Urban Revival in America, 2000 to 2010*

Victor Couture
University of California, Berkeley

Jessie Handbury
University of Pennsylvania and NBER

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Abstract

This paper documents and explains the striking reversal of fortune of urban America from 2000 to 2010. We show that almost all large American cities have experienced large increases in young professionals near their Central Business Districts over the last decade. We assemble a rich database at a fine spatial scale to test a number of competing hypotheses explaining this recent trend. We first estimate a residential choice model to assess the relative roles of changing amenities, job locations, and housing prices, as well as changing attitudes regarding these factors, in drawing the young and college-educated downtown. We find that diverging preferences for consumption amenities - such as retail, entertainment, and service establishments - explain the diverging location decisions of the young and college-educated relative to their non-college-educated peers and their older college-educated counterparts. In complementary analyses, our data rejects other hypotheses, such as changes in home ownership rates or changes in household formation rates due to delayed marriage and childbirth. These stark new trends within cities have important implications for the future of America's downtowns, whose current revival does not appear to be driven by temporary trends.

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1 Introduction

Mounting anecdotal evidence indicates that urban areas in American cities have experienced a reversal of fortunes since 2000, but a clear characterization of this trend has proven largely elusive. In this paper, we show that urban revival affects almost all large CBSAs in the United States, and that it is a highly localized phenomenon, characterized by large increases in young professionals near the Central Business District (CBD) of each CBSA. After documenting the extent of urban revival in the US from 2000 to 2010, we assemble of a rich database at a fine spatial scale to test a number of hypotheses explaining the urbanization of young professionals. We devote particular attention to recent trends in the location of jobs and consumption amenities, and changes in the preference of different socio-economic groups for living in proximity to jobs and amenities. We find that changes in preferences for proximity to highly urbanized amenities like theaters, restaurants, and bars have more explanatory power than changes in the job and amenity environment, which rarely favored downtowns over the last decade. Given the importance of the distribution of the college-educated for spatial success *across* cities (Glaeser et al. 2004; Moretti 2012; Diamond 2012), these stark *within*-city trends have important implications for the future of urban America, whose current good fortune does not appear to be driven by temporary trends.

We document the scope and size of urban revival by presenting a set of stylized facts, many of them new. We first confirm that, as in previous decades, the aggregate population is growing faster in the suburbs, relative to downtowns. However, in the 50 largest CBSAs, the population of 25-to-44 year old college-educated Americans is growing three times faster in downtown areas than in the suburbs.[1] The downtown areas experiencing urban revival are small in size, but the aggregate effects are large. For instance, in large CBSAs, downtown areas representing 5% of the population account for nearly 25% of the total growth in college-educated 25-35 year olds. Young professionals are urbanizing so fast in the largest 50 CBSAs that, despite the surburbanization of older age cohorts, a majority of these cities have seen their total college-educated population grow faster in downtowns relative to suburbs.[2] This last result stands in stark contrast with the poor relative performance of almost all downtowns from 1970 to 2000. In many ways, our work on urban revival complements the existing litterature documenting and explaining the suburbanization era of the last century (Glaeser and Kahn (2004); Baum-Snow (2007); Boustan (2010) and others).

A number of competing hypotheses have the potential to explain our stylized facts on recent changes in the location choices of college-educated Americans. We are able to test many of these hypotheses by estimating a nested-logit residential choice model at the tract level. In this model, individuals first choose a CBSA to live in, and then choose a residential tract within that CBSA, based on tract characteristics like amenities, jobs and house prices. We allow individual preference parameters to vary both across age-education groups and over time, our estimated model explains the differential growth of various age-education groups across tracts, and, crucially, distinguishes the impact of recent changes in tract characteristics from that of recent changes in group-specific preferences for these characteristics. [3] Unfortunately, a lack of micro-geographic data prevents us from testing other plausible hypotheses within the confines of our tract-level model. For instance, urban revival could originate from recent trends in household formation, crime rates, or mortgage credit availability, which may have favored downtowns over the last decade. We therefore test these hypotheses using more aggregated data, at the end of the paper.

[1]This trend is much more uneven in smaller cities.

[2]Some preliminary trends, notably in gateway cities like New York, Chicago, Boston and San Francisco are already apparent in the 1990s and before. Carlino and Saiz (2008) also show that while central cities do not experience a revival in the 1990s, some recreational districts were already seeing college-educated growth by then. Our finding is that urban revival really emerges as a widespread phenomenon in the 2000s, and is restricted to areas smaller than the central city.

[3]Our identification strategy relies primarily on a number of new instrumental variables, described below. In an extension of the model, we also show how a residential-workplace choice model using commute data offers a sharper way of separately identifying the role of consumption amenities from that of job location.

These exercises require the assembly of a rich dataset of geographically-consistent tracts in 2000 and 2010. To obtain our stylized facts and data on residential choices by demographic group, we use Census and American Community Survey (ACS) tables. Our main database for the location of consumption amenities is the NETS data, which contains the universe of US establishments in 2000 and 2010. To measure job location, we use the LODES database, which contains data on the universe of tract-to-tract commute flows for different demographic and socio-economic groups. The commute data also allows us to extend the residential choice model, estimated using census data on residences, to a residential-workplace choice model, estimated using LODES data on residential-workplace pairs. The residential-workplace choice model provides a sharper way of separately identifying the role of consumption amenities from that of job location. We complement these primary datasets with data on natural amenities from Lee and Lin (2013), house prices, school quality, and crime.

Our empirical framework contrasts with existing work in four important ways. First, we provide new measures of proximity to consumption amenities in the retail and service sectors, which we define precisely in both product (e.g., food vs apparel stores) and geographical space. Second, we estimate a two-period model using data for all CBSAs, instead of using a cross-section of data from a small survey sample, as is standard when estimating residential choice or residential-workplace choice models at fine spatial scale (e.g., Waddell et al. (2007)).[4] This first-difference specification allows us to control for some omitted variables that are constant in each location. Third, we introduce a number of new instruments to tackle reverse causality issues. In particular, we construct instruments for changes in consumption amenities in a given category, by interacting national growth in an establishment type (at the chain or SIC8 level) with the attactiveness of the pre-existing business environment for this type of establishment. This instrument combines insight from the IO literature on cannibalization, preemption, competition, and agglomeration (e.g., Igami and Yang 2015) with the standard Bartik instrument in labor and urban economics. Fourth, we show how to extend our residential choice model to a residential-workplace choice model, which allows us to consider the changing residential location choices of individuals who work in the same location in each period. This framework convincingly disentangles the role of job location from that of residential characteristics in explaining location choices. The intuition for this result is similar to that in Glaeser et al. (2001) who suggest that an increase in reverse commuting (from central cities to the suburbs) signals the importance of urban amenities.

Our preference parameter estimates successfully explain the urbanization of the young and college-educated, especially in larger cities, and the suburbanization of the old and non-college educated everywhere. Of course, city size and proximity to downtowns are not themselves parameters of our estimated model. Instead, we show that the downtowns of large cities have special characteristics that attract the young and college-educated. We find that the parameters that signal changing tastes for urban consumption amenities, in particular, play an important role in explaining why the young and college-educated are disproportionately moving downtown in big cities. One potential explanation for these changing tastes is recent income growth amongst the college-educated, which will tend to increase their willingness to pay for locations with a high perceived quality of life, as hypothesized by Rappaport (2009) and Gyourko et al. (2013). We are further investigating this hypothesis and its implications in complementary work.

Our empirical work also explores the relevance of other prominent explanations for urban revival that cannot be tested in our tract level residential choice framework. A particularly salient hypothesis is that recent national trends in household formation among young professionals, such as an increasing propensity to live alone or to delay child birth, could favor the downtowns of large cities, in which childless or solo households have traditionally been over-represented. Despite frequent claims in the popular press that such trends determine spatial location choices,

[4] Albouy and Lue (2015) for instance, estimates a within-city residential-workplace model using data for all CBSAs in 2000, and using large geographical unit of analysis (PUMAs). They find that the variation in quality of life is as important within metropolitan areas as across them, which motives the within-city analysis in our paper.

we are the first to formally test this hypothesis. We find that national trends in household formation are unlikely to explain urban revival over the last decade. In particular, we show that household formation trends clearly favor the suburbs for the 35-44 college-educated group, whose members are, for instance, more likely to have children in 2010 than in 2000.

Second, we consider evidence on whether the recent decline in central city crime explains the return of college-educated Americans to urban areas. These results are preliminary and will be updated in future versions of this draft. We find that CBSAs with relatively low urban crime levels in 2000 are not more likely to subsequently experience urban revival, thus casting doubts on the hypothesis that a safe environment is a key driver of young professionals' location choices. That being said, we document a strong correlation between the relative drop in urban versus suburban crime in large cities, and the relative increase in urban versus surburban college growth. In other words, urban revival goes hand-in-hand with a relative decline in urban crime. The new within-city trends that we document in this paper could therefore be related to a fundamental shift in the location of crime and poverty in the United States, away from urban areas and towards (some) suburbs.

Finally, we consider the hypothesis that mortgage lending practices increased the demand of younger individuals for rental housing - which is highly urbanized - by restricting credit availability to new homeowners in the aftermath of the 2007-2009 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. In fact, we find that homeownership rates among young professionals have *increased* from 2000 to 2010, in both urban and surburban areas. Further supporting the view that the housing crisis did not drive urban revival, we use the earliest ACS data available (2005-2009) and find patterns of urban revival that are very similar to those observed by comparing 2000 to later ACS averages. More than half of the 2005-2009 time period comes *before* the housing crisis, which again challenges the notion that reduced access to homeownership drives urban revival.

The rest of the paper is divided as follow. We describe the data in section 2. Section 3 presents the stylized facts on urban revival. Section 4 delineates a standard monocentric city model with two income groups (as in Brueckner et al. (1999) and Duranton and Puga (2015)) that we use the derive hypothesis on the location choices of the rich and poor people within a city. Section 5 present the residential choice model and estimation. Section 6 presents robustness checks for our main analysis as well as the analysis testing the household formation, crime, and housing tenure hypotheses and section 7 concludes.

2 Data

To establish the stylized facts on recent urban growth that motivate our empirical analysis, we assemble a database of constant geography census tracts using the Longitudinal Tract Data Base (LTDB). The tract-level population counts by age and education levels are from the decennial censuses of 1970 to 2000 and from the American Community Survey (ACS) 2008-2012 aggregates, downloaded from the National Historical Geographic Information System (NHGIS). We construct CBSAs from census tracts, using constant 2010 CBSA boundaries. We build urban areas around the Central Business District of the principal city of each CBSA using the CBDs defined in the 1982 Census of Retail Trade.[5] To explain these stylized facts, our empirical analysis depends on three main datasets describing residential and workplace location choices, consumption amenities, and house prices. We describe these datasets and how we use them briefly below. More detailed variable definitions are provided in section 5.

[5]CBD coordinates are sourced from Holian and Kahn (2012).

Location Choice Data The dependant variable in our residential location choice model is the change in the share of an age-education group living in a given tract. We construct this variable using data from the 2000 Census and 2008-2012 ACS. To estimate our residential-workplace choice model, we use the LEHD Origin-Destination Employment Statistics (LODES) data from 2002 and 2011. The LODES data provides counts of people in different age and income groups who live and work in a given census block pair. We aggregate these counts at the census tract level to obtain changes between 2002 and 2011 in the share of individuals in each demographic group who live and work in a given tract pair.[6]

We also use LODES data to derive residential characteristics such as accessibility to jobs and commute times, which serve as explanatory variables for changes in shares. We use the LODES data to compute, for each demographic group, job counts in each workplace tract, which we in turn use to calculate accessibility to jobs from each residential tract. We use job counts by industry and demographic group to compute Bartik instruments for job growth in each tract. We obtain data on commute times between each tract pair by car and transit from Google Maps.

Consumption Amenities Data We compute consumption amenity indices for different type of amenities like restaurants, grocery stores, and theaters, as in Couture (2013). These amenity indices have an interpretation as CES "gains from variety" price indices but in practice they capture the density of establishments around a given point, accounting for differences in travel speed across areas. We obtain these indices for the centroid of each census tract, by combining three datasets: First, data on the type and exact location of each establishment from the National Establishment Time-Series (NETS); second, travel time data by foot, car and transit from Google Maps; and third, data on average expenditure per visit for each amenity category from the Consumption Expenditure Survey (CEX). We compute amenity indices using NETS data for the year 2000 and 2010.We refine these indices using ratings of national chains from Yelp.com, and ESRI's Market Potential Index (MPI), which measures the propensity of different socio-economic or demographic groups to shop in a given chain store or to perform a given activity. We use MPI to compute quality weighted indices that give high weight to stores that have high MPI for young professionals (e.g., Trader's Joe) or high income people (e.g., Whole Foods). We also use MPI to measure changes in amenity composition within a category. The next version of this paper will feature results using the MPI indices.

House Price Data Our house price index for 2000 and 2010 is the Zillow "All Home Index" at the zip code level, that we match to 2010 tract geography using Census shapefiles. We expand the dataset beyond those tracts that the Zillow data covers by approximately 30% by spreading the house price indexes that we observe in 2000 and 2010 across all tracts within a tract-group, a set of three to four neighboring tracts defined in Ferreira and Gyourko (2011).[7] The next version of the paper will feature tract-group level hedonic price indexes calculated using DataQuick transaction data as in Ferreira and Gyourko (2011).

Additional datasets We complement these three main datesets with information on other residential characteristics. We obtain data on within-state ranking of school districts in 2004 and 2010 from schooldigger.com, that we transform into 2010 tract level data using Census shapefiles.[8] We also use data on natural amenities, like precipita-

[6]In early versions of the LODES data, census block pairs with very few individuals were simply censored. In the more recent version of the LODES that we use, confidentiallty issues are addressed by making the data partially synthetic, in a way that preserves some key aggregate statistics from the data. We describe the procedure through which the synthetic data is generated in appendix A. Note that we do not use the census block data directly, but we instead aggregate the data at the census tract level, as recommended in the LODES documentation.

[7]Ferreira and Gyourko (2011) do similarly estimating hedonic price indexes at the tract-group level.

[8]There are usually a few census tracts within each school district. 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.

tion or coastal proximity for each census tract, from Lee and Lin (2013). We suspect that natural amenities affect house prices through supply elasticity as in Saiz (2010) and use these amenities as an instrument for changes in house prices.[9]

Finally, a number of hypotheses that can explain the urbanization of young professionals require data that is not available at the census tract level. We test these hypotheses by running CBSA-level regressions in section 6. To test the hypothesis that recent trends in household formation explain the urbanization of young professionals, we require counts of individuals by household types within each age-education group. To obtain these counts, we aggregate microdata from the 5% Integrated Public Use Microdata Series (IPUMS) sample of the 2000 census and the 5% IPUMS sample from 2008-2012 ACS surveys. In this case, we construct CBSAs and downtowns out of 2000 Public Use Microdata Areas (PUMA). Given the size of PUMAs, we are only able to construct downtowns for the 50 largest CBSAs. Crime data is also rarely available in census tract time-series, so we use the county and city level Uniform Crime Reporting (UCR) data from 2000 and 2010. We construct CBSAs as an aggregation of counties, and define the urban area as a principal city of each CBSA.

3 Stylized Facts

In this section, we establish a number of stylized facts about urban revival in US cities from 2000 to 2010, most of them new. These facts motivate the rest of our empirical analysis. We find that the average American is still suburbanizing, but uncover strong localized evidence of urban revival. We characterize this urban revival phenomenon as large increases in young professionals near the Central Business District of almost all large CBSAs. To conduct this analysis, we assemble a dataset of geographically-consistent census tracts with decennial census data from 1970 to 2000, and ACS data for 2010 (using the 2008-2012 aggregates). We define urban areas by sequentially adding census tracts closest to the CBD until the total urban population reaches no more than 5% of total CBSA population. Such areas are best thought of as downtowns.[10]

We then refine these stylized facts using data on the universe of tract-to-tract residential-workplace pairs. This commute data allows us to describe changes in both workplace and residential location by age and income groups. Disentangling the role of job location from that of residential location characteristics in explaining the urbanization of high income people is an objective motivating much of our empirical analysis. The commute data shows that both residences and jobs are decentralizing, within the set of all CBSAs. Within the 10 largest CBSAs, however, the reverse is true and both residences and jobs are centralizing. This centralization trend is *entirely* driven by high-income people, in the upper third of the income distribution. Most importantly, the data clearly shows that high-income people working at any distance from the CBD are more likely to be living near the CBD in 2011 than in 2002. This centralization of residential location holding job location fixed demonstrates that job centralization alone cannot explain our urban revival stylized facts.

3.1 Urban revival

Claims of urban revival are not new. The 1960s and 1970s were catastrophic for urban areas in America, with many central cities losing a significant share of their population. Various forms of urban comeback have been documented since at least the early 1990s (e.g., Frey (1993)). In recent years, tales of urban revival in American

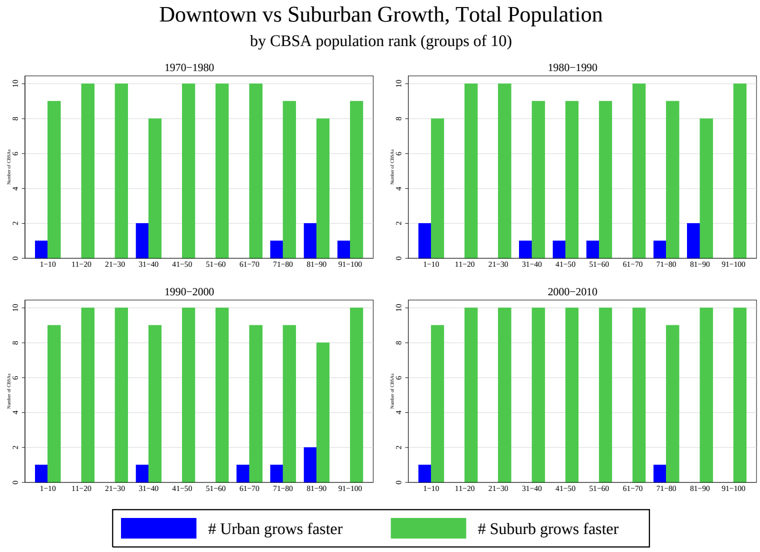
[9]As we explain in section 5, we use a first difference framework which differences out the constant characteristics of each residential tract. This implies that we cannot put natural amenities directly in the regression as controls, but, as we will show, they can be used as instruments for other endogenous variables.

[10]We can replicate all of our main stylized facts with alternative downtown definitions (e.g., 5%, 10% or 15% of population, or keeping all tracts with centroids within 2, 3, 4 or 5 miles of the CBD) as long as the urban area is small enough.

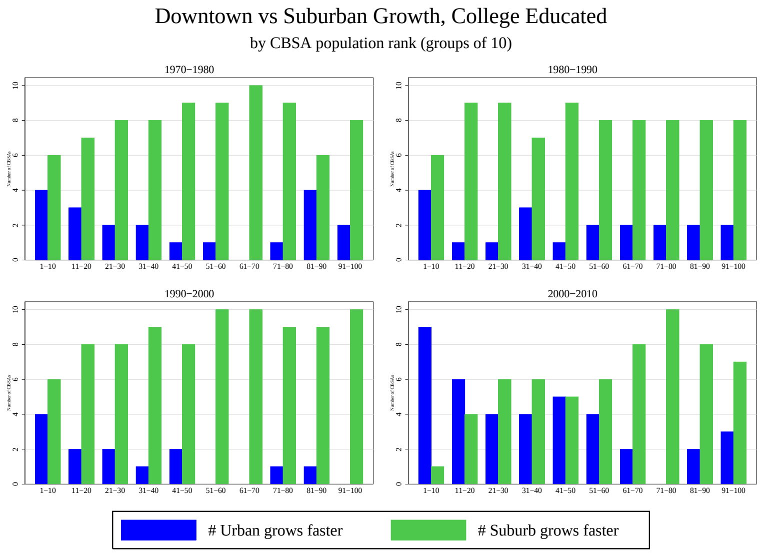
cities have become commonplace, and widely relayed by the the popular press. Census tables, however, tell an unequivocal story of continued suburbanization (Kotkin and Cox (2011)).

Figure 1: Downtown vs. Suburban Growth in the Largest 100 U.S. CBSAs, 1970-2010

(a) Total Population



(b) College-Educated



Notes: Data from decennial census 1970–2000 and ACS 2008–2012. Each of the figures' four plots present data for a different decade, starting from 1970–1980 in the upper left-hand plot to 2000–2010 in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, downtown is defined as all census tracts nearest to the CBD and totaling at most 5% of a CBSA population. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown college-educated (at least 4 year degree) population has been growing faster than suburban college-educated population within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban college-educated population has been growing faster.

Figure 1a provides one way to visualize the continuing suburbanization of American cities since 1970. There is a plot for each decade between 1970 and 2010. Each plot shows the number of CBSAs in which either suburban or urban growth has been faster, for the 100 largest CBSAs. These CBSAs are ranked by 2010 population on the x-axis, and results are aggregated by groups of 10 CBSAs. The blue bar represents the number of CBSAs in which downtown population has been growing faster than suburban population within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban population has been growing faster, with the green and blue bars always adding up to 10. For instance, the plot on the lower right shows that within the 10 largest CBSAs in the United States, only one experienced faster growth downtown relative to its suburbs. Looking instead at CBSAs with size ranking from 10 to 20, we see that none of them have urbanized during this period. Indeed, only 2 of the 100 largest CBSAs have experienced faster urban growth between 2000 and 2010. This pattern of faster suburban growth applies as well to previous decades for which we have data, and it is robust to different definitions of "urban," such as using central cities (see Appendix C.1.1).[11]

Slower urban population growth does not necessarily preclude urban revival. Downtowns are often already built up and subject to heavy housing regulations (Glaeser et al., 2006), so their desirabilty is more likely to manifest itself through higher house prices and a demographic shift towards wealthier individuals than simply through faster population growth. In fact, many authors argue that in recent decades, the best indicator of spatial success is the share of an areas inhabitants that received a college education (Glaeser et al. (2004), Moretti (2012)). It is therefore natural to define urban revival as the urbanization of a city's college-educated population.

Figure 1b replicates Figure 1a, but considering growth in college-educated population alone. The results undercover a new, previously undocumented trend: between 2000 and 2010, a majority of the 50 largest CBSAs have experienced faster urban than suburban growth in college-educated individuals. This is not the case for any decade between 1970 and 2000. In the 1990s for instance, the college-educated population urbanized in only 11 out of the 50 largest CBSAs. The recent urbanization of college-educated individuals occurs mostly in the largest cities, and a sizable majority of CBSAs ranked 50 to 100 have not experienced faster urban than suburban growth in college-educated individuals from 2000-2010. It is important to highlight that college-educated Americans are growing fast in downtown areas relatively close to the CBD, so this localized trend is not apparent when defining urban areas as central cities; this probably explains why the urbanization of college-educated Americans has not been documented before.[12]

We now further refine our investigation, and break down the growth in college-educated population between 2000 and 2010 by age groups.[13] Americans become considerably less mobile as they age, and we do not expect new locational trends to predominantly affect older cohorts. We also expect the residential and workplace preferences of the younger generation to differ from that of older Americans.[14] Moreover, the popular press emphasizes the urbanization of both young people and retiring baby-boomers. A recent report by CEO for Cities (Cortright (2014)) - and covered extensively by the New York Times (Miller (2014)) - also uses 2000 census data and 2007-2012 ACS data, and shows that the 25-34 college-educated population are growing faster downtown than in the suburbs in the majority of the 51 largest MSAs.[15] We confirm and expand this narrative to the older 35-44 college-educated group, but interestingly we find that the popular press gets it wrong for educated baby-boomers, whose relative

[11] We use the term 'suburb' for simplicity, to describe everything outside the downtowns that we define. Clearly, some of these areas within our suburbs are quite urban by most standard definitions. When we define downtowns as central cities, our definition of suburb becomes the usual one.

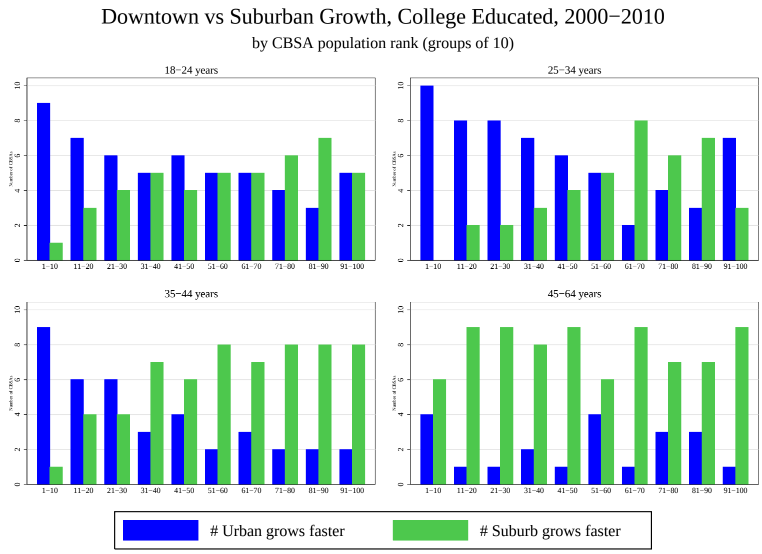
[12] Fee and Hartley (2012) document localized changes in aggregate population at various distances from CBDs and find that cities with increasing near-CBD population density have higher per capita income growth at the MSA level.

[13] Data on education by age group is only available at the census tract level starting in 2000, so this investigation is only possible for the last decade.

[14] For instance, Ihrke et al. (2011) use the 2009 ACS to show that 15.4% of American changed residence over the previous year. This percentage drops to 7% for Americans older than 45.

[15] In an earlier report for CEO for Cities, Cortright (2005) documents the growth in college-educated americans in "close-in" neighborhoods, defined as all tract within 3 miles from the CBD, from 1990 to 2000. These close-in neighborhoods are relatively similar in size to our downtowns, and our results are robust to using this definition. However, Cortright (2005) uncovers only very uneven trends, because, as we show, urban revival really picks up only in the 2000s.

Figure 2: Downtown vs. Suburban Growth in the Largest 100 U.S. CBSAs, 2000-2010
College Educated



Notes: Data from decennial census 2000 and ACS 2008–2012. All plots are for 2000–2010. Each of the figure's four plots presents data for a different age group within the college-educated (at least 4 year degree) population, starting from 18-24 year old college-educated in the upper left-hand plot to 45-64 year old college-educate in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, downtown is defined as all census tracts nearest to the CBD and totaling at most 5% of a CBSA population. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown college-educated population in a given age group has been growing faster than suburban college-educated population of that age group within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban college-educated population of a given age group has been growing faster.

growth is much faster in the suburbs of almost all large cities.

Figure 2 shows the number of CBSAs in which urban growth in faster than suburban growth between 2000 and 2010, for four age groups. A sizable majority of the 50 largest CBSAs register faster urban growth for college-educated 18-24 year olds, 25-34 year olds and 35-44 year olds. However, the 45-64 age group is still suburbanizing, as is the 65+ group (not shown), contrary to the claim that retiring baby-boomers are increasingly likely to choose urban locations.[16] Strikingly, we find that the college-educated 25-34 age group grows faster in the urban area of 23 of the 25 largest CBSAs. The exceptions are Riverside, which essentially lacks a downtown, and Detroit, which is famously struggling. In the smaller CBSAs, however, young professionals are much less likely to be urbanizing.

While Figure 2 is suggestive, it is important to emphasize the magnitudes of these recent trends in the locational preferences of young professionals for the downtowns of large cities. To do so, we compute the aggregate growth of each age-education group, in both urban and suburban areas. We consider the 50 largest CBSAs, in which about 150 million people live. We find that the 25-34 year old college-educated population grew 3.2 times faster downtown, with 44% growth downtown versus 14% growth in the suburbs. Similarly, the 35-44 year old college educated group grew 3 times faster downtown, with 30% growth downtown versus 10% growth in suburban areas.

It is interesting to note how localized the urbanization trend we document is. Panels A and B in Figure 3 show the population share of 25-34 year old college-educated individuals in all tracts located within the Philadelphia CBSA in 2000 and 2010, where urban tracts are indicated by the area outlined in black, with the areas outlined in the upper right borders of the CBSA are tracts classified as urban for the Trenton and Wilmington CBSAs. Panel C shows the growth in this share between 2000 and 2010. Outside the urban area, we see a mix of tracts where this young-college share has increased and decreased. The left-hand plots show the young-college shares in all tracts in the CBSA, while the right-hand plots show these shares in tracts closer to the CBD. In the zoomed-in plots we see that the young-college share has typically increased in tracts within and close to the urban area. We see this more clearly in the right-hand plots, which show the young-college shares for only those tracts close to the CBD. Right-hand plot in Panel A shows that the Center City area of Philadelphia had a relatively high young-college share in 2000 but was surrounded by a ring of tracts with very low shares of young professionals. The right-hand plot in Panel C indicates that the young-college share in fact grew in almost all urban tracts in Philadelphia between 2000 and 2010 and, by 2010, resulting in the spreading of the downtown area with young-college shares above 10% beyond the center city area.

Though our urban areas are small, the aggregate impact of the urban revival patterns we document is not negligible. To show this, we compute the percentage of total young professionals growth that occurs within the urban areas of the 50 largest CBSAs. We find that although urban areas account for 5% of the population (by construction), they account for 24% of the total increase in the college-educated 25-34 year old population and 11.5% of the total increase in the college-educated 35-44 year old population between 2000 and 2010.[17]

Finally, we note that these results are robust to using income and age-income groups instead of education, and to using alternative datasets. For instance, the LODES data that we use to estimate our residential-workplace choice model contains data on workers by age group and income group (but not their interactions). Using the same downtown definition, we show that high-income workers in the LODES data are also urbanizing in a sizable majority of large CBSAs between 2002 and 2011. In the next two subsections, we further characterize urban revival from 2000-2010. We then devote the rest of the paper to explaining these patterns.

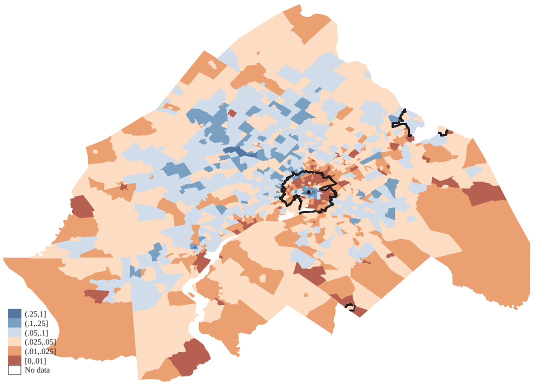
[16] Recent work by Rappaport (2015) suggests that the aging baby-boomer generation will continue to support strong demand for multi-family units, but posits that these downsizing households will select to remain close to their original locations. This is consistent with our finding that baby-boomers do not contribute to urban revival.

[17] We find a higher number for the college-educated 25-34 year old group because they were more likely to live in urban areas in 2000, suggesting perhaps that this group had experienced fast urban growth in the 1990s. The 35-44 year old group, however, was less likely to live in urban areas in 2000, and almost certainly their urbanization is an entirely new trend.

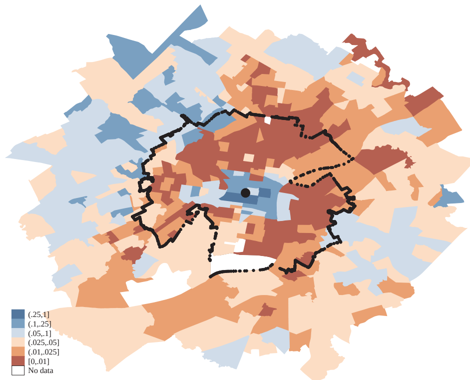
Figure 3: Population share of 25-34 year-old college-educated individuals in tracts located in the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD CBSA

Panel A: 2000 Level

All Tracts

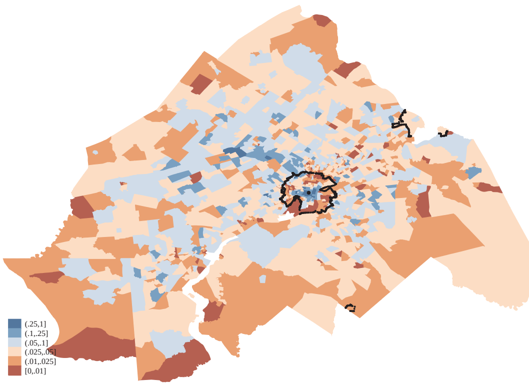


Closer-In Tracts

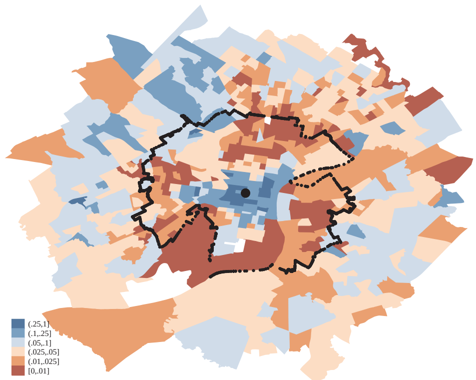


Panel B: 2010 Level

All Tracts

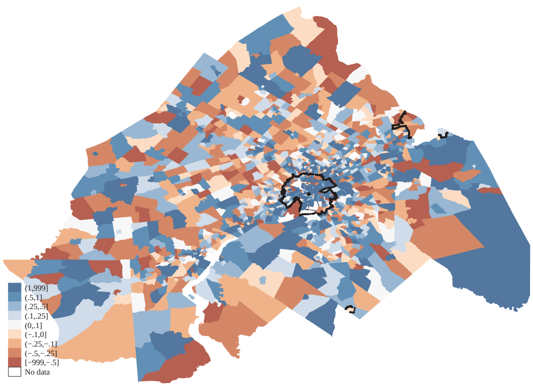


Closer-In Tracts

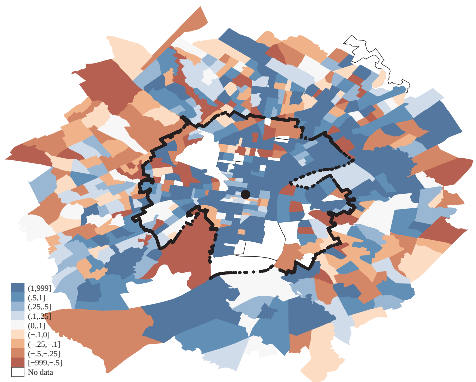


Panel C: 2000-2010 Growth

All Tracts



Closer-In Tracts



Notes: The maps in Panels A and B above reflect the population of 25-34 year old college-educated individuals as a share of the total population in tracts in the Philadelphia-Camden-Wilmington, PA-NJ-DE-MD CBSA. The maps in Panel C show the log change in this population share from 2000 to 2010. The olots on the left-hand side of each panel show the population shares and growth in all tracts in the CBSA, while the plots on the right-hand side of each panel show the population shares and growth for tracts whose centriods are 15km or less from the CBD.

3.2 Is urban revival a result of population growth or of changing composition?

In Appendix B, we perform a detailed growth decomposition, to assess the relative importance of changing population density versus changing composition as drivers of urban revival. We decompose the difference between urban and suburban college-educated growth into four components: the change in the college-educated population shares in urban and suburban tracts, reflecting their changing composition, and the change in the urban and suburban populations in urban and suburban tracts, reflecting changing population density.

We find that urban revival in the 50 largest cities is accounted for almost entirely by the rising share of college-educated individuals in urban areas. Strikingly, the urban population in these large cities is stable on average from 2000-2010, while the suburban population is growing. A key feature of the last decade of urban revival is therefore that the change in urban composition is dramatic enough to generate faster young professional growth in urban relative to suburban areas, *despite* stagnant urban and rising suburban populations.

3.3 Urban revival and changing commute patterns

The previous section documents strong centralization trends in the residential choice of younger, college-educated and high-income Americans living in large cities. We now show that while both residences and workplaces are decentralizing in the general population, the reverse is true for high-income people in large cities, whose residences and workplace are simultaneously centralizing. Crucially, our use of commute data allows us to show that holding workplace distance from the CBD fixed, high-income workers in large cities live closer to the CBD in 2011 than in 2000. This result implies that they incur longer commute costs than before to live near these CBDs, and suggests that factors other than job centralization also drive residential centralization.

The LODES commute data contain counts of workers by workplace-residential census block pairs, for three income terciles (high, middle, and low-income) and three age groups (29 or younger, 30-54, and 55 or older). We aggregate these data at the census tract level in all of our empirical work. To visualize the data, we aggregate worker counts into commute matrices whose cells are defined by the distance from the CBD of the centroid of the tracts in they live and work. The rows of the commute matrix shows the number of workers *living* within different distance bins from the CBD. The eight bins are: between 0-1 mile, between 1-2 mile, 2-4 mile and so on until 16-32 mile, with an extra cell for individuals living more than 32 miles from the CBD. The column of the commute matrix represent the number of workers *working* at different distance from the CBD, using the same distance bins.

Figure 4 shows the percentage change from 2002 to 2011, for workers within each cell for such commute matrices in Panels a) to d). The color of the cell varies from dark blue indicating the most negative change and dark red indicating the most positive change. The matrix in Panel a) displays data for all workers living and working in each of the 333 CBSAs covered by the LODES data. Looking down each column of Panel a) provides a particularly stark representation of the national suburbanization trends. The workplace distance from the CBD is constant within each column, so a matrix with blue at the top and red at the bottom shows that the American working population is increasingly living in locations further out from the CBD than their workplaces. Residential locations farthest from the CBD (32+ miles) have experienced the largest percentage increase in population, amongst workers working anywhere within 32 miles of the CBD. Looking right to left at each row of Panel a) shows that workers living within 8 miles of the CBD are working farther from the CBD in 2011 than in 2002, but there is no job decentralization trend for residents who have already suburbanized.

The stylized facts in the previous subsection indicate that certain locations and populations have been bucking this national suburbanization trend in the past 10 years. Panel b) focuses exclusively on high-income workers. For this set of workers, we do not see the systematic decentralization of both workplaces and residences that we observed for the entire population, but we do not observe systematic centralization of both workplaces and residences either. We instead observe increases in the number of high-income households either commuting from the suburbs to jobs downtown or from downtown to jobs in the suburbs. Finally, focusing on high-income workers in the 10 largest CBSAs, panel c) displays commute patterns consistent with our stylized facts. High-income workers are living and working closer to CBDs in large CBSAs. This correlation alone does not help us make much progress on the question of whether jobs explain the urbanization of the young and college-educated since it does not tell us whether they are following jobs or jobs are following them. To make progress on this question, it is useful to look again at the patterns that we see within each column, holding workplace location fixed. Recall that, the red cells below the diagonal in panel a) indicated relatively high growth in the population of *all* workers living further from the CBD than where they worked. In panel b), we saw groups of red cells both below *and* above the diagonal. This indicated that high-income workers are increasingly commuting from the suburbs to downtown, with the rest of the population, but also increasingly commuting from downtown to jobs in the suburbs. That is, high-income workers are moving to the downtowns in spite of the commute to jobs in the suburbs. In panel c), where we focus on high-income workers in the largest 10 CBSAs, we see that this increase in reverse commuting is, in fact, stronger than the increase in standard commuting. This demonstrates that factors other than job locations are driving the urbanization of high-income people, particularly in large cities. The attractiveness of large cities' downtowns as residential locations for high-income workers must be increasing, to explain why they are willing to incur larger commute costs than before to live closer to the these CBDs.[18]

We now present a monocentric city model showing how job location, amenity location, and endogenous house prices determine the location choices of rich and poor households.

4 Monocentric city model

Given the focus of our empirical work on explaining location choices near the CBDs of cities, the monocentric city model is an attractive starting point to obtain empirical predictions. A monocentric model with amenities and two income groups was first suggested by Brueckner et al. (1999). Duranton and Puga (2015) provide a useful review of these models. We use a solution method similar to that in Guerrieri et al. (2013) and show how it can be adapted to characterize the equilibrium without solving for the land market. This monocentric city model is useful because it features the key variables in our empirical analysis within a single theoretical framework, which is closely related to the discrete-choice model that we estimate. The model is particularly well-suited to showing how levels and changes in preferences interact with levels and changes in the environment to explain changes in the location choices of different income group.

We consider a linear monocentric city, in which x denotes distance from a CBD at $x = 0$. There are two types of households: $d = r$ (rich) and $d = p$ (poor). Job location is exogenous and captured by a type-specific commute cost function $\tau_d T_d(x)$, in which τ_d represents the monetary cost of commute time and $T_d(x)$ is a commute time function such that $T_d' > 0$. This gradient implies that households living closer to the CBD have shorter commutes, because jobs are centralized.[19] Amenities are exogenous and their type-specific utility value is denoted by $\alpha_d A(x)$, in which α_d represents a preference for amenities, and $A(x)$ is the quantity of amenities available at a location x. Amenities are centralized, so that $A' < 0$. The utility of a household in income group d living in location x depends on housing consumption $h_d(x)$, consumption of a numeraire good $C_d(x)$, and amenities $A(x)$. The utility

[18] Appendix F shows that this reverse-commuting pattern is less pronounced amongst middle-income workers in the largest 10 CBSAs and amongst younger workers in both the national data and the largest 10 CBSAs.

[19] It is important to note that job location is not endogenized in the model (see Lucas and Rossi-Hansberg (2002), or Fujita and Ogawa (1982)). As a result the model does not illustrate a key endogeneity problem - jobs follow workers and workers follow jobs - which motivates the various identification strategies that we use in the paper, for instance the use of commute data that allow to hold workplace location fixed and study residence location.

Figure 4: Commute Patterns

(a) **All Workers in All CBSAs**

Residence-CBD Dist.	Workplace-CBD Distance (miles)						
	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+
[0, 1)	-15.02	-15.02	-12.92	-3.84	6.21	9.02	14.76
[1,2)	-14.08	-12.85	-14.67	-7.36	3.12	6.88	7.22
[2,4)	-11.56	-9.70	-10.68	-6.38	0.67	4.14	10.25
[4, 8)	-2.81	0.17	-3.39	-3.93	1.46	6.16	6.15
[8, 16)	8.88	13.82	8.60	8.00	2.54	10.27	14.76
[16, 32)	20.75	27.81	22.38	22.62	16.36	3.33	15.59
32+	32.28	41.13	33.81	37.91	40.84	31.67	10.69

(b) **High-Income Workers in All CBSAs**

Residence-CBD Dist.	Workplace-CBD Distance (miles)						
	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+
[0, 1)	48.50	57.94	56.53	68.80	80.03	67.23	80.11
[1,2)	42.10	43.55	35.84	49.18	60.61	57.19	66.97
[2,4)	33.58	41.49	33.63	38.97	46.45	48.02	62.66
[4, 8)	38.48	48.31	33.84	33.99	38.82	40.87	43.56
[8, 16)	45.42	61.98	45.57	42.76	35.51	40.58	42.34
[16, 32)	56.01	71.58	55.56	54.37	44.16	36.48	47.12
32+	75.52	83.88	73.26	76.90	76.83	61.85	51.69

(c) **High-Income Workers in Largest 10 CBSAs**

Residence-CBD Dist.	Workplace-CBD Distance (miles)						
	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+
[0, 1)	78.44	97.24	110.60	105.37	80.36	65.39	69.00
[1,2)	93.22	69.63	62.09	82.21	62.21	55.85	68.90
[2,4)	81.85	95.44	60.68	69.70	49.80	39.92	59.27
[4, 8)	68.30	103.79	43.34	42.56	34.18	24.82	30.15
[8, 16)	47.63	81.92	34.83	28.67	19.68	25.19	29.50
[16, 32)	35.92	62.33	30.79	30.58	23.24	25.76	36.93
32+	67.69	96.85	53.77	56.41	54.16	46.80	40.21

Notes: Data from LODES 2002 and 2011. The top three matrices present national commuting patterns for young workers($\leq$29), middle-age workers (30-54), and old workers ($\geq$ 55); the bottom three matrices present national commuting patterns for low-income workers($\leq$\$1250/month), mid-income workers (\$1250/month-\$3333/month), and high-income workers (>\$3333/month). Given a row, the distance between workplace tracts and CBDs increases from left to right; in each column, the distance between residence tracts and CBDs increases from top to bottom. Each cell represents the percentage change from 2002 to 2011 of the number of certain type of people working and living at given distances from CBDs. Red cells indicate increase in the number of people working and living at given distances from CBDs whereas blue cells indicates small changes, even decrease, in the number of people working and living at given distances. The darker the cell colors are, the more dramatic changes are. Top ten CBSAs are New York-Newark-Jersey City, Chicago-Naperville-Elgin, Dallas-Fort Worth-Arlington, Dallas-Fort Worth-Arlington, Houston-The Woodlands-Sugar Land, Washington-Arlington-Alexandria, Miami-Fort Lauderdale-West Palm Beach, Atlanta-Sandy Springs-Roswell, San Francisco-Oakland-Hayward, and Detroit-Warren-Dearborn.

function is quasi-linear in housing, and defined as:

$$u_d = \gamma_d \ln(h_d(x)) + \alpha_d A(x) + C_d(x), \tag{1}$$

subject to the budget constraint: $w_d = \tau_d T_d(x) + p_d(x) h_d(x) + C_i(x)$.[20]

This model differs from a standard utility maximization problem in that consumption depends on location x, and house prices are determined endogenously through a spatial equilibirum condition. In a model with two groups, house prices are equal to the upper envelope of $p_r(x)$ and $p_p(x)$. These functions determine the willingness to pay of each group to live in a location, and are often called the 'bid-rent' functions. The first-order condition of the utility maximization problem with respect to housing is:

$$\frac{\gamma_d}{h_d(x)} = p_d(x) \tag{2}$$

The spatial equilibrium condition requires that utility at all location x be constant, for all otherwise identical households. The bid-rent function $p_d(x)$ adjusts to satisfy this condition. So we have:

$$\gamma_d \ln(h_d(x)) + \alpha_d A(x) + C_d(x) = \bar{u}$$

We now use this condition to determine $p_d(x)$ up to a constant K_d, as in Guerrieri et al. (2013). Using the budget constraint to substitute for $C_d(x)$ and the first-order condition to substitute for $h_d(x)$, we obtain:

$$\gamma_d ln\left(\frac{\gamma_d}{p_d(x)}\right) + \alpha_d A(x) + w_d - \tau_d T_d(x) - \gamma_d = \bar{u}.$$

It follows easily that the bid-rent functions:

$$p_d(x) = K_d e^{\frac{\alpha_d}{\gamma_d} A(x) - \frac{\tau_d}{\gamma_d} T_d(x)}$$

ensure a constant utility for all $x > 0$.

4.1 Determining the location choices of rich and poor

Given that location choices are determined by willingness to pay, rich people live at location x whenever $p_r(x) > p_p(x)$. Define $\tilde{x}$ as the location at which the bidding function of the poor equals that of the rich. We assume parameter values such that this location $\tilde{x}$ is unique and larger than 0. Given this definition, we must have $p_r(\tilde{x}) = K_r e^{\frac{\alpha_r}{\gamma_r} A(\tilde{x}) - \frac{\tau_r}{\gamma_r} T_r(\tilde{x})} = K_p e^{\frac{\alpha_p}{\gamma_p} A(\tilde{x}) - \frac{\tau_p}{\gamma_p} T_p(\tilde{x})} = p_p(\tilde{x})$, which we rewrite as:

$$\frac{K_r}{K_p} = \frac{e^{\frac{\alpha_p}{\gamma_p} A(\tilde{x}) - \frac{\tau_p}{\gamma_p} T_p(\tilde{x})}}{e^{\frac{\alpha_r}{\gamma_r} A(\tilde{x}) - \frac{\tau_r}{\gamma_r} T_r(\tilde{x})}}$$

We can now look for the conditions under which an equilibrium exists in which the poor live in the suburb and the rich live downtown. This equilibrium requires that $p_p(x) > p_r(x)$ for all $x > \tilde{x}$ and $p_p(x) < p_r(x)$ for all $x < \tilde{x}$.

[20] The advantage of a quasi-linear utility specification is that income itself has no direct impact on location choices. These effects would be inconsistent with our empirical stratgey of estimating preference parameters for different income groups and explaining location choices based on these preferences. An alternative to a quasi-linear specification is a Cobb-Douglas utility, in which the amenity choice is endogenous and $A(x)$ denotes the price of amenities. As long as the monetary cost of commute time τ_d is directly proportional to income w_d - consistent with empirical evidence - this Cobb-Douglas utility also lacks any direct impact of income on location choices, and generates the same comparative statics as a quasi-linear specification..

We can write the first of these two conditions as:

$$K_r e^{\frac{\alpha_r}{\gamma_r}A(x)-\frac{\tau_r}{\gamma_r}T_r(x)} > K_p e^{\frac{\alpha_p}{\gamma_p}A(x)-\frac{\tau_p}{\gamma_p}T_p(x)}, \forall x > \tilde{x}.$$

Plugging the ratio for K_r/K_p, we obtain:

$$\frac{e^{\frac{\alpha_p}{\gamma_p}A(\tilde{x})-\frac{\tau_p}{\gamma_p}T_p(\tilde{x})} * e^{\frac{\alpha_r}{\gamma_r}A(x)-\frac{\tau_r}{\gamma_r}T_r(x)}}{e^{\frac{\alpha_r}{\gamma_r}A(\tilde{x})-\frac{\tau_r}{\gamma_r}T_r(\tilde{x})} * e^{\frac{\alpha_p}{\gamma_p}A(x)-\frac{\tau_p}{\gamma_p}T_p(x)}} > 1, \forall x > \tilde{x}.$$

Taking logs on both sides and rearranging, we obtain:

$$\frac{1}{\gamma_p}\left(\alpha_p\left(A(x)-A(\tilde{x})\right)-\tau_p\left(T_d(x)-T_d(\tilde{x})\right)\right) > \frac{1}{\gamma_r}\left(\alpha_r\left(A(x)-A(\tilde{x})\right)-\tau_r\left(T_r(x)-T_r(\tilde{x})\right)\right), \forall x > \tilde{x}.$$

Before performing comparative statics, we note that $\tilde{x}$ is an endogenous variable that depends on the model's parameters. Solving for $\tilde{x}$ directly requires many more assumptions that we have made here. In order to obtain comparative statics without having to solve for $\tilde{x}$, we assume that the amenity and commute cost functions are linear in x. We obtain:[21]

$$\frac{1}{\gamma_p}\left(-\alpha_p A\left(x-\tilde{x}\right)-\tau_p T_d(x-\tilde{x})\right) > \frac{1}{\gamma_r}\left(-\alpha_r A\left(x-\tilde{x}\right)-\tau_r T_r(x-\tilde{x})\right), \forall x > \tilde{x}. \tag{3}$$

4.2 Comparative statics: changes in preferences vs. changes in the environment

We now use the equilibrium condition in equation 3 to illustrate the factors driving rich households closer to the CBD, and that can explain our key stylized facts. The condition shows that the rich live downtown if they have: a small preference for housing γ_p (e.g., smaller families), a strong preference for amenities α_r (especially amenities are very centralized i.e., if A is large), a high monetary value of commute time τ_r, and if the commute time gradient T_r is large (i.e., jobs for the rich are very centralized.) The model is not dynamic and does not include a time component, but we can interpret a change in coefficient from 2000 to 2010, e.g., $\alpha_{r10} > \alpha_{r00}$ as driving rich people downtown.

It is worth delineating the role that changes in preferences and changes in the environment play in delivering conditions under which large cities experience a centralization of the rich - or college-educated - as documented in section 3. The model delivers two broad types of hypotheses explaining urban revival in large cities. In the first type of hypothesis, large cities have a different pre-existing environment, and the preference of the rich for that environment becomes stronger relative to that of the poor. This happens, for instance, if large cities have a steeper amenity gradient A', and there is an increase in the relative preferences of the rich for amenities. This implies that a variable's ability to explain urban revival depends on this variable's centralization in large relative to small cities, and on changes in the preferences of the rich relative tothe poor for that variable. As an example, consider theaters, an amenity that is relatively more centralized in large cities. If the preferences of the rich for theaters become more pronounced relative to that of the poor, then such change in preferences can explain urban revival.

In the second type of hypothesis, it is the environment that changes in large cities relative to small cities, in a way that makes their downtown more attractive to the rich given the pre-existing preferences of the rich and poor. This happens, for instance, if the rich have a stronger taste for amenities ($\alpha_r > \alpha_p$) and if the gradient A' for that amenity becomes steeper in large cities. This implies that a variable's ability to explain urban revival depends on the relative preferences of rich and poor households for that variable, and on changes in the centralization of that

[21] This equilibrium is unique for a given set of parameter values. We close the model in Appendix D, and show how to derive $\tilde{x} \in (0, \bar{x})$,where $\bar{x}$ is the boundary of the city.

variable in large relative to small cities. So if the rich have a relatively stronger taste for theaters than the poor, then a relative centralization of theaters in large cities has the potential to explain urban revival.

Such distinctions are important for the interpretation of our empirical results, where we are particularly interested in whether large cities experienced urban revival as a result of changes in preferences or of changes in the environment.

4.3 Deriving an indirect utility function from the model.

We now derive an indirect utility function from the model, as a starting point for our empirical implementation. We substitute the first-order condition $p_d(x) = \frac{\gamma_d}{h_d(x)}$ (equation 2) and the budget constraint into the utility function (equation 1) to obtain:

$$v_d(x) = -\gamma_d ln\left(p_d(x)\right) + \alpha_d A(x) - \tau_d T_d(x) + k_d, \tag{4}$$

where $k_d = w_d - \gamma_d + \gamma_d \ln(\gamma_d)$ is a constant that does not vary with location x. This utility function features amenities, house prices, and job locations. It captures the main variables and parameters of the residential discrete-choice model that we propose in the next section. In practice, we do not expect the preference of households for a location to be entirely deterministic conditional on their type, so in our empirical implementation we add a stochastic household-specific taste shock for each location to the indirect utility function above.

5 Estimating a Residential Choice Model

We now specify and estimate a discrete-choice model of residential location. In appendix G we augment this model to study the joint workplace-residential location decision. The starting point for our specification is the indirect utility function from the monocentric city model. Our empirical implementation of this equation differ in four ways from equation 4. First, residents choose a tract j instead of a location x. Second, we add a time dimension t. Third, we let individuals choose both a CBSA and a tract, to capture the preferences of movers across CBSAs. Fourth and most important, we add an error term to the model, to obtain a discrete-choice model in which location choices are stochastic instead of deterministic as in the monocentric city model. The resulting utility specification is therefore a variant of the random utility model developed by (McFadden, 1972; McFadden and others, 1978))

Each person i of type d chooses its residential location tract j in CBSA c in year t to maximize its indirect utility function V^{id}_{jtc}:

$$\max_j V^{id}_{jct} = \alpha^d_t \mathbf{A_{jct}} + \beta^d_t \mathbf{T^d_{jct}} - \gamma^d_t p_{jct} + u^d_{jc} + \xi^d_{jct} + \theta^d_{ct} + \psi^{id}_{ct}(\sigma^d) + (1-\sigma^d)\varepsilon^{id}_{jct} \tag{5}$$

where $\mathbf{A_{jt}}$ is a vector of observable time-varying amenities in tract j, such as accessibility to services and shopping, location within a good school district, or proximity to other young college-educated individuals.[22] $\mathbf{T^d_{jt}}$ is a vector of observable time-varying characteristics of accessibility to jobs in tract j, in particular proximity to job opportunities and average commute length of residents in tract j. $\mathbf{p}_{jt}$ is a house price index in tract j at time t. Preference parameter α^d_t, β^d_t and γ^d_t are time- and group-specific, to capture different preferences across age and education group, and changes in such preferences. u^d_{jc} represents the unobserved time-invariant quality of each residential location for an individual of type d whileξ^d_{jt} represents a time-varying quality. θ^d_{ct} represents an unobserved time-varying quality of CBSA c for all individuals of type d.

We assume a nested-logit error structure, where $\psi^{id}_{ct}(\sigma^d)$ and ε^{id}_{jct} are random individual- and time-specific taste shocks for CBSA c and residential tract j, respectively. The CBSA taste shocks, $\psi^{id}_{ct}(\sigma^d)$, are independent

[22]Note that such endogenous amenities are not in the model developed in section 4, but adding them is relatively straightforward.

draws from a random distribution that goes to zero as σ^d goes to zero. The residential tract taste shocks, ε^{id}_{jct}, are independent draws from the extreme value distribution. The parameter $0 \leq \sigma^d < 1$ governs the within-group correlation in the error term $\psi^{id}_{ct}(\sigma^d) + (1-\sigma^d)\varepsilon^{id}_{jct}$. As σ^d approaches zero, the model collapses to a standard logit model. We derive linear regression for both the nested and standard logit specifications, as in Berry (1994), modified to use first-differenced data.

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

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

and

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

where J_c denotes the set of residential locations in CBSA c, C denotes the universe of CBSAs, $D^d_{ct} = \sum_{j\in J_c} \exp\left(V^d_{jct}/(1-\sigma^d)\right)$ and $V^d_{jct} = \left(\alpha^d_t \mathbf{A_{jct}} + \beta^d_t \mathbf{T_{jct}} - \gamma^d_t p_{jct} + \theta^d_{ct} + u^d_{jc} + \xi^d_{jct}\right)$ denotes the mean utility for an individual of type d from residential location j in year t. Following Berry (1994), this collapses to:

$$s^d_{jkt} = \frac{\exp\left(V^d_{jct}/(1-\sigma^d)\right)}{\left(D^d_{ct}\right)^{\sigma^d}\sum_{c\in C}\left(D^d_{ct}\right)^{1-\sigma^d}} \tag{6}$$

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:

$$\ln s^d_{jct} - \ln s^d_{\bar{j}\bar{c}t} = \frac{V^d_{jct} - V^d_{\bar{j}\bar{c}t}}{1-\sigma^d} - \sigma^d\left(\ln D^d_{ct} - \ln D^d_{\bar{c}t}\right) \tag{7}$$

Substituting $D^d_{ct} = \sum_{j\in J_c} \exp\left(V^d_{jct}/(1-\sigma^d)\right)$ and $\ln s^d_{jct} = \ln s^d_{ct} + \ln s^d_{j|ct}$ into (7) and rearranging terms we have that:

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

Substituting in for the relative mean utility from location j relative to location $\bar{j}$ we have that:

$$\widetilde{\ln s^d_{jc}} = \theta^d \alpha^d_t \tilde{\mathbf{A}}_{\mathbf{jct}} + \beta^d_t \tilde{\mathbf{T}}_{\mathbf{jct}} - \tilde{\gamma}^d_t p_{jct} + \tilde{\theta}^d_{ct} + \mu^d_{jc} + \tilde{\xi}^d_{jct} - \sigma^d \widetilde{\ln s^d_{j|c}} \tag{8}$$

where $\tilde{Y}_l = Y_l - Y_{\bar{l}}$ for each variable Y and we normalize $\mu_{\bar{j}c}$ to equal zero.

We estimate the parameters governing these choices using data from 2000 and 2010. Differencing from 2010 to 2000, we obtain our estimating equation:

$$\Delta\widetilde{\ln s^d_{jc}} = \alpha^d_{2010}\Delta\tilde{\mathbf{A}}_{\mathbf{jc}} + \Delta\alpha^d\tilde{\mathbf{A}}_{\mathbf{jc,2000}} + \beta^d_{2010}\Delta\tilde{\mathbf{T}}_{\mathbf{jc}} + \Delta\beta^d\tilde{\mathbf{T}}_{\mathbf{jc,2000}} + \gamma^d_{2010}\Delta\tilde{p}_{jc} + \Delta\gamma^d\tilde{p}_{jc,2000} + \Delta\tilde{\theta}^d_c + \Delta\tilde{\xi}^d_j + \sigma^d\Delta\widetilde{\ln s^d_{j|c}} + \epsilon^d_{jct} \tag{9}$$

where $\Delta X = X_{2010} - X_{2000}$ for both variables and coefficients.[23]

Note that unobserved time-invariant tract characteristics (e.g., nice weather or architecture) cancel out in first-

[23] Note that $\alpha_{2010}X_{2010} - \alpha_{2000}X_{2000} = \alpha_{2010}\left(X_{2010} - X_{2000}\right) + \left(\alpha_{2010} - \alpha_{2000}\right)X_{2000} = \alpha_{2010}\Delta X + \Delta\alpha X_{2000}$

difference. The error term of this regression is therefore $\Delta\tilde{\xi}_j^d + \epsilon_{jkt}^d$, i.e., the sum of any unobserved changes in the perceived quality of a residential location and an additional term ϵ_{jkt}^d capturing any remaining measurement error. $\Delta\tilde{\theta}_c^d$ is simply a CBSA fixed-effect, to be estimated.

5.1 Variable Definitions

In this subsection, we provide details on the computation of our dependent variable, as well as of our measures of amenities, job availability, and house prices. We discuss instruments and identification in the next subsection.

5.1.1 Dependent Variable: Share of residents of type d living in tract j

The dependent variable 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. We study six different demographic groups indexed by d, consisting of the interaction of three age groups (25-34 year olds, 35-44 year olds and 45-64 year olds) and two education groups (individuals with and without a 4-year college degree). For instance one group is '25-34 year olds with a college degree.' Let n_{jct}^d be the number of individuals of type d in tract j in CBSA c. Then the share of all type d residents who live in tract j in CBSA c at time t is:

$$\text{resident share}_{jct}^d = s_{jct}^d = \frac{n_{jct}^d}{\sum_c \sum_j n_{jct}^d}.$$

5.1.2 Amenity Variables

We now describe the variables that we use to measure the amenities available in each tract, $\mathbf{A_{jct}}$. In our main specification, these variables include consumption amenity indexes and local population shares that are included to control for changes in other endogenous amenities. In robustness exercises, we also include measures of school quality, which we observe for only a subset of CBSAs.

Consumption Amenity Indexes We create variables measuring both the level and change in consumption amenities in each tract. These indexes are based on the price index methodology developed in Couture (2013) and measure the availability of 11 different types of retail and cultural establishments around the centriod of each census tract. Each price index is low if there are many establishments of a given type within a short travel time of a centroid. These indexes account for tract-specific speed and exact establishment location, and are considerably more precise than controls for amenities used in existing studies such as proximity to Central Business District or density of establishments over a large area.

These indexes require the travel times from the centroid of each census tract to the universe of establishments that households might feasibly visit. We employ the NETS database, which contains the exact locations of the universe of U.S. establishments in 2000 and 2011, as well as each establishment's SIC8 industry and name. We compute travel times using the results from Google maps searches.[24]

The amenity index for a given category is a CES price index, in which the price of visiting an establishment *includes transport cost.* The price of a visit to an establishment is equal to a constant expenditure derived from the Consumer Expenditure Survey, plus a cost of transportation from the tract centroid that assumes a value of time

[24]Our methodology starts with the linear distance from a centroid to an establishment, and uses information from Google Maps to obtain a predicted travel time. To go from a linear to an actual driving distance, we use a representative sample of establishments around each tract to compute an average ratio of linear to actual distance by car, transit and foot for this tract. Using the same establishment sample, we also use Google Maps to compute functions relating trip speed to trip distance in each tract.

equal to \$12 dollars per hour, plus \$5 per hour in fuel cost if using a car.[25] We assume an elasticity of substitution of 9, estimated by Couture (2013) for restaurants. The higher this elasticity, the lower the weight on establishments far away from an individual, and the more localized the amenity index. We estimate indexes for the following 11 categories of establishments, selected using their SIC8 codes:

- 'Theater' (theater, operas, symphonies, etc.)
- 'Museum' (museums, art galleries, libraries, etc.)
- 'Movie' (movie theater and bowling center)
- 'Golf' (golf courses and amusement park)
- 'Sport' (gym, tennis court, etc.)
- 'Restaurants' (full-service, fast food, etc.)
- 'Drink' (bar, clubs, lounge, etc.)
- 'Personal' (personal services, nails, hair, etc.)
- 'Groceries' (food stores small and large)
- 'Apparel' (apparel stores)
- General Merchandise Stores'

In some specifications we refine this classification and compute indexes for establishments that young college-educated individuals are more likely to enjoy. We will present these specifications in future version of this paper. We propose two such refinements. In the first, we use data from ESRI business data analyst. ESRI divides each neighborhood in the United States into market segments, and conducts surveys of shopping habits and activity of individuals living in neighborhoods within each segment. For instance, one segment whose demographic profile contains a lot of young professionals is called 'Laptop and latte.' ESRI then assigns a 'Market Potential Index' (MPI) to the set of chains or activities that it surveyed. The MPI of a chain or activity for a given segment corresponds to the propensity of an individaul in that particular segment to shop in a given chain or to perform a given activity relative to the average individual. By considering only segments containing the largest share of young professionals, we are able to use the MPI in these segments to select the chains or activities that young professionals prefer. For instance, Whole Foods receives an MPI of 2.17, meaning that individuals living in young professional neighborhoods are 2.17 times more likely to shop at Whole Foods than the average American. Whole Food therefore receives a high weight in our MPI_groceries index, and tracts near a Whole Food will receive a low MPI price index for groceries. Of course, young professionals may be attracted to independent establishments (e.g., restaurants not part of chains) and this cannot be captured by MPI indexes.[26] We then compute amenity indices as explained above, but selecting only establishments that fall into 'preferred chains' or 'preferred activites' with $MPI > 1.25$. [27] Using this methodology, we create 6 additional indexes:[28]

[25]Some amenity categories like restaurants have a low price per visit (\$10.20) while other categories like apparel stores have a high price per visit (\$60.40). When the price per visit is high, transport costs become a relatively less important factor in the travel decision, and therefore the amenity index puts more weight on establishments far away. As a result, amenity indexes for cheap amenities are more localized.

[26]Note that the MPI weight is exactly equivalent to a quality parameter in our CES price indices.

[27]Some MPIs indicate the likelihood of individuals in different market segments to shop or eat at different retail or restaurant chains. We use the chain name to match these MPIs to establishment locations in the NETs data. Other MPIs indicate the likelihood of individuals to partake in various activities. We use SIC8 codes to match these MPIs to the locations of establishments offering these services in the NETS data (e.g., SIC8 code 79991123 for Yoga Instruction).

[28]We also produced an MPI index for high-income people. MPIs for high-income and young professionals are usually highly correlated, with some exceptions. For instance, Express is a fashion store that caters to younger consumers, and it receives an MPI of 1.16 for high-income people, versus 1.76 for young professionals.

- 'MPI_restaurant' (Chipotle, California Pizza Kitchen, etc)
- 'MPI_personal' (massage, facial, etc)
- 'MPI_groceries' (Whole Food, Trader's Joe, etc)
- 'MPI_sport' (participated in yoga, attend baseball, etc)
- 'MPI_apparel' (H&M, Nordstrom, Banana Republic, etc)

The second methodology uses ratings from Yelp.com to select chains that presumably are attractive to the young, connected crowd that disproportionately contributes to Yelp reviews. We collect data on the 40 top-rated establishments for groceries, apparel and home furniture in a sample of 84 US cities. We define the set of 'preferred' chains, that we will use to compute our Yelp indexes, as all chains that appear in the top 40 of at least 10 cities. We use the invert of each chain average ranking across all cities in which it appears as a quality parameter in our computation. These Yelp indexes give more weight to the best rated chains. We use this methodology to create 3 additional indices:

- 'Yelp_groceries' (Trader's Joe, Publix, etc)
- 'Yelp_apparel' (Goorin Bros, Lululemon, etc)
- 'Yelp_home' (Patina, World Market, etc)

Change in amenity composition In some specifications, we also use the MPI and Yelp weights to measure amenity composition, as the average quality of establishments around a tract. These indexes allow us to describe the evolution of environments that are not getting denser, but whose amenity composition is shifting towards establishments that are particularly attractive to young professionals.

Local Demographic Shares in 2000 Recent work demonstrates the relevance of endogenous consumption amenities - amenities that correlate with the share of college-educated residents - in explaining cross-CBSA location choices. We suspect that similar mechanisms are at work within CBSAs, which draw households towards (or away) from neighborhoods depending on their demographic or socio-economic composition. Although we expect our consumption amenity indexes will account for some of these endogenous amenities, we control for any residual effects with control variables for tract population density in 2000 as well as the shares of household in different demographic groups in 2000.

Another possibility is that growth in some group is accounted for by 'stayers', for instance some growth in 35-44 year old between 2000 and 2010 may be accounted for by the share of 25-34 year old in 2000. To capture this, we control for share of individuals in same educational group but 10 years younger in 2000.

Schools School quality is a key determinant of the location choice of families with children. We use data from Schooldigger.com a website compiling test scores for schools all over the United States. The website provides a ranking of each school district within each state. The ranking averages over test scores in different fields for schools from grade 1 to 12. We use the invert of that ranking in 2004 - earliest year available - and in 2010 in the school district that a tract falls into as our measure of school quality in 2000 and 2010.

5.1.3 Jobs Variables

Here we describe the variables that we use to measure the proximity of each tract to employment opportunities, $\mathbf{T_{jct}}$. Being close to work obviously implies a shorter commute, but may also alleviate the location choice problem of dual-career households, and proximity to other job opportunities may become relevant depending on future career events. We measure this in two ways:

Job opportunity index First, we use the LODES data to compute a distance-weighted average of the number of jobs in tracts surrounding each residential tract. We compute this index for three types of jobs: high-income jobs paying more than \$3333 per month, middle-income job paying between \$1000-\$3333 per month, and low-income jobs paying less than \$1000 per month. These three groups correspond roughly to income terciles in 2002. The job opportunity index for a tract j' for income group g is:[29]

$$\text{avg num job opp}^{g}_{j't} = \sum_{j} w(d_{j'j}) n^{g}_{j'jt} \text{ where } w(d_{j'j}) = \frac{1/(d_{j'j}+1)}{\sum_j 1/(d_{j'j}+1)}$$

, where $n^{g}_{j'jt}$ is the number of persons who work in tract j, but do not live in tract $j^{'}$.

Average distance to work Second, we use the LODES data to compute the average commute distance of workers living in tract j, weighted by job numbers in surrounding tracts

$$\text{avg dist to work}_{jt} = \sum_{j'} \tilde{w}_{jj't} d_{jj'} \text{ where } \tilde{w}_{jj't} = \frac{n_{j'jt}}{\sum_{j'} n_{j'jt}}$$

5.1.4 Housing Costs

We measure the level and change in housing prices using zipcode level data from Zillow.com, that we match to census tracts. We use the Zillow House Value Index (ZHVI) from 2000 and 2010 , which measures the median value of all (non-distressed) properties.[30]

5.2 Identification

There are various challenges to identifying the effect of the variables above on residential location decisions. The first-difference regression allows us to control for time-invariant tract characteristics that could be correlated with our regressors. The vast array of controls alleviates - but does not eliminate - omitted variable bias. Clearly, however, neither first-differencing nor adding controls can resolve reverse causality, which affects variables appearing in changes (Δ). For instance, a change in the share of young professionals in a tract may have a direct effect in attracting consumption amenities and jobs. We therefore instrument for changes in amenity indices, job opportunities and house prices. We describe these instruments below. We do not have an instrument for changes in school quality - which also is available only for half of our tract sample - and therefore we consider school quality controls only in robustness checks of the model, and we remove it from our prefered specification.

Our regressors for 2000 amenity, jobs, and house price levels do not suffer from reverse causality, and the first-difference controls for correlation with any time-invariant omitted variables. However, omitted variable bias can remain if some time-varying factors are missing from our regression - the most obvious of which is crime

[29]Note that our job opportunity index is defined over three income group g, while our dependant variable in our main specification is defined over age-education group d. We do not have measures of jobs by age and education group at the tract level.

[30]The index and methodology are available at: http://www.zillow.com/research/data/.

for which we do not have tract level data. If households and businesses move into areas in anticipation of future changes in unobservable factors, then omitted variables could bias the coefficients on our 2000 level variables (which we interpret as capturing changes in preferences). To alleviate this concern we instrument for 2000 levels of house prices and local demographic shares.

As a robustness exercise, we also implement another identification strategy based using data on worker commutes. The commute data allows to hold constant the workplace location of individuals when estimating the discrete-choice model, thereby convincingly isolating the effect of changes in residential characteristics from changes in job location.

Instruments for Housing Prices and Local Demographic Shares Changes in housing prices suffer from reverse causality, because they depend on our dependent variable, i.e., the share of college-educated or high-income residents. 2000 house price levels and local demographic shares capture many tract characteristics, and are therefore at risk of being correlated with time-varying unobservables. To overcome this endogeneity, we exploit the correlation between housing prices, the spatial income distribution, and plausibly exogenous fixed natural amenities identified by Lee and Lin (2013). The idea is that natural amenities (oceans, lakes, mountains, etc.) act like anchors to high-income populations. These natural features also impose supply constraints on land, whereby driving up housing prices, as described in Gyourko et al. (2013). These supply constraints also plausibly amplify the reaction of house prices to demand shocks, so we also use these natural amenities as instruments for changes in house prices.[31] Our vector of natural amenity measures includes the log Euclidian distances (in km) of the centriod 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 and the census tract's average slope, an indicator for whether the tract is at high risk for flooding, and, finally, the logs of the annual precipitation, July maximum, and January minimum temperatures in the tract averaged over 1971 and 2000. Based on Lee and Lin (2013)'s theory, we expect that housing prices and high-income demographic shares will be positively correlated with the presence of positive amenities and negatively correlated with negative amenities. As an additional instrument for housing prices and local demographic shares, we include historical tract-level 1970 population shares for each of the age-education demographic groups represented in our analysis.

The exclusion restriction is that conditional on all controls in the regression, natural amenities and historical shares affect changes in demographic shares only via the effects outlined above (the anchoring effect of natural amenities for high-income households, its impact on housing supply, and the mean reversion/within-group agglomeration effects for historical shares).[32] The key is that neither natural amenities or historical shares are correlated with unobserved changes in the characteristics of a residential tract that attract (or detract) households of a given demographic group to (from) that tract between 2000 and 2010 (i.e., $\Delta\tilde{\xi}^{d}_{jc}$). For instance, we assume constant preferences for proximity to natural amenities.

Instruments for Consumption Amenity Indexes Changes in the density and type of local establishments are likely correlated with changing neighborhood demographics. To design an instrument for the consumption amenity indexes, we seek factors explaining variation in amenity location from 2000 to 2010 but exogenous to neighborhood demographics. Specifically, we exploit variation across firms in their national business expansion strategy in conjunction with spatial variation in the attractiveness of the pre-existing business landscape for establishment

[31] Such instruments have been criticized in the context of cross-CBSA regressions, for instance by Davidoff (n.d.), who argues that such constraints are correlated with demand factors (i.e., constrained cities like New York also have productive workers.) Such arguments carry less weight in a within-city context, in which very localized constraints are less likely to be correlated with demand factors.

[32] Of course, some natural amenities may act both as an anchor for a high-income or college-educated neighborhood, and as a constraint on housing supply. In this case, the conditional exogeneity assumption matters, and it is important that both levels of demographic shares and levels of house prices be included as controls.

entry. This strategy draws both from the Bartik (1991) instrument methodology familiar in labor and urban economics, and from recent evidence from the industrial organization literature on the importance of cannibalizaton and preemption concerns in determining firm entry (Igami and Yang (2015); Toivanen and Waterson (2005))

Our instrument is a measure of predicted change in the amenity index, and its computation proceeds in three steps:

1. First, we regress chain-level or SIC8-level establishment entry from 2000 to 2010 in a tract, on variables capturing the pre-existing commercial environment in 2000. We obtain predictions for entry of establishments in each tract from the fitted value of these regressions (one regression per chain or SIC8 code). For the standard amenity indices we model tract entry at the SIC8 level, whereas for the MPI indices defined by chain we model entry at the chain level.[33]

2. Second, we aggregate all SIC8 or chain-level predictions at the amenity category level. We therefore obtain the predicted change in the number of establishments in this amenity category in each tract (e.g., predicted restaurant entry in each tract as the sum of burger entry, Mexican entry, etc.)

3. Third, we use the predicted change in each tract from step 2 to compute predicted changes in amenity indices. This predicted change in the index is our instrument.

In the first step, we model the business entry and exit decisions of establishments in each tract j. This decision is a function of the business environment, more precisely of the number of establishments at different distance from the tract centroid that are in the same chain, in the same SIC8 code but not in the same chain, in the same SIC6 code but not in the same SIC8 code, and in the same SIC4 code but not in the same SIC6 code, and of the number of establishments that are plausibly wholesalers for this chain. Define n_{jt}^{C} as the number of establishments in a chain C in tract j in period t. Let $n_{jt,dist}^{sic\#(C)}$ be number of establishments in the same sic# code as chain C (where # takes value 4, 6, 8 and 10) within distance interval 2^{dist} to 2^{dist+1} (where $dist$ takes values from 0 to 3) from the centroid of tract j. Note that SIC10 codes are not defined by the government; we just create $SIC10(C)$ codes to identify chains, because it simplifies the notation. [34] We then model the business entry and exit decisions using the following linear regression:

$$\begin{aligned} n_{j10}^{C} - n_{j00}^{C} = \alpha^{C} + \sum_{dist=1}^{3} \beta_{dist}^{sic\#(10)} \left(n_{j00,dist}^{C} - n_{j00,(dist-1)}^{C} \right) + \\ \sum_{dist=1}^{3} \beta_{dist}^{sic8C} \left(\left(n_{j00,dist}^{sic8C} - n_{j00,dist)}^{C} \right) - \left(n_{j00,(dist-1)}^{sic8C} - n_{j00,(dist-1))}^{C} \right) \right) + \\ \sum_{dist=1}^{3} \left(\sum_{\#\in\{6,4\}} \beta_{dist}^{sic\#(C)} \left(\left(n_{j00,dist}^{sic\#(C)} - n_{j00,dist)}^{sic(\#+2)(C)} \right) - \left(n_{j00,(dist-1)}^{sic\#(C)} - n_{j00,(dist-1)}^{sic(\#+2)(C)} \right) \right) \right) + \varepsilon_{jt}^{chain} \end{aligned} \tag{10}$$

We omit the CBSA subscript and the wholesaler variables to simplify the notation. Regression results highlight the very local nature of entry and exit decisions. Only a small fraction of coefficients for the environment beyond

[33]There are various reasons why entry might be correlated with the existing commercial environment. Looking within a small radius in close proximity to a given location, we expect that entry will be decreasing in the concentration of establishments offering similar services, due to competition and cannibalization concerns. On the other hand, once we control for the density of existing businesses in close proximity to a point of entry, we expect that entry will be increasing in the broader density of existing establishments under the same chain, since this will indicate proximity to the chain's upstream suppliers or distribution centers and some pre-existing market knowledge. In addition to these within-chain scale economies, we also account for sector-level coagglomeration externalities, in the form of positive spillovers from local activity from non-competing or differentiated firms within the same industry. In addition to these direct effects, we expect that the existing landscape captures location-specific barriers to entry, such as existing density and either natural or regulatory supply constraints, as well as direct effects. Finally, proximity to wholesalers may lower the cost of entry for establishments.

[34]All establishment counts are based on the NETS geocoded census of establishments. We estimate the model using data from 2000 and 2010.

0-1 mile from the tract centroid are significant. For regressions on entry by SIC8 codes, the coefficient on the number of establishments with the same SIC8 code within 0-1 mile is negative and significant at the 0.05 level in 93% of all codes across our 11 amenity categories (regression results not shown). Therefore, cannibalization and competition concerns are the key predictors of entry. Coefficients on initial presence of firms in same SIC6 but other SIC8 is *positive* and significant in 68% of cases, meaning that aggomeration forces are also important. The best existing business environment for entry is therefore one with other establishments doing closely related business nearby, but none that are in exactly the same market segment.

In the second step, we sum up, within every tract, the fitted value of the regression in equation 10 over all chains (or all SIC8) within a given amenity category. Denote by $\Delta\hat{A}_{aj}$ this prediction for the change in the number of estabalishment in amenity category a in tract j, and denote by $\Delta\hat{n}_j^C$ the fitted value from equation 10. We obtain:

$$\Delta\hat{A}_{aj} = \sum_{C \in a} \Delta\hat{n}_j^C.$$

In the third step, we compute the actual instrument. We do so by starting from the vector of all establishments in 2000, and adding the predicted change in the number of establishments $\Delta\hat{A}_{aj}$ to the centroid of each tract j. Using this vector of predicted 2010 establishments, we compute predicted amenity indices for 2010. The difference between the predicted amenity index in 2010 and the actual amenity index in 2000, denoted by ΔA_{aj}^{IV} is our instrument for the change in the amenity index from 2000 to 2010 in amenity category a in tract j.

A valid instrument requiresΔA_{aj}^{IV} to be relevant, i.e., $corr(\Delta A_{aj}^{IV}, \Delta A_{aj}|Z_j) \neq 0$ and exogenous, i.e., $corr(\Delta A_{aj}^{IV}, \Delta\tilde{\xi}_j^d + \epsilon_{jct}^d|Z_j) = 0$ conditional on all other regressors Z_j. The instrument is relevant and has the expected positive effect in 10 of our 11 basic amenity categories.

The exclusion restriction deserves discussion. The key feature of this instrument is its exogeneity to changes in local preferences for amenities; all the predictions are obtained using coefficients estimated at the national level, unaffected by any single tract. More generally, the exclusion restriction for a Bartik-type instrument is that the initial distribution of establishments in 2000 is exogenous to changes in the number of establishments in tract from 2000-2010. One concern with this Bartik assumption is that changes in national preferences for some amenities could lead some input to the instrument (i.e., the existing environments that include these amenities) to affect the dependant variable (changes in residential shares) directly. This concern is alleviated through the vast array of controls for amenity levels already in the regression.[35]

Instruments for Job-Related Variables We also instrument for changes in the job opportunity (avg num job opp$_{jt}^g$) and average distance to work (avg dist to work$_{jt}^g$) indexes. We use the same LODES data to obtain Bartik-type predictions for the change in the number of workers in each income group (i.e., high-income, mid-income, and low-income). These predictions depend on the industrial composition of each tract, and on the national growth of each industry across 20 NAICS sectors. We index each income group by g and industry by i. The predicted change in the number of group g workers in tract j between 2002 and 2011 is:

$$\widehat{\Delta n_j^g} = \sum_i \left(\frac{n_{ij2002}^g}{\sum_i n_{ij2002}^g} \right) \Delta n_i^g$$

[35]To understand the exogenous variation underlying the instrument, on should think about comparing two areas with broadly similar amenity levels - which we control for - one with a Trader Joe's, and one with a Whole Foods. If Whole Foods is expanding faster than Trader Joe's from 2000 to 2010, then the area that lacks a Whole Foods is predicted to have higher growth in groceries. Whether an area had a Trader's Joe or a Whole Foods, i.e., the exact distribution of chains or SIC8 codes in 2000, is assumed exogenous, and the national expansion strategy of Whole Foods is exogenous to local conditions in any given tract.

where n^g_{ij2002} denotes the number of group g workers working in industry i in tract j in 2002, and$\Delta n^g_i = \sum_j (n^g_{ij2011} - n^g_{ij2002})$ denotes the nationwide growth in group g workers in industry i between 2002 and 2011. We can use these predictions to compute instruments for the change in residence-tract job opportunity average distance to work in tract j':

$$\text{instr}(\Delta\text{avg num job opp}^g_{j'}) = \sum_j w(d_{j'j})\widehat{\Delta n^d_j} \text{ where } w(d_{j'j}) = \frac{1/(d_{j'j}+1)}{\sum_j 1/(d_{j'j}+1)}$$

To calculate the instrument for average distance to work in tract $j^{'}$, we use a weighted average of distance between tracts where the weights are determined by the change in the share of group g workers commuting between those tracts, as predicted above,

$$\text{instr}(\Delta\text{avg dist to work}^g_{j'}) = \sum_j d_{jj'}\Delta\tilde{w}^g_{jj'} \text{ where } \Delta\tilde{w}^g_{j'j} = \left(\frac{n^g_{jj'2002}}{\sum_j n^g_{jj'2002}}\right)\widehat{\Delta n^g_j}$$

Instrument for change in the share of type d individual within CBSA c who live in tract j We now derive instruments for $\Delta s^d_{j|c}$, the change in the share of type d individual within CBSA c who live in tract. We calculate a set of instruments that capture various exogenous factors that affect the attractiveness of tract j relative to all other tracts in a CBSA. For each instrument described above, we compute an instrument for the within-CBSA share, $instr(\Delta s^d_{j|c})$, as the average value of an instrument $instr$ (e.g., instrument for change in job opportunities) in tract j relative to all other tracts k in the CBSA c in which tract j is located. So we compute each instrument as:

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

where N_{c_j} is the number of tracts in CBSA c.

5.3 Regression Results

Table 1 presents regression results for the nested-logit model in equation 9, with the full set of instruments described in section 5.2. In Appendix A.2 we also present the OLS and CBSA fixed-effect with IV specification.

Panel A of Table 1 compares the preferences of young college versus non-college educated individuals, and Panel B compares the preferences of the middle-aged versus the old college-educated individuals. Column 1 and 2 of Panel A displays parameter estimates for a regression on changes in the share of 25-34 year olds college-educated individuals living in a tract. Coefficients for variables in first-difference (i.e., the change in that variable from 2000 to 2010) are in column 1, while coefficients for variables in 2000 levels are in column 2. Columns 3 and 4 contain results for the same regression for non-college-educated 25-34 year olds. Most coefficients in the table are significant at the 1% level. Given that almost all our variables are logged indexes whose quantitative interpretation is not straightforward, we present only standardized coefficients. For instance, the -0.17 coefficient on changes in the theater index for the college-educated group means that a one standard deviation increase in the theater index *reduces* the share of 24-35 year-old college educated living in this tract by 17% (recall that our amenity indexes are gains-from-variety price indexes which take a low value in dense environments). The structural interpretation of the coefficient on a variable in first-difference is that of a preference parameter in 2010, while the coefficient on a variable in 2000 level has an interpretation as a change in preference from 2000 to 2010. We often adopt this interpretation in our discussion of the results. Therefore, the negative coefficient on changes in the theater index for the college-educated group captures a preference for living near this amenity, and the negative

Table 1: Nested-Logit Residential Location Choice Regression Results

Panel A: 25-34 Year Old College-Educated vs. 25-34 Year Old Non-College Educated

	25-34, College Educated		25-34, Non-college Educated	
	Change	Level	Change	Level
Variable	[1]	[2]	[3]	[4]
House Price Index	0.02***	-0.005	-0.07***	-0.003
Cohort Share	–	-0.04***	–	0.06
Job Opportunities – Low Inc.	-0.14***	-0.06***	-0.41***	-0.23***
Job Opportunities – Mid Inc.	-0.06**	0.04**	-0.13**	0.05
Job Opportunities – High Inc.	0.2***	0.05***	0.45***	0.14***
Avg. Travel Distance	0.1***	0.04***	0.41***	0.19***
Population Density	–	-0.07***	–	-0.16***
College share	–	-0.11***	–	-0.1***
Within-CBSA share	0.57***	–	0.16	–
Theater	-0.17***	-0.12***	0.009	0.04
Museums	0.04**	0.06***	0.08**	0.13***
Movie Theaters	-0.03*	-0.003	-0.27***	-0.2***
Outdoor activities	0.12***	0.06***	0.06*	0.02
Sports	-0.07***	-0.11***	-0.05	-0.08
Restaurants	-0.04	-0.03	0.07	0.12**
Bars	-0.11***	-0.12***	0.04	0.04
Personal Services	-0.03	0.01	-0.37***	-0.54***
General Merchadise Stores	-0.04***	-0.04*	0.03	0.02
Food Stores	0.07***	0.18***	0.21***	0.36***
Apparel Stores	0.01	0	-0.13***	-0.16***
R-squared	0.706		-0.123	
Observations	31,818		37,350	

Panel B: 35-44 Year Old College-Educated vs. 45-64 Year Old Non-College Educated

	35-44, College Educated		45-65, College Educated	
	Change	Level	Change	Level
Variable	[1]	[2]	[3]	[4]
House Price Index	-0.03***	0.03***	-0.06***	0.009**
Cohort Share	–	0.08***	–	0.22***
Job Opportunities – Low Inc.	-0.12***	-0.15***	0.03*	-0.05***
Job Opportunities – Mid Inc.	0.13***	0.17***	-0.07***	0.09***
Job Opportunities – High Inc.	0.06***	0.06***	0.09***	0.009
Avg. Travel Distance	0.03**	0.02**	0.003	-0.002
Population Density	–	-0.05***	–	-0.15***
College share	–	-0.14***	–	-0.3***
Within-CBSA share	0.7***	–	0.64***	–
Theater	-0.07***	-0.04***	-0.07***	-0.04***
Museums	0.06***	0.06***	-0.1***	-0.1***
Movie Theaters	-0.11***	-0.06***	-0.03*	-0.003
Outdoor activities	0.15***	0.07***	0.16***	0.08***
Sports	-0.06***	-0.08***	-0.16***	-0.22***
Restaurants	0.12***	0.19***	0.06***	0.15***
Bars	-0.12***	-0.13***	-0.08***	-0.08***
Personal Services	-0.02	-0.06**	-0.08***	-0.05*
General Merchadise Stores	-0.03**	0.009	-0.11***	-0.13***
Food Stores	0.06***	0.14***	0.004	0.12***
Apparel Stores	-0.12***	-0.11***	0.05***	0.16***
R-squared	0.787		0.737	
Observations	35,863		36,734	

Notes: * – 10% significance level; ** – 5% significance level; ***–1% significance level. The change in house prices, level of local demographic share, change in consumption, change in job opportunities, change in average distance to work, and change in the share of type d individuals within CBSA c who live in tract j are considered endogenous variables and instrumented in first stage regressions. The F-statistics for these regressions are above 100 for all endogenous regressors, with the exception of the nested-logit within-share, which has a first-stage F-statistics of 32 (for 25-34 college) and 60 (35-44 college) and may be weakly instrumented. Critical values for weak identification tests (Stock and Yogo (2005)) are not readily available for models with more than 2 endogenous regressors.

coefficient on the level of the theater index suggests that this taste is becoming stronger through time. In contrast with the preferences of the young and college-educated, the young but non-college educated are almost indifferent to theaters (they are a disamenity for them, but not significantly so) and this preference has changed very little over the last decade. [36] Overall, we find that the preference of the young and college-educated differ from those of their non-college-educated counterparts, and in particular college-educated individuals are more attracted to proximity to amenities like theaters and bars, and less sensitive to house prices.[37] Both college and non-college-educated individuals are attracted to proximity to high-income jobs, but surprisingly the non-college-educated group has a stronger preference for proximity to these jobs. These differences in preferences are generally becoming more pronounced.

Panel B's format is similar to that of Panel A, and it shows, side-by-side, the preferences of middle-age college-educated and old college-educated individuals. For amenities like theaters and bars - which we emphasize here because they turn out to have explanatory power on urban revival - preferences tend to decline with age. The coefficients for the young, middle-aged and old are -0.17, -0.07, and -0.07 for change in the theater index and -0.11, -0.12, -0.08 for change in the bars index. These differences in the preferences of the young and old are also become more pronounced through time.[38] It it interesting to note that preferences for some of the same amenities that separate the young from the old college-educated individuals also distinguish college from non-college individuals in panel A.

In the next two subsections we refine this analysis by showing that the model can indeed explain urban revival, and by identifying the variable that most contributes to the model's success.

5.4 Does the model explain urban revival?

We now investigate whether the model can generate the stylized facts from Section 3, in which we document the fast growth of young-college educated individuals near the CBD of large cities. It is worth emphasizing that we do not perform out-of-sample predictions, and that we fit our model with the same data that we use to estimate it. However, fitting the model is interesting because our regressions do not include any controls for either distance from the CBD or for city size. The goal of this exercise is therefore to ask whether the variables included in the model capture the special characteristics of the downtown of large cities that made them ripe for urban revival over the last decade.

The first step to replicating our stylized facts is to derive urban and suburban growth from the fitted model. We start from the fitted value of the regression in equation 9, to obtain the fitted change in the share of group d who lives in tract j from 2000 to 2010, relative to a base tract. We always exclude the term for change in within-CBSA share (i.e., the 'nested-logit' term) from this fitted value, because it has explanatory power by construction. Starting from this fitted value, we easily obtain the fitted 2010 share of group d in tract j, by differencing out the actual share change in base tract, and the actual initial share in 2000. We then recover the fitted *population* of group d living in tract j in 2010 by multiplying this fitted share by the total population of group d. With fitted 2010 tract population of group d in hand, we can compute urban and suburban growth since 2000 within each CBSA exactly as in Section 3.

Figure 5 compares model-generated urban vs suburban growth obtained using fitted 2010 population with actual urban vs suburban growth obtained using actual 2010 population. We use fitted values from the nested-logit

[36] Note that we do not expect every group to have a preference for living near every amenity category. Built amenities that one rarely visit are probably disamenities, and indeed most neighborhoods have zoning regulations preventing commercial use in the vicinity of residential areas.

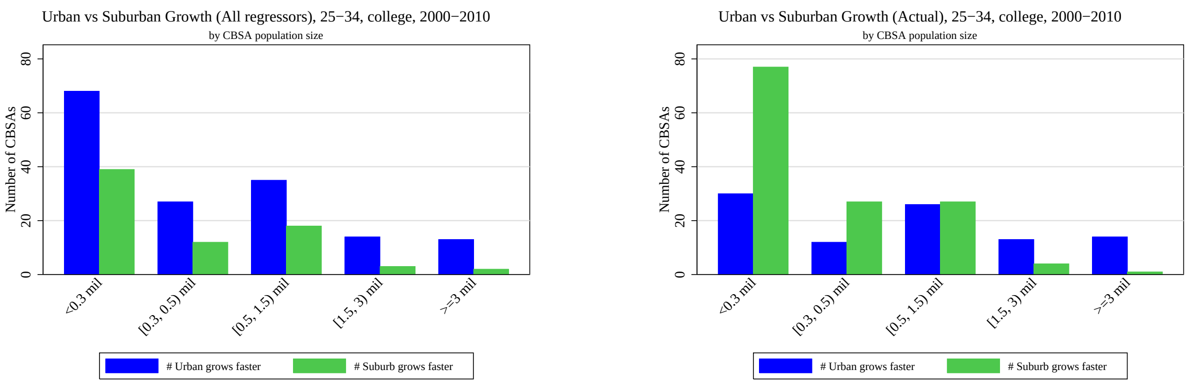
[37] The coefficient on house prices is negative for all age-education groups, except for 25-34 year-old college educated. Given how endogenous house prices are to increase in demand for living in a tract - especially from college-educated - we take this success rate in estimating negative coefficients as supporting the specification.

[38] The reverse pattern is true for other amenities like sports (e.g. gym) and general merchandise store that older sollege educated seem to prefer.

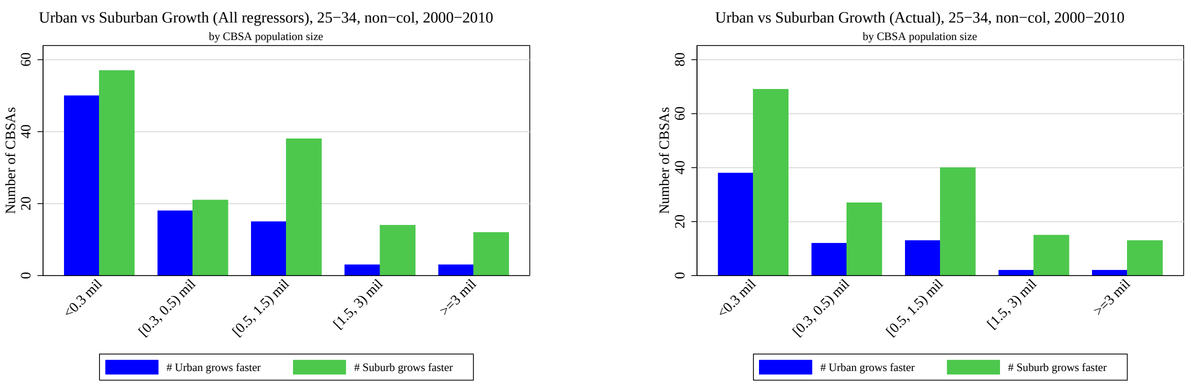
model with instrumental variables shown in Table 1. The histograms in Table 5 replicate those of Section 3, with the blue bar representing the number of CBSAs in which urban growth is faster than suburban growth, and the green bar representing the number of CBSAs in which suburban growth is faster than urban growth.[39] We again group CBSAs by population size bins, but this time we define five bin sizes: very large (>3M), large (1.5-3M), medium-sized (0.5-1.5M), small (0.3-0.5M) and very small (<0.3M) CBSAs. Panel A displays model-generated growth on the left and actual growth on the right, for the 24-35 year-old college-educated group. The model clearly captures the urbanization of young professionals, and generates faster urban than suburban growth in large and very large cities. The model also successfully explains our finding that very large and large cities almost all experience urban revival, while outcomes are much more uneven in smaller cities. Nevertheless, the model generates relatively faster urban growth in the smaller cities than what actually happened. Overall, the model does a great job at capturing the special features of downtowns, but it imperfectly captures the characteristics that make large cities special.[40]

Figure 5: Predicted vs Actual Urban-Suburban Growth: 25-34 year olds

Panel A



Panel B



In Panel B we produce the same histogram, but for 25-34 non-college-educated individuals, a group that is not urbanizing. In this case, the model correctly generates faster suburban growth in cities of all sizes. Interestingly, it also captures the better performance of smaller cities' downtowns for this group. Section F provides similar

[39] Note that the set of CBSAs is Figure 5 is not the same as that in the stylized facts of section 3, because some CBSAs drop out of our sample because of data issue, mostly due to lack of house price data.

[40] One could interpret this discrepancy as an optimistic statement on the future prospects of downtowns in medium and small cities, whose characteristics may be conducive to urban revival in the near future.

histograms for the remaining older age-education groups. Our predictions for these older cohorts match the data even better than those for the 25-34 year-old cohort.

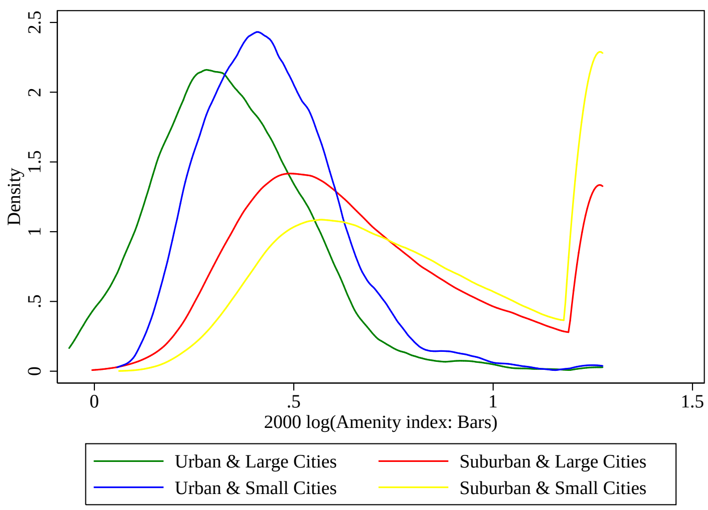
5.5 What variables explain urban revival?

We now investigate the ability of each of our control variable to explain urban revival. Given our stylized facts of fast urbanization of young professionals in large cities, we need to analyze each variable along three dimensions: first, its distribution in urban versus suburban areas, second, the relative preference of different age-education group for this variable, and third, its urban-suburban differential in large versus small cities. These characteristics suggest a rich variable classification. For instance, a variable that explains the urbanization of young professionals may fail to explain why this urbanization happens mostly in large cities, or may fail to explain why individuals lacking a college-education are not urbanizing. To reduce the number of possible cases, we emphasize three types of variables:

1. *Variables that explain the urbanization of young college-educated individuals:* Such a variable takes a larger (smaller) value in urban relative to suburban areas, and its coefficient is positive (negative) for young college-educated individuals.

2. *Variables that explain the faster urbanization of young college-educated individuals relative to non-college educated or older individuals:* Such a variable takes a larger (smaller) value in urban relative to suburban areas, and its coefficient is more positive (more negative) for young college-educated individuals relative to older or non-college educated individuals. Figure 6 provides an example of such a variable: the 2000 level of the bars amenity index (we provide a more systematic analysis in the next subsection). The plot shows the distribution of this index within 4 set of tracts: urban areas of large cities, urban areas of small cities, suburban areas of large cities, and suburban areas of small cities. In 2000, this index is lower in urban relative to suburban areas in both small and large cities. Table 1 also shows that the coefficient on this variable is larger for young college-educated individuals, relative to non-college-educated and older individuals. We conclude from this analysis that the 2000 level of bars is one factor explaining the urbanization of young professionals relative to older and non-college-educated individuals.

Figure 6: 2000 Log(Bars Amenity Index)



3. *Variables that explain the faster urbanization of young college-educated relative to older or non-college educated individuals in large cities:* Such a variable has an urban-suburban differential that is more positive (more negative) in large cities, and its coefficient is more positive (more negative) for young college-educated individuals relative to older or non-college educated individuals. The theater amenity index is one example of such a variable. Note, however, that theaters are an exception among amenities, which are generally urbanized but less so in large cities. For instance, the urban-suburban differential for bars is very similar in large and small cities, and actually more negative in smaller cities.

Before discussing the prevalence of each type of variable, it is useful to recall the importance of distinguishing variables in first-differences from variables in levels. The coefficient on a variable representing a 2000 level captures changes in preferences from 2000 to 2010, and tell us about the effect of the initial environment on location choices. The coefficient on a variable in first-difference captures the level of preferences in 2010 and tells us about the effect of changes in the environment on location choices.

For explanatory variables in levels, one can easily use the classification above to identify variables of type 1, which explain the urbanization of young professionals. Urban areas are denser, and therefore usually have lower amenity indexes and young professionals are attracted to these amenities. Most variables of the first type are also of the second type, because of the stronger shift in preferences of young college-educated individuals towards urbanized amenities relative to that of older, non-college-educated indivdiuals. There are, however, many fewer variables of the third type, because large cities tend to be denser everywhere, and do not necessarily have downtowns that are dense relative to their suburbs. This lack of type 3 variables corresponds to our finding above that our fitted model generates more urbanization in medium and small cities than what actually happened.

For explanatory variables in first-differences, however, it is harder to find variables that explain the urbanization of young prefessionals, because amenities have often been growing faster in suburban than in urban areas, and therefore changes in the density of amenities that young professionals like often work *against* their urbanization.

Table 7 helps to organize and vizualize these results. Panel A highlights variables of the second type, that can explain the urbanization of young college-educated individuals relative to non-college-educated individuals. Column 1 and 2 contain *non-standardized* coefficients for 25-34 year-old non-college group and for the 25-34 year-old college group, side-by-side. Column 3 and 4 contain the standardized mean value of different variables in urban and suburban areas. Combining this information is useful because variables explaining the urbanization of young professionals must have both a large difference in coefficients between college and non-college individuals and a large difference in mean value between urban and suburban areas. Column 5 contains the product of these two differences, and allows us to highlight (in green) the variables making the largest contribution to explaining the relative urbanization of young professionals, as well as highlight (in red) those variables delivering the strongest push in the opposite direction. Clearly, variables for levels of highly urbanized service amenities like theaters, bars and restaurants have the most explanatory power. Also apparent from Panel A is that many variables in first-difference, including bar and restaurant indexes, work against the urbanization of the college-educated, because such amenities have been growing faster in suburban areas over the last decade. The 2000 level of high-income job opportunities also work against the relative urbanization of young college-educated individuals, because it is an urbanized variable that the non-college educated are more attracted to.

Panel B allows us to classify variables of the third type, that can explain the relatively faster urbanization of college-educated individuals in large cities. Columns 1 and 2, as in Panel A, and show regression coefficients for the 25-34 year old non-college-educated and college-educated group. Columns 3 and 4, however, now display the mean urban-suburban differential in these variables. Looking at both Panels A and B, we see that only two variables, theater and general merchandize stores, show up in the "green" part of both panels, and are therefore able to perfectly explain our stylized facts on their own. In other words, college-educated individuals have a stronger

Figure 7

Panel A: What variables explain relative urbanization of college vs non-college?

Variable	Coefficient		Mean Value		Contribution
	Non-College	College	Suburban	Urban	
	[1]	[2]	[3]	[4]	[5] = ([2]-[1])*([4]-[3])
Theater	0.13	-0.57***	0.69	0.44	0.17
Bars	0.07	-0.28***	0.77	0.38	0.14
Restaurants	0.23**	-0.08	0.73	0.43	0.10
Food Stores	0.98***	0.67***	0.58	0.35	0.07
Δ Personal Services	-2.3***	-0.25	0.00	0.03	0.05
Job Opportunities -- Low Inc.	-0.41***	-0.14***	-1.10	-0.91	0.05
General Merchadise Stores	0.07	-0.16*	0.54	0.35	0.04
Sports	-0.26	-0.5***	0.57	0.39	0.04
		… … …			
Δ General Merchadise Stores	0.23	-0.41***	-0.04	-0.02	-0.01
Δ Restaurants	0.35	-0.27	-0.02	0.00	-0.01
Δ Food Stores	1.95***	0.9***	-0.01	0.00	-0.02
Δ Bars	0.12	-0.51***	0.01	0.04	-0.02
Job Opportunities -- High Inc.	0.15***	0.07***	-1.76	-1.49	-0.02
Apparel Stores	-0.38***	0	0.68	0.43	-0.10
Movie Theaters	-0.63***	-0.01	0.60	0.43	-0.10
Personal Services	-1.23***	0.04	0.56	0.32	-0.30

Panel B: What variables explain faster urbanizaton of college relative to non-college in large cities?

Variable	Coefficient		Urban-Suburban Differential		Contribution
	Non-College	College	Small Cities	Large Cities	
	[1]	[2]	[3]	[4]	[5] = ([2]-[1])*([4]-[3])
Personal Services	-1.23***	0.04	-0.29	-0.21	0.10
Theater	0.133	-0.57***	-0.20	-0.28	0.06
Job Opportunities -- Low Inc.	-0.41***	-0.14***	0.08	0.25	0.05
Δ Avg. Travel Distance	0.21***	0.07***	0.03	-0.16	0.03
Δ House Price Index	-0.15***	0.08***	-0.01	0.09	0.02
General Merchadise Stores	0.07	-0.16*	-0.17	-0.21	0.01
Δ Sports	-0.37	-0.77***	0.02	0.00	0.01
		… … …			
Bars	0.07	-0.28***	-0.41	-0.37	-0.01
Δ Personal Services	-2.3***	-0.25	0.03	0.02	-0.02
Job Opportunities -- High Inc.	0.15***	0.07***	0.11	0.38	-0.02
Movie Theaters	-0.63***	-0.01	-0.15	-0.18	-0.02
Restaurants	0.23**	-0.08	-0.35	-0.28	-0.02
Δ Theater	0.05	-1.18***	-0.01	0.00	-0.02
Δ Movie Theaters	-1.31***	-0.21*	0.05	0.00	-0.05

preference for these variables, they are relatively urbanized, and relatively more so in larger cities.

Table 7 therefore reiterates our key finding that many variables in levels, which we interpret as capturing changes in preferences, can explain the urbanization of young and college-educated individuals relative to old and non-college-educated individuals, while changes in the environment appear less important. Only a small set of variables explain why urban revival mostly happens in large cities, and as a result our model generates faster urban growth in medium and small cities than what actually happened.

6 Alternative Hypotheses

We now present various robustness exercises where we explore the role of other factors for which we have only limited data, and therefore choose not to include in our main analysis.

6.1 Commuting Analysis

One obvious unobservable in our analysis above is the location in which households in our data work. We can use the LODES commuting data to study whether this unobservable biases our results. To do this, we estimate a discrete-choice logit model that describes how households allocate across both residential and workplace tracts.[41] Preliminary results suggest that controlling for workplace location with workplace fixed effects only has a small effect on our regression coefficients.[42]

6.2 Household formation

Many urban observers, for instance Burayidi (2013), suggest that recent trends in household formation favor downtowns, for instance delayed marriage, family formation or childbearing. The underlying argument is simple; if household types more likely to live downtown have been growing faster among young professionals, then we predict young professionals to grow faster in urban areas relative to suburbs. For instance, if childless couples and singles have a higher propensity for urban living than families with children, then a national decline in these household types among young professionals may explain their urbanization.

Fortunately, this household formation hypothesis does not suffer from endogeneity concerns. In fact, the hypothesis that a household type decomposition predicts population growth has an exact counterpart in how Bartik (1991) and others use a sectoral decomposition to obtain an exogenous predictor of employment growth. We compute predicted population growth in an area based on national trends in household type composition from 2000 to 2010, interacted with the 2000 share of each household type in that area. We then assess the importance of these national trends in household formation by comparing the predicted growth of young professionals in the urban and suburban areas of each CBSA. Note that this household-type decomposition requires precise micro-data on the prevalence of each type of households within each demographic groups. This data is only available - i.e., geocoded - at the PUMA level. This is why we only perform this analysis in CBSA-level regressions.

6.2.1 Estimating Equation

The dependent variable in our CBSA-level regressions is our measure of urban revival, i.e., the difference between urban and suburban population growth from 2000 to 2010 in demographic group d in CBSA c. We denote this

[41] Details on this model are provided in Appendix G.

[42] The LODES data describes the locations of employed people and is disaggregated into three age and three wage groups and not the interaction between these groups. This population breakdown is not sufficiently disaggregated to replicate our main stylized facts presented in Section 3. While we explore obtaining the underlying micro data, we reserve the residential-workplace model for this robustness exercise and do not make it part of our main analysis.

actual growth differential by $\Delta g^{d}_{c,00-10}$.[43]

The household type decomposition generates a predicted population growth differential between urban and suburban areas for group d and CBSA c, that we denote by $\Delta\hat{g}^{d}_{c,00-10}$. To obtain this prediction, we exploit variation in the propensity of each household type to locate in urban areas, as well as variation in national growth across household types. That is, if household types that disproportionately choose to locate in urban areas are growing faster nationally, then we predict faster urban growth. We proceed as follow: For each demographic group d, denote by $s^{h,d}_{c,urb,00}$ the share of individuals in the urban area of CBSA c in 2000 who live in households of type h. For instance $s^{h,d}_{c,urb,00}$ could be the share of 25-35 college-educated individuals in the urban area of Chicago who lives in childless non-married couples. The equivalent suburban share is $s^{h,d}_{c,sub,00}$. The national growth rate in type h households within demographic group d between 2000 and 2010 is $g^{h,d}_{national,00-10}$. We compute this national growth by excluding CBSA c, although for simplicity this is not reflected in the notation. To obtain predicted growth in an area, we multiply the share of a given household type in 2000 in that area by the national growth of that household type between 2000 and 2010, and sum over all household types. So if households are decomposed into H household types, then the predicted population growth differential between the urban and suburban area of CBSA c for demographic group d can be written as:

$$\begin{aligned}\Delta\hat{g}^{d}_{c,00-10} &= \hat{g}^{d}_{c,urb,00-10} - \hat{g}^{d}_{c,sub,00-10} \\ &= \sum_{h=1}^{H} s^{h,d}_{c,sub,00} * g^{h,d}_{national,00-10} - \sum_{h=1}^{H} s^{h,d}_{c,sub,00} * g^{h,d}_{national,00-10}\end{aligned} \tag{11}$$

So we run the following regressions for each demographic group d, with each CBSA c as an observation:

$$\Delta g^{d}_{c,00-10} = \beta_1 \Delta\hat{g}^{d}_{c,00-10} + \epsilon^{d}_{c} \tag{12}$$

6.2.2 Data

The household type decomposition requires data on population by age-education groups and household types, at a geographic scale small enough to define urban areas. The Public Use Microdata Area (PUMA) is the smallest geographical unit at which Census and ACS microdata are available. Such microdata are necessary to decompose population into age-education group and household types. We therefore define urban areas as groups of PUMAs, and construct them by sequentially adding the PUMAs closest to the CBD until the total urban population reaches no more than 10% of total CBSA population. These urban areas are twice as large as those defined from census tracts in Section 3, because PUMAs are large and contain at least 100,000 individuals. This forces us to exclude the smallest CBSAs from our sample, because in this case a single PUMA encompasses the entire CBSA, and we are unable to define downtowns. We therefore restrict our CBSA sample to the 50 largest CBSAs. Within this sample, even the smallest CBSAs have an urban area, generally a single central PUMA, whose population is close to 10% of the CBSA's total.

To obtain the share of different household types within each age-education group in each area, we aggregate microdata from the 5% IPUMS sample of the 2000 census and the 5% IPUMS sample of the 2008-2012 editions of the ACS. We decompose each age-education group into 6 types of households:

1. Solo[44]

2. Non-married couple with no children

[43] Here we use Δ to denote an urban-suburban differential, unlike in previous sections in which Δ denotes a first-difference in time.

[44] Some solo individuals probably do not live alone, but instead live with unreported roommate(s).

3. Married couple with no children

4. Households with oldest children younger than 5 years old

5. Household with oldest children older than 5 years old

6. Others.

This decomposition accounts for the possibility that married couples have different locational preferences than non-married couples, for instance if marriage complements the purchase of a suburban house. It also distinguishes between households with only young children and households with at least one school age child, because better schools are often a key advantage of suburban living. Note that households with children can include any number of adults, for instance a single parent.

6.2.3 Results

We now test the household formation hypothesis. We first evaluate the claim that recent trends in household formation have favored downtowns generally. We then perform the growth decomposition described in subsection 6.2.1 to find out whether the hypothesis can predict which CBSAs will experience urban revival.

Figure 8: Demographic Decomposition

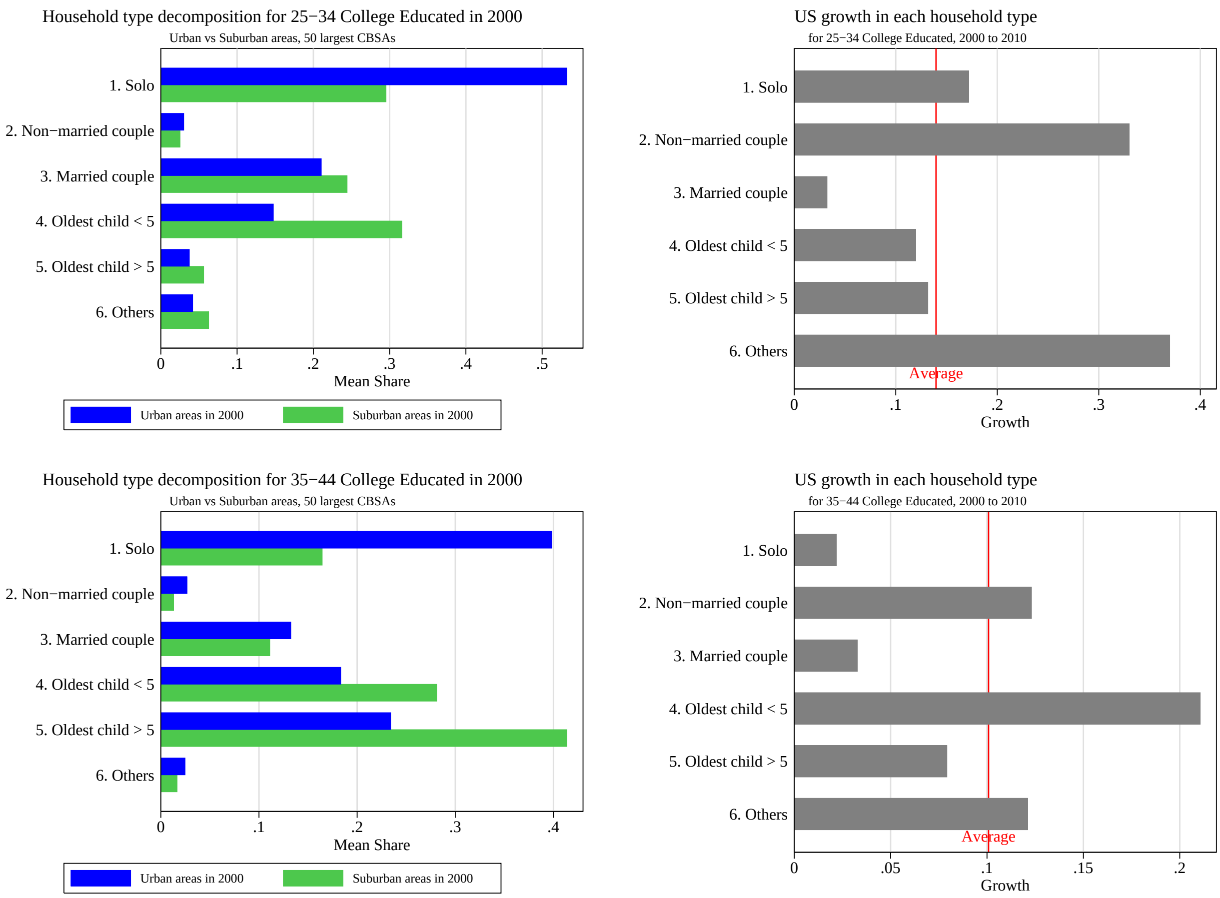


Figure 8 illustrates the component of this decomposition for the two demographic groups driving urban revival: college-educated 25-34 year olds (Panel A) and college-educated 35-44 year olds (Panel B). The left-hand side of each panel displays the share of individuals in each demographic group living in each household type within the 50 largest CBSAs. The blue bar represents the share of each household type among urban dwellers and the green bar represents this share among suburban dwellers (so the sum of all blue bars within a group is 1.) The right-hand side of each panel shows US growth rates for each household type, with the average growth rate for the entire demographic group denoted by a red line. Unsurprisingly, the share of individuals living solo is much larger in urban areas, for both demographic groups. For instance, 56% of urban college-educated 25-34 year old live solo, versus only 29% in the suburbs. For both groups, the share of childless non-married couple is small at less than 5%, and slightly larger in urban areas. The share of married childless couple is special because the younger and older groups display different locational patterns; among the younger 25-34 year old group married childless couple are more prevalent in the suburbs, while the reverse is true for the older 35-44 year old group. Finally, the share of individuals living in household types with children is higher in the suburbs for both groups.

To interpret the US growth rate in the right-hand graphs, recall that our hypothesis requires that household types more likely to live in urban areas experience faster national growth. For the younger group, this is true for 5 out of 6 household types. That is, the urbanized household types (solo people, childless non-married couples) are growing faster than average, while the suburbanized household types (childless married couples, household with oldest child < 5, household with oldest child > 5) are growing slower than average. The only exception is the household type "others" which is a small suburban group that is growing faster than average. We therefore confirm the basic intuition behind the household formation hypothesis for the younger group, and indeed aggregated over all 50 largest CBSAs, the decomposition in equation 11 predicts a difference of about 1 percentage point between urban and suburban growth. Note, however, that the actual urban-suburban growth differential for this group is about 10 times as large, at 11 percentage points.[45]

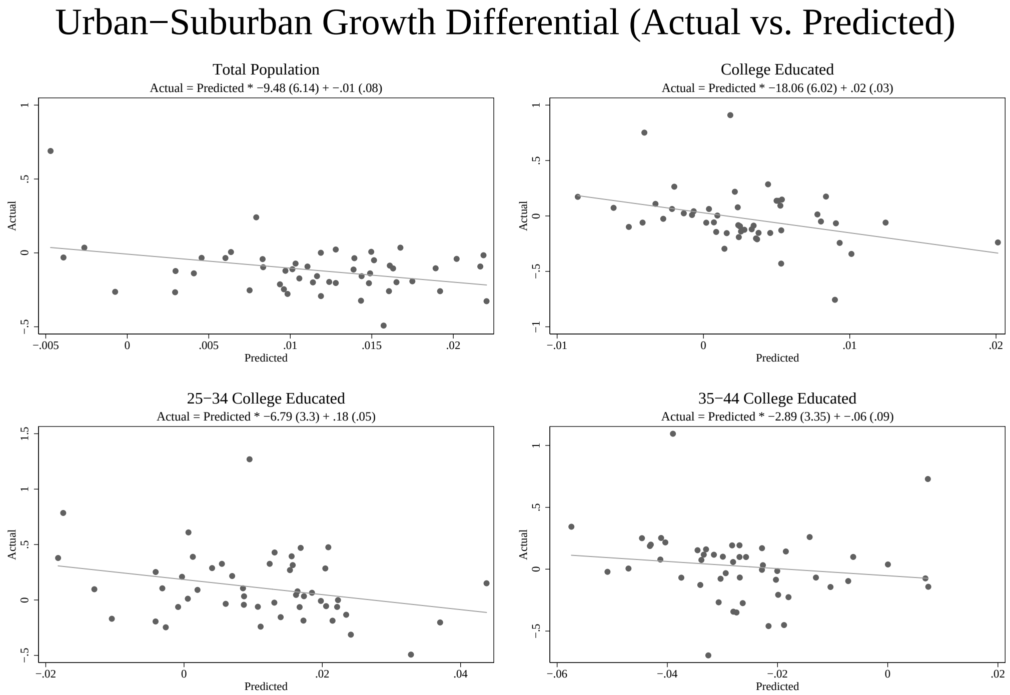
We now turn to the older group, and show that in this case the data *does not* support the household formation hypothesis. For instance, solo households, which are common in urban areas, have been growing much *slower* than average within the 35-44 year old college-educated group over the last decade. Families with young children, that are more common in the suburbs, have been growing *faster* than average. Overall, our household type decomposition predicts that the 35-44 year old college-educated group should grow on average 3 percentage point *slower* in urban areas relative to the suburbs within the 50 largest CBSAs. The actual urban-suburban growth differential for this group is positive at 2.5 percentage point.

Regression analysis confirms that recent trends in household formation do not explain the relative urban-suburban growth differentials in young professionals. Estimating the regression in equation 12 tells us whether urban-suburban growth differentials were larger in CBSAs in which the share of faster growing household type was larger in urban relative to suburban areas. Figure 9 contains estimation results for four different groups; total population, all college-educated, 25-34 year old college-educated and 35-44 year old college-educated individuals. Coefficients are never positive and significant, and in fact the coefficients are negative for all four groups, and significant for two of them. We also explore a number of alternative specifications, all of which confirm the irrelevance of household formation in explaining recent urbanization trends. For instance, we tried predicting CBSA urban growth using CBSA-level growth in given household types or initial urban shares of given household types, without success. It is particularly striking that urban growth has very little correlation with CBSA solo growth or with initial solo urban share.

Before concluding, we briefly evaluate a related hypothesis based on Costa and Kahn (2000)'s finding that college-educated couples have grown relatively faster in larger metropolitan areas from 1970 to 1990. Costa and Kahn (2000) argue that large labor markets solve a colocation problem for dual career households. Similar

[45] In Section 3, we obtain a larger, 30 percentage point differential betwen urban and suburban growth for this group. This is because urban areas constructed using PUMAs are about twice as large as those in Section 3 constructed out of tracts. The lower differential growth obtained when defining larger downtowns is consistent with our claim that urban revival happens in areas close to the CBD.

Figure 9: Can household formation patterns explain urban-suburban differentials in population growth?



Note: Predicted growth rates are calculated applying U.S. growth rates to local demographic shares.

forces may be pushing college-educated couples towards downtowns, in which high job concentration can provide both workers in a couple with a short commute. One testable implication of the hypothesis that urban revival is driven by married couples is that in urban areas, the share of married couples should increase relative to that of other household types. Figure A.8 in Appendix C.3 provides evidence against this claim. The share of different household types in the urban areas of the 50 largest CBSAs is relatively stable over the time period from 2000 to 2010. For the 25-34 college-educated group living in urban areas, there is in fact a small *increase* in the share of solo individuals and non-married couples, and a small *decrease* in the share of married couples or families with children.

We conclude that recent trends in household formation cannot explain the urbanization of young professionals between 2000 and 2010. This result is especially stark for college-educated 35-44 year olds, for whom household types that are relatively suburbanized have experienced faster national growth.

6.3 Crime

The well-documented decline in crime since 1990 (e.g., Levitt (2004)) is another explanation for the reurbanization of young college-educated Americans. If this reduction in crime affects the urban areas of large cities disproportionately, then it has the potential to explain urban revival. Kneebone and Garr (2010) study recent trends in property and violent crime in the 100 largest metropolitan areas. They document a clear trend towards lower crime from 1990 to 2008, especially in urban areas. Strikingly, 90 out of 100 metro areas saw faster decline in violent crime in their principal city than in their suburbs, which reduced the positive urban-suburban violent crime gap by two-thirds during this time period. Property crime trends are similar but less pronounced. For the purpose of our paper, it is important to note that the 1990s saw 80% of the net decline in violent and property crime from 1990 to 2008. As a result, much of the urban-suburban gap closes during the 1990s, and reductions in the urban-suburban crime gap are much smaller during the 2000s, during which urban revival happens.

A plausible, testable hypothesis is therefore that urban areas that had become relatively safe by 2000 experienced a reurbanization of young professionals in the following decade. Importantly, initial crime levels do not suffer from reverse causality in a regression on changes. However, they can be correlated with omitted variables that explain subsequent urban revival. We also run regressions using changes in crime as an independent variable, and we interpret these results as suggestive correlations. Unfortunately, Bartik-type predictions or plausible within-city instruments are not available to test the hypothesis that a decline in crime causes urban revival. We emphasize that the results of this section are a preliminary analysis, and we hope to investigate the relationship between urban revival and crime more thoroughly in future work.

6.3.1 Estimating equation

We define our explanatory crime variable as the initial difference in *per capita* crime level between the urban and suburban areas of CBSA c in 2000, denoted by $\Delta crime_{c,00}$.[46] So we run the following regression for each demographic group d, with each CBSA c as an observation:

$$\Delta g^{d}_{c,00,10} = \beta_3 \Delta crime_{c,00} + \epsilon^{d}_{c}. \tag{13}$$

6.3.2 Data

The crime regressions require data on reported crime in urban and suburban areas. We use the FBI Uniform Crime Reporting data for 2000 and 2010. The data is available at both the county level and at the place level.[47] We construct CBSAs out of counties and define urban areas at the place level, as the principal city of each CBSA, as in Kneebone and Garr (2010).[48] We define suburbs as all areas outside the principal city. For this draft, we use total reported crime divided by area population as our measure of per capita crime.[49]

6.3.3 Results

We estimate equation 13, which tells us whether CBSAs that had low per capita crime in their principal city relative to their suburbs in 2000 are experiencing a relatively faster increase in urban relative to suburban population for different demographic groups. The results are in Figure 10. The top panel contains regression results for all CBSAs and the bottom panel contains regression results for the 50 largest CBSAs, of which 40 are in our sample. The plots on the right-hand side present results for the entire population whereas the left-hand panel present results for the 25-34 year old college-educated group. As expected, all coefficients are negative, but only significant for the regression on the general population in the sample of all CBSAs. This casts doubt on the hypothesis that college-educated individuals moved back to principal cities of large CBSAs in the 2000s because of low urban crime. An important caveat is that coefficients are actually quite large for the college-educated groups, but with even larger standard errors. We therefore cannot reject the hypothesis of relatively important effects of 2000 crime level on subsequent urban revival. Another caveat of these regressions is that the urban-suburban crime differential may not

[46] We are also interested in how differential growth in urban and suburban per capita crime growth $\Delta g^{crime}_{c,00,10}$, correlates with the urbanization trends of different demographic group d.

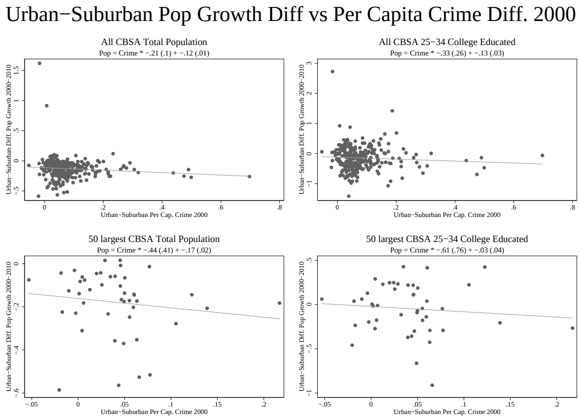
[47] We take the county level data from the University of Michigan version, which resolves inconsistencies in reporting through time, and provides a coverage indicator warning, for instance, if data was only reported for a few months in a given year. We take the place level data directly from the FBI website. In CBSAs for which the principal city is made out of counties - like New York City - we are able to verify that the place and county level datasets are consistent.

[48] Principal cities contain about 30% of the population on average for the 100 largest CBSA

[49] In future drafts we will run regressions on four different crime measures: the grand total of all reported crime, the number of arrests for violent crime, the number of arrests for property crime, and the number of arrest for individual crime (e.g., vandalism). We will also experiment with finer breakdowns for violent crimes (murder, rape, robbery, aggragravated assault) and property crime (burglary, larceny, motor vehicle, theft and arson).

be the correct regressor, if movers across CBSAs are an important driver of urban revival.[50] However, results are very similar if we estimate equation 5 with per capita urban crime in 2000 - instead of the urban-suburban crime differential - as a dependent variable.

Figure 10: Can differences in crime rates help explain urban-suburban differentials in population growth?



Finally, it is instructive to run a change-on-change regression, and to look at the correlation between urban-suburban population growth differential and urban-suburban per capita crime growth differential from 2000 to 2010. These regressions suffer from a reverse causality problem, but they confirm that urban revival goes hand-in-hand with a relative decline in urban per capita crime. Figure 11 presents the results, with again the top panel for all CBSAs, the bottom panel for the 50 largest CBSAs, total population on the right and the 25-34 year old college-educated on the left. For the sample of all CBSAs, we find very small coefficients, at the margin of significance.[51] The results for the 50 largest CBSAs, however, are striking. The coefficient is twice as large for young professionals than for the general population. For the 25-34 college-educated group, the coefficient on differential crime growth is -0.94, with a surprisingly good fit. Therefore, a 1 percentage point decrease in the urban-suburban per capita crime growth differential leads to a 1 percentage point increase in the urban-suburban young professional growth differential. Urban revival in large cities is therefore strongly correlated with a relative drop in urban relative to suburban crime.

These results either derive from a direct effect of crime on the location choices of young professionals, or from reverse causality if young professionals commit less crime than the general population, or else from omitted variables driving both trends. Further investigation reveals that within the 50 largest CBSAs, per capita urban crime declined by on average 20% across CBSAs, a reduction almost entirely due to a decline in total crime in the face of constant population. In the suburbs, per capita crime declined by 15% across CBSAs, a decline almost entirely due to rising population in the face of constant total crime. In fact, CBSA-level changes in the urban-suburban crime gap from 2000 to 2010 correlate with changes in urban composition and suburban population about equally, but not with changes in urban population or suburban composition. This is at least consistent with a story in which lower crime affects urban composition because of inelastic housing supply in downtowns, and suburban population because of elastic housing supply in suburbs.

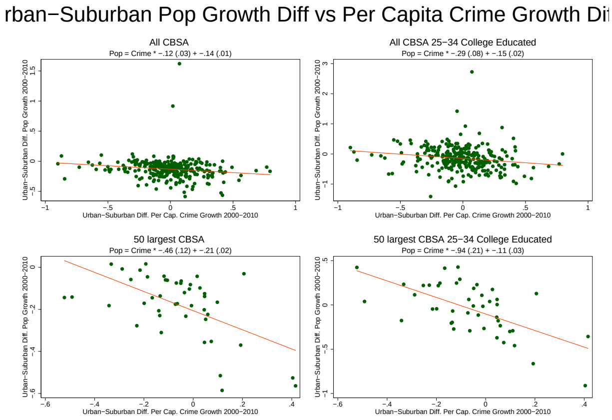
Overall, the evidence of this section is mixed. The large drop in crime of the 1990s did affect urban areas disproportionately (Kneebone and Garr (2010)), but 2000 crime levels do not predict urban revival with any degree

[50] Note that in the discrete-choice models of section 5 and G, individuals choose among all tracts in all CBSAs - so movers are allowed - with correlated error terms within CBSAs in the nested-logit specification.

[51] We removed 7 small CBSAs which were severe outliers with huge decreases in urban per capita crime. With these CBSAs the results for all CBSAs are not significant.

of precision. Within large - but not small - CBSAs, urban revival is highly correlated with a drop in urban relative to suburban per capita crime, but half of this effect depends on suburban dynamics. In future work, we hope to further investigate these trends, and in particular to assess the impact of urban revival on suburban poverty and crime.

Figure 11



6.4 Housing market hypothesis: Demand for owner-occupied housing

Another hypothesis with the potential to explain urban revival is reduced access to homeownership following the housing crisis and recession of 2007-2009. Given that rental units (almost always multifamily) are more urbanized that owner-occupied units (generally single-family homes), a decline in accessibility to home ownership that dispropotionately affected young professionals could pull them out of the suburbs and push them into urban areas.

There is much evidence that 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 the Fannie Mae and Freddie Mac rose from 725 in 2007 to more than 760 by 2010 (Parrott and Zandi 2013).[52] Presumably, this reduction in credit availability has been disproportionately harmful to younger individuals about to enter the housing market, and who may have been driven away from home ownership towards 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 includes more years of historically easy mortgage credit than of restricted credit. Using IPUMS data and a methodology similar to that in the household type decomposition of Subsection 6.2, we decompose the growth of 25-34 year old and 35-44 year old college-educated individuals by tenure type (owners and renters) from 2000 to 2010 (results not shown). We confirm that renters are more prevalent in urban areas, and that the younger group is more likely to rent. However, we find that homeowners have grown *faster* nationally than renters in both age groups.[53] Therefore, the premise of the housing market hypothesis that young professionals have been forced into renting from 2000 to 2010 is not supported by the data. In fact, further analysis reveals that ownership rates among young professionals have

[52] In 2010, Fannie and Freddie acquired 61% of total new home mortgage originations (Jaffee and Quigley, 2011).

[53] The number of 24-35 year old college-educated owners has grown by 19%, versus 8% for renters. For 35-44 year old college-educated, the number of owners has grown by 11% over the last decade, versus 6% for renters.

increased from 2000 to 2010, in both urban and suburban areas.

To provide additional support for this conclusion, in Appendix C.1.1 we replicate our stylized facts, but using the earliest available ACS data, from 2005-2009. We find patterns of urban revival that are very similar to those observed in later years. The housing crisis only covers half of the 2005-2009 time period, which again challenges to notion that reduced access to mortgage credit drives urban revival.

In future versions of this draft, we will perform a decomposition by tenure status of the location choices of young professionals. This decomposition, similar to the household type decomposition from section 6.2, will evaluate the claim that young college-educated individuals are more likely to rent in 2000 than in 2010, and that areas with a larger stock of rental units have experienced urban revival.

6.5 School quality

TBD

7 Discussion

Urban revival currently gathers considerable media attention and interest from the general public. We have shown that this revival is indeed happening in almost all large US cities, and is driven by the location decisions of the young and college-educated. While the rest of the country continues to move disproportionately to suburban areas, college-educated 25-44 year olds have flocked to downtown areas.

In this paper, we evaluate the importance of various explanations for this trend. In our main analysis, we find that diverging preferences for consumption amenities - such as retail, entertainment, and service establishments - explain the diverging location decisions of the young and college-educated relative to their non-college-educated peers and their older college-educated counterparts. In the same model, we find limited evidence that factors like changes in urban relative to suburban neighborhood characteristics, tastes for living in close proximity to job locations, or willingness-to-pay for housing help to explain why the young and college-educated are moving downtown in big cities, while the rest of the country is moving to the suburbs. In complementary analyses, our data rejects other hypotheses, such as changes in mortgage lending practices during the housing crisis and changes in household formation rates due to delayed marriage and childbirth. The evidence on crime is mixed and deserves further analysis.

The diverging preferences for consumption amenities to which we attribute urban revival are identified from a correlation between changes in the location choices of individuals in different age-education groups and the spatial distribution of consumption amenities in 2000. It is possible that this correlation is the result of some unobserved factor that we do not control for in our model. We note, however, that confounding factors must be both unobserved and time-varying, because the first-difference specification controls for any constant unobserved characteristics. Given the large number of (instrumented) controls for changes and levels that we include in our main analysis, as well as the checks that we perform to rule out alternative hypotheses, we find this unlikely. Of course, the source of such changing preferences for urban amenities remains unexplained. One possibility that we will explore in future version of this draft is that what we interpret as a change in preferences for proximity to amenities is in fact a change in amenity quality that is correlated with amenity density. This could happen if in urban areas stores like Whole Foods, which are popular with young professionals, are replacing stores like Save-A-Lot, which they avoid. Other explanations, such as a complementarity between urban living and mobile technology that benefits digitally savvy young professionals, are harder to test and remain speculative. Yet another explanation, which we are exploring in complementary work, is that young professionals now have higher disposable income than in

2000, and that downtown amenities are luxury goods. That being said it is striking that the classic factors used to explain household residential location decisions (jobs, housing, crime, and schooling) struggle to explain urban revival.

If the key factor at play is indeed a changing preference for urban consumption amenities, then there are important consequences for the sustainability of the urban revival trend and its welfare implications. Since these amenities are endogenous, their concentration will grow with local demand and may act as an anchor for the new generation of college-educated households, keeping them downtown even as they form families and as their demand for space and schooling rises. If we believe that tastes are diverging between the college-educated and their non-college-educated peers, then these consumption amenities will compensate the young and college-educated for the high housing prices that they will increasingly face in gentrifying downtown neighborhoods, but will offer little compensation for the non-college-educated households already living in downtown neighborhoods. These poorer households will either be displaced or have to pay the high housing costs to continue to live in downtown locations where the businesses offer fewer of the consumption amenities that suit their less luxurious tastes. We leave exploring these welfare implications to future work.

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Appendices

A Data Appendix

TBD

B Is urban revival a result of population growth or of changing composition?

Our finding that the general population is suburbanizing while the college-educated population is urbanizing suggests that changes in socio-economic composition within CBSAs are an important feature of urban revival. To assess the relative importance of changing population density versus changing composition as drivers of urban revival, we decompose the differences between urban and suburban growth into four components: the change in urban composition, the change in suburban composition, the change in urban population and the change in suburban population. To perform this decomposition, we denote by $s^d_{urb,00}$ the share of the total population of a given CBSA in 2000 that belongs to group d and lives in the urban area of that CBSA. $s^d_{sub,00}$ is similarly defined for suburban areas. Denote the number of individuals in group d living in the urban area of that CBSA in 2000 as $pop^d_{urb,00}$, and the number of individuals in group d in the surburban area as $pop^d_{urb,00}$. To refer to the general population in a CBSA - i.e., to the sum of all group d - we use the superscript $d = all$. The notation is the same for 2010 variables. Using this notation, $\frac{pop^d_{urb,10}/pop^d_{urb,00}}{pop^d_{sub,10}/pop^d_{sub,00}}$ measures the ratio of urban to suburban growth for group d, and it takes a value larger than 1 in CBSAs experiencing urban revival.[54] So for each group and each CBSA, our decomposition is:

$$\frac{pop^d_{urb,10}/pop^d_{urb,00}}{pop^d_{sub,10}/pop^d_{sub,00}} = \left(\frac{s^d_{urb,10}}{s^d_{urb,00}}\right)\left(\frac{s^d_{sub,00}}{s^d_{sub,10}}\right)\left(\frac{pop^{all}_{urb,10}}{pop^{all}_{urb,00}}\right)\left(\frac{pop^{all}_{sub,00}}{pop^{all}_{sub,10}}\right). \tag{A.1}$$

It is instructive to first look at the correlation between the 5 terms in equation A.1.

These correlations are in Table A.1. The table shows correlations for five different groups: all college-educated in panel A and 18-24 year old, 25-34 year old, 35-44 year old, and 45-64 year old college-educated in panels B through E. The most striking result from Table A.1 is the very high correlation (0.94 for the 25-34 year olds) between changes in urban composition $\left(\frac{s^d_{urb,10}}{s^d_{urb,00}}\right)$ and urban revival (the ratio of urban to suburban growth for group d, $\left(\frac{pop^d_{urb,10}/pop^d_{urb,00}}{pop^d_{sub,10}/pop^d_{sub,00}}\right)$). All other correlations are relatively small. This suggests that urban revival happens mostly through changing demographic and socio-economic composition within urban areas, rather than through urban population growth or changes in suburban composition. For instance, CBSAs experiencing urban revival do not display faster urban population growth $\left(\frac{pop^{all}_{urb,10}}{pop^{all}_{sub,00}}\right)$).

We also compute the mean value of each element in equationA.1, across the 50 largest CBSAs. The mean ratio of urban population in 2010 to urban population in 2000 $\left(\frac{pop^{all}_{urb,10}}{pop^{all}_{urb,00}}\right)$ is equal to 0.99. In other words, the downtown population of large cities barely changed, *on average,* from 2000 to 2010. For the same set of CBSAs, the mean ratio of suburban population in 2000 to suburban population in 2010 $\left(\frac{pop^{all}_{sub,00}}{pop^{all}_{sub,10}}\right)$ is 0.89, capturing a significant increase in the suburban population of large cities. Such an increase provides a strong force *against* urban revival as we define it. The average change from 2000 to 2010 in the share of a CBSA's population that

[54] Note that we express growth as a ratio x_{10}/x_{00} instead of $(x_{10} - x_{00})/x_{00} = x_{10}/x_{00} - 1$ as elsewhere in the paper.

Table A.1: Correlations Between Components of Urban vs. Surburban College-Educated Population Growth

Panel A: Total College-Educated Population

	(1)	(2)	(3)	(4)	(5)
(1)	1.00	0.03	-0.07	0.02	0.06
(2)	0.03	1.00	-0.02	-0.00	0.43
(3)	-0.07	-0.02	1.00	0.13	-0.05
(4)	0.02	-0.00	0.13	1.00	-0.01
(5)	0.06	0.43	-0.05	-0.01	1.00

Panel B: College-Educated Population aged 18-24

	(1)	(2)	(3)	(4)	(5)
(1)	1.00	-0.03	0.01	-0.00	0.10
(2)	-0.03	1.00	-0.01	-0.00	-0.68
(3)	0.01	-0.01	1.00	0.13	0.04
(4)	-0.00	-0.00	0.13	1.00	-0.02
(5)	0.10	-0.68	0.04	-0.02	1.00

Panel C: College-Educated Population aged 25-34

	(1)	(2)	(3)	(4)	(5)
(1)	1.00	0.08	0.08	0.11	-0.01
(2)	0.08	1.00	-0.01	0.00	-0.83
(3)	0.08	-0.01	1.00	0.13	0.05
(4)	0.11	0.00	0.13	1.00	-0.01
(5)	-0.01	-0.83	0.05	-0.01	1.00

Panel D: College-Educated Population aged 35-44

	(1)	(2)	(3)	(4)	(5)
(1)	1.00	-0.03	0.04	0.00	0.08
(2)	-0.03	1.00	-0.00	-0.00	0.01
(3)	0.04	-0.00	1.00	0.13	-0.04
(4)	0.00	-0.00	0.13	1.00	-0.05
(5)	0.08	0.01	-0.04	-0.05	1.00

Panel E: College-Educated Population aged 45-64

	(1)	(2)	(3)	(4)	(5)
(1)	1.00	-0.02	-0.16	-0.06	0.02
(2)	-0.02	1.00	0.01	-0.00	-0.53
(3)	-0.16	0.01	1.00	0.13	-0.09
(4)	-0.06	-0.00	0.13	1.00	-0.04
(5)	0.02	-0.53	-0.09	-0.04	1.00

Notes: This table depicts the correlations between tract-level relative urban-suburban college-educated population growth and the four components of this growth derived in equation (A.1). Column 1 is the ratio between the 2010 urban college share and the 2000 urban college share; column 2 is the ratio between the 2000 suburban college share and the 2010 suburban college share; column 3 is the ratio between the 2010 urban population and the 2000 urban population; column 4 is the ratio between the 2000 suburban population and the 2010 suburban population; and column 5 is the urban-suburban college popualation ratio in 2010 divided by the urban-suburban college population ratio in 2000.

is, 25-34 year old college-educated and lives in urban areas $\left(\frac{s^d_{urb,10}}{s^d_{urb,00}}\right)$ is 1.43 confirming a strong shift in urban composition towards young professionals. There is much less change in suburban composition over the same period, and the average value of $\left(\frac{s^d_{sub,00}}{s^d_{sub,10}}\right)$ is 0.97.[55] While these results highlight clear patterns, they also hide interesting underlying variation. For instance, a rust-belt city like Cleveland has experienced urban revival in the face of a rapidly declining urban population (2010 to 2000 ratio of 0.88), thanks to huge improvements in urban composition (2010 to 2000 ratio of 1.78 for the 25-34 year old college-educated group).[56] To summarize, urban composition is changing fast enough to generate a strong trend towards the urbanization of young professional in large cities, despite stagnant urban and rising suburban populations.

C Additional figures

C.1 Additional figures for stylized facts

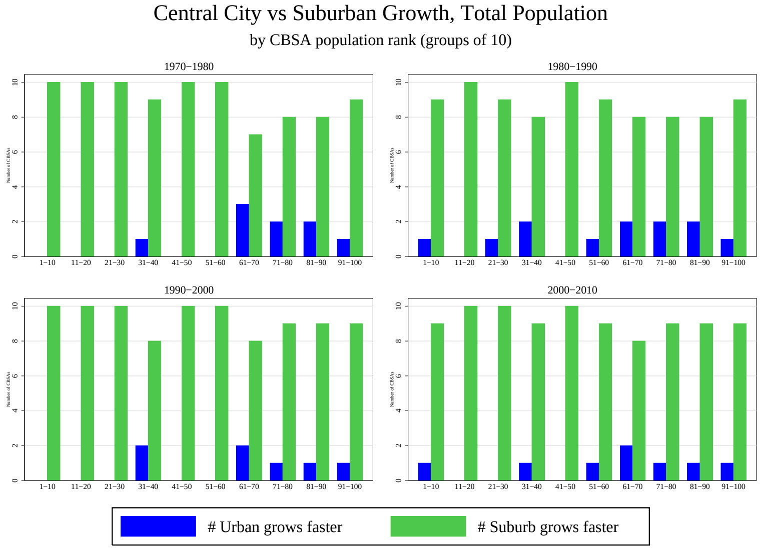
C.1.1 Alternative "urban" definitions

Figure A.1, A.2 and A.3 replicate figure 1, 1b and 2 but urban areas defined as a central cities instead of downtowns. The recent trends in the urbanization of young professional is still visible, but substantially attenuated. The urban areas in the text contain 5% of the population, while central cities, in the 50 largest CBSAs, account on average for about 30% of CBSA population.

[55] For the 35-44 year-old group these numbers are 1.21 and 0.99 and for the 18-24 year-old group we find 1.59 and 0.84. It particularly interesting to note that for the 65+ group, these numbers are 1.4 and 0.71. Clearly, then, urban areas have experienced population shifts towards 65+ (or 45-65) college-educated that are as fast as those for young professionals, which may explain the conventional widsom that baby-boomers are returning to urban areas. However, the population of older college-educated Americans has grown even faster in the suburbs, and therefore does not appear to display a strong new preference for downtown living. This large growth in educated baby-boomers everywhere is of course of function of the large relative size of this generation.

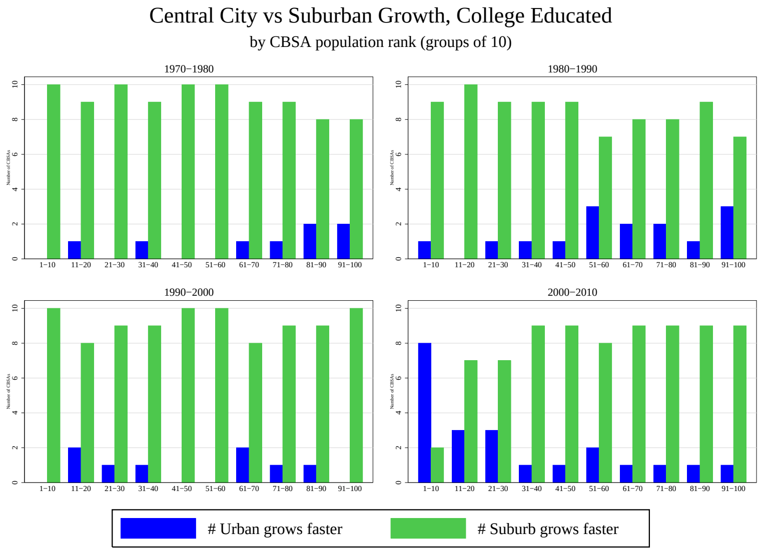
[56] Detroit is the only city in which young professionals are not growing faster downtown relative the surburbs so it is interesting to consider its recent growth dynamics. In fact Detroits young professional composition is favoring urban areas. For the 25-34 year old college-educated group, Detroit has a 2010 to 2000 urban composition ratio of 1.02, which is the worse performance among the 50 largest CBSAs, but still an improvement. The suburbs are doing even worse, however, with a 2000 to 2010 suburban composition ratio of 1.10, which is the 3rd worse among the 50 largest CBSAs. So in Detroit composition change favor urban areas. Unfortunately, Detroit has experienced the largest urban population drop among the 50 largest CBSAs, with a 2010 to 2000 ratio of 0.77. Even Detroit‘s stable suburban population ranks it 47th out of 50 in terms of suburban growth. Clearly Detroit is stuggling. One bright spot is that younger 18-24 college-educated group, a very small cohort, is actually growing faster in urban areas relative to the suburbs, thanks to huge composition changes. This may annouce future trends.

Figure A.1



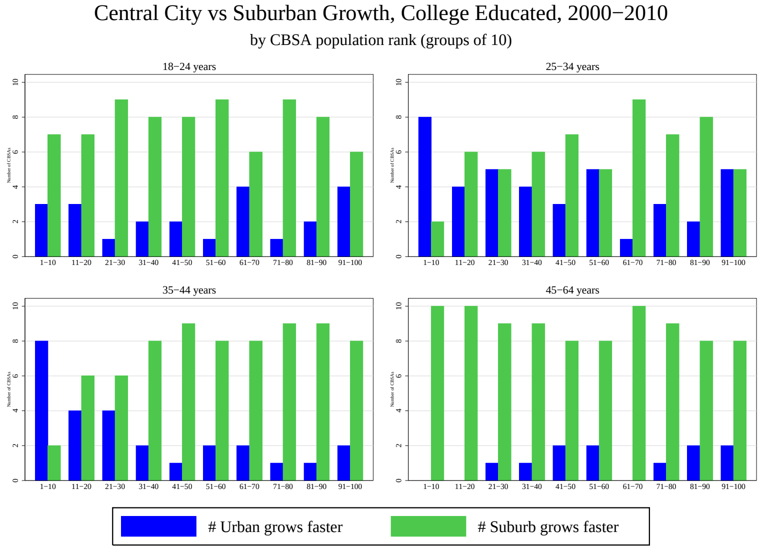
Notes: Data from decennial census 1970–2000 and ACS 2008–2012. Each of the figure's four plots presents data for a different decade, starting from 1970–1980 in the upper left-hand plot to 2000–2010 in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, the urban area is defined as the central city, and the suburb contains the rest of the CBSA. The blue bar represents the number of CBSAs in which urban population has been growing faster than suburban population within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban population has been growing faster.

Figure A.2



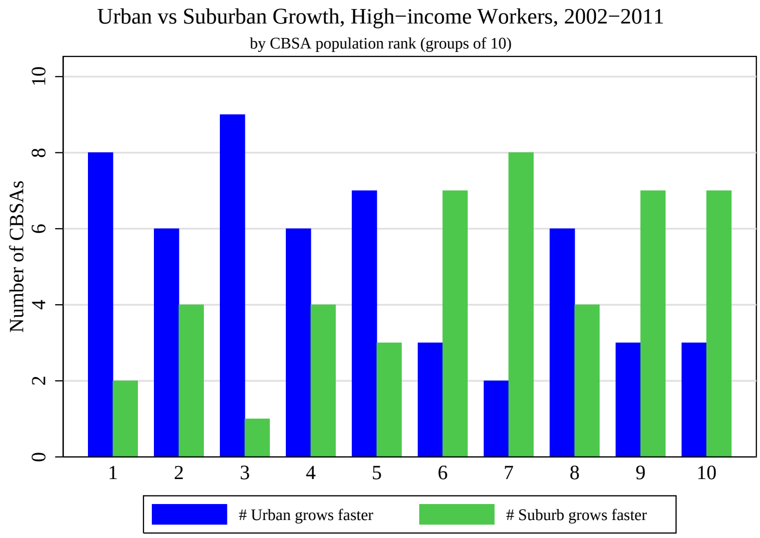
Notes: Data from decennial census 1970-2000 and ACS 2008-2012. Each of the figure's four plots presents data for a different decade, starting from 1970-1980 in the upper left-hand plot to 2000-2010 in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, the urban area is defined as the central city, and the suburb contains the rest of the CBSA. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown college-educated (at least 4 year degree) population has been growing faster than suburban college-educated population within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban college-educated population has been growing faster.

Figure A.3



Notes: Data from decennial census 2000 and ACS 2008-2012. All plots are for 2000-2010. Each of the figure's four plots presents data for a different age group within the college-educated (at least 4 year degree) population, starting from 18-24 year old college-educated in the upper left-hand plot to 45-64 year old college-educate in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, the urban area is defined as the central city, and the suburb contains the rest of the CBSA. The suburb contains the rest of a CBSA. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown college-educated population in a given age group has been growing faster than suburban college-educated population of that age group within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban college-educated population of a given age group has been growing faster.

Figure A.4



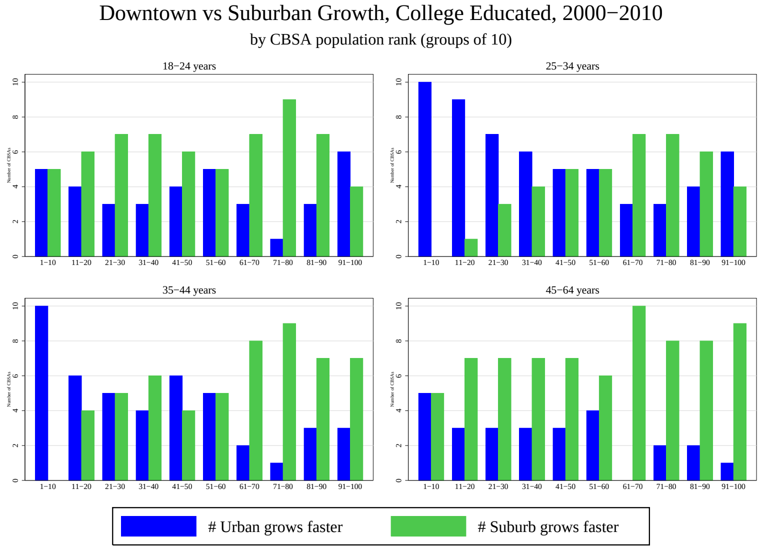
Notes: Data from LODES 2002 and 2011. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, downtown is defined as all census tracts nearest to the CBD and totaling at most 5% of a CBSA population. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown high-income worker (>$3333 per month) population has been growing faster than suburban high-income worker population within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban population has been growing faster.

Figure A.4 shows urban and suburban growth using the same urban areas as in the main text, but using a different data set (LODES) and a different demographic group; high income workers earning more than $3333 per month. Again, we find that most large cities have experienced faster urban growth between 2002 and 2011, a pattern less pronounced in smaller cities.

C.1.2 Alternative time-frame

Figure A.5 replicates Figure 2, but uses 2005-2009 ACS data to measure 2010 population.

Figure A.5: Downtown vs. Suburban Growth in the Largest 100 U.S. CBSAs, 2000-2010, College Educated (2010 population measured using 2005-2009 ACS)



Notes: Data from decennial census 2000 and the ACS 2005–2009. All plots are for 2000–2010. Each of the figure's four plots presents data for a different age group within the college-educated (at least 4 year degree) population, starting from 18-24 year old college-educated in the upper left-hand plot to 45-64 year old college-educate in the lower right-hand plot. The x-axis ranks the 100 largests CBSAs by 2010 population, in groups of 10. For each CBSA, downtown is defined as all census tracts nearest to the CBD and totaling at most 5% of a CBSA population. The suburb contains the rest of a CBSA. The blue bar represents the number of CBSAs in which downtown college-educated population in a given age group has been growing faster than suburban college-educated population of that age group within a group of 10 CBSAs. The green bar represents the number of CBSAs in which suburban college-educated population of a given age group has been growing faster.

C.2 Additional figures for commuting patterns

Figure A.6: National Commuting Patterns by Age and Income

Young Workers (29 or younger) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-23.29	-24.41	-20.68	-12.36	0.39	1.24	9.59	-69.53
[1,2)	-21.52	-20.53	-22.66	-15.37	-4.94	-0.91	0.31	-85.61
[2,4)	-20.45	-17.44	-19.13	-14.55	-8.46	-5.32	2.47	-82.88
[4, 8)	-14.93	-9.40	-12.75	-13.87	-8.94	-5.20	-0.78	-65.87
[8, 16)	-6.44	0.17	-3.55	-4.37	-8.74	-0.08	6.82	-16.19
[16, 32)	1.43	11.84	8.29	7.66	2.01	-8.16	6.61	29.68
32+	14.47	27.55	21.58	22.91	25.14	19.13	1.58	132.37
All	-70.73	-32.20	-48.89	-29.95	-3.55	0.70	26.60	

Middle-Age Workers (30 to 54) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-18.99	-18.12	-16.50	-7.44	1.28	4.44	9.03	-46.28
[1,2)	-19.26	-18.25	-18.34	-11.58	-1.13	2.05	4.23	-62.28
[2,4)	-17.46	-15.24	-15.07	-11.01	-3.81	0.09	5.49	-57.00
[4, 8)	-8.89	-6.58	-8.68	-8.66	-2.90	2.01	1.77	-31.92
[8, 16)	2.20	7.03	2.32	2.47	-2.39	4.74	9.11	25.49
[16, 32)	14.58	20.95	15.78	16.31	10.37	-2.30	8.19	83.88
32+	26.26	34.69	27.47	32.63	35.39	24.29	3.64	184.37
All	-21.55	4.49	-13.01	12.73	36.82	35.32	41.47	

Old Workers (55 or older) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	19.88	24.01	27.38	40.91	51.00	57.79	57.00	277.96
[1,2)	22.15	23.94	20.82	34.84	47.79	54.17	37.51	241.21
[2,4)	27.26	25.53	22.90	31.66	45.21	50.68	53.87	257.12
[4, 8)	41.73	42.26	34.54	33.02	43.34	54.48	43.03	292.41
[8, 16)	61.98	64.39	57.25	55.09	42.53	54.40	58.56	394.21
[16, 32)	81.37	88.45	81.05	83.71	71.72	43.86	62.49	512.64
32+	94.65	101.31	95.07	102.61	105.42	93.01	53.06	645.14
All	349.03	369.89	339.01	381.84	407.02	408.39	365.52	

Low-Income (=< $1250/month) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-38.73	-37.71	-33.83	-25.29	-19.17	-17.83	-11.33	-183.89
[1,2)	-36.40	-33.54	-33.53	-25.14	-18.02	-17.42	-15.96	-180.02
[2,4)	-31.83	-30.41	-29.15	-23.22	-16.79	-14.01	-11.76	-157.17
[4, 8)	-23.89	-21.68	-21.55	-20.68	-14.53	-8.53	-9.60	-120.45
[8, 16)	-12.88	-12.11	-11.48	-10.53	-13.95	-4.08	-0.47	-65.50
[16, 32)	-3.49	0.78	0.52	3.91	-0.74	-13.34	-1.07	-13.43
32+	8.71	20.55	13.90	17.26	20.55	16.59	-7.08	90.48
All	-138.50	-114.12	-115.12	-83.69	-62.65	-58.63	-57.27	

Middle-Income ($1250/month ~$3333/month) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-25.54	-23.11	-19.97	-10.01	-9.80	-9.58	-3.34	-101.36
[1,2)	-28.48	-21.92	-21.31	-14.38	-10.58	-9.64	-11.93	-118.23
[2,4)	-28.54	-22.70	-19.00	-13.70	-11.47	-11.85	-4.37	-111.63
[4, 8)	-24.30	-18.50	-15.93	-11.64	-9.65	-7.15	-4.15	-91.32
[8, 16)	-18.50	-12.11	-9.77	-5.48	-8.39	-2.22	6.51	-49.97
[16, 32)	-10.35	-0.50	2.51	4.75	-0.58	-8.45	3.45	-9.17
32+	14.75	25.67	24.29	30.13	29.49	18.42	-0.38	142.36
All	-120.95	-73.17	-59.19	-20.32	-20.99	-30.48	-14.21	

High-Income (>$3333/month) — Distance between Residence and CBD (miles) (rows) × Distance between Workplace and CBD (miles) (columns)

	[0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	48.50	57.94	56.53	68.80	80.03	67.23	80.11	459.14
[1,2)	42.10	43.55	35.84	49.18	60.61	57.19	66.97	355.43
[2,4)	33.58	41.49	33.63	38.97	46.45	48.02	62.66	304.81
[4, 8)	38.48	48.31	33.84	33.99	38.82	40.87	43.56	277.87
[8, 16)	45.42	61.98	45.57	42.76	35.51	40.58	42.34	314.14
[16, 32)	56.01	71.58	55.56	54.37	44.16	36.48	47.12	365.30
32+	75.52	83.88	73.26	76.90	76.83	61.85	51.69	499.92
All	339.61	408.73	334.22	364.97	382.40	352.23	394.45	

Notes: Data from LODES 2002 and 2011. The top three matrices present national commuting patterns for young workers(<= 29), middle-age workers (30-54), and old workers (>= 55); the bottom three matrices present national commuting patterns for low-income workers(<=$1250/month), mid-income workers ($1250/month-$3333/month), and high-income workers (>$3333/month). Given a row, the distance between workplace tracts and CBDs increases from left to right; in each column, the distance between residence tracts and CBDs increases from top to bottom. Each cell represents the percentage change from 2002 to 2011 of the number of certain type of people working and living at given distances from CBDs. Red cells indicate increase in the number of people working and living at given distances from CBDs whereas blue cells indicates small changes, even decrease, in the number of people working and living at given distances. The darker the cell colors are, the more dramatic changes are.

Figure A.7: Commuting Patterns by Age and Income in the Top Ten CBSAs

Young Workers (29 or younger)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-23.29	-24.41	-20.68	-12.36	0.39	1.24	9.59	-69.53
[1,2)	-21.52	-20.53	-22.66	-15.37	-4.94	-0.91	0.31	-85.61
[2,4)	-20.45	-17.44	-19.13	-14.55	-8.46	-5.32	2.47	-82.88
[4, 8)	-14.93	-9.40	-12.75	-13.87	-8.94	-5.20	-0.78	-65.87
[8, 16)	-6.44	0.17	-3.55	-4.37	-8.74	-0.08	6.82	-16.19
[16, 32)	1.43	11.84	8.29	7.66	2.01	-8.16	6.61	29.68
32+	14.47	27.55	21.58	22.91	25.14	19.13	1.58	132.37
All	-70.73	-32.20	-48.89	-29.95	-3.55	0.70	26.60	

Middle-Age Workers (30 to 54)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-18.99	-18.12	-16.50	-7.44	1.28	4.44	9.03	-46.28
[1,2)	-19.26	-18.25	-18.34	-11.58	-1.13	2.05	4.23	-62.28
[2,4)	-17.46	-15.24	-15.07	-11.01	-3.81	0.09	5.49	-57.00
[4, 8)	-8.89	-6.58	-8.68	-8.66	-2.90	2.01	1.77	-31.92
[8, 16)	2.20	7.03	2.32	2.47	-2.39	4.74	9.11	25.49
[16, 32)	14.58	20.95	15.78	16.31	10.37	-2.30	8.19	83.88
32+	26.26	34.69	27.47	32.63	35.39	24.29	3.64	184.37
All	-21.55	4.49	-13.01	12.73	36.82	35.32	41.47	

Old Workers (55 or older)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	19.88	24.01	27.38	40.91	51.00	57.79	57.00	277.96
[1,2)	22.15	23.94	20.82	34.84	47.79	54.17	37.51	241.21
[2,4)	27.26	25.53	22.90	31.66	45.21	50.68	53.87	257.12
[4, 8)	41.73	42.26	34.54	33.02	43.34	54.48	43.03	292.41
[8, 16)	61.98	64.39	57.25	55.09	42.53	54.40	58.56	394.21
[16, 32)	81.37	88.45	81.05	83.71	71.72	43.86	62.49	512.64
32+	94.65	101.31	95.07	102.61	105.42	93.01	53.06	645.14
All	349.03	369.89	339.01	381.84	407.02	408.39	365.52	

Low-Income (=< $1250/month)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-38.73	-37.71	-33.83	-25.29	-19.17	-17.83	-11.33	-183.89
[1,2)	-36.40	-33.54	-33.53	-25.14	-18.02	-17.42	-15.96	-180.02
[2,4)	-31.83	-30.41	-29.15	-23.22	-16.79	-14.01	-11.76	-157.17
[4, 8)	-23.89	-21.68	-21.55	-20.68	-14.53	-8.53	-9.60	-120.45
[8, 16)	-12.88	-12.11	-11.48	-10.53	-13.95	-4.08	-0.47	-65.50
[16, 32)	-3.49	0.78	0.52	3.91	-0.74	-13.34	-1.07	-13.43
32+	8.71	20.55	13.90	17.26	20.55	16.59	-7.08	90.48
All	-138.50	-114.12	-115.12	-83.69	-62.65	-58.63	-57.27	

Middle-Income ($1250/month ~$3333/month)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	-25.54	-23.11	-19.97	-10.01	-9.80	-9.58	-3.34	-101.36
[1,2)	-28.48	-21.92	-21.31	-14.38	-10.58	-9.64	-11.93	-118.23
[2,4)	-28.54	-22.70	-19.00	-13.70	-11.47	-11.85	-4.37	-111.63
[4, 8)	-24.30	-18.50	-15.93	-11.64	-9.65	-7.15	-4.15	-91.32
[8, 16)	-18.50	-12.11	-9.77	-5.48	-8.39	-2.22	6.51	-49.97
[16, 32)	-10.35	-0.50	2.51	4.75	-0.58	-8.45	3.45	-9.17
32+	14.75	25.67	24.29	30.13	29.49	18.42	-0.38	142.36
All	-120.95	-73.17	-59.19	-20.32	-20.99	-30.48	-14.21	

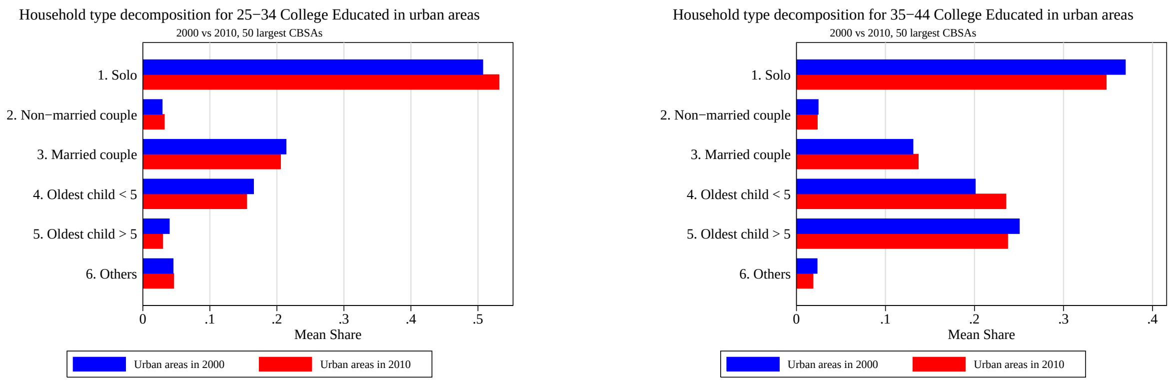
High-Income (>$3333/month)

Distance between Residence and CBD (miles)	Distance between Workplace and CBD (miles): [0, 1)	[1,2)	[2,4)	[4, 8)	[8, 16)	[16, 32)	32+	All
[0, 1)	48.50	57.94	56.53	68.80	80.03	67.23	80.11	459.14
[1,2)	42.10	43.55	35.84	49.18	60.61	57.19	66.97	355.43
[2,4)	33.58	41.49	33.63	38.97	46.45	48.02	62.66	304.81
[4, 8)	38.48	48.31	33.84	33.99	38.82	40.87	43.56	277.87
[8, 16)	45.42	61.98	45.57	42.76	35.51	40.58	42.34	314.14
[16, 32)	56.01	71.58	55.56	54.37	44.16	36.48	47.12	365.30
32+	75.52	83.88	73.26	76.90	76.83	61.85	51.69	499.92
All	339.61	408.73	334.22	364.97	382.40	352.23	394.45	

Notes: Data from LODES 2002 and 2011. The top three matrices present national commuting patterns for young workers($\leq$29), middle-age workers (30-54), and old workers ($\geq$ 55); the bottom three matrices present national commuting patterns for low-income workers($\leq$\$1250/month), mid-income workers (\$1250/month-\$3333/month), and high-income workers (>\$3333/month). Given a row, the distance between workplace tracts and CBDs increases from left to right; in each column, the distance between residence tracts and CBDs increases from top to bottom. Each cell represents the percentage change from 2002 to 2011 of the number of certain type of people working and living at given distances from CBDs. Red cells indicate increase in the number of people working and living at given distances from CBDs whereas blue cells indicates small changes, even decrease, in the number of people working and living at given distances. The darker the cell colors are, the more dramatic changes are. Top ten CBSAs are New York-Newark-Jersey City, Chicago-Naperville-Elgin, Dallas-Fort Worth-Arlington, Dallas-Fort Worth-Arlington, Houston-The Woodlands-Sugar Land, Washington-Arlington-Alexandria, Miami-Fort Lauderdale-West Palm Beach, Atlanta-Sandy Springs-Roswell, San Francisco-Oakland-Hayward, and Detroit-Warren-Dearborn.

C.3 Additional figures for household type decomposition

Figure A.8: Household type decomposition in urban areas



D Full solution of monocentric city model

To close the monocentric city model we solve the land market equilibrium. We assume a fixed population of poor households $N_p$and of rich household N_r. We consider a case with absentee landlords who collect all the rent. We ignore the market for housing construction - see Duranton and Puga (2015) for an example in which this is explicitely modeled - so h can be thought of in unit of land, and $1/h$ becomes population density. Using the FOC of the utility maximization problem $\gamma/h_d(x) = p_d(x)$ and our solution for $p_d(x)$ we can rewrite density as $1/h_d(x) = K_d p_d(x) = K_d e^{-\frac{\alpha_d}{\gamma_d}A_d x - \frac{\tau_d}{\gamma_d}T_d x}$.To simplify this expression we define $\theta_d = \frac{\alpha_d}{\gamma_d}A_d + \frac{\tau_d}{\gamma_d}T_d$ and rewrite density as $1/h_d(x) = e^{-\theta_d x}$. We know construct an equilibrium in which the poor live in the suburbs and the rich live downtown. Solving for the land market equilibrium conditions allows us to recover K_d as a function of the model's parameter. The land market equilibrium condition for the rich is:

$$N_r = K_r \int_0^{\tilde{x}} e^{-\theta_r x} dx = K_p \frac{1}{\theta_r}(1 - e^{-\theta_r \tilde{x}}),$$

from which we isolate $K_r = \frac{\theta_r N_r}{1-e^{-\theta_r \tilde{x}}}$ from which we can find $p_r(x) = \frac{\theta_r N_r e^{-\theta_r x}}{1-e^{-\theta_r \tilde{x}}}$. Before solving the land market equilibrium of the poor, we need an assumption on land value outside the city, which determines the city boundary $\bar{x}$. For simplicity, we assume that land has a value of 0 outside the city, which by inspection of the bid-rent funciton implies that a city of infinite size. We are not ready to solve for the land market equilibrium of the poor as:

$$N_p = K_p \int_{\tilde{x}}^{\bar{x}} e^{-\theta_p x} dx = K_p \frac{1}{\theta_p} e^{-\theta_p \tilde{x}}.$$

Using this condition we isolate $K_p = \frac{\theta_p N_p}{e^{-\theta_p \tilde{x}}}$, from which we can find $p_p(x) = \frac{\theta_p N_p e^{-\theta_p x}}{e^{-\theta_p \tilde{x}}}$. Remind that $\tilde{x}$ is defined such that $p_p(\tilde{x}) = p_r(\tilde{x})$. We write this condition as:

$$\frac{\theta_p N_p e^{-\theta_p \tilde{x}}}{e^{-\theta_p \tilde{x}}} = \frac{\theta_r N_r e^{-\theta_r \tilde{x}}}{1 - e^{-\theta_r \tilde{x}}}.$$

Some simple algebra yields:

$$\tilde{x} = -\frac{1}{\theta_r} ln \left(\frac{\theta_p N_p}{\theta_p N_r + \theta_p N_p} \right)$$

Note here that the natural logarithm of a positive number smaller than 1 is negative. So this closes the model; we have shown that $\tilde{x}$ is unique and that $\tilde{x} \in (0, \bar{x})$.

E Additional Regression Results

Table A.2: OLS Nested-Logit Regression for Census Residential Model

	Non-college			College		
	(1) 25-34	(2) 35-44	(3) 45-65	(4) 25-34	(5) 35-44	(6) 45-65
log(*share of 10 yrs younger, same inc*)_2000	0.0411*** (0.0013)	0.0396*** (0.0014)	0.0162*** (0.0015)	-0.00111 (0.00073)	0.0215*** (0.0012)	0.0225*** (0.0019)
Δ log(*housing index- all homes*)	0.00343*** (0.00096)	-0.00174 (0.00092)	-0.00102 (0.00095)	0.0582*** (0.00074)	-0.0126*** (0.00068)	-0.0119*** (0.00068)
log(*housing index- all homes*)_2000	-0.0208*** (0.0012)	0.0272*** (0.0011)	0.0115*** (0.0012)	-0.00220* (0.00086)	0.0138*** (0.00076)	-0.0141*** (0.00073)
Δ log(*avg. num job opp–low inc.*)	-0.191*** (0.0029)	-0.186*** (0.0028)	-0.0994*** (0.0029)	-0.0758*** (0.0020)	-0.0983*** (0.0019)	-0.0447*** (0.0019)
Δ log(*avg. num job opp–mid inc.*)	0.166*** (0.0037)	0.292*** (0.0036)	0.160*** (0.0037)	0.0592*** (0.0027)	0.130*** (0.0024)	0.0996*** (0.0024)
Δ log(*avg. num job opp–high inc.*)	0.0260*** (0.0027)	-0.0621*** (0.0025)	-0.0351*** (0.0026)	0.0313*** (0.0020)	-0.00434* (0.0018)	-0.0101*** (0.0017)
log(*avg. num job opp–low inc.*)_2002	-0.216*** (0.0032)	-0.247*** (0.0030)	-0.110*** (0.0031)	-0.0482*** (0.0023)	-0.186*** (0.0021)	-0.158*** (0.0021)
log(*avg. num job opp–mid inc.*)_2002	0.259*** (0.0034)	0.416*** (0.0033)	0.219*** (0.0034)	0.120*** (0.0027)	0.255*** (0.0024)	0.265*** (0.0024)
log(*avg. num job opp–high inc.*)_2002	-0.0468*** (0.0023)	-0.0987*** (0.0021)	-0.0748*** (0.0022)	-0.0578*** (0.0016)	-0.0356*** (0.0014)	-0.0603*** (0.0014)
Δ log(*avg. dist to work*)	0.00651*** (0.00088)	0.00209* (0.00085)	0.00346*** (0.00088)	-0.00327*** (0.00060)	-0.00632*** (0.00055)	-0.00900*** (0.00056)
log(*avg. dist to work*)_2002	0.0546*** (0.0011)	0.0288*** (0.0010)	0.0525*** (0.0011)	0.00100 (0.00075)	-0.000222 (0.00069)	-0.00169* (0.00069)
Δ log(*within-CBSA share*)	0.960*** (0.0011)	0.957*** (0.0010)	0.949*** (0.0012)	0.973*** (0.00083)	0.978*** (0.00078)	0.976*** (0.00086)
log(*college share*)_2000	0.0106*** (0.0012)	-0.00796*** (0.0013)	-0.0278*** (0.0013)	-0.0301*** (0.0012)	-0.0344*** (0.0014)	-0.0249*** (0.0021)
log(*pop density*)_2000	-0.0239*** (0.0020)	-0.0114*** (0.0018)	-0.00352 (0.0019)	0.00179 (0.0015)	-0.000505 (0.0013)	0.00306* (0.0013)
Observations	38469	38558	38681	32679	36944	37862
R^2	0.958	0.963	0.952	0.979	0.981	0.977

Table A.3: OLS Nested-Logit Regression for Census Residential Model (Continued)

	Non-college			College		
	(1) 25-34	(2) 35-44	(3) 45-65	(4) 25-34	(5) 35-44	(6) 45-65
Δ log(*Theater*)	0.00318***	-0.00244**	-0.000236	0.0000226	-0.00189**	0.00104
	(0.00087)	(0.00084)	(0.00088)	(0.00063)	(0.00058)	(0.00058)
Δ log(*Museums*)	0.00630***	0.00347***	0.00123	0.00406***	0.000445	-0.000737
	(0.00091)	(0.00083)	(0.00087)	(0.00066)	(0.00055)	(0.00056)
Δ log(*Movie theaters*)	-0.00555***	-0.00222**	-0.00190*	-0.00456***	-0.00344***	-0.00108
	(0.00086)	(0.00083)	(0.00086)	(0.00062)	(0.00056)	(0.00057)
Δ log(*Outdoor activities*)	0.00368***	0.00625***	0.00547***	0.00242***	0.00411***	0.00440***
	(0.00088)	(0.00085)	(0.00088)	(0.00061)	(0.00056)	(0.00057)
Δ log(*Sports*)	-0.0166***	-0.00699***	-0.0135***	-0.0118***	-0.00893***	-0.0138***
	(0.0011)	(0.00098)	(0.0010)	(0.00096)	(0.00077)	(0.00076)
Δ log(*Restaurants*)	-0.00572***	-0.00290**	-0.00613***	-0.00464***	-0.000636	0.000649
	(0.0011)	(0.00095)	(0.00096)	(0.00088)	(0.00067)	(0.00065)
Δ log(*Bars*)	-0.00391***	0.00460***	0.000328	0.000494	-0.00396***	-0.00209***
	(0.0010)	(0.00093)	(0.00096)	(0.00073)	(0.00059)	(0.00059)
Δ log(*Personal services*)	-0.0138***	-0.00859***	-0.0122***	-0.00498***	-0.00465***	-0.00727***
	(0.0013)	(0.0011)	(0.0011)	(0.0011)	(0.00080)	(0.00078)
Δ log(*General merch. stores*)	0.0119***	0.00681***	0.00965***	0.00143*	-0.000634	-0.00334***
	(0.0010)	(0.00094)	(0.00096)	(0.00070)	(0.00057)	(0.00057)
Δ log(*Food stores*)	-0.00700***	-0.0120***	-0.00274**	0.000893	-0.00201**	-0.00574***
	(0.0012)	(0.0010)	(0.0010)	(0.00092)	(0.00071)	(0.00071)
Δ log(*Apparel stores*)	-0.0121***	-0.0202***	-0.0208***	-0.00657***	-0.00994***	-0.00534***
	(0.0011)	(0.00097)	(0.00099)	(0.00084)	(0.00067)	(0.00067)
log(*Theater*)_2000	0.00440***	0.00559***	0.00459***	0.00547***	0.000477	0.00899***
	(0.0011)	(0.0011)	(0.0011)	(0.00080)	(0.00075)	(0.00075)
log(*Museums*)_2000	0.0354***	0.0295***	0.0256***	0.0172***	0.0147***	0.0119***
	(0.0016)	(0.0015)	(0.0016)	(0.0012)	(0.0010)	(0.0010)
log(*Movie theaters*)_2000	-0.0135***	0.000682	-0.000847	-0.00152	-0.00412***	-0.000816
	(0.0012)	(0.0011)	(0.0012)	(0.00090)	(0.00080)	(0.00079)
log(*Outdoor activities*)_2000	0.000898	0.00494***	0.00239**	-0.00163*	-0.000870	0.00159**
	(0.00093)	(0.00088)	(0.00091)	(0.00064)	(0.00058)	(0.00058)
log(*Sports*)_2000	-0.0390***	-0.0127***	-0.0275***	-0.0248***	-0.0164***	-0.0269***
	(0.0023)	(0.0021)	(0.0022)	(0.0020)	(0.0017)	(0.0016)
log(*Restaurants*)_2000	-0.00582*	0.00983***	-0.00873***	-0.00539*	0.0111***	0.00721***
	(0.0026)	(0.0023)	(0.0023)	(0.0021)	(0.0017)	(0.0016)
log(*Bars*)_2000	0.00855***	0.0397***	0.0234***	0.000696	0.00115	0.00620***
	(0.0017)	(0.0015)	(0.0016)	(0.0012)	(0.0010)	(0.0010)
log(*Personal services*)_2000	-0.0135***	-0.0184***	-0.0233***	0.0000867	-0.00958***	-0.00413*
	(0.0031)	(0.0027)	(0.0028)	(0.0026)	(0.0020)	(0.0019)
log(*General merch. stores*)_2000	0.0536***	0.0377***	0.0464***	0.0229***	0.0132***	0.00560***
	(0.0024)	(0.0021)	(0.0022)	(0.0016)	(0.0013)	(0.0013)
log(*Food stores*)_2000	-0.00167	-0.0293***	0.0233***	0.00809**	0.00215	0.00558*
	(0.0035)	(0.0031)	(0.0032)	(0.0029)	(0.0023)	(0.0023)
log(*Apparel stores*)_2000	-0.0203***	-0.0469***	-0.0399***	-0.0106***	-0.0101***	0.000693
	(0.0028)	(0.0025)	(0.0026)	(0.0021)	(0.0017)	(0.0017)
Observations	38469	38558	38681	32679	36944	37862
R^2	0.958	0.963	0.952	0.979	0.981	0.977

Table A.4: CBSA-FEs Regression for Census Residential Model

	Non-college			College		
	(1) 25-34	(2) 35-44	(3) 45-65	(4) 25-34	(5) 35-44	(6) 45-65
log(*share of 10 yrs younger, same inc*)_2000	0.0815	0.254***	0.0415	-0.0979*	0.317***	0.468**
	(0.046)	(0.045)	(0.051)	(0.038)	(0.056)	(0.16)
Δ log(*housing index- all homes*)	-0.109	0.0785	0.128	0.147*	0.132	-0.0781
	(0.083)	(0.072)	(0.086)	(0.066)	(0.078)	(0.086)
Δ log(*avg. num job opp–low inc.*)	-0.234	-0.565***	0.244	-0.655***	-0.738***	-0.347*
	(0.15)	(0.17)	(0.21)	(0.17)	(0.18)	(0.18)
Δ log(*avg. num job opp–mid inc.*)	-0.150	0.591**	-0.0253	0.117	0.0716	0.277
	(0.22)	(0.21)	(0.27)	(0.18)	(0.20)	(0.20)
Δ log(*avg. num job opp–high inc.*)	-0.220	-0.157	-0.321	0.555*	0.517*	-0.301
	(0.25)	(0.23)	(0.32)	(0.22)	(0.25)	(0.27)
Δ log(*avg. dist to work*)	0.367*	0.603***	0.627***	0.121	0.229*	0.286**
	(0.16)	(0.15)	(0.18)	(0.080)	(0.10)	(0.095)
log(*college share*)_2000	0.00746	-0.0305	-0.105*	-0.279***	-0.438***	-0.517***
	(0.043)	(0.040)	(0.045)	(0.058)	(0.080)	(0.15)
log(*pop density*)_2000	-0.270***	-0.258***	-0.336***	-0.277***	-0.231***	-0.318***
	(0.043)	(0.043)	(0.054)	(0.040)	(0.044)	(0.045)
log(*housing index- all homes*)_2000	0.0836***	0.0661**	0.0700*	0.0267	0.0946***	0.101***
	(0.025)	(0.022)	(0.028)	(0.020)	(0.020)	(0.022)
log(*avg. num job opp–low inc.*)_2002	-0.0923	-0.407***	0.0543	-0.283**	-0.501***	-0.376**
	(0.11)	(0.11)	(0.15)	(0.11)	(0.11)	(0.12)
log(*avg. num job opp–mid inc.*)_2002	-0.258	0.361	-0.0694	-0.313	-0.0626	0.221
	(0.21)	(0.21)	(0.26)	(0.18)	(0.20)	(0.20)
log(*avg. num job opp–high inc.*)_2002	-0.127	-0.0524	-0.180	0.738***	0.608**	-0.108
	(0.23)	(0.22)	(0.30)	(0.21)	(0.23)	(0.25)
log(*avg. dist to work*)_2002	0.154	0.289***	0.308**	0.0605	0.116*	0.132*
	(0.086)	(0.081)	(0.098)	(0.047)	(0.059)	(0.058)
Observations	37345	37418	37510	31813	35858	36729
R^2	-0.661	-0.500	-2.027	-0.282	-0.504	-0.830
CBSA FEs	Yes	Yes	Yes	Yes	Yes	Yes

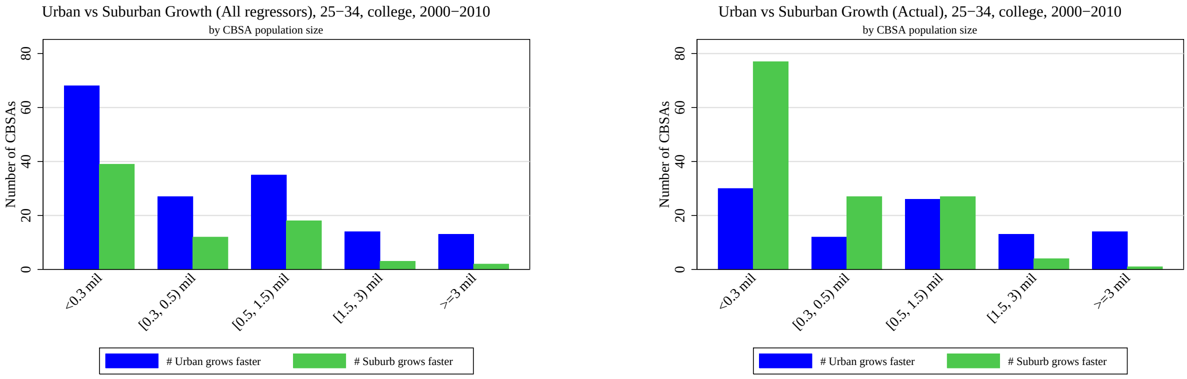
Table A.5: CBSA-FEs Regression for Census Residential Model (Continued)

	Non-college			College		
	(1) 25-34	(2) 35-44	(3) 45-65	(4) 25-34	(5) 35-44	(6) 45-65
Δ log(*Theater*)	0.228	0.185	-0.103	-0.282***	-0.0232	-0.0681
	(0.12)	(0.099)	(0.11)	(0.073)	(0.064)	(0.065)
Δ log(*Museums*)	0.108	0.0609	-0.132	-0.0386	0.276***	-0.0805
	(0.096)	(0.092)	(0.10)	(0.081)	(0.078)	(0.075)
Δ log(*Movie theaters*)	-0.0374	0.0614	-0.204	0.138	-0.410***	-0.550***
	(0.13)	(0.11)	(0.17)	(0.090)	(0.12)	(0.12)
Δ log(*Outdoor activities*)	0.241*	-0.00238	-0.448***	0.000921	0.0184	0.0407
	(0.098)	(0.10)	(0.14)	(0.069)	(0.11)	(0.12)
Δ log(*Sports*)	-0.0869	-0.0492	0.503***	-0.127	0.0359	0.0777
	(0.11)	(0.10)	(0.12)	(0.12)	(0.12)	(0.14)
Δ log(*Restaurants*)	0.420*	0.159	-0.539***	-0.0490	0.255*	-0.217*
	(0.20)	(0.14)	(0.15)	(0.14)	(0.11)	(0.11)
Δ log(*Bars*)	-0.485***	-0.0329	0.310**	-0.153	-0.0186	-0.159*
	(0.13)	(0.092)	(0.12)	(0.081)	(0.072)	(0.066)
Δ log(*Personal services*)	-0.103	-0.150	-0.473***	-0.162	-0.281***	-0.222**
	(0.11)	(0.098)	(0.13)	(0.10)	(0.077)	(0.079)
Δ log(*General merch. stores*)	-0.0518	0.0858	-0.209	-0.143*	0.151*	-0.158*
	(0.088)	(0.090)	(0.11)	(0.058)	(0.074)	(0.070)
Δ log(*Food stores*)	-0.176	-0.134	0.0468	0.0488	-0.140	-0.163
	(0.13)	(0.11)	(0.16)	(0.095)	(0.087)	(0.090)
Δ log(*Apparel stores*)	-0.0653	-0.238**	-0.137	0.161*	-0.0873	0.236***
	(0.081)	(0.078)	(0.11)	(0.079)	(0.070)	(0.067)
log(*Theater*)_2000	0.158	0.128	-0.0421	-0.214***	-0.0280	-0.0247
	(0.087)	(0.070)	(0.077)	(0.054)	(0.046)	(0.048)
log(*Museums*)_2000	0.0714	0.103	-0.0702	-0.00502	0.266**	-0.0874
	(0.096)	(0.094)	(0.10)	(0.087)	(0.083)	(0.082)
log(*Movie theaters*)_2000	-0.0493	0.00789	-0.118	0.109	-0.288***	-0.328***
	(0.086)	(0.075)	(0.11)	(0.064)	(0.081)	(0.077)
log(*Outdoor activities*)_2000	0.123*	-0.00763	-0.234***	0.00610	0.00322	0.0264
	(0.051)	(0.052)	(0.068)	(0.037)	(0.054)	(0.057)
log(*Sports*)_2000	-0.0998	-0.0358	0.712***	-0.217	0.0180	0.144
	(0.14)	(0.14)	(0.16)	(0.16)	(0.17)	(0.19)
log(*Restaurants*)_2000	0.582*	0.252	-0.538**	-0.0229	0.436**	-0.121
	(0.26)	(0.18)	(0.21)	(0.18)	(0.15)	(0.15)
log(*Bars*)_2000	-0.496***	-0.0381	0.295*	-0.143	-0.0126	-0.135
	(0.13)	(0.095)	(0.12)	(0.095)	(0.084)	(0.075)
log(*Personal services*)_2000	-0.0845	-0.207	-0.606**	-0.0829	-0.483***	-0.127
	(0.17)	(0.15)	(0.21)	(0.16)	(0.13)	(0.12)
log(*General merch. stores*)_2000	-0.0782	0.126	-0.205	-0.205*	0.286**	-0.135
	(0.13)	(0.12)	(0.14)	(0.081)	(0.096)	(0.088)
log(*Food stores*)_2000	-0.357	-0.216	0.352	0.228	-0.230	-0.0723
	(0.24)	(0.20)	(0.28)	(0.18)	(0.18)	(0.18)
log(*Apparel stores*)_2000	-0.0493	-0.294*	-0.0889	0.179	-0.169	0.371***
	(0.12)	(0.12)	(0.16)	(0.11)	(0.11)	(0.097)
Observations	37345	37418	37510	31813	35858	36729
R^2	-0.661	-0.500	-2.027	-0.282	-0.504	-0.830
CBSA FEs	Yes	Yes	Yes	Yes	Yes	Yes

F Additional stylized fact predictions

Figure A.9: Predicted vs Actual Urban-Suburban Growth: 25-34 year olds

Panel A



Panel B

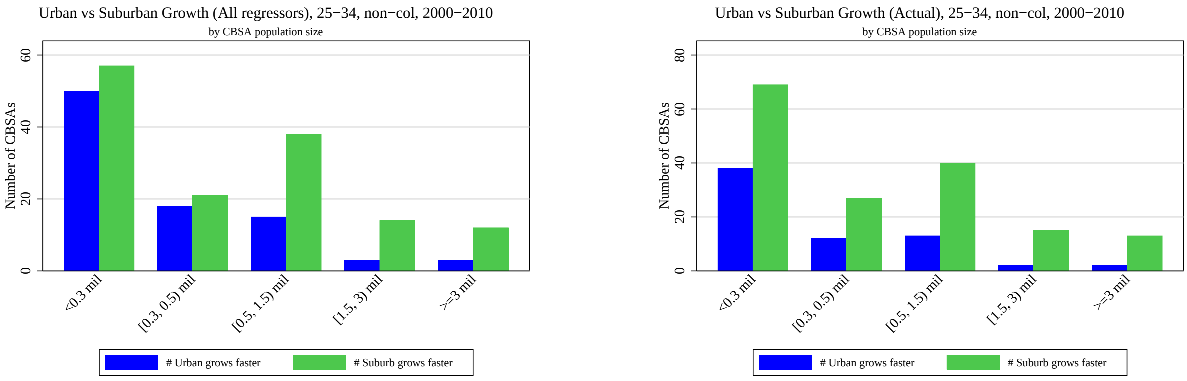
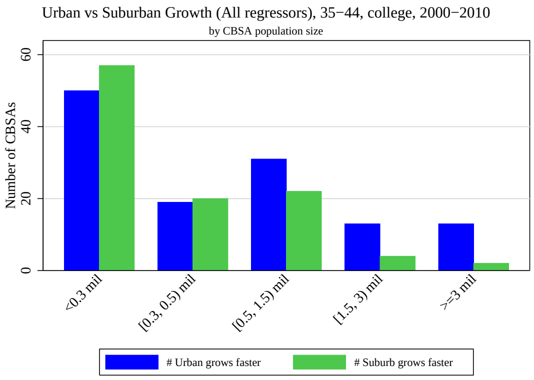
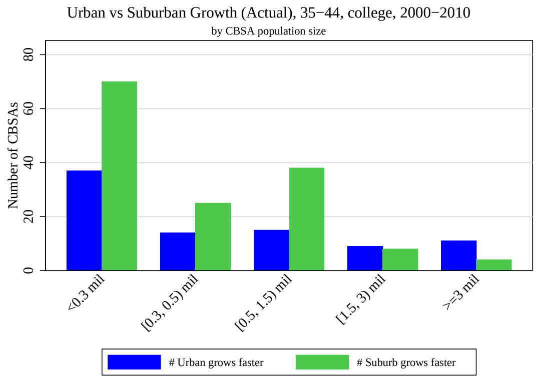


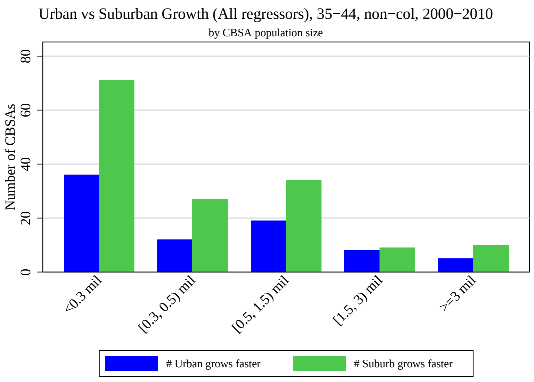
Figure A.10: Predicted vs Actual Urban-Suburban Growth: 35-44 year olds

Panel A





Panel B



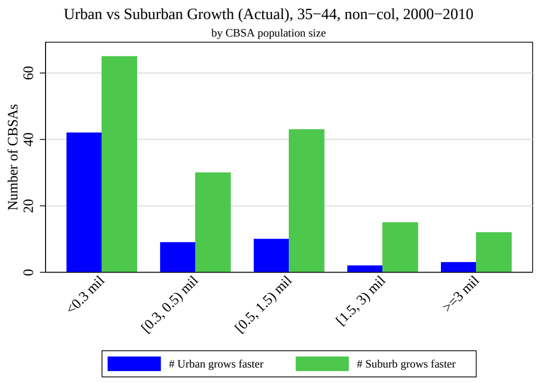
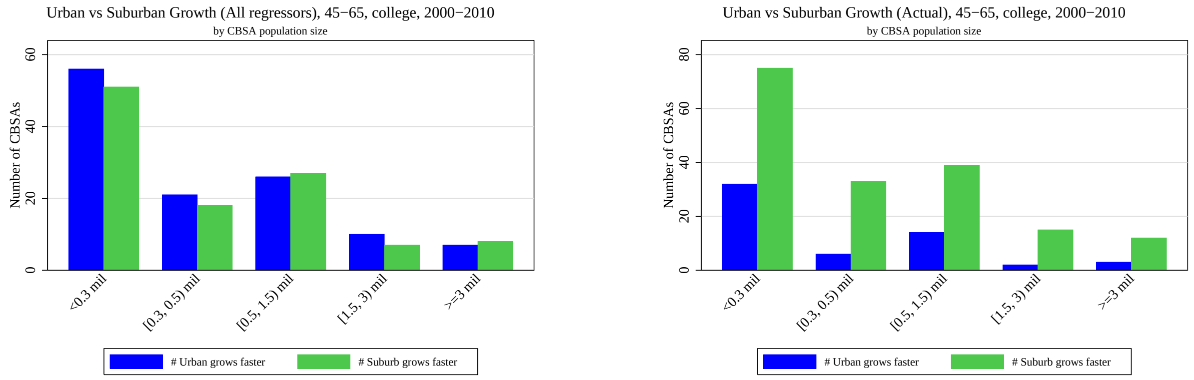
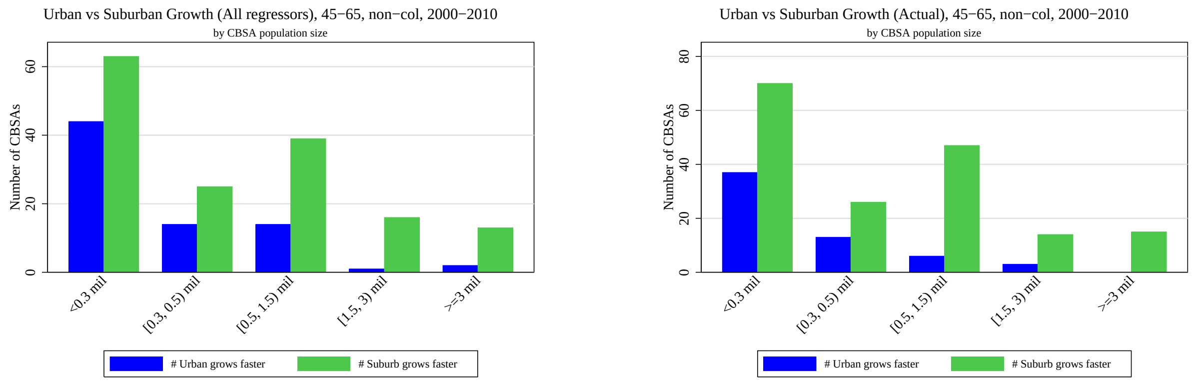


Figure A.11: Predicted vs Actual Urban-Suburban Growth: 45-64 year olds

Panel A



Panel B



G Commuting Analysis

In section 3 we used the LODES commute data to show that job location cannot explain all of the high-income residential shift towards downtown. The reason is that even when holding distance to workplace fixed, high-income workers in large cities still live closer to the CBD in 2011 than in 2002. We now formalize this argument by specifying and estimating a residential-workplace choice model. This model permits the addition of a workplace fixed-effect, and delivers within-worktract preference coefficients for residential characteristics that are convincingly free of simultaneity with job location.

G.1 Commute Model

The model is similar to that in section 5, but now the location decision of a person is a discrete choice of a single residence-workplace pair. Each person i chooses its residential location j and workplace location k in year t to maximize its indirect utility function V^i_{jkt}:

$$\max_{j,k} V^{id}_{jkct} = \alpha^d_t \mathbf{X_{jct}} + \beta^d_t \mathbf{X_{kct}} - \omega^d d_{jkc} + \xi^d_{jct} + \psi^d_{kct} + \mu^d_{jkc} + \theta^d_{ct} + \psi^{id}_{ct}(\sigma^d) + (1-\sigma^d)\varepsilon^{id}_{jkct} \tag{A.2}$$

$\mathbf{X_{jt}}$ and $\mathbf{X_{kt}}$ are vectors of observable time-varying characteristics of residences and workplaces, respectively. d_{jk}, a variable absent from the simple residential choice model, denotes the travel distance from residential location j

to workplace location k, and ω^d reflects group d's marginal disutility from commuting. ξ^d_{jct} and ψ^d_{kct} represents the unobserved group-specific, time-varying quality of each residential location and workplace location. To ease the notation, we omit all time-invaryring residential, workplace, and residential-workplace unobserved characteristics, because they eventually drop out in first-difference. Exactly as in the residential choice model,θ^d_{ct} represents an unobserved time-varying quality of CBSA c for individuals in group d. We assume a nested-logit error structure, where $\psi^{id}_{ct}(\sigma^d)$ and ε^{id}_{jkct} are a random individual- and time-specific taste shocks for CBSA c and residential-workplace tract pair jk, respectively.[57][58]We solve the model exactly as in section 5 and obtain:

$$\Delta\widetilde{\ln s^d_{jk}} = \alpha^d_{2011}\Delta\tilde{\mathbf{X}}_{\mathbf{jc}}+\Delta\alpha^d\tilde{\mathbf{X}}_{\mathbf{jc},\mathbf{2002}}+\beta^d_{2011}\Delta\tilde{\mathbf{X}}_{\mathbf{kc}}+\Delta\beta^d\tilde{\mathbf{X}}_{\mathbf{kc},\mathbf{2002}}-\Delta\omega^d d_{jkc}+\Delta\tilde{\xi}^d_{jc}+\Delta\tilde{\psi}^d_{kc}+\Delta\tilde{\theta}^d_c+\sigma^d\widetilde{\Delta s^d_{jk|c}}+\epsilon^d_{jkct}$$

Instead of estimating workplace characteristics directly, we add a workplace fixed-effect σ^d_{kc} which captures both observed and unobserved group-specific and time-varying workplace characteristics.[59] The resulting estimating equation is:

$$\Delta\ln\left(s^d_{jk}\right) = \alpha^d_{2011}\Delta\tilde{\mathbf{X}}_{\mathbf{jc}} + \Delta\alpha^d\tilde{\mathbf{X}}_{\mathbf{jc},\mathbf{2002}} + \sigma^d_{kc} - \Delta\omega^d d_{jkc} + \Delta\tilde{\xi}^d_{jc} + \Delta\tilde{\theta}^d_c + \sigma^d\Delta s^d_{jk|c} + \epsilon^d_{jkct} \tag{A.3}$$

.

G.2 Commute Model Variable Definition

Before estimating the model, we describe all the variables in equation A.3 were not in the residential model of Section 5.

Commute Shares The dependent variable in the commute model is the change in the share of residents of group d living and working in a residential-workplace tract pair, between 2002 and 2011, relative to a base tract pair. Let n^d_{jkct} be the number of group-d people who live in tract j and work in tract k in year t in CBSA c. We obtain these numbers from the LODES data in 2002 and 2011 for high-income, medium-income and low-income workers. Let c be the CBSA of tract k and $L_c$be the set of tracts located in CBSA c. The the share of CBSA c workers who live in tract j and work in tract k in year t:

$$s^d_{jkct} = \frac{n^d_{jkct}}{\sum_c\sum_j\sum_{k\in L_c} n^d_{jktc}}$$

[57]We assume that (i) that people select both their place of work and residence simultaneously and (ii) each person gets an independent residential-workplace pair taste draw in each period. We use long differences in our estimation, making each of these assumptions more plausible. The transportation literature has explored richer substitution patterns allowing for sequential decision-making (Waddell et al., 2007) and joint-location decisions for households with multiple workers (Waddell, 1995). By ignoring each of these factors, we are overestimating the flexibility of workers in moving to their optimal workplace and residential location pair, perhaps moreso for older workers who are more likely to live in larger households and be tied to residential locations that are convenient to the workplaces and schools of family members.

[58]The logit distribution on the random taste shocks imposes the independence of irrelevant alternatives (IIA) property on within-CBSA individual location choices. This property implies that, when agents substitute away from one option within a CBSA tract-pair choice set, they substitute to all other options in equal proportions - regardless of how similar those alternatives are to the alternative that agents are substituting away from.

[59]We focus on estimating the effect of residential characteristics separately from the effect of changes in workplace location, but our model can also be fully estimated without the workplace tract fixed-effect. In this case, the number of jobs in tract k - possibly excluding own workers in own tract j - becomes a workplace characteristics. The coefficient on this variable provides a measure of the impact of workplace reallocation in space on residential choices. This measure is valid under an independent of irrelevant alternative (logit) assumption. That is, the effect of an increase in jobs in tract k on 2002 to 2011 changes in the number of individuals in tract pair jk depends only on the initial 2002 share of people in jk, and is directly proportional to that original share. In this model, $\Delta\ln\left(s^d_{jk}\right)$ depends on the characteristics of tract j and tract k, but not on that of any other tracts.

Commute time In the current draft, we proxy for the commute time between the workplace and residence tract d_{jkc} using a flexible quadratic function of the Haversine distance between workplace and residence tracts. That is, we include both the level and the squared distance between tracts j and k in the estimating equation. In future drafts, we will replace this proxy with a snapshot of driving and transit times collected from Google Maps. Alternatively, we could infer a time varying measure by using tract-to-tract commuting times in 2000 and 2010 from the Census Transportation Package (CTP).

Residence Tract Characteristics Our CBSA residential characteristics are the same as in the residential choice model of Section 5. Note that the variables for job opportunities and average distance to work now take an interpretation as a purely residential characteristics. These variables capture the possibility that households choose residential locations based on their proximity to employment locations other than their own, as such job opportunites may become relevant to future career events. We control for local demographic shares in 2002 defined by income groups instead of age-education group, and we derive these shares from the LODES data.

Table A.6: Data Summary by the Order of Housing-Retailing

region	numLODES	ratioretail	ratiohousing	ratiotractpopchar	CBSAwithbase
CBSA	858	1.00	0.86	0.86	1
Workplace Tract	62190	1.00	0.82	1.00	49364
Residence Tract	70416	1.00	0.54	1.00	37515
Population (2002)	91582232	1.00	0.60	1.00	53274640

Notes: This table depicts the coverage of the amenity index data as well as the Zillow housing price data. Column 1 depicts the number of CBSAs, tracts, and 2000 population in the LODES data. Columns 2 depicts the share of CBSAs, tracts, and population that remains after merging the amenity index data into the LODES population data, while Column 3 depicts the share of CBSAs, tracts, and population that remains after merging the amenity-LODES dataset with the Zillow house price indexes. Column 4 depicts the share of CBSAs, tracts, and population that remains after merging the housing-amenity-LODES dataset with Census tract characteristics. The last column depicts the number of CBSAs and tracts, and the population represented by these tracts, that enter into the regression sample.

Data Limitations

G.3 Commute Model Identification

As in section 5, the identification strategy for the commute model relies on first-differencing, the addition of a rich set of controls, and the set of instrumental variables described in that section. However, the specification in equation A.3 provides and additional, sharper way of controlling for the simultaneous determination of workplace and residential location changes. This simultaneity problem is straightforward; for instance we expect high-income workers to move to areas that experience an influx of firms hiring them, to reduce their commute costs. The reverse is also true; we expect firms hiring high-income workers to move to areas that experiences an influx of these workers, as a mean of attracting talent. Moving closer to a young, educated talent pool is often the stated objective of employers like Amazon, Twitter or Google when they move to new downtown offices (Johnson and Wingfield (2013)). Our work-tract fixed-effect specification solves this simulataneity problem by delivering the within-worktract impact of residential characteristics i.e., by considering the change in residential choice of people working within the same tract in 2002 and 2011. In this case, changes in residential location are not affected by a change in workplace location. In terms of equation A.3, the workplace fixed-effect captures all unobserved changes in workplace characteristics ($\Delta\tilde{\psi}^{d}_{kc}$).

G.4 Commute model results

TBD