0.079***	0.146***
	(0.017)	(0.011)	(0.016)	(0.010)	(0.009)	(0.006)
High Wage Job Density	0.265***	0.015***	0.073***	-0.020***	-0.031***	-0.041***
	(0.014)	(0.006)	(0.013)	(0.006)	(0.007)	(0.003)
Restaurant Density	0.155***	0.184***	0.042**	0.044**	0.013	0.013
	(0.025)	(0.023)	(0.021)	(0.020)	(0.012)	(0.011)
Food Store Density	-0.038***	-0.104***	0.007	-0.011	0.008	-0.011
	(0.013)	(0.019)	(0.011)	(0.018)	(0.006)	(0.010)
(Nearby) Population Density	0.065***	0.059***	0.045***	0.069***	0.073***	0.052***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.005)	(0.006)
(Nearby) Share of Same Type	0.056***	0.108***	0.127***	0.205***	0.017***	0.066***
	(0.010)	(0.014)	(0.007)	(0.011)	(0.003)	(0.005)
Population Density		-0.093***		-0.136***		-0.089***
		(0.008)		(0.010)		(0.006)
Share of Same Type		-0.103***		-0.121***		-0.055***
		(0.008)		(0.006)		(0.003)
Distance to City Center		-0.009***		-0.009***		-0.010***
		(0.003)		(0.002)		(0.001)
Within-CBSA Share	0.704***		0.693***		0.839***	
	(0.017)		(0.015)		(0.007)	
Observations	22,911		22,789		23,386	

Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates and associated standard errors for our main residential tract choice regression (Equation 3). Only the change in the share of type within CBSA who live in tract is instrumented in our "OLS" specification (Panel A), while all change variables are instrumented in our IV specification (Panel B). Instruments are described in Section 2.3 of the paper. Columns 1 and 2, 3 and 4, and 5 and 6 report coefficients estimated for 25-34 year old, 35-44 year old, and 45-65 year old college educated households, respectively. In all regressions, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000.

Table 3: Nested-Logit Residential Location Choice Regression Results for All Non-College Educated Age Groups

Panel A: OLS

	25-34 Year-Olds		35-44 Year-Olds		45-65 Year-Olds	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]
House Price Index	-0.013***	-0.019***	-0.009***	-0.007***	-0.007***	-0.024***
	(0.003)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
Low Wage Job Density	-0.041***	-0.045***	-0.057***	-0.089***	0.002	-0.046***
	(0.012)	(0.012)	(0.005)	(0.005)	(0.005)	(0.004)
Med. Wage Job Density	-0.050***	0.004	0.092***	0.137***	-0.021***	0.062***
	(0.017)	(0.015)	(0.007)	(0.006)	(0.006)	(0.006)
High Wage Job Density	0.046***	-0.021**	-0.001	-0.015***	0.025***	-0.022***
	(0.011)	(0.009)	(0.004)	(0.004)	(0.004)	(0.003)
Restaurant Density	0.001	0.001	-0.002	-0.029***	-0.003	-0.028***
	(0.006)	(0.012)	(0.002)	(0.005)	(0.002)	(0.004)
Food Store Density	0.049***	0.075***	0.034***	0.072***	0.021***	0.043***
	(0.007)	(0.015)	(0.003)	(0.006)	(0.002)	(0.005)
(Nearby) Population Density	0.066***	0.042***	0.050***	0.067***	0.046***	0.039***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.004)
(Nearby) Share of Same Type	0.125***	0.288***	0.071***	0.088***	0.057***	0.080***
	(0.005)	(0.022)	(0.002)	(0.011)	(0.002)	(0.011)
Population Density		-0.083***		-0.031***		-0.061***
		(0.012)		(0.005)		(0.005)
Share of Same Type		-0.103***		-0.048***		-0.079***
		(0.007)		(0.003)		(0.003)
Distance to City Center		0.021***		0.010***		-0.008***
		(0.004)		(0.001)		(0.001)
Within-CBSA Share	0.289***		0.720***		0.704***	
	(0.025)		(0.009)		(0.007)	
Observations	23,682		23,690		23,758	

Panel B: IV

	25-34 Year-Olds		35-44 Year-Olds		45-65 Year-Olds	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]
House Price Index	-0.031***	0.011***	-0.049***	0.012***	-0.079***	-0.002
	(0.009)	(0.004)	(0.004)	(0.002)	(0.004)	(0.002)
Low Wage Job Density	-0.093***	-0.045***	-0.115***	-0.067***	-0.064***	-0.015**
	(0.019)	(0.012)	(0.011)	(0.007)	(0.010)	(0.007)
Med. Wage Job Density	0.014	0.037**	0.061***	0.097***	-0.073***	0.010
	(0.028)	(0.016)	(0.017)	(0.010)	(0.014)	(0.008)
High Wage Job Density	0.095***	0.033***	0.105***	0.022***	0.122***	-0.009*
	(0.022)	(0.010)	(0.013)	(0.006)	(0.011)	(0.005)
Restaurant Density	0.105***	0.112***	0.086***	0.086***	-0.035*	-0.018
	(0.040)	(0.036)	(0.023)	(0.022)	(0.021)	(0.019)
Food Store Density	0.002	-0.025	-0.035**	-0.040**	-0.021*	0.016
	(0.026)	(0.033)	(0.015)	(0.020)	(0.013)	(0.016)
(Nearby) Population Density	0.065***	0.059***	0.045***	0.069***	0.073***	0.052***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.005)	(0.006)
(Nearby) Share of Same Type	0.263***	0.225***	0.172***	0.036***	0.121***	0.044***
	(0.010)	(0.019)	(0.006)	(0.013)	(0.005)	(0.013)
Population Density		-0.056***		-0.044***		-0.072***
		(0.010)		(0.006)		(0.006)
Share of Same Type		-0.092***		-0.045***		-0.078***
		(0.006)		(0.003)		(0.004)
Distance to City Center		-0.005		-0.005**		-0.019***
		(0.003)		(0.002)		(0.002)
Within-CBSA Share	0.521***		0.744***		0.737***	
	(0.022)		(0.010)		(0.009)	
Observations	23,682		23,690		23,758	

Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates and associated standard errors for our main residential tract choice regression (Equation 3). Only the change in the share of type within CBSA who live in tract is instrumented in our "OLS" specification (Panel A), while all change variables are instrumented in our IV specification (Panel B). Instruments are described in Section 2.3 of the paper. Columns 1 and 2, 3 and 4, and 5 and 6 report coefficients estimated for 25-34 year old, 35-44 year old, and 45-65 year old non-college educated households, respectively. In all regressions, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000.

Table 4: First Stage for Base IV Specification for 25-34 Year Olds

Endogeneous Variable Name	Reduced-Form F Stat [1]	Conditional SW F Stat [2]	Under-ID SW Chi-2 [3]
Change in House Price Index	592.1	82.4	3963
Change in Low Wage Job Density	286.0	73.3	3524
Change in Med. Wage Job Density	231.7	130.8	6289
Change in High Wage Job Density	383.1	52.7	2536
Change in Restaurant Density	43.0	14.2	684
Change in Food Store Density	209.6	27.3	1312
Change in Nearby Population Density	342.5	54.5	2622
Change in Nearby Share of Same Type	289.2	134.0	6442
Change in Within CBSA share	66.8	29.5	1420

Notes: This table reports the first-stage statistics for each of the instrumented variables in our main IV specification for the young and college-educated (the second stage estimates are reported in columns 1 and 2 of Panel B of Table 2). Column 1 reports the reduced-form first-stage statistics, column 2 reports the first-stage SW conditional F-statistic from Sanderson and Windmeijer (2016), and column 3 reports an under-identification test, also from Sanderson and Windmeijer (2016). Sanderson and Windmeijer (2016) do not report critical values for their F-statistic and recommend the use of Cragg-Donald critical values from Stock and Yogo (2005), which are unavailable for regressions with more than two endogenous variables. The standard rule of thumb is that an F-statistic smaller than ten is weak, in the sense that either the bias of the IV estimator is larger than 10 percent of the bias of the OLS estimator at the 5 percent confidence level or else that a 5-percent Wald test rejects hypotheses at more than the 10-percent level (Stock and Yogo, 2005).

Table 5: Share of Non-Tradable Services' Urbanizing Contribution Across Specifications for the Young and College-Educated

	Rank [1]	Share [2]	Rank [3]	Share [4]
Panel A: Basic Set of Controls				
Base IV Specification	1	45%	1	72%
Base OLS Specification	4	17%	1	48%
Non-nested IV with CBSA Fixed Effects	2	19%	2	23%
Non-nested OLS with CBSA Fixed Effects	2	20%	1	59%
Panel B: Base IV Specification with Additional Amenity controls				
Adding Density of Nightlife and Apparel Stores	1	28%	1	51%
Amenity Diversity and Quality	1	42%	1	73%
1992 Amenity Density in Place of 2000	1	51%	1	75%
Adding School Quality	1	31%	1	65%
Adding Crime	1	43%	1	79%
Adding Crime (1990 Crime in place of 2000)	1	41%	1	77%
Adding Transit	1	44%	1	69%

Notes: This table reports statistics characterizing the contribution of the increasing taste for non-tradable services towards the urbanization of 25-34 year old college graduates depicted in the bottom left plot in Figure 1. Columns 1 and 2 compare the contribution of the level of non-tradable service density in explaining the centralizing tendency of 25-34 year old college graduates to that of all variables used in our prediction. Column 1 reports the rank of the contribution of non-tradable service density, while column 2 reports its share amongst all variables that provide a positive contribution. Columns 3 and 4 remove from consideration the population density and share of own type controls. The contribution of any given variable is defined as the y-axis intercept of the contribution curve of a given variable, as depicted in Figure 6 for the Base IV Specification and described in Section 3.2 of the paper. The other specifications listed are outlined in Section 3.3 of the paper. Non-tradable service density is measured using only restaurant density in all but the specification with the density of nightlife and apparel stores, where non-tradable services include both restaurant and nightlife density.

Table 6: Robustness of Nested-Logit Residential Location Choice Regression Results

	Base (Nested)				Non-Nested CBSA FE			
	IV		OLS		IV		OLS	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
House Price Index	-0.038***	-0.028***	0.026***	-0.024***	-0.190***	-0.035***	0.034***	-0.039***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.064)	(0.010)	(0.006)	(0.007)
Low Wage Job Density	-0.063***	0.040***	-0.031***	-0.014**	-0.814***	-0.370***	-0.056**	-0.076***
	(0.012)	(0.007)	(0.006)	(0.006)	(0.183)	(0.072)	(0.022)	(0.027)
Med. Wage Job Density	-0.167***	-0.045***	-0.006	0.047***	-0.466**	-0.833***	-0.053	0.022
	(0.017)	(0.011)	(0.008)	(0.008)	(0.238)	(0.313)	(0.033)	(0.043)
High Wage Job Density	0.265***	0.015***	0.051***	-0.040***	1.139***	1.303***	0.005	-0.009
	(0.014)	(0.006)	(0.005)	(0.004)	(0.359)	(0.397)	(0.022)	(0.036)
Restaurant Density	0.155***	0.184***	0.023***	0.044***	0.576***	0.595***	0.078***	0.125***
	(0.025)	(0.023)	(0.003)	(0.006)	(0.108)	(0.099)	(0.008)	(0.017)
Food Store Density	-0.038***	-0.104***	0.009***	0.008	0.095*	-0.077	0.036***	0.054***
	(0.013)	(0.019)	(0.003)	(0.007)	(0.050)	(0.080)	(0.008)	(0.021)
(Nearby) Population Density	0.065***	0.059***	0.066***	0.042***	-0.051	-0.120**	0.100***	0.055***
	(0.009)	(0.011)	(0.003)	(0.006)	(0.057)	(0.055)	(0.008)	(0.020)
(Nearby) Share of Same Type	0.056***	0.108***	0.090***	0.161***	0.323***	0.613***	0.199***	0.488***
	(0.010)	(0.014)	(0.003)	(0.008)	(0.061)	(0.059)	(0.007)	(0.017)
Population Density		-0.093***		-0.091***		-0.324***		-0.280***
		(0.008)		(0.006)		(0.023)		(0.015)
Share of Same Type		-0.103***		-0.113***		-0.396***		-0.325***
		(0.008)		(0.005)		(0.015)		(0.008)
Distance to City Center		-0.009***		-0.008***		-0.036*		-0.076***
		(0.003)		(0.002)		(0.020)		(0.006)
Within-CBSA Share	0.704***		0.652***					
	(0.017)		(0.013)					
CBSA Fixed Effects	No		No		Yes		Yes	
Observations	22,911		22,911		22,911		24,228	

Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates and associated standard errors for our main residential tract choice regression (Equation 3) estimated for 25-34 year old college graduates. Columns 1 through 4 replicate our base OLS and IV specifications (the first two columns of Panels A and B, respectively, of Table 2). Columns 5 through 8 show estimates from alternate non-nested specifications (in OLS and IV, respectively) that replace the within-CBSA share term from our base nested-logit specification with CBSA fixed effects. In all specifications, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000. All change variables are instrumented as described in Section 2.3 of the paper.

Table 7: Nested-Logit Residential Location Choice Regression Results with Different Amenity Controls

	Base		With More Amenities		With Amenity Diversity		With Amenity Diversity and Quality				Amenity Base Year = 1992	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,Base}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
House Price Index	-0.038***	-0.028***	-0.029***	-0.028***	-0.045***	-0.030***	-0.010**	-0.025***	-0.015***	-0.021***	-0.037***	-0.028***
	(0.005)	(0.002)	(0.005)	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)
Low Wage Job Density	-0.063***	0.040***	-0.086***	0.032***	-0.075***	0.031***	-0.092***	-0.009	-0.122***	-0.004	-0.055***	0.044***
	(0.012)	(0.007)	(0.013)	(0.008)	(0.013)	(0.007)	(0.012)	(0.008)	(0.011)	(0.006)	(0.012)	(0.007)
Med. Wage Job Density	-0.167***	-0.045***	-0.079***	-0.021*	-0.163***	-0.040***	-0.069***	0.024**	-0.127***	0.011	-0.166***	-0.054***
	(0.017)	(0.011)	(0.016)	(0.011)	(0.018)	(0.011)	(0.015)	(0.010)	(0.014)	(0.009)	(0.018)	(0.011)
High Wage Job Density	0.265***	0.015***	0.220***	0.022***	0.273***	0.020***	0.185***	-0.006	0.286***	0.018***	0.258***	0.020***
	(0.014)	(0.006)	(0.014)	(0.007)	(0.015)	(0.006)	(0.012)	(0.006)	(0.010)	(0.005)	(0.014)	(0.006)
Restaurant Density	0.155***	0.184***	0.101***	0.106***	0.164***	0.170***	0.234***	0.223***	0.183***	0.136***	0.193***	0.246***
	(0.025)	(0.023)	(0.031)	(0.030)	(0.027)	(0.024)	(0.035)	(0.030)	(0.023)	(0.020)	(0.022)	(0.027)
Food Store Density	-0.038***	-0.104***	-0.004	-0.044*	-0.042***	-0.124***	-0.057***	-0.129***	-0.021**	-0.082***	-0.048***	-0.112***
	(0.013)	(0.019)	(0.016)	(0.024)	(0.013)	(0.020)	(0.014)	(0.022)	(0.009)	(0.015)	(0.015)	(0.025)
Nightlife Density			0.048***	0.040***								
			(0.011)	(0.011)								
Apparel Store Density			-0.039**	-0.041**								
			(0.017)	(0.017)								
Restaurant Diversity					0.055***	0.014**	0.081***	0.029***	0.074***	0.022***		
					(0.015)	(0.006)	(0.016)	(0.006)	(0.012)	(0.005)		
Food Store Diversity					0.047***	0.024**	-0.031**	-0.031***	0.028*	0.007		
					(0.016)	(0.011)	(0.015)	(0.011)	(0.016)	(0.011)		
Restaurant Quality							-0.001	-0.001	0.024***	0.009***		
							(0.007)	(0.003)	(0.005)	(0.002)		
(Nearby) Population Density	0.065***	0.059***	0.064***	0.040***	0.059***	0.056***	0.058***	0.065***			0.051***	0.047***
	(0.009)	(0.011)	(0.011)	(0.013)	(0.010)	(0.012)	(0.011)	(0.012)			(0.008)	(0.011)
(Nearby) Share of Same Type	0.056***	0.108***	0.093***	0.148***	0.058***	0.093***	0.086***	0.131***			0.067***	0.119***
	(0.010)	(0.014)	(0.011)	(0.015)	(0.011)	(0.015)	(0.011)	(0.015)			(0.010)	(0.013)
Population Density		-0.093***		-0.095***		-0.086***		-0.097***		-0.029***		-0.115***
		(0.008)		(0.009)		(0.009)		(0.010)		(0.007)		(0.009)
Share of Same Type		-0.103***		-0.115***		-0.103***		-0.115***		-0.063***		-0.113***
		(0.008)		(0.008)		(0.008)		(0.009)		(0.004)		(0.007)
Distance to City Center		-0.009***		-0.003		-0.006**		0.002		-0.003		-0.007**
		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.003)
Within-CBSA Share	0.704***		0.656***		0.721***		0.712***		0.846***		0.694***	
	(0.017)		(0.019)		(0.018)		(0.019)		(0.014)		(0.016)	
Observations	22,911		22,911		22,911		20,379		20,379		22,911	

