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Abstract

Neighborhoods within 2 km of most central business districts of U.S. metropolitan areas experienced population declines from 1980 to 2000 but have rebounded markedly since 2000 at greater pace than would be expected from simple mean reversion. Statistical decompositions reveal that 1980-2000 departures of residents without a college degree (of all races) generated most of the declines while the return of college educated whites and the stabilization of neighborhood choices by less educated whites promoted most of the post-2000 rebound. The rise of childless households and the increase in the share of the population with a college degree, conditional on race, also promoted 1980-2010 increases in central area population and educational composition of residents, respectively. Estimation of a neighborhood choice model shows that changes in choices to live in central neighborhoods primarily reflect a shifting balance between rising home prices and valuations of local amenities, though 1980-2000 central area population declines also reflect deteriorating nearby labor market opportunities for low skilled whites. Rising 1980-2000 central neighborhood home prices were about equally offset by rising amenity valuations among college educated whites; declining amenity valuations reinforced rising home prices to incentivize departures of other demographic groups from central neighborhoods during this period. Greater increases in amenity valuations after 2000 encouraged college educated whites to move in and other whites to remain but were not large enough to offset rising housing costs for minorities.

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1 Introduction

In the decades following WWII, the central regions of most U.S. metropolitan areas were in decline. Between 1960 and 2000, the aggregate central city population share in the 100 largest