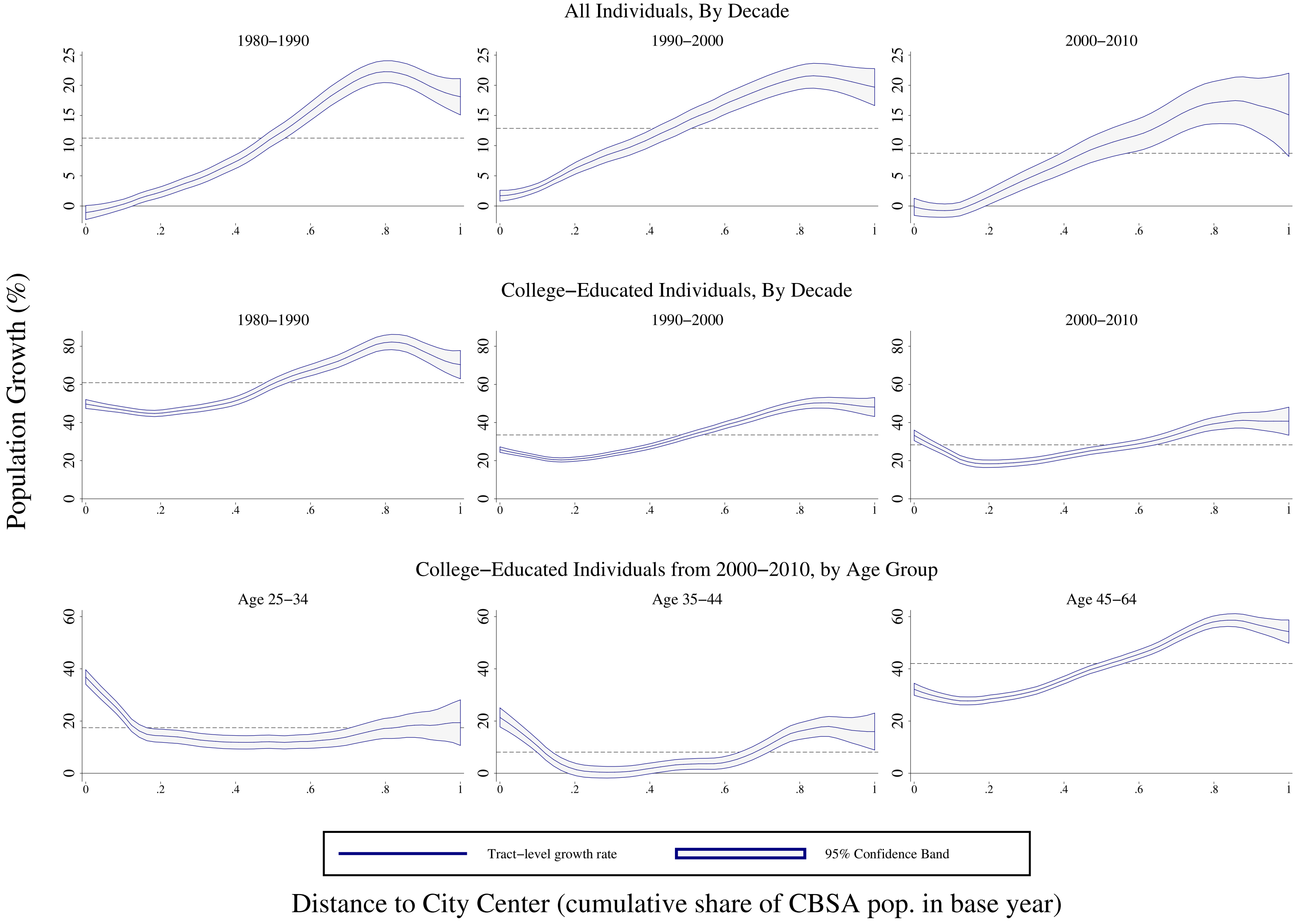
Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates and associated standard errors for our main residential tract choice regression (Equation 3) estimated for 25-34 year old college graduates. Columns 1 and 2 replicate columns 1 and 2 of our base IV specification from Panel B of Table 2. The remaining columns present variants of this specification adjusting how consumption amenities are modeled. Columns 3 through 10 include additional controls for amenity density, diversity, and quality. Columns 11 and 12 use 1992 as the base year for the restaurant and food store density variables, while keeping 2000 as the base year for all other variables. In all specifications, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000. All change variables except for diversity and quality are instrumented as described in Section 2.3 of the paper.

Table 8: Nested-Logit Residential Location Choice Regression Results Including School, Crime and Transit

	Violent Crime Rate			School Quality			Transit Time	
	2000-10	2000		2000-10	2000		2014	
	Change	Level	Obs.	Change	Level	Obs.	Level	Obs.
Demographic Group	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
College-Educated:								
25-34 Year-Olds	-0.005*	0.005	18,949	0.003	-0.002	10,107	-0.011***	22,911
35-44 Year-Olds	-0.004**	0.001	18,831	0.009***	-0.005**	10,025	-0.010***	22,789
45-65 Year-Olds	-0.005***	0.000	19,345	0.008***	0.010***	10,306	-0.014***	23,386
Less than College Education:								
25-34 Year-Olds	0.012***	0.019***	19,637	0.012*	0.001	10,462	-0.017***	23,682
35-44 Year-Olds	0.005**	0.017***	19,627	0.001	0.000	10,469	-0.017***	23,690
45-65 Year-Olds	0.011***	0.025***	19,686	-0.006*	-0.008**	10,495	-0.022***	23,758

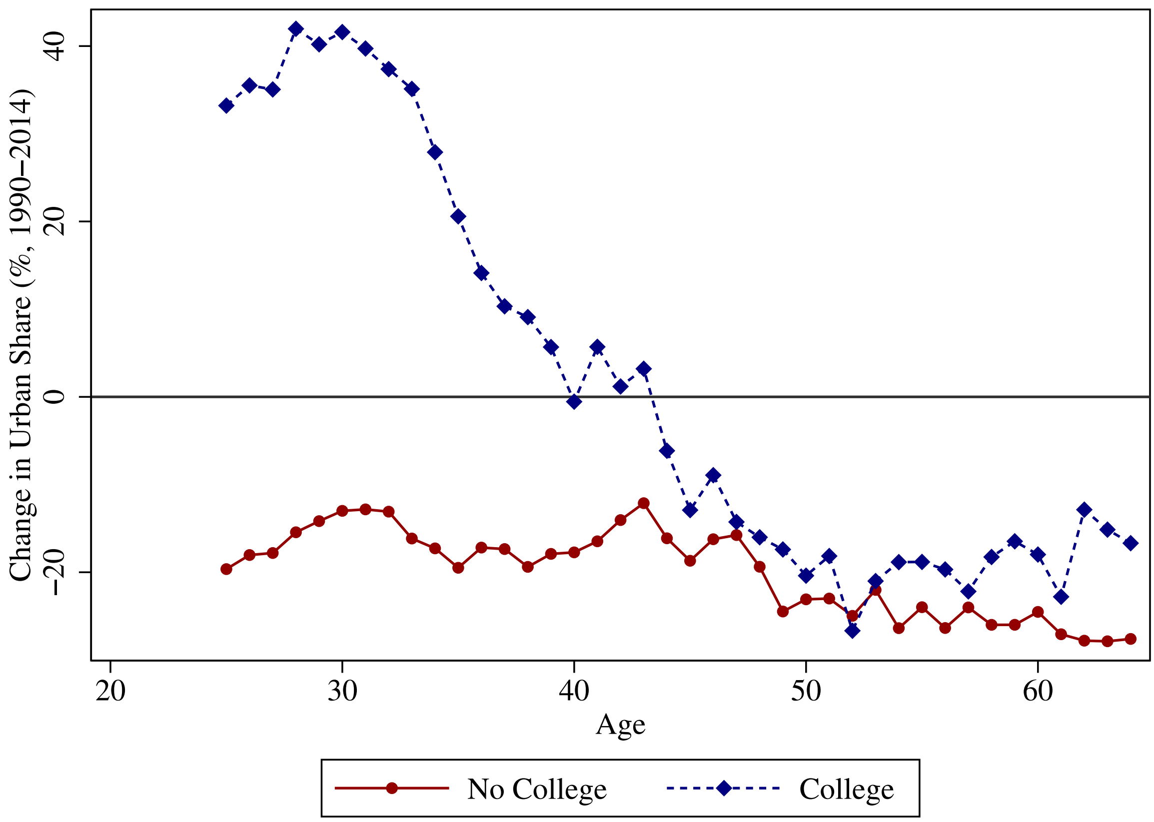
Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates on public amenity variables added to the IV specification of our main residential tract choice regression (Equation 3) as described in Section 3.3. Columns 1 and 2 show the estimated coefficients on the change and level of violent crime when these variables are added to the main specification (columns 1 and 2 of Panel B of Table 2). Each row shows the estimates based on a different demographic group d. Column 3 shows the number of observations in each of these regressions. Columns 4 and 5 similarly show the estimated coefficients on the change and level of school quality when added to the main IV specification. Column 7 shows the estimated coefficients on the 2014 transit time variable when added to the main IV specification. In all specifications, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000.

Figure 1: Population Growth at Various Distances from the City Center



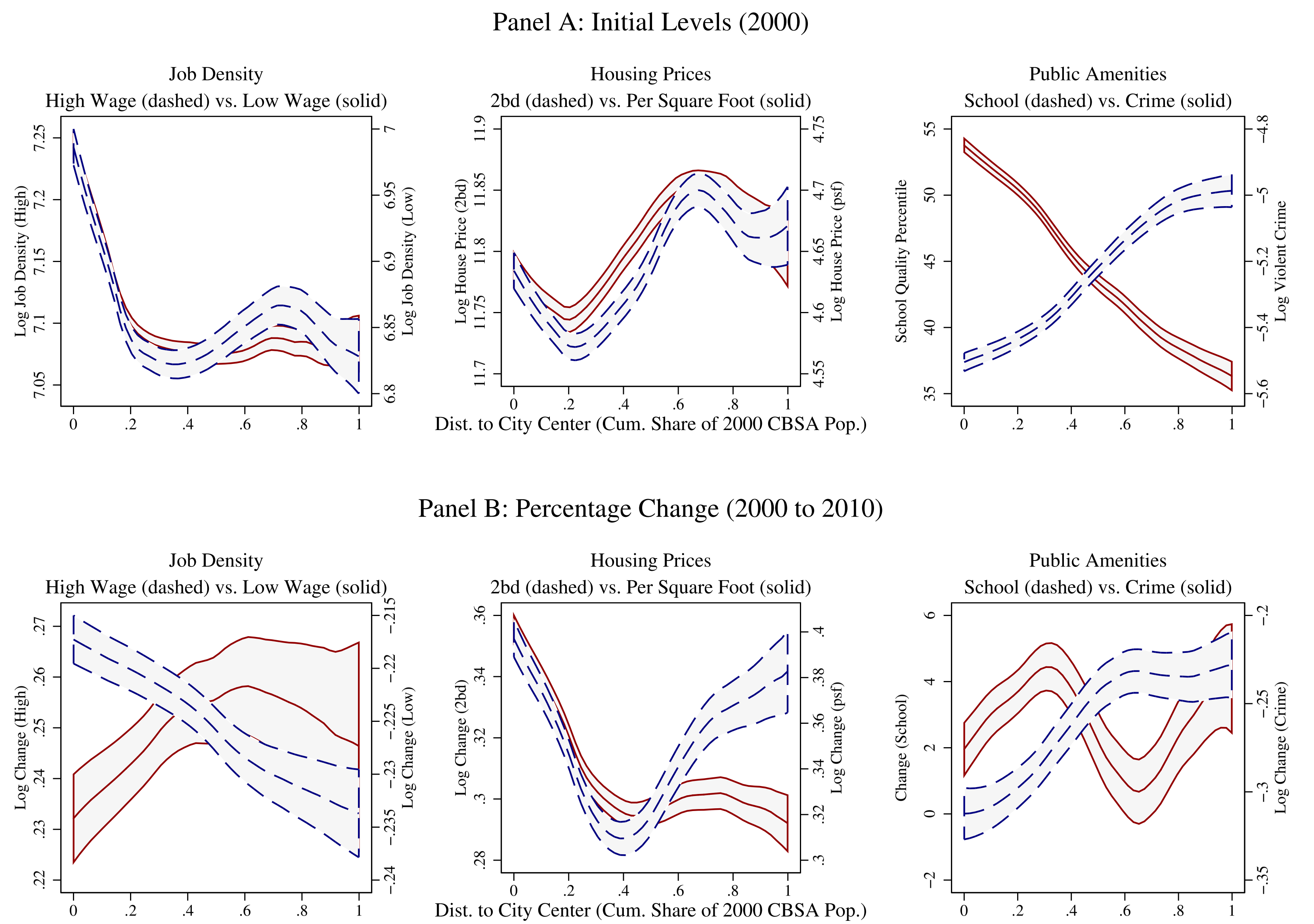
Notes: Each figure shows a non-parametric kernel fit of percent change in tract population at different distances from the city center. Each kernel regression observation is weighted by initial tract population. Distance from the city center is measured as the cumulative share of CBSA population in the base year. The top row of plots presents kernels for the percent change in total population between 1980 and 1990, 1990 and 2000, and 2000 to 2010. The second row is similar but for the college-educated population. The final row presents kernels for the 2000-2010 percent change in the college-educated population in three age brackets. The shaded region around kernel fit depicts the 95% confidence interval. The dashed row in each plot shows the average population growth rate for the relevant demographic group over the relevant decade. Data are from the 1980–2000 decennial censuses and the 2008–2012 ACS.

Figure 2: Percent Change in Urban Share by Age and Education (1990-2014)



Notes: The figure shows the percent change between 1990 and 2014 (2012-2016 ACS) of the average urban share of college and non-college educated individuals by age. The data comes from the IPUMS Public Use Microdata Sample and is restricted to the set of 25-64 year-olds in the 27 CBSAs where we can define constant geography urban areas in 1990 and 2012-2016. The urban area of each CBSA is the set of tracts closest to city center that constitute 10% of the total CBSA population in 2000. See Appendix A for further description of methodology.

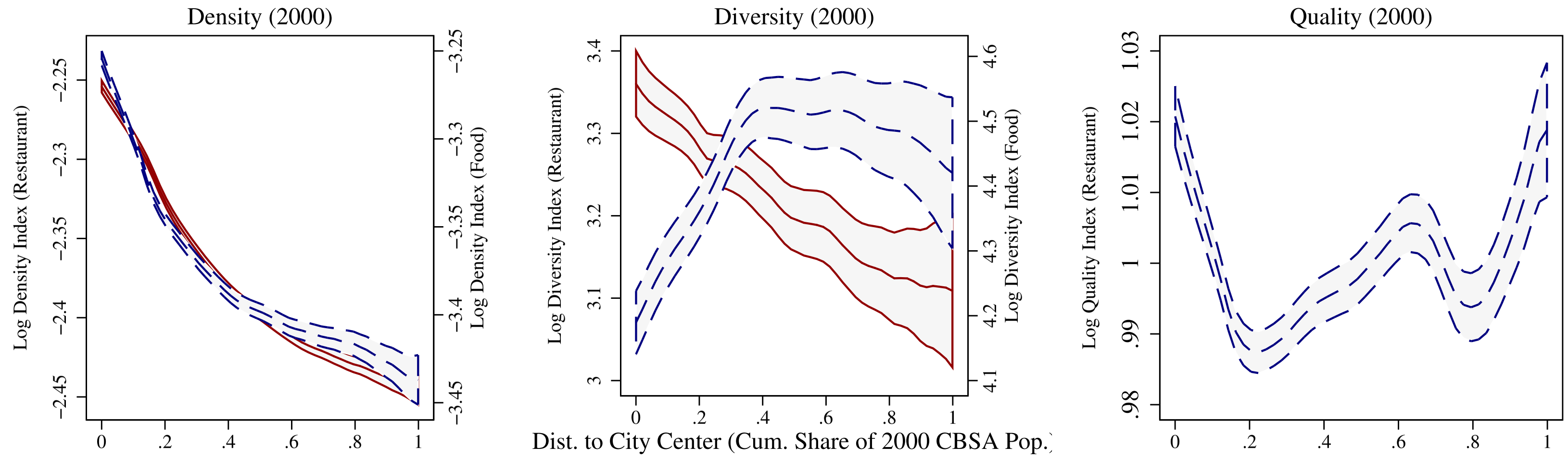
Figure 3: Initial Level and Change in Job Density, Housing Prices, and Public Amenities at Various Distance from the City Center



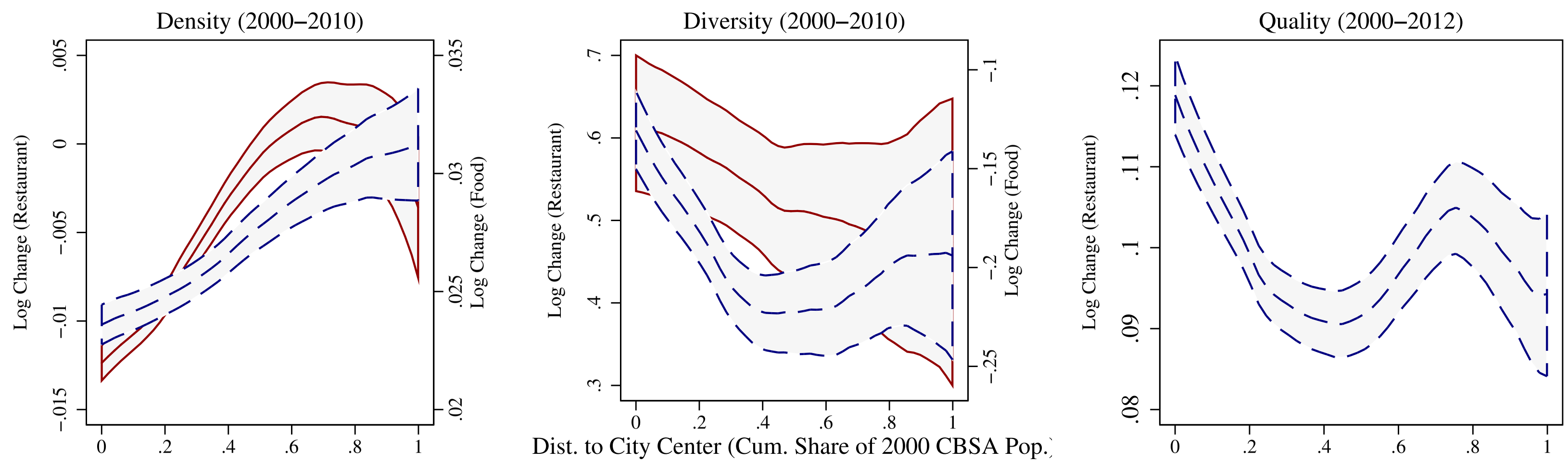
Notes: Panel A shows a non-parametric kernel fit of the log of job density, log house price, log per capita violent crime and school ranking in 2000 plotted against the young-college population-weighted distance from the city center for all tracts in our estimation sample. Panel B shows a similar kernel of percent changes from 2000 to 2010. The shaded region around kernel fit depicts the 95% confidence interval. The job data is from LODES in 2002 and 2011, the house price data is from Zillow.com, the crime data is from UCR, and school data is from SchoolDigger.com (see Appendix A for details on data sources).

Figure 4: Initial Level and Change in Restaurant and Food Store Density, Diversity, and Quality Indexes at Various Distance from the City Center

Panel A: Initial Levels in Restaurants (dashed) and Food Stores (solid)

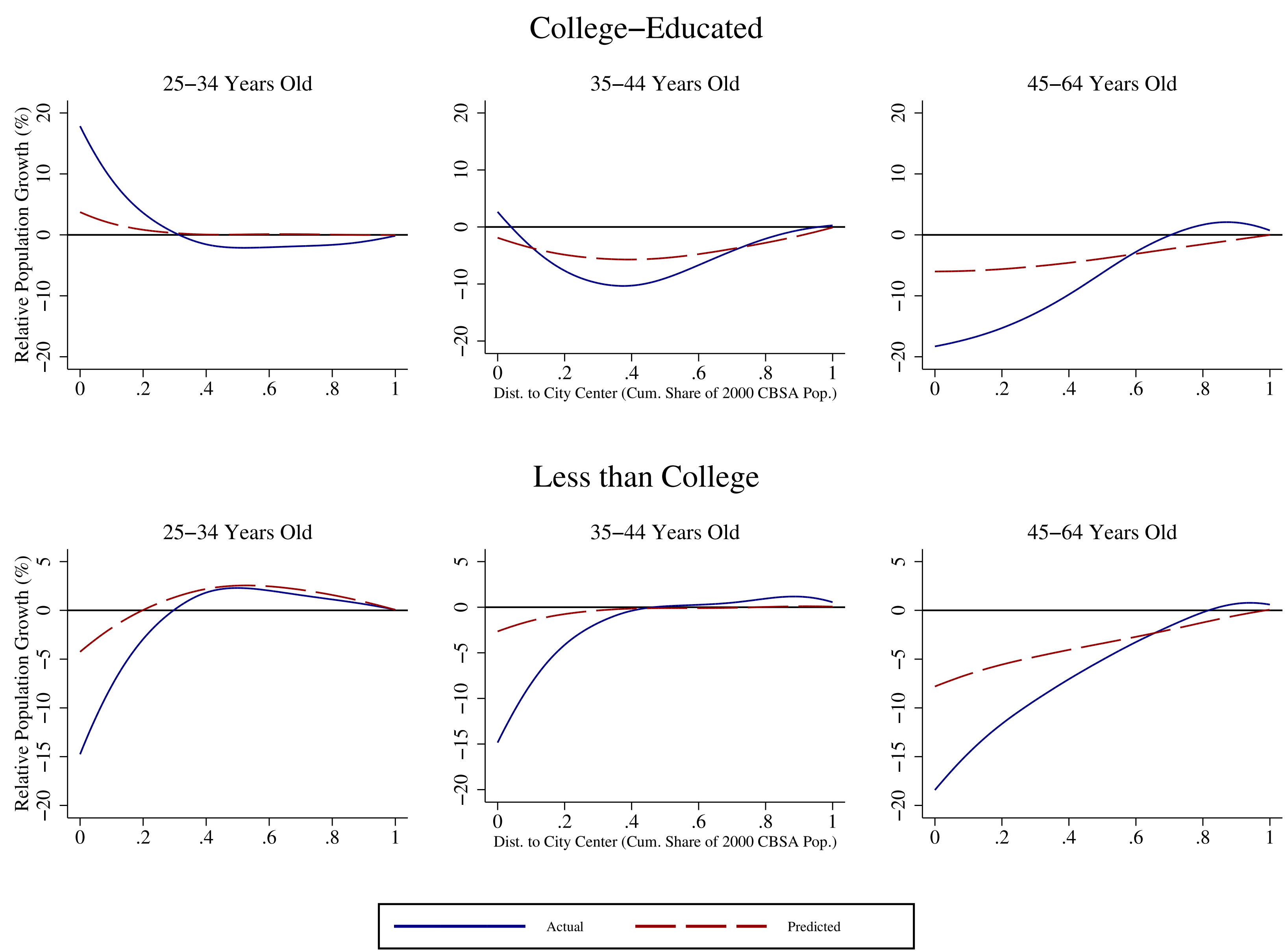


Panel B: Percentage Change in Restaurants (dashed) and Food Stores (solid)



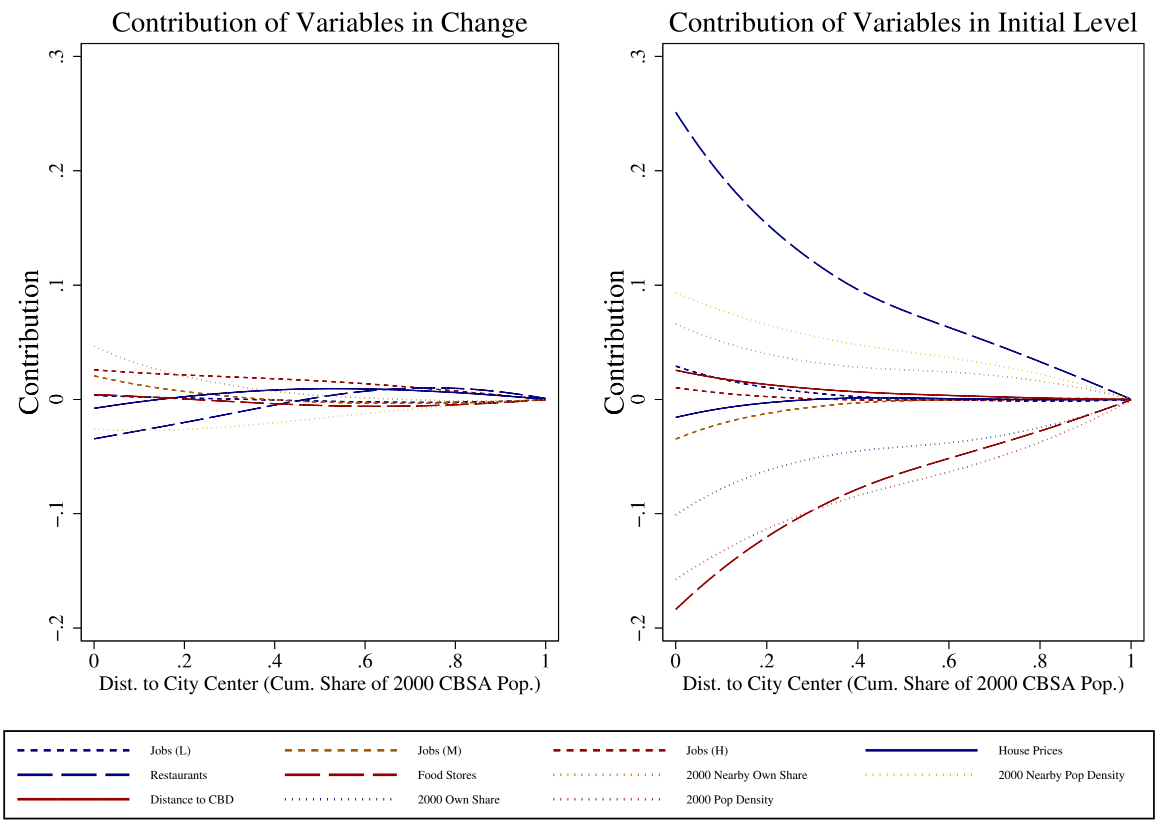
Notes:Panel A shows a non-parametric kernel fit of the log of amenity density and diversity indexes in 2000 for restaurants and food stores and the amenity quality index in 2000 for restaurants, plotted against the young-college population-weighted distance from the city center for all tracts in our estimation sample. Panel B shows a kernel of the 2000 to 2010 percent change in these indexes. The shaded region around kernel fit depicts the 95% confidence interval. Amenity establishment location is from the NETS data. See Appendix B for details on consumption amenity index construction.

Figure 5: Model Fit by Age and Education Group



Notes: These figures plot the average predicted change in the share of the population in each age-education group at different distances from the city center. These predictions are based on coefficient estimates from our base IV specification in panel B of Tables 2 and 3, excluding distance to city center and the within-CBSA share as described in Section 3.2 of the paper.

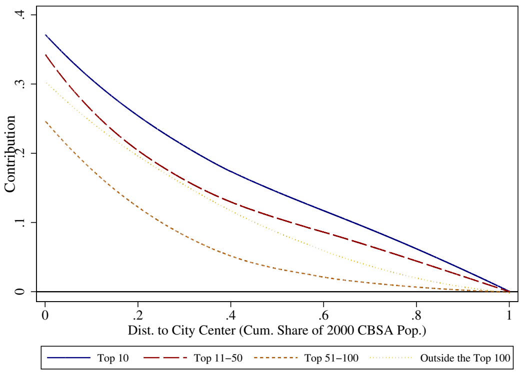
Figure 6: Variables Contributing to Young College-Educated Growth at Various Distance from the City Center



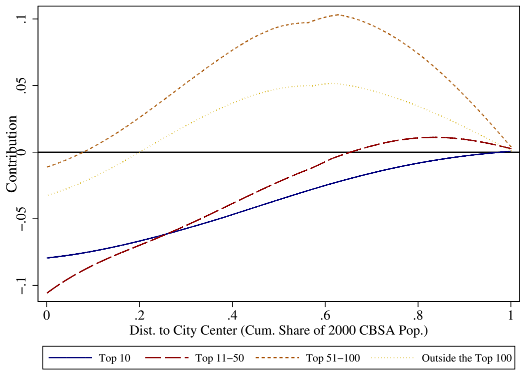
Notes: This figure plots the contribution of each variable in our base IV specification for the young and college-educated (columns 1 and 2 of panel 2 of Table 2) towards the change in the share of the young college-educated population at different distances from the city center, as described in Section 3.2 of the paper. The y-axis intercepts are reported in online Appendix Table A.6.

Figure 7: Contribution of Restaurant Density to Young College-Educated Growth at Various Distance from the City Center by CBSA Size

(a) Level



(b) Change



Notes: This figure plots the contribution of the level and change in restaurant density in our base IV specification for the young and college-educated (columns 1 and 2 of panel 2 of Table 2) towards the change in the share of the young college-educated population at different distances from the city center in CBSAs of different sizes, as described in Section 3.2 of the paper.

Figure 8: Change in Commute Patterns

Panel A: All Workers in All CBSAs

Miles from Residence to City Center	Miles from Workplace to City Center: [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+
[0, 1)	-15.0	-15.0	-12.9	-3.8	6.2	9.0	14.8
[1,2)	-14.1	-12.8	-14.7	-7.4	3.1	6.9	7.2
[2,4)	-11.6	-9.7	-10.7	-6.4	0.7	4.1	10.3
[4, 8)	-2.8	0.2	-3.4	-3.9	1.5	6.2	6.2
[8, 16)	8.9	13.8	8.6	8.0	2.5	10.3	14.8
[16, 32)	20.7	27.8	22.4	22.6	16.4	3.3	15.6
32+	32.3	41.1	33.8	37.9	40.8	31.7	10.7

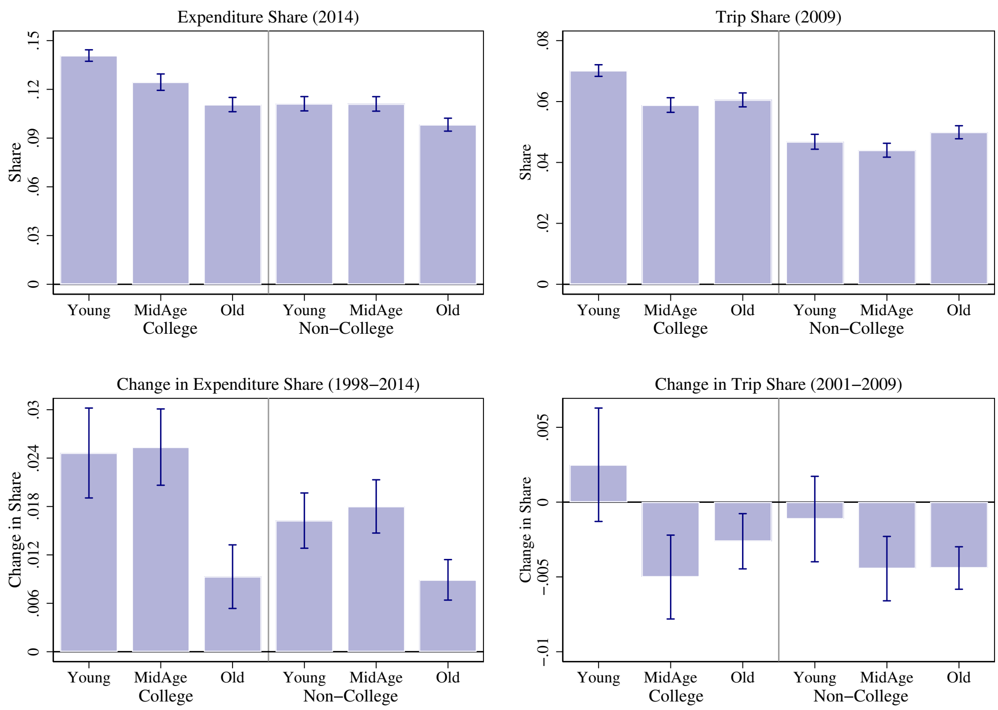
Panel B: High-Wage Workers in Largest 10 CBSAs

Miles from Residence to City Center	Miles from Workplace to City Center: [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+
[0, 1)	78.4	97.2	111	105	80.4	65.4	69.0
[1,2)	93.2	69.6	62.1	82.2	62.2	55.8	68.9
[2,4)	81.9	95.4	60.7	69.7	49.8	39.9	59.3
[4, 8)	68.3	104	43.3	42.6	34.2	24.8	30.2
[8, 16)	47.6	81.9	34.8	28.7	19.7	25.2	29.5
[16, 32)	35.9	62.3	30.8	30.6	23.2	25.8	36.9
32+	67.7	96.9	53.8	56.4	54.2	46.8	40.2

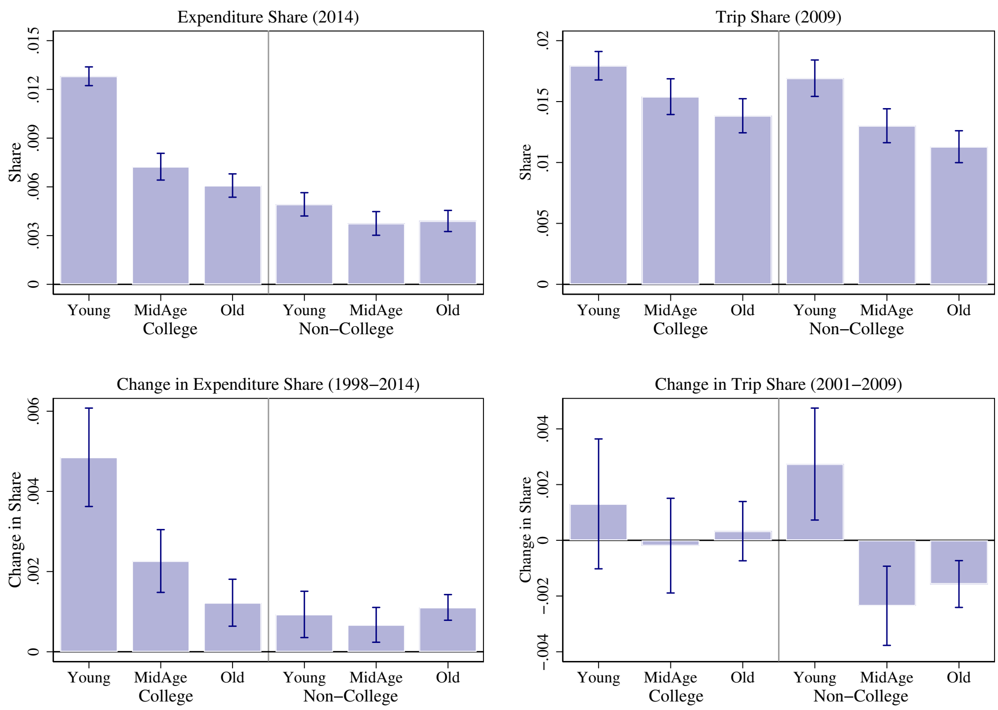
Notes: These tables show the percentage change from 2002 to 2011 in the number of workers living and working at different distances from the city center. High-wage workers earn more than $3333/month in nominal dollars. The underlying data are from LODES 2002 and 2011.

Figure 9: Expenditure and Trip Share on Non-Tradable Services by Age and Education Group

Panel A: Restaurants



Panel B: Nightlife Establishments

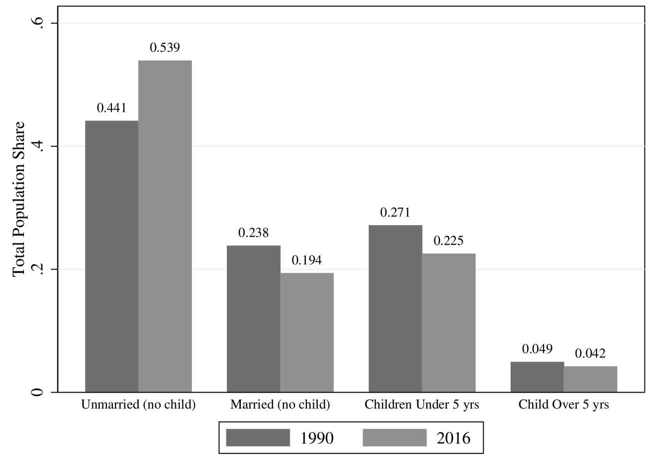


Notes: The left-hand chart in each panel shows mean CEX expenditure shares for each age-education group and the right-hand chart shows mean NHTS trip shares. In the CEX, restaurants expendidture is “food away from home" (UCC Codes 190111-190926), and nightlife is “alcohol away from home" (UCC Codes 200511-200536). In the NHTS, restaurant trips are to get a meal (not grocery). Nightlife trips are all trips categorized as “Go out/hang out". The bands around the end of each bar depict 95% confidence intervals.

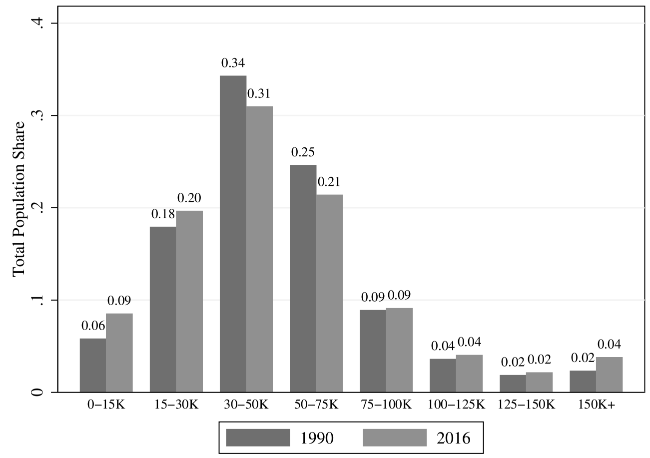
Figure 10: Family and Income Type Shift Share Analysis of Urbanization Rates

Panel A (shift): Population Share in 1990 vs. 2012-2016

By Family Type

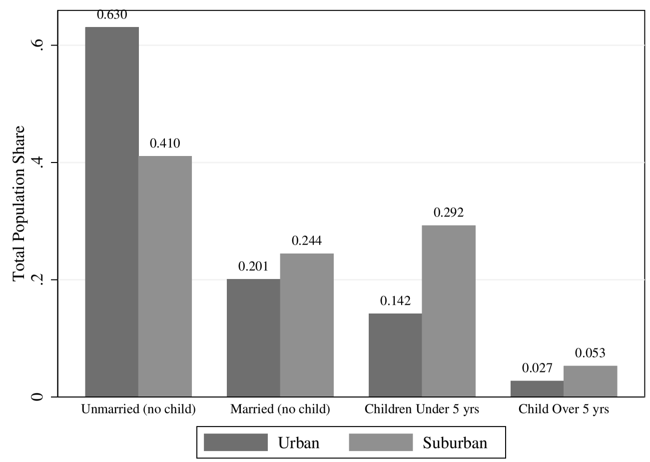


By Income Type

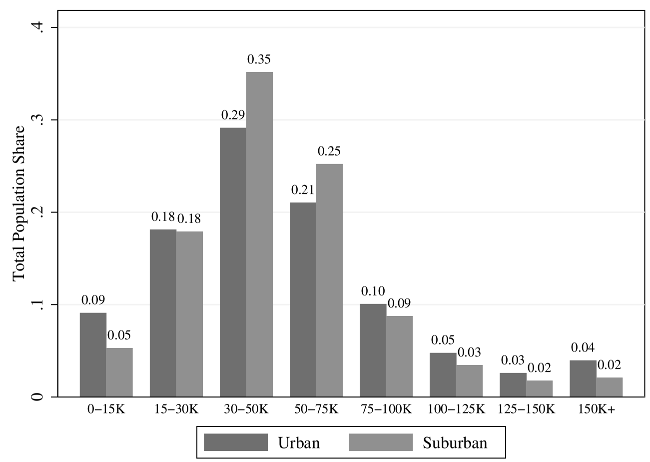


Panel B (initial share): Share in Urban vs. Suburban Area in 1990

By Family Type



By Income Type

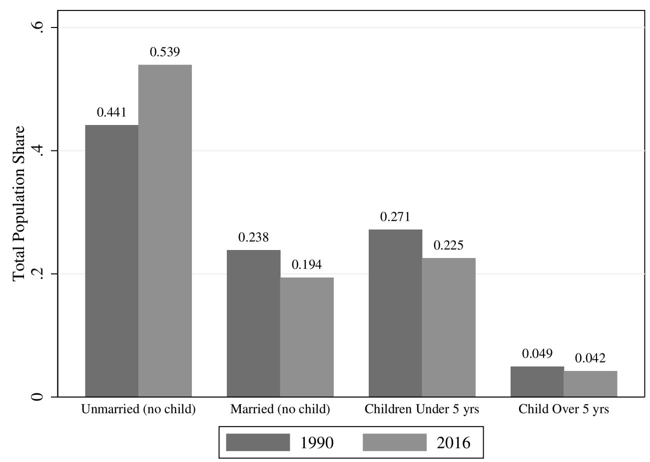


Notes: These plots depict the data used in the shift-share analysis described in Section 5 of the paper. Panel A depicts changes in the composition of 25-34 year old college graduates between 1990 and 2012-2016 across family type and income brackets and Panel B shows how these subpopulations were distributed between urban and suburban areas of U.S. cities in 1990. Both Panels A and B use data from the IPUMS Public Use Microdata Sample and depict shares computed out of all 25-34 year-old college graduates in the 27 CBSAs where we can define constant geography urban areas in 1990 and 2012-2016. The urban area of each CBSA is the set of tracts closest to city center that constitute 10% of the total CBSA population in 2000. See Appendix A for further description.

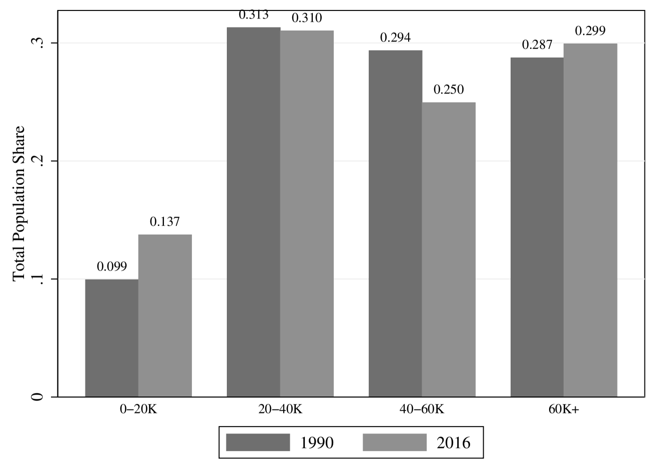
Figure 11: Family and Income Type Shift Share Analysis of Restaurant and Nightlife Consumption

Panel A (shift): Population Share in 1990 vs. 2012-2016

By Family Type

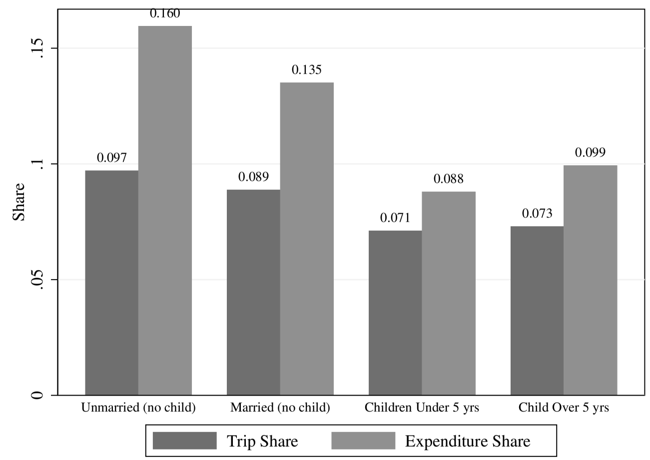


By Income Type

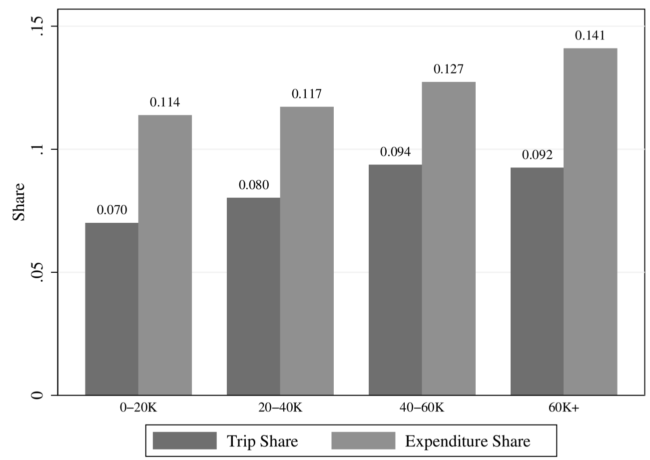


Panel B (initial share): Restaurant and Nightlife Trip and Expenditure Shares in 2001

By Family Type



By Income Type



Notes: These plots depict the data used in the shift-share analysis described in Section 5 of the paper. Panel A depicts changes in the composition of 25-34 year old college graduates between 1990 and 2012-2016 across family type and income brackets. Panel A uses data from the IPUMS Public Use Microdata Sample and depict shares computed out of all 25-34 year-old college graduates in the 27 CBSAs where we can define constant geography urban areas in 1990 and 2012-2016. The urban area of each CBSA is the set of tracts closest to city center that constitute 10% of the total CBSA population in 2000. See Appendix refap:data for further description. Panel B depicts the trip and expenditure shares each subpopulation allocated to restaurants and nightlife in 2001 using data from the Consumer Expenditure Survey (CEX) and the National Household Travel Survey (NHTS). In the CEX, restaurants expendidture is “food away from home" (UCC Codes 190111-190926), and nightlife is “alcohol away from home" (UCC Codes 200511-200536). In the NHTS, restaurant trips are to get a meal (not grocery). Nightlife trips are all trips categorized as “Go out/hang out".

Appendices

A Data Appendix

The following appendix provides detailed information on all data sources.

A.1 Census Data and ACS Data

Census Tract Data and Definitions For our stylized facts on recent urban growth, we assemble a database with the population of constant 2010 geography census tracts using a geographical crosswalk from the Longitudinal Tract Data Base (LTDB) and the 1980-2000 census and the 2008-2012 ACS data from the National Historical Geographic Information System (NHGIS). In each of the censuses from 1980 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 tract level variable from 1980, 1990, and 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 2008-2012 ACS data, which already use 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 2013 CBSA definitions. Our model estimation sample covers all 355 metropolitan area CBSAs.

IPUMS Data PUMA geography is also not constant from 1990 to 2014, so we use a crosswalk between PUMAs (Public-Use Microdata Areas) and CBSAs in each year to link each PUMA to a CBSA. To construct constant downtowns from PUMAs across years, we develop the following methodology. We first intersect PUMA geographies in 1990 and 2014 with a constant downtown geography 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 in census blocks whose centroid falls within the urban area (i.e., downtown) of that CBSA.

In most 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.

A.2 LODES Data

The LODES data comes from the Longitudinal Employer-Household Dynamics (LEHD) data. The LODES data has three parts: origin-destination (OD), workplace area characteristics (WAC), and residence area characteristics (RAC). The WAC data provides counts of workers in each census block by wage groups and 20 NAICS sectors that we use to compute our job density indexes and wage group-specific Bartik instruments. We use the OD data to study commuting patterns in section 1.1. The OD data provides counts of workers working and living in a census block pair by age and income groups (but not for age-income interactions). For each census block pair, counts are available for three age groups (29 or younger, 30 to 54, and 55 or older) and three nominal wage groups ($1,250/month or less, $1,251/month to $3,333/month, and greater than $3,333/month). We aggregate the OD data at the tract level and exclude federal workers.

The LODES data for general public use is processed to protect the workers' confidentiality (Graham et al., 2014).[41] There are two aspects to confidentiality protection in the LODES data.[42] First, the residential location of workers is synthesized. That is, the residential census block of a worker is "coarsened" and drawn from a distribution of blocks within the same census tract, PUMA or Super-PUMA. Graham et al. (2014) note that only 10 percent of residences are coarsened above the census tract level, so synthesis has no impact on 90 percent of our sample, which is aggregated at the tract level. Moreover, only residential-workplace pairs with very small shares – generally for long commutes - have residences coarsened at a geography larger than a census tract. Our weighted regressions ensure that these small cells have little impact on our estimation results. Second, the workplace location of residents is subject to noise infusion and small cell imputation. These procedures again have the most impact on block-pairs with very small worker counts, and both tract-level aggregation and weighted regressions ensure a minimal impact of these procedures on our estimates.[43]

[41] The complexity and opacity of these procedures may discourage academic use of the data. We share these concerns, but argue that too much caution is unwarranted in many empirical contexts including ours.

[42] Another source of measurement error comes from the LEHD source data, in which 40 percent of jobs are at multi-establishment employers. The state of Minnesota reports establishment level data, so the LEHD uses Minnesota data to impute an establishment to workers at multi-establishment employers in other states. For instance, workers are more likely imputed to establishments closer to their residence.

[43] See Graham et al. (2014) for additional technical details on these procedures, comparison with the ACS commute data, and further references on the LEHD and LODES data creation.

A.3 NETS Data

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

Neumark et al. (2007) assess the reliability of the NETS data 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 10-year difference in establishment density. They report that NETS has better coverage than other data sources of very small establishments (1-4 persons), many of which serve consumption amenities. Table A.1 reports the number of establishments nationally in 2000 and 2010 in each of our four consumption amenity types, as well as the SIC codes used to define these types.[44]

Table A.1: NETS Establishment Counts and SIC codes

Category	Description [1]	00 Estab. Counts [2]	10 Estab. Counts [3]	SIC Codes [4]
Non-Tradable Services				
Restaurants	full service, fast food, etc.	437570	416807	581200 - 581209
Nightlife	bar, clubs, lounge, etc.	64948	75261	581300 - 581302
Stores				
Food Stores	grocery stores, markets, bakeries, etc.	281269	335802	54
Apparel Stores	apparel stores	197909	239863	56

Notes: Columns 2 and 3 show the total number of establishments in the NETS data for each type of consumption amenity in 2000 and 2010 respectively.

[44]The NPD Group, a marketing agency, reports 579,416 restaurants in the spring of 2010. Couture (2016) reports 273,000 restaurants on Google Local in States accounting for 50 percent of the U.S. population, suggesting close to 550,000 restaurants nationally. By comparison, the NETS reports 416,807 restaurants nationally in 2010.

A.4 House Price Indexes

Our main house price index comes from Zillow.com.[45] Our "two-bedroom home" index is the Zillow House Value Index (ZHVI) for all two-bedroom homes (i.e., single family, condominium, and cooperative), which is available monthly for 7,423 zip codes in 2000 and 8,941 zip codes in 2010. In robustness checks, we use the per square foot Zillow House Value Index for All Homes, which is available monthly for 10,452 zip codes in 2000 and 11,118 zip codes in 2010 and HUD's Fair Market Rent Series (FMR) for one bedroom, two bedroom and three bedroom homes, which is calculated annually for 3,038 counties in 2000 and 3,042 counties in 2010. For each zip code in the Zillow data, we compute a yearly index by averaging over all months of the year. We map zip codes to tracts with a crosswalk from HUD. We compute the tract-level index as the weighted average of the home value index across all zip codes overlapping with the tract, using as weights the share of residential address in the tract falling into each each zip code. For tracts falling partly into missing zip codes, we normalize the residential share in zip codes with available data to one. The final data set contains home value indexes for 51,165 tracts in 2000 and 53,784 tracts in 2010.

A.5 UCR Crime Data

The crime data comes from the Uniform Crime Reporting Program (UCR) from 1990, 2000, and 2010. As in Ellen et al. (2019), we use data on violent crimes, which include murder, rape, robbery, and aggravated assault. UCR relies on each city's police district to self-report their crime statistics to the FBI. Therefore, we lack coverage for police districts that did not report. There are multiple police districts within each CBSA. The number of police districts reporting increased from 9,222 in 1990 to 11,044 in 2010, partially because new cities were incorporated. To impute district-level data to census tracts, we use GIS software to map every 2010 census tract into the corresponding district or districts that it overlaps with. We then assign the crime total for each district to the tracts that overlap with it (population-weighted overlap) assuming that population and crime are uniformly distributed within tracts and within districts. The final data set contains crime data for 54,745 tracts in 1990 and 57,095 tracts in 2010 after discarding tracts that do not overlap with any districts.

A.6 Consumption Expenditure Survey (CEX) Data

The Consumer Expenditure Survey (CEX) is conducted by the U.S. Department of Labor's Bureau of Labor Statistics. We use the public-use micro-data from the CEX Diary Survey for years

[45] The index and methodology are available at `http://www.zillow.com/research/data/`, accessed 31 December, 2018.

1996 to 2000 and 2012 to 2016. These surveys record all expenditures for each respondent, including expenditures on small, frequently purchased items over two consecutive one-week periods, as well as characteristics, income and weights for the consumer unit (household). Each CEX expenditure receives a Universal Classification Code (UCC) that we match to our amenity types as follows:

1. Restaurants (UCC 190111 - 190926, "Food away from home" (excluding beer, wine and other alcohol))

2. Nightlife (UCC 200511 - 200536, Beer, wine and other alcohol in "Food away from home")

3. Food Stores (UCC 10110 - 180720, "Food")

4. Apparel stores (UCC 360110 - 410901, "Apparel")

To obtain population estimates of mean expenditure shares, we use weights at the consumer unit level (total sample weight). Our sample size for the 24-35 year-old college-educated group (the smallest considered in our analysis) is 8,045 individuals in 1998-2002 and 8,077 individuals in 2008-2012.

A.7 National Household Transportation Survey (NHTS) Data

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 2001 and 2009 NHTS surveys. Each trip has a WHYTO (trip purpose) code that we match to our amenity types as follow:

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. Food Stores (WHYTO 41, "Buy goods: groceries/clothing/hardware store")

4. Apparel stores (WHYTO 41, "Buy goods: groceries/clothing/hardware store")

We use weights at the person level to compute population estimates of mean trip shares. Our sample size for the 24-35 year-old college-educated group (the smallest considered in our analysis) is 6,228 individuals in 2001 and 7,309 individuals in 2009.

For our analysis of the broader secular trends driving urban revival in section 5, we use the income and household composition information provided in the NHTS. The NHTS reports household income in brackets. We use the midpoint of each bracket, and $167,000 for the top bracket "$100,000+" , as an estimate for household income. The 2009 survey excludes children under five, but we know the age-range of the youngest child. If any child in a household does not fill the survey and we know that the youngest child in the household is younger than five, then we assume that the child who did not fill the survey is younger than five.

B Variable Definitions

This appendix details the computation of the dependent variable in our regression, as well as the measures of job density, and consumption amenity density, quality, and diversity.

B.1 Dependent Variable

The dependent variable, $\Delta \ln \tilde{s}^d_{jc}$, is the 2000 to 2010 log change in the share of age-education group d that lives in tract j of CBSA c relative to a base tract. It comes from tract-level population counts by age and education from the decennial census of 2000 and from the American Community Survey (ACS) 2008-2012 aggregates, as in our stylized facts. Let n^d_{jct} be the number of individuals of group d in tract j in CBSA c. The share of all type d residents who live in tract j in CBSA c at time t is then:

$$s^d_{jct} = \frac{n^d_{jct}}{\sum_c \sum_j n^d_{jct}}.$$

B.2 Job Density Index

We use the LODES data to compute a distance-weighted average of the number of jobs in tracts surrounding each residential tract in 2002 and in 2011. The job density index for a tract j' for wage group g is:

$$\text{job density}^g_{j't} = \sum_j w(d_{j'j}) n^g_{j'jt} \text{ where } w(d_{j'j}) = \frac{1/(d_{j'j}+1)}{\sum_j 1/(d_{j'j}+1)},$$

where $n^g_{j'jt}$ is the number of workers who work in tract j but do not live in tract $j^{'}$,and $d_{j'j}$ is the linear distance in miles between the centroids of tract j and j'.

B.3 Amenity Variables

Consumption Amenity Density Indexes We measure the level and change in the availability of different types of establishments around each tract's centroid. The amenity density index for, say, restaurants in tract j is high if there are many restaurants within a short travel time of tract

j's centroid. The amenity density index for a given type is the inverse of a CES price index, in which the price of visiting an establishment includes transport cost, as in Couture (2016). We assume an elasticity of substitution of 8.8, estimated by Couture (2016) with restaurant data. The higher the elasticity, the lower the weight on establishments far away from the tract centroid, and the more localized the amenity index. The price of a visit to an establishment is a constant derived from the CEX for that type, plus a transport cost by foot from the tract centroid.[46] So for each type a, the density index in tract j is:

$$A_{aj} = \frac{1}{\left(\sum_{i=1}^{I_j} (p_a + t_{ij})^{1-\sigma} \right)^{1/1-\sigma}}, \tag{A.1}$$

where p_a is the average price of a visit to an establishment in amenity type a, t_{ij} is the travel cost of a two-way trip to establishment i from the tract centroid j, I_j is the set of all NETS establishments in type a within 50 miles of a tract, and σ is the elasticity of substitution equal to 8.8. To compute travel costs, we start with the linear distance from tract j's centroid to an establishment i.[47] To go from the linear distance to the actual travel distance, we use an average ratio of actual to linear travel distance computed from each tract's centroid to a random sample of 100 NETS establishments on Google Maps. To go from travel distance to travel time, we use Google Maps' constant walking speed of 20 minutes per mile.

Consumption Diversity Index

The amenity diversity indexes of section 3.3 are inverse Herfindahl indexes, which capture the diversity of the 70 restaurant SIC8 types and 66 food store SIC8 types:

$$\mathrm{H}_{ji} = \frac{1}{\sum_i {m_{ij}}^2}, \tag{A.2}$$

where m_{ij} is the market share of SIC8 code i within 50 miles of tract j. When computing market shares, each restaurant receives the same CES weight as in equations A.1.

[46] Using CEX expenditures that most closely match our amenity types, we set a price of \$10.2 for restaurants, \$12.4 for nightlife, \$36.5 for food stores and \$60.4 for apparel stores. Note that we do not observe the prices of different varieties, so our weights assume that each variety within a given amenity type has the same price. Transport costs assume a value of time equal to \$12 dollars per hour (equal to 50 percent of the average U.S. wage as suggested in Small and Verhoef, 2007).

[47] When there are no establishments within 50 miles of a tract centroid, a tract receives a top code for that amenity type equal to the highest non-missing value in the tract sample. Usually less than 1 percent of tracts are top-coded, except for nightlife which is 9 percent top-coded in 2010 and 4 percent top-coded in 2000.

Consumption Quality Index The methodology to compute the restaurant quality index is described in detail in Couture et al. (2019) using data from smartphone visits from 2016-2018 also described in that paper. Couture et al. (2019) compute a quality measure for each of the 100 largest restaurant chains, based on the average propensity of people living in block groups with median income larger than $100,000 to visit that chain relative to the average individual, controlling for variation in choice sets. They then find the average quality measure within each tract in 2000 and 2012, using chains in tract farther away if there are fewer than three chains within tract.

Here we replicate this methodology, but instead compute our quality measure based on the visit propensity of people living in tracts with the top 10% largest share of young and college-educated individuals in each CBSA in the latest ACS (2013-2017). The average share of college-educated 25-to-34 year old college educated individuals in these tracts is 21%. We calculate highly correlated indices when restricting to tracts with an even higher share of young college graduates. Overall the restaurant chain ranking makes sense. The two highest ranking chains are Shake Shack (which famously targets young professionals) and Pot Belly, and the two lowest ranking are Huddle House and Cotton Patch Café. Among the 10 largest chains, the two highest ranking chains are Starbucks and Subway, and the lowest ranking are KFC and Dunkin Donuts.[48]

B.4 Transit Performance Index

Our transit performance index comes from a sample of 100 simulated transit trips originating in each tract, obtained from Google Maps in 2014. Each trip is from the centroid of a tract to a randomly chosen NETS establishment. If there is no transit available for a given trip, then Google Maps returns the walking time of 20 minutes per mile.

For each tract, we then run a linear regression of transit time on the distance from the centroid to each establishment.[49] We compute, for each tract, a fitted value from this regression at a distance of 5 miles. This fitted value is our measure of transit performance, which captures the average time of a 5 mile trip using transit, starting from each tract's centroid.

[48] Among the 50 largest chains, the five highest ranking chains are Quiznos, Jimmy John's, Chipotle, Panera Bread, and Jamba Juice (Starbucks is 6th)

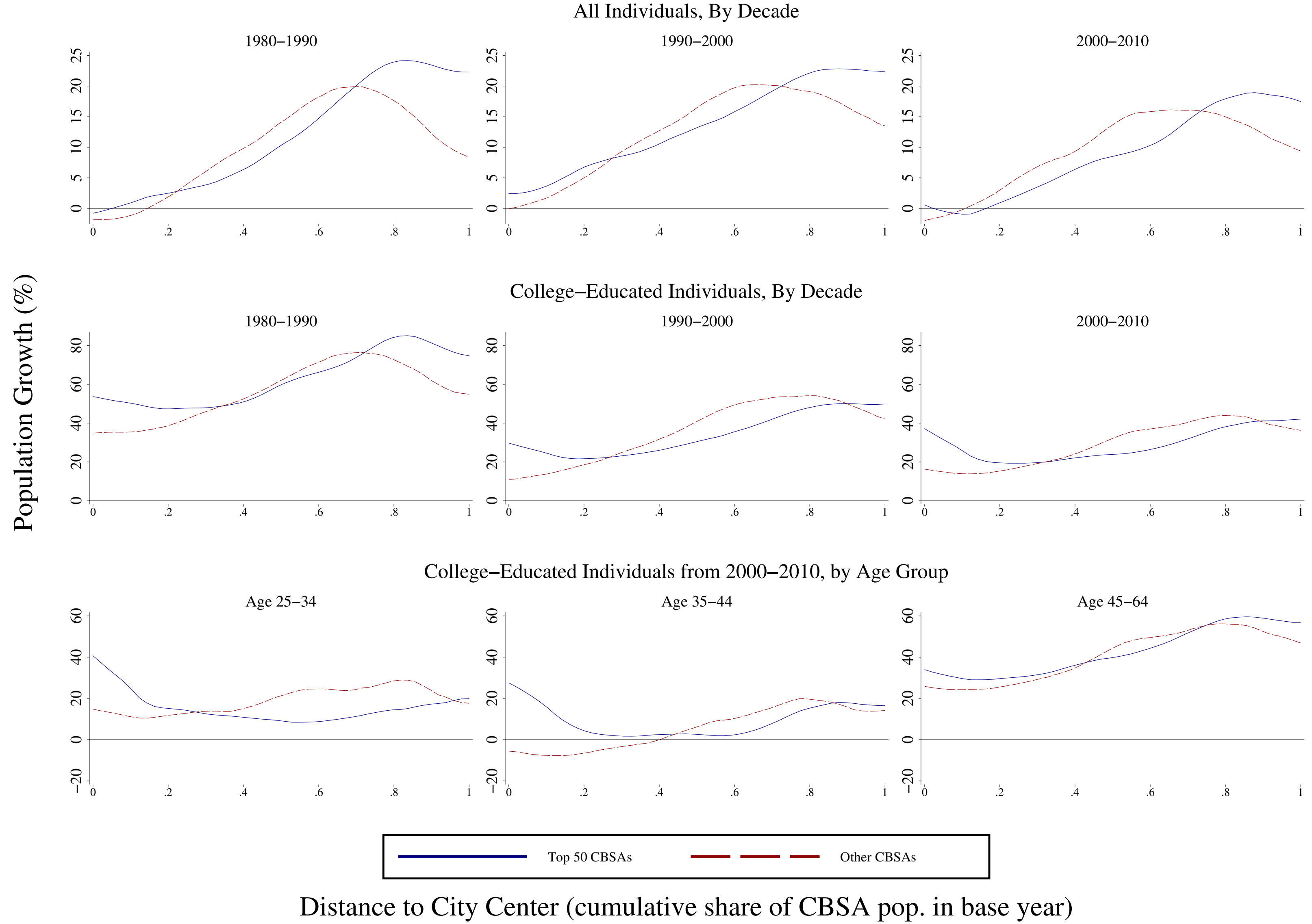
[49] This linear specification is consistent with a fixed cost of walking to and waiting for transit, and a constant time cost of distance once in a train. While buses may experience congestion, acceleration, and, we experimented with other more flexible polynomials and found highly correlated indices.

Online Appendix

This document contains supplementary material for the paper "Urban Revival in America," by Victor Couture and Jessie Handbury. Appendix C contains additional stylized facts documenting growth across CBSAs of different sizes from 1980 to 2010. Appendix E contains additional results not shown in the paper. Appendix F contains detailed derivation for the estimating equation and the urbanization contribution plots in the paper. Appendix G discusses two alternative hypotheses for urban revival: first that reduced access to homeownership following the housing crisis explains the urbanization of young college graduates, and second that changes in mobile technology and review platforms made urban areas more desirable for young college graduates.

C Additional Stylized Facts

Figure A.1: Population Growth at Various Distances from the City Center by CBSA Size



Notes: Each figure shows a non-parametric kernel fit of percent change in tract population at different distances from the city center. Each kernel regression observation is weighted by initial tract population. Distance from the city center is measured as the cumulative share of CBSA population in the base year. The top row of plots presents kernels for the percent change in total population between 1980 and 1990, 1990 and 2000, and 2000 to 2010. The second row is similar but for the college-educated population. The final row presents kernels for the 2000-2010 percent change in the college-educated population in three age brackets. The two lines show the percent change for the top 50 CBSAs and all CBSAs outside the top 50, as ranked by CBSA population in the base year of each plot. Data are from the 1980–2000 decennial censuses and the 2008–2012 ACS.

Table A.2: Counts of CBSAs: Urban Population Growth Greater than Suburban Population Growth

		All Individuals			College-Educated Indviduals			College-Educated Individuals 2000-2010		
Urban Def.	CBSA Pop. Rank	1980-1990 [1]	1990-2000 [2]	2000-2010 [3]	1980-1990 [4]	1990-2000 [5]	2000-2010 [6]	Age 25-34 [7]	Age 35-44 [8]	Age 45-64 [9]
5 pct.	1-10	1	1	3	4	4	9	10	9	4
5 pct.	11-50	3	1	3	5	6	19	33	18	5
5 pct.	51-100	4	4	3	9	2	12	23	15	9
5 pct.	101-355	67	46	36	84	49	66	104	97	93
10 pct.	1-10	2	0	2	4	3	7	9	9	3
10 pct.	11-50	1	2	0	4	3	11	29	14	2
10 pct.	51-100	5	3	3	9	3	9	21	10	6
10 pct.	101-355	64	28	21	61	28	41	78	72	73
15 pct.	1-10	2	0	2	3	1	7	8	8	1
15 pct.	11-50	2	2	1	2	3	9	24	12	2
15 pct.	51-100	7	3	4	8	2	5	18	6	4
15 pct.	101-355	60	30	23	65	21	33	79	63	50
2 Miles	1-10	1	2	5	3	6	10	10	9	5
2 Miles	11-50	1	2	7	4	10	26	36	23	10
2 Miles	51-100	5	3	3	9	2	9	20	10	6
2 Miles	101-355	76	37	38	85	28	40	100	66	60
3 Miles	1-10	1	1	4	4	3	10	10	10	5
3 Miles	11-50	2	2	1	5	6	17	31	20	3
3 Miles	51-100	6	3	4	9	2	6	19	9	4
3 Miles	101-355	85	48	45	94	30	40	100	56	55
5 Miles	1-10	2	0	2	4	3	9	10	9	5
5 Miles	11-50	2	0	0	1	3	10	30	16	1
5 Miles	51-100	4	3	5	6	2	6	15	6	3
5 Miles	101-355	96	66	58	102	41	43	94	59	51
Central	1-10	1	0	1	1	0	8	8	8	0
Central	11-50	3	2	1	3	4	8	19	10	4
Central	51-100	8	5	6	11	4	9	17	8	5
Central	101-355	79	42	23	75	31	28	75	46	41

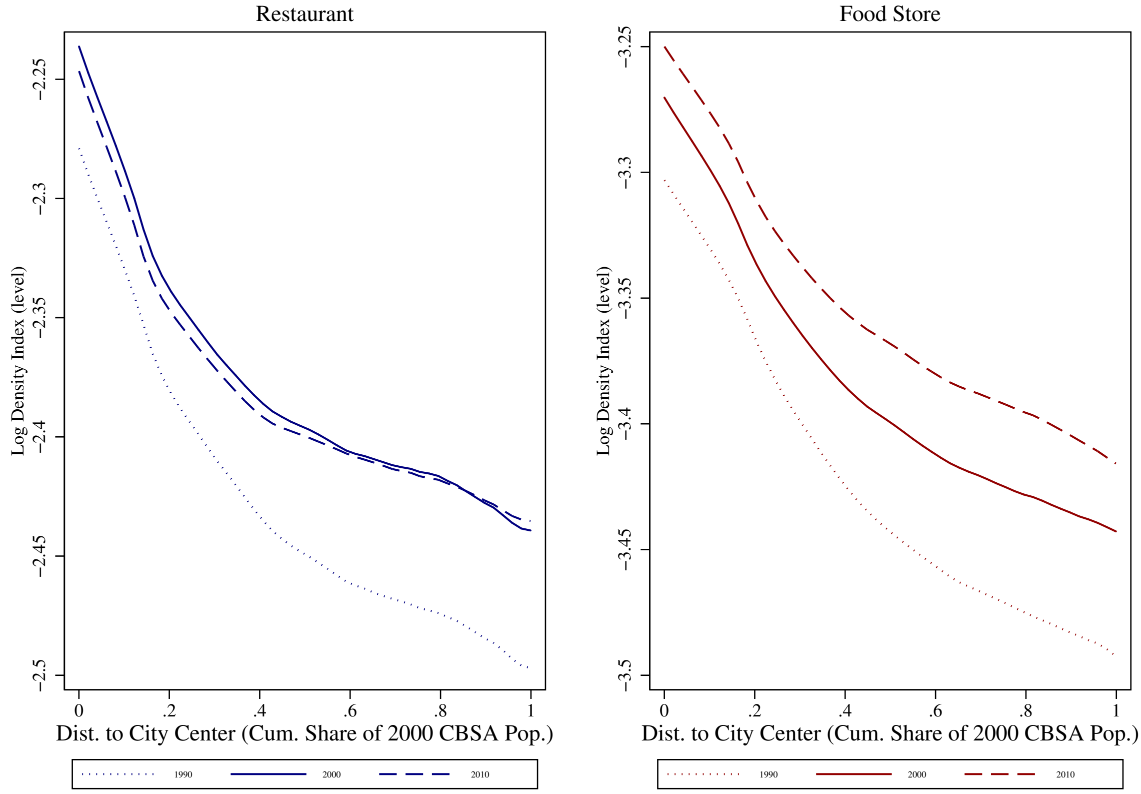
Notes: Columns 1 to 3 give the number of CBSAs for which the total urban population grew faster than the total suburban population for the given decade. Columns 4 to 6 give the number of CBSAs for which the college-educated population grew faster in urban areas relative to suburban areas for the given decade. Finally, columns 7 to 9 give the number of CBSAs for which the college-educated population grew faster in urban areas relative to suburban areas from 2000 to 2010 by age group. These counts are given for various urban definitions and CBSA population rankings. The X pct. urban area is the set of all tracts closest to the city center accounting for X percent of a CBSA's population, and the X miles urban area is the set of all tracts with centroids within X miles of the city center.

Table A.3: Population Growth in Urban and Suburban Areas by CBSA Size

		All Individuals						College-Educated Individuals						College-Educated Individuals, 2000-2010					
	CBSA	1980-1990		1990-2000		2000-2010		1980-1990		1990-2000		2000-2010		Age 25-34		Age 35-44		Age 45-64	
Urban	Pop.	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub	Urb	Sub
Def.	Rank	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
5 pct.	1-10	0.00	0.14	0.04	0.14	0.05	0.09	0.56	0.70	0.31	0.32	0.46	0.29	0.53	0.16	0.38	0.09	0.38	0.46
5 pct.	11-50	0.01	0.26	0.00	0.14	-0.05	0.11	0.48	0.76	0.29	0.42	0.37	0.34	0.43	0.18	0.23	0.15	0.33	0.50
5 pct.	51-100	-0.05	0.19	-0.01	0.17	-0.03	0.13	0.41	0.72	0.08	0.36	0.18	0.33	0.22	0.23	-0.02	0.10	0.24	0.46
5 pct.	101-355	-0.02	0.18	-0.02	0.14	-0.03	0.13	0.51	0.87	0.11	0.37	0.11	0.31	0.09	0.23	-0.10	0.08	0.22	0.40
10 pct.	1-10	0.00	0.15	0.03	0.15	0.02	0.10	0.53	0.71	0.29	0.33	0.39	0.29	0.45	0.14	0.31	0.08	0.35	0.47
10 pct.	11-50	-0.03	0.21	0.01	0.18	-0.03	0.14	0.48	0.78	0.25	0.44	0.30	0.35	0.31	0.18	0.19	0.15	0.32	0.51
10 pct.	51-100	-0.01	0.20	0.00	0.15	-0.01	0.14	0.41	0.74	0.11	0.37	0.18	0.34	0.17	0.23	-0.03	0.10	0.26	0.46
10 pct.	101-355	0.05	0.27	0.01	0.15	-0.02	0.12	0.55	0.89	0.11	0.39	0.11	0.33	0.08	0.24	-0.09	0.09	0.20	0.41
15 pct.	1-10	0.02	0.16	0.04	0.16	0.01	0.11	0.51	0.73	0.26	0.34	0.33	0.29	0.37	0.14	0.24	0.08	0.32	0.47
15 pct.	11-50	0.06	0.29	0.02	0.16	0.00	0.12	0.56	0.92	0.13	0.41	0.12	0.34	0.26	0.19	0.14	0.16	0.31	0.52
15 pct.	51-100	-0.02	0.23	0.02	0.19	-0.02	0.15	0.49	0.81	0.24	0.46	0.26	0.36	0.15	0.24	-0.04	0.11	0.27	0.48
15 pct.	101-355	0.00	0.21	0.01	0.16	0.01	0.15	0.42	0.77	0.13	0.39	0.17	0.35	0.09	0.25	-0.08	0.10	0.20	0.43
2 Miles	1-10	0.01	0.13	0.05	0.14	0.12	0.09	0.57	0.69	0.31	0.32	0.51	0.29	0.61	0.17	0.37	0.10	0.41	0.46
2 Miles	11-50	-0.05	0.18	0.00	0.17	0.01	0.13	0.50	0.75	0.33	0.42	0.41	0.34	0.44	0.19	0.32	0.15	0.36	0.50
2 Miles	51-100	-0.01	0.19	0.00	0.14	-0.01	0.14	0.45	0.72	0.08	0.37	0.17	0.33	0.18	0.23	-0.03	0.10	0.26	0.46
2 Miles	101-355	0.08	0.29	0.03	0.16	0.01	0.12	0.61	0.91	0.13	0.42	0.12	0.34	0.11	0.25	-0.09	0.11	0.20	0.43
3 Miles	1-10	0.00	0.14	0.03	0.14	0.07	0.09	0.59	0.70	0.31	0.32	0.49	0.29	0.58	0.15	0.40	0.09	0.39	0.46
3 Miles	11-50	-0.04	0.19	-0.01	0.17	-0.02	0.14	0.49	0.77	0.28	0.43	0.32	0.34	0.34	0.18	0.23	0.15	0.32	0.50
3 Miles	51-100	0.01	0.21	0.01	0.16	0.00	0.15	0.43	0.76	0.11	0.39	0.16	0.35	0.16	0.24	-0.04	0.11	0.26	0.47
3 Miles	101-355	0.10	0.31	0.05	0.17	0.03	0.13	0.64	0.97	0.18	0.45	0.15	0.37	0.14	0.26	-0.08	0.13	0.22	0.46
5 Miles	1-10	0.00	0.14	0.02	0.15	0.04	0.09	0.59	0.70	0.29	0.33	0.44	0.29	0.52	0.14	0.35	0.09	0.37	0.46
5 Miles	11-50	-0.03	0.21	0.00	0.18	-0.03	0.14	0.48	0.79	0.25	0.44	0.29	0.35	0.15	0.27	-0.05	0.15	0.24	0.49
5 Miles	51-100	0.01	0.23	0.02	0.17	0.01	0.16	0.44	0.80	0.13	0.41	0.17	0.36	0.30	0.18	0.19	0.15	0.31	0.51
5 Miles	101-355	0.11	0.34	0.07	0.17	0.05	0.14	0.67	1.01	0.21	0.48	0.17	0.40	0.14	0.25	-0.04	0.12	0.27	0.49
Central	1-10	0.05	0.17	0.07	0.16	0.02	0.12	0.51	0.77	0.22	0.36	0.28	0.31	0.29	0.15	0.14	0.09	0.30	0.50
Central	11-50	0.06	0.23	0.08	0.19	0.02	0.17	0.59	0.83	0.30	0.47	0.25	0.38	0.20	0.20	0.11	0.17	0.35	0.54
Central	51-100	0.06	0.21	0.07	0.16	0.04	0.16	0.50	0.80	0.19	0.41	0.15	0.38	0.12	0.27	-0.07	0.14	0.27	0.51
Central	101-355	0.09	0.31	0.06	0.16	0.03	0.13	0.59	0.98	0.18	0.44	0.13	0.37	0.11	0.27	-0.10	0.14	0.21	0.46

Notes: Columns 1 to 6 give the percentage change in the total population for a given CBSA group in urban areas and suburban areas by decade. Columns 7-12 give the percentage change in the college-educated population for a given CBSA group in urban areas and suburban areas by decade. Columns 13 to 18 give the percentage change in the college-educated population from 2000 to 2010 for a given CBSA group in urban areas and suburban areas by age group. The X pct. urban area is the set of all tracts closest to the city center accounting for X percent of a CBSA's population, and the X miles urban area is the set of all tracts with centroids within X miles of the city center.

Figure A.2: Restaurant and Food Store Density Indexes at Various Distance from the City Center in 1990, 2000, and 2010



Notes: These plots show a non-parametric kernel fit of the log of amenity density indexes for restaurants and food stores in 1992, 2000, and 2010, plotted against the young-college population-weighted distance from the city center for all tracts in our estimation sample. See Appendix B for details on consumption amenity index construction.

D Robustness to Alternative Housing Cost Data

The house price index in our base specification is the Zillow House Value Index for two-bedroom homes, which measures the median value of two-bedroom homes in at the zipcode level. This index does not capture rental units that are prevalent in urban areas, and it depends on the average size and quality of housing units, as well as on market supply and demand conditions. We test the robustness of our results to our treatment of house prices in four different ways. First, we include the median age of housing units in a tract to capture the amount of new housing development as a proxy for quality. Second, we include HUD's Fair Market Rent Series, in addition to the Zillow house price index. Third, we try different measures of house prices in place of the Zillow two-bedroom index. These include Zillow's per square foot index and Ferreira and Gyourko (2011)'s hedonic price index that controls for more housing characteristics. We also run a specification where the change in house prices is measured using the FHFA tract-level repeat sales index (keeping the Zillow two-bedroom index as our measure of the relative level of house prices across tracts, since the FHFA index does not compare house price levels). Finally, we use the Cobb-Douglas preference structure to remove endogenous housing prices by differencing out CEX group-specific housing expenditure shares from utility and running regressions on these housing-adjusted shares. Panel B in Table A.5 shows that, in all cases, initial levels of non-tradable services still make the largest contribution to urban revival.[50]

In an online Appendix G we investigate the possibility that urban revival is explained by limited mortgage credit availability following the housing crisis and recession of 2007-2009, which pushed individuals into urbanized rental housing. We find no support for this hypothesis in the ACS and IPUMS data, which instead suggests that urban revival starts before the recession, during a period of rising homeownership rates.

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[50]Online Appendix Table A.4 shows the underlying regression coefficient estimates used in calculating these contribution factors.

Table A.4: Robustness of Nested-Logit Residential Location Choice Regression Results: House Prices

							Replacing Zillow 2-bedroom Index with:							
	Base		Housing Age Control		HUD Rent Control		Zillow Per Square Foot		Gyourko-Ferriera		FHFA for Changes		Housing on the LHS	
Coefficient on:	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$	ΔX_{jc}	$X_{jc,2000}$
Structural Interpretation:	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$	$\beta^d_{X,2010}$	$\Delta\beta^d_X$
Variable (X_{jc})	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
House Price Index	-0.038***	-0.028***	-0.020***	-0.021***	-0.023***	-0.012***	-0.032***	-0.035***	0.002	-0.038***	-0.033***	-0.037***		
	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.003)	(0.006)	(0.004)	(0.007)	(0.004)		
Age of Housing Stock			-0.045***	-0.035***										
			(0.003)	(0.004)										
Rent					0.006	-0.023***								
					(0.004)	(0.004)								
Low Wage Job Density	-0.063***	0.040***	-0.034***	0.028***	-0.085***	0.024***	-0.055***	0.037***	-0.062***	-0.023***	-0.066***	0.042***	0.206***	0.119***
	(0.012)	(0.007)	(0.012)	(0.007)	(0.012)	(0.006)	(0.011)	(0.006)	(0.012)	(0.008)	(0.019)	(0.010)	(0.018)	(0.009)
Med. Wage Job Density	-0.167***	-0.045***	-0.149***	-0.020**	-0.108***	-0.011	-0.167***	-0.043***	-0.069***	0.056***	-0.156***	-0.027*	-0.194***	0.090***
	(0.017)	(0.011)	(0.017)	(0.010)	(0.015)	(0.009)	(0.017)	(0.010)	(0.017)	(0.011)	(0.024)	(0.014)	(0.022)	(0.012)
High Wage Job Density	0.265***	0.015***	0.214***	-0.008	0.239***	0.004	0.273***	0.024***	0.187***	0.000	0.290***	0.026***	-0.089***	-0.382***
	(0.014)	(0.006)	(0.013)	(0.005)	(0.013)	(0.007)	(0.014)	(0.006)	(0.015)	(0.008)	(0.026)	(0.010)	(0.016)	(0.007)
Restaurant Density	0.155***	0.184***	0.113***	0.125***	0.044*	0.075***	0.108***	0.131***	0.148***	0.161***	0.188***	0.217***	0.224***	0.274***
	(0.025)	(0.023)	(0.027)	(0.022)	(0.023)	(0.022)	(0.022)	(0.021)	(0.030)	(0.024)	(0.035)	(0.034)	(0.037)	(0.035)
Food Store Density	-0.038***	-0.104***	-0.029**	-0.072***	-0.007	-0.021	-0.025**	-0.067***	-0.041***	-0.101***	-0.053***	-0.128***	-0.123***	-0.207***
	(0.013)	(0.019)	(0.013)	(0.018)	(0.012)	(0.018)	(0.011)	(0.017)	(0.012)	(0.018)	(0.016)	(0.027)	(0.017)	(0.027)
(Nearby) Population Density	0.065***	0.059***	0.111***	0.061***	0.093***	0.047***	0.056***	0.064***	0.113***	0.065***	0.064***	0.052***	0.107***	0.098***
	(0.009)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.009)	(0.010)	(0.012)	(0.011)	(0.015)	(0.016)	(0.013)	(0.015)
(Nearby) Share of Same Type	0.056***	0.108***	0.061***	0.096***	0.065***	0.116***	0.062***	0.120***	0.051***	0.117***	0.067***	0.130***	0.093***	0.126***
	(0.010)	(0.014)	(0.009)	(0.012)	(0.010)	(0.014)	(0.009)	(0.012)	(0.012)	(0.016)	(0.016)	(0.022)	(0.014)	(0.018)
Population Density		-0.093***		-0.061***		-0.088***		-0.083***		-0.066***		-0.065***		-0.109***
		(0.008)		(0.007)		(0.007)		(0.007)		(0.008)		(0.012)		(0.011)
Share of Same Type		-0.103***		-0.096***		-0.093***		-0.096***		-0.105***		-0.139***		-0.124***
		(0.008)		(0.007)		(0.007)		(0.007)		(0.009)		(0.014)		(0.011)
Distance to City Center		-0.009***		-0.007***		0.000		-0.005*		-0.003		-0.017***		-0.049***
		(0.003)		(0.002)		(0.003)		(0.002)		(0.003)		(0.004)		(0.003)
Within-CBSA Share	0.704***		0.713***		0.721***		0.706***				0.651***		0.555***	
	(0.017)		(0.016)		(0.016)		(0.016)				(0.027)		(0.025)	
Observations	22,911		18,844		21,692		27,044		13,304		15,053		27,761	

Notes: * – 10%; ** – 5%; ***–1%. This table lists the coefficient estimates and associated standard errors for different versions of our main residential tract choice regression (Equation 3) estimated for 25-34 year old college graduates. Columns 1 and 2 replicate columns 1 and 2 of our base IV specification from Panel B of Table 2. The remaining columns present variants of this specification adjusting how housing costs are measured. Columns 3 and 4 and columns 5 and 6 include controls for the average age of housing and rental rates. Columns 7 through 12 replace the Zillow 2-bedroom house price index with alternative indexes and columns 13 and 14 adjust our left-hand side variable for housing costs using a Cobb-Douglas assumption, as described in Section 3.3 of the paper. In all specifications, observations are at the tract j and demographic group d level and weighted by the share of group d that resides in tract j in 2000. All change variables are instrumented as described in Section 2.3 of the paper.

Table A.5: Share of Non-Tradable Services' Urbanizing Contribution Across Specifications for the Young and College-Educated

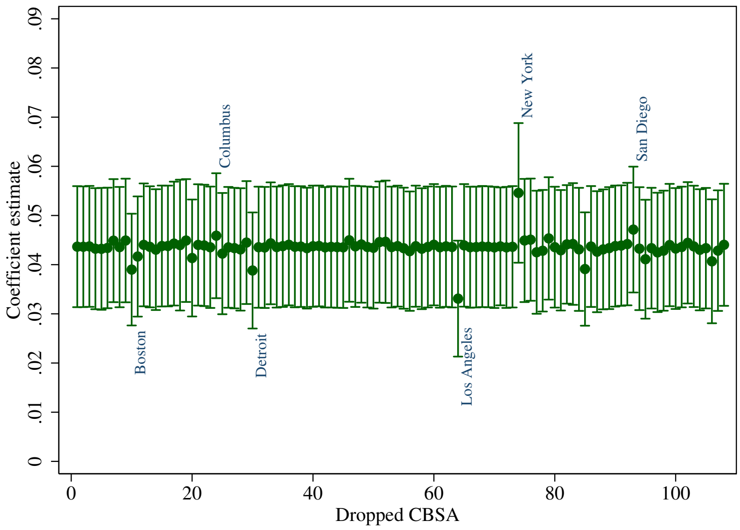
	Rank [1]	Share [2]	Rank [3]	Share [4]
Panel A: Basic Set of Controls				
Base IV Specification	1	45%	1	72%
Base OLS Specification	4	17%	1	48%
Panel B: Base IV Specification with Alternative Housing Index				
Adding Housing Age Control	1	36%	1	65%
Adding HUD Fair Market Rent Control	1	28%	1	60%
Ferreira/Gyourko Hedonic Index	1	42%	1	72%
Zillow Per Square Foot Index	1	36%	1	65%
FHFA Index for House Price Changes	1	41%	1	63%
Housing on the LHS	1	50%	1	78%

Notes: This table reports statistics characterizing the contribution of the increasing taste for non-tradable services towards the urbanization of 25-34 year old college graduates depicted in the bottom left plot in Figure 1. Columns 1 and 2 compare the contribution of the level of non-tradable service density in explaining the centralizing tendency of 25-34 year old college graduates to that of all variables used in our prediction. Column 1 reports the rank of the contribution of non-tradable service density, while column 2 reports its share amongst all variables that provide a positive contribution. Columns 3 and 4 remove from consideration the population density and share of own type controls. The contribution of any given variable is defined as the y-axis intercept of the contribution curve of a given variable, as depicted in Figure 6 for the Base IV Specification and described in Section 3.2 of the paper. The other specifications listed are outlined in Section D of the paper. Non-tradable service density is measured using only restaurant density in all specifications.

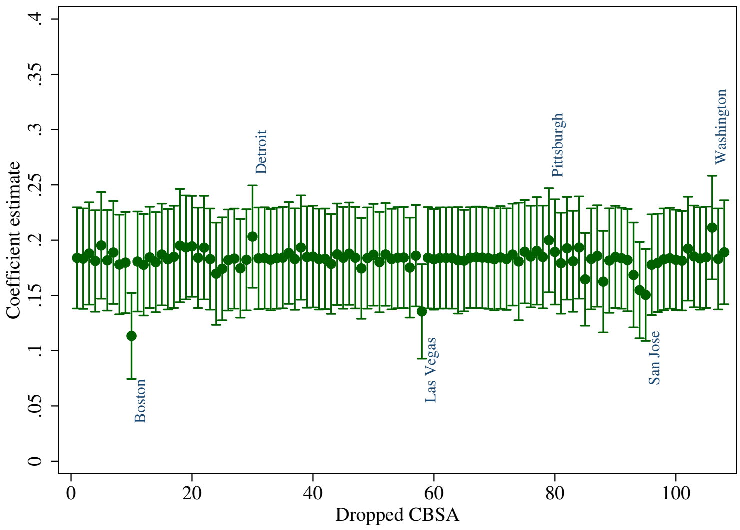
E Additional Results

Figure A.3: Coefficient Estimates Dropping One CBSA at a Time

Panel A: OLS Coefficients on 2000 Level of Restaurant Density



Panel B: IV Coefficients on 2000 Level of Restaurant Density



Notes: These plots show the coefficients on the 2000 restaurant density index estimated when replicating our base OLS and IV specifications for the young and college-educated (Columns 1 and 2 of Panel A and B of Table 2) dropping one CBSA at a time. Each point reflects the point estimate of the coefficient plotted against an index for the CBSA that is dropped from the sample (the ranking of the CBSA when ordered alphabetically). The bars reflect the 95% confidence bands around the point estimate.

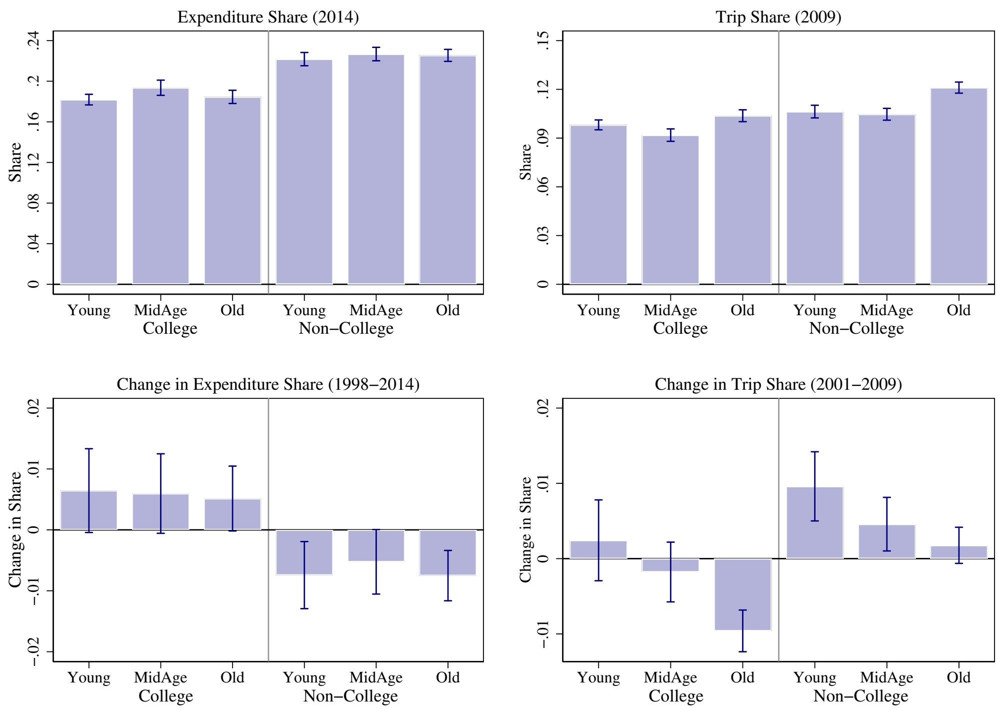
Table A.6: Y-Axis Intercepts Characterizing the Contribution of Different Varaibles towards the Urbanization of the Young and College-Educated

	Base (Nested)				Non-Nested CBSA FE			
	IV		OLS		IV		OLS	
Rank	Variable [1]	Intercept [2]	Variable [3]	Intercept [4]	Variable [5]	Intercept [6]	Variable [7]	Intercept [8]
1	Restaurant Density	1.30	Nearby Share of Same Type	0.52	High Wage Job Density	9.56	Nearby Share of Same Type	1.57
2	Nearby Pop. Density	0.48	Δ Nearby Share of Same Type	0.40	Restaurant Density	3.82	Restaurant Density	0.90
3	Nearby Share of Same Type	0.35	Nearby Pop. Density	0.34	Nearby Share of Same Type	1.98	Δ Nearby Share of Same Type	0.88
4	Δ Nearby Share of Same Type	0.25	Restaurant Density	0.33	Δ Low Wage Job Density	1.58	Nearby Pop. Density	0.44
5	Low Wage Job Density	0.16	Med. Wage Job Density	0.22	Δ Nearby Share of Same Type	1.44	Food Store Density	0.42
6	Δ High Wage Job Density	0.13	Food Store Density	0.06	Δ High Wage Job Density	1.01	Med. Wage Job Density	0.10
7	Δ Med. Wage Job Density	0.11	Δ Housing Costs	0.03	Δ Med. Wage Job Density	0.34	Δ Housing Costs	0.04
8	High Wage Job Density	0.06	Δ High Wage Job Density	0.02	Δ Nearby Pop. Density	0.09	Δ Med. Wage Job Density	0.03
9	Δ Food Store Density	0.02	Δ Low Wage Job Density	0.01	Δ Food Store Density	-0.08	Δ Low Wage Job Density	0.02
10	Δ Low Wage Job Density	0.02	Δ Med. Wage Job Density	0.00	Housing Costs	-0.11	Δ High Wage Job Density	0.00
11	Δ Housing Costs	-0.04	Δ Food Store Density	-0.01	Δ Housing Costs	-0.21	Δ Food Store Density	-0.03
12	Housing Costs	-0.09	Δ Restaurant Density	-0.02	Food Store Density	-0.68	High Wage Job Density	-0.03
13	Δ Nearby Pop. Density	-0.12	Low Wage Job Density	-0.05	Low Wage Job Density	-1.05	Δ Restaurant Density	-0.07
14	Δ Restaurant Density	-0.17	Housing Costs	-0.08	Nearby Pop. Density	-1.19	Housing Costs	-0.12
15	Med. Wage Job Density	-0.19	Δ Nearby Pop. Density	-0.12	Δ Restaurant Density	-1.59	Δ Nearby Pop. Density	-0.19
16	Share of Same Type	-0.53	High Wage Job Density	-0.15	Share of Same Type	-1.81	Low Wage Job Density	-0.27
17	Population Density	-0.80	Share of Same Type	-0.58	Med. Wage Job Density	-1.95	Share of Same Type	-1.52
18	Food Store Density	-0.94	Population Density	-0.78	Population Density	-3.67	Population Density	-3.00

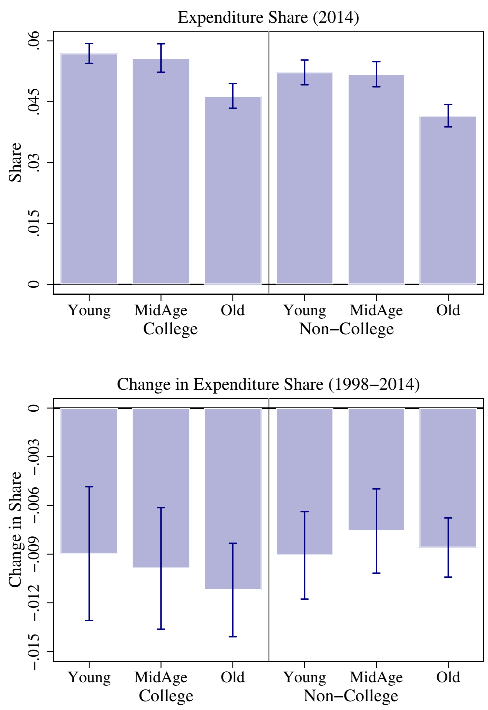
Notes: Columns 1 and 2 of this table report the y-axis intercept of the contribution curve of each variable depicted in Figure 6 for the base (Nested) IV specification and described in Section 3.2 of the paper. The remaining columns report the corresponding intercepts of the contribution curves for each variable as estimated in the base (Nested) OLS specification, as well as the non-nested CBSA fixed effect specifications in IV and OLS (outlined in Section 3.3 of the paper). Removed from consideration are the nested-logit within-CBSA share control (where relevant) and the distance to city center control.

Figure A.4: Expenditure and Trip Share on Tradable Retail by Age and Education Group

Panel A: Food Stores

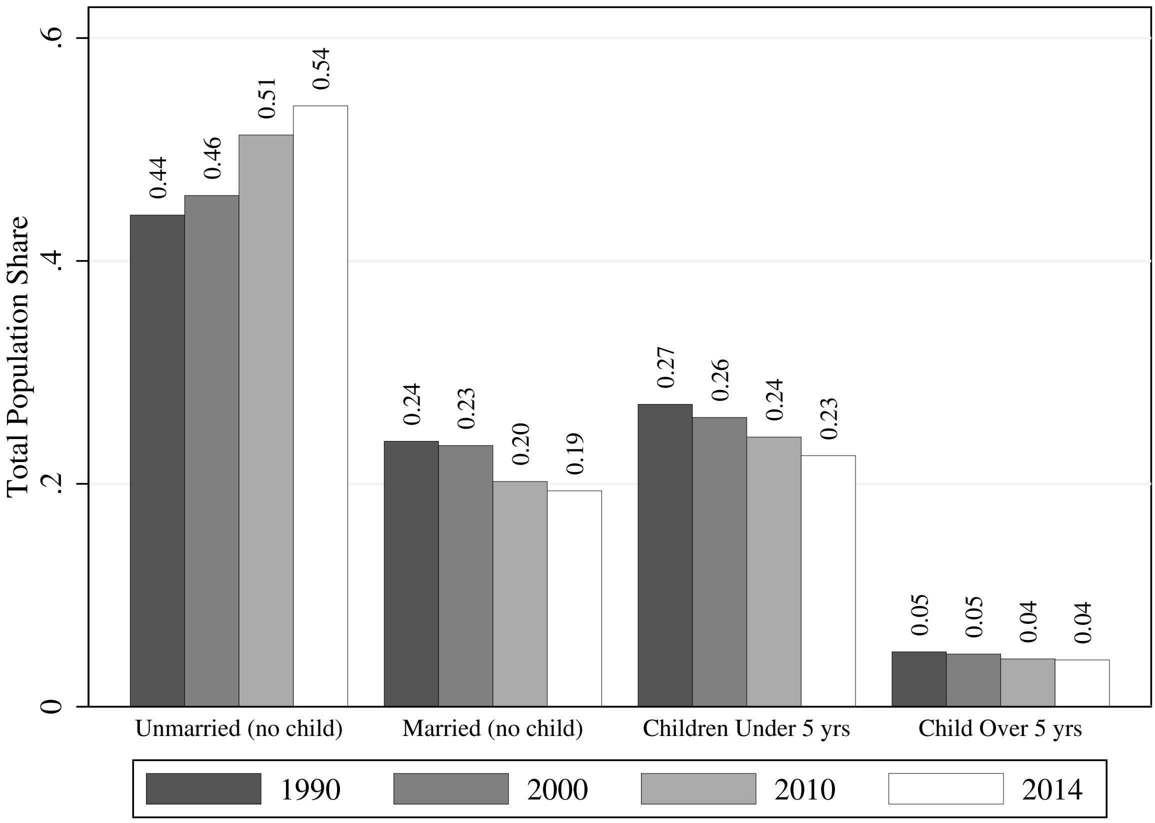


Panel B: Apparel Stores



Notes:The left-hand chart in each panel shows mean CEX expenditure shares for each age-education group and the right-hand chart shows mean NHTS trip shares. In the CEX, food store expendidture is at grocery stores or food stores (UCC codes 10110-180720), and apparel store expenditure is for apparel and accessories (UCC codes 360110-410901). In NHTS, trips to food stores are all trips to buy goods which includes grocery stores, but also clothing and hardware stores. The bands around the end of each bar depict 95% confidence intervals.

Figure A.5: Population Share of Young College-Educated Individuals by Household Type



Notes: This plot depicts the composition of 25-34 year old college graduates in 1990, 2000, 2010 (2008-2012 ACS), and 2014 (2012-2016 ACS) across family type. The data comes from the IPUMS Public Use Microdata Sample and shows shares computed out of all 25-34 year-old college graduates in the 27 CBSAs where we can define urban areas in 1990 and 2012-2016. We restrict to these set of CBSAs to match the data used in the shift-share analysis described in Section 5. The urban area of each CBSA is defined by a fixed geography corresponding to the set of tracts closest to city center that constitute 10% of the total CBSA population in 2000. See Appendix A for further description.

F Additional Derivations

F.1 Derivation of Estimating Equation in Section 4.2

The utility maximization problem of each individual i of type d is to choose its residential location tract j in CBSA c in year t to maximize its indirect utility function V^i_{jct}:

$$\text{(A.3)} \qquad \begin{aligned} \max_j V^i_{jct} &= \beta^{d(i)}_{wt} \ln w^{d(i)}_{jct} - \beta^{d(i)}_{At} \ln p_{Ajct} - \beta^{d(i)}_{Ht} \ln p_{Hjct} + \beta^{d(i)}_{at} \ln a_{jct} \\ &\quad + \mu^{d(i)}_{jc} + \xi^{d(i)}_{jct} + \psi^i_{ct}(\sigma^{d(i)}) + (1-\sigma^{d(i)})\nu^i_{jct}. \end{aligned}$$

This equation is described in the main text and, as outlined in Berry (1994), it yields a linear equation for the share $\tilde{s}^d_{jct}$ of individuals in group d who choose tract j in CBSA c relative to a base tract $\bar{j}$. We can write the share of type d individuals living in residential location j in year t as the product of the within-CBSA share of individuals living in location j in year t and the CBSA share of individuals in year t:

$$s^d_{jct} = s^d_{j|ct} s^d_{ct},$$

where

$$s^d_{j|ct} = \frac{\exp\left(V^d_{jct}/(1-\sigma^d)\right)}{D^d_{ct}},$$

$$s^d_{ct} = \frac{\left(D^d_{ct}\right)^{1-\sigma^d}}{\sum_{c\in C}\left(D^d_{ct}\right)^{1-\sigma^d}},$$

and

$$D^d_{ct} = \sum_{j\in J_c} \exp\left(V^d_{jct}/(1-\sigma^d)\right),$$

where J_c denotes the set of residential locations in CBSA c, C denotes the universe of CBSAs, and $V^d_{jct} = \beta^d_{wt}\ln w^d_{jct} - \beta^d_{At}\ln p_{Ajct} - \beta^d_{Ht}\ln p_{Hjct} + \beta^d_{at}\ln a_{jct} + \mu^d_{jc} + \xi^d_{jct}$ denotes the mean utility for an individual of type d from residential location j in year t. Following Berry (1994), this collapses to:

$$\text{(A.4)} \qquad s^d_{jct} = \frac{\exp\left(V^d_{jct}/(1-\sigma^d)\right)}{\left(D^d_{ct}\right)^{\sigma^d}\sum_{c\in C}\left(D^d_{ct}\right)^{1-\sigma^d}}.$$

Fixing some tract $\bar{j}$ in CBSA $\bar{c}$ as the base residential location, we have that the log expected share of type-d people who reside in location j in CBSA c in year t relative to the log expected share that reside in location $\bar{j}$ in CBSA $\bar{c}$ in year t is equal to:

$$\text{(A.5)} \qquad \ln s^d_{jct} - \ln s^d_{\bar{j}\bar{c}t} = \frac{V^d_{jct} - V^d_{\bar{j}\bar{c}t}}{1-\sigma^d} - \sigma^d \left(\ln D^d_{ct} - \ln D^d_{\bar{c}t} \right).$$

Substituting $s^d_{ct} = \frac{\left(D^d_{ct}\right)^{1-\sigma^d}}{\sum_{c\in C}\left(D^d_{ct}\right)^{1-\sigma^d}}$ (or rather $D^d_{ct} = \left(s^d_{ct}\right)^{\frac{1}{1-\sigma^d}} \left[\sum_{c\in C}\left(D^d_{ct}\right)^{1-\sigma^d}\right]^{\frac{1}{1-\sigma^d}}$) and $\ln s^d_{jct} = \ln s^d_{ct} + \ln s^d_{j|ct}$ into (A.5) and rearranging terms, we have that:

$$\ln s^d_{jct} - \ln s^d_{\bar{j}ct} = \left(V^d_{jct} - V^d_{\bar{j}\bar{c}t}\right) + \sigma^d \left(\ln s^d_{j|ct} - \ln s^d_{\bar{j}|\bar{c}t} \right).$$

From this, we obtain equation (2) from the main text:

$$\text{(A.6)} \qquad \ln \tilde{s}^d_{jct} = \beta^d_{wt} \ln \tilde{\mathbf{w}}_{\mathbf{jct}} + \beta^d_{At} \ln \tilde{\mathbf{A}}_{\mathbf{jct}} - \beta^d_{Ht} \ln \tilde{p}_{Hjct} + \mu^d_{jc} + \tilde{\xi}^d_{jct} + \tilde{\xi}^d_{wjct} + \sigma^d \ln \tilde{s}^d_{j|c},$$

where $\tilde{X}_j = X_j - X_{\bar{j}}$ and we normalize $\mu_{\bar{j}c}$ to equal zero. To simplify the presentation, we use the vector $\tilde{\mathbf{A}}_{\mathbf{jct}}$ to denote the sum of the public and consumption amenity terms, $\beta^d_{At} \ln\left(1/p_{Ajct}\right) + \beta^d_{at} \ln a_{jct}$. $\mathbf{w}_{\mathbf{jct}}$ denotes a vector of time-varying accessibility to jobs in three different wage brackets, which we use to proxy for w^d_{jct}, the group's wage net of commute costs. $\xi^d_{w,jct}$ reflects the residual variation in the wages earned by group d individuals residing in location j.

F.2 Derivation of Contribution Plots in Figure 6

We first outline how these fitted moments are calculated. We start with the fitted value from equation 3 for the expected change in the share of the total national population in a given demographic group d that resides in tract j relative to the share of that demographic group that resides in our base tract l:

$$\widehat{\Delta \ln \tilde{s}^d_{jc}} = \sum_k \widehat{\delta}^d_k X_k,$$

where $\sum_k \widehat{\delta}^d_k X_k = \widehat{\beta^d_{w,2010}} \ln \Delta \tilde{\mathbf{w}}_{\mathbf{jc}} + \widehat{\Delta\beta^d_w} \ln \tilde{\mathbf{w}}_{\mathbf{jc,2000}} + \widehat{\beta^d_{A,2010}} \Delta \ln \tilde{\mathbf{A}}_{\mathbf{jc}} + \widehat{\Delta\beta^d_A} \ln \tilde{\mathbf{A}}_{\mathbf{jc,2000}} + \widehat{\beta^d_{p_H,2010}} \Delta \ln \tilde{p}_{Hjc} + \widehat{\Delta\beta^d_{p_H}} \ln \tilde{p}_{Hjc,2000}$, and we exclude the distance to city center control and within-CBSA share. We un-difference this fitted value from the change in the observed share of demographic group d in the base tract l and from the observed share of demographic group d residing in tract j in 2000 to get a fitted value for the log share of demographic group d that resides in tract j in 2010:

$$\widehat{\ln s^d_{jc,2010}} = \widehat{\Delta \ln \tilde{s}^d_{jc}} + \widetilde{\Delta \ln s^d_{lc}} + \ln s^d_{jc,2000}.$$

We take the exponent of this fitted 2010 log share and multiply it by the population of demographic group d in 2010 to get the fitted value for the population of demographic group d in tract j in 2010:

$$\widehat{pop^d_{jc,2010}} = \exp\left(\widehat{\ln s^d_{jc,2010}}\right) * pop^d_{2010}.$$

We divide this fitted population for demographic group d by the observed total population of tract j in 2010 to arrive at the share of tract j's population in demographic group d in 2010. We then difference this 2010 fitted level from the observed value of this share in 2000 to get a fitted prediction of the change in population share that is represented in the contribution plots:

$$\Delta\widehat{s_{d|jc,2010}} = \frac{\widehat{pop^d_{jc,2010}}}{pop^{all}_{jc,2010}} - \frac{pop^d_{jc,2000}}{pop^{all}_{jc,2000}}.$$

Putting this together and rearranging terms we have that:

$$\text{(A.7)} \qquad \Delta\widehat{s_{d|jc,2010}} = \left(\frac{pop^d_{jc,2000}}{pop^{all}_{jc,2000}}\right)\left(\underbrace{\left[\prod_k \exp\left(\widehat{\delta^d_k} X_{jc,k}\right)\right]}_{\text{Estimated Scaling Factors}}\underbrace{\exp\left(\Delta \ln \tilde{s}^d_{jc}\right)\left(\frac{pop^d_{2010}}{pop^d_{2000}}\right)\left(\frac{pop^{all}_{jc,2010}}{pop^{all}_{jc,2000}}\right)^{-1}}_{\text{Observed Changes in Population Shares and Levels}} - 1\right).$$

Equation A.7 shows that the contribution of any single regression factor, X_k, to the spatial distribution of demographic group d across tracts j (and, therefore, to the change in each demographic group's population share in each tract) depends on a scaling factor $\exp\left(\widehat{\delta^d_k} X_{jc,k}\right)$, where $\widehat{\delta^d_k}$ is the estimated non-standardized regression coefficient on tract characteristic $X_{jc,k}$. The change in demographic group d's population share of tract j from 2000 to 2010 is determined by the product of these estimated scaling factors multiplied by the product of various observed demographic changes, including the change in demographic group d's population share of the base tract l from 2000 to 2010, the change in the aggregate population of demographic group d from 2000 to 2010, and the inverse of the change in tract j's population from 2000 to 2010.

G Additional Hypotheses

G.1 Homeownership and Credit Constraints

One prominent hypothesis to explain the recent urbanization of certain population groups is reduced access to homeownership following the housing crisis and recession of 2007-2009. Given that rental units (generally multifamily) are more urbanized than owner-occupied units (generally single-family homes), a decline in accessibility to homeownership that disproportionately affects young college graduates could push them into urban areas.

In the aftermath of the housing crisis, credit score requirements for access to mortgage credit became more stringent. For instance, the average FICO credit score of mortgages acquired by Fannie Mae and Freddie Mac rose from 725 in 2007 to more than 760 by 2010 (Parrott and Zandi 2013).[51] Presumably, this reduction in credit availability has been disproportionately harmful to younger individuals about to enter the housing market, and may have driven them away from homeownership and toward rental options. Consistent with this story, Rappaport (2015) documents the rapid increase in multifamily construction starting in 2010, and the increased propensity of young adults to live in multifamily units as opposed to single-family homes following the housing crisis.

The main flaw in this hypothesis is the timing of the housing crisis: the 2000s include more years of historically easy mortgage credit than of restricted credit. Using IPUMS data and a methodology similar to that in Section 7.3, we decompose the growth of the young and college-educated by tenure type (owners and renters) from 2000 to 2010. Renters are indeed more prevalent in urban areas. However, homeowners have grown *faster* nationally than renters.[52] Therefore, the premise of the housing market hypothesis that young college graduates have been forced into renting from 2000 to 2010 is not supported by the data. In fact, further analysis reveals that homeownership rates among young college graduates increased in both urban and suburban areas over that period.

To provide additional support for this conclusion, we replicate our stylized facts using the earliest available ACS data, from 2005-2009 (not shown). We find patterns of urban revival very similar to those observed in later years. Given that the housing crisis only covers half of the 2005-2009 time period, this result again challenges to notion that reduced access to mortgage credit drives urban revival.

[51] In 2010, Fannie and Freddie acquired 61 percent of total new home mortgage originations (Jaffee and Quigley, 2012).

[52] The number of young and college-educated homeowners has grown by 19 percent from 2000 to 2010, versus 8 percent for renters.

G.2 Changing Mobile Technology and Review Platforms

Recent innovations in mobile technology like mapping applications and establishment-rating aggregators may complement urban amenities and disproportionately benefit digitally savvy young college graduates. This hypothesis is hard to test directly. Here we add a measure of the share of NETS establishments that are independent to our regressions. Our idea is that independent establishments plausibly benefit more than chains from maps and review portals.[53]

Our independent establishment index is a weighted average of the share of independent establishments near a tract, using the same CES weight as the consumption amenity density index in the main text.[54] After adding this index to our base IV regression, we find a positive preference for independent restaurants that is marginally significant, but a negative change in that preference, contrary to the hypothesis above. Both effects are very small, and do not suggest that independent restaurants are an important determinant of the location choice of the young and college-educated. This is a coarse test of the technology hypothesis. A better test would exploit spatial variation in the timing of the introduction of key applications or platforms (e.g., Yelp), but such variation is hard to isolate. That said, we again note that our stylized facts replicate using data from 2000 to 2007 (2005-2009), and that the first iPhone is introduced only in 2007, and by the start of 2007 Yelp is still only available in 12 cities.

[53]We define independent establishments in the NETS data as having fewer than five other establishments with the same name. The NPD Group, a marketing agency, reports 53.8 percent of independent restaurants in the spring of 2010. We find 49.6 percent with our methodology.

[54]The index in area j is computed as: $\text{Independent}_j = \frac{\sum_{i=1}^{I_j} Dummy_i \times (p+t_{ij})^{(1-\sigma)}}{\sum_{i=1}^{I_j} (p+t_{ij})^{(1-\sigma)}}$, where $Dummy_i$ is equal to 0 for all establishments part of chains with at least five establishments with the same name, and 1 for all other "independent" establishments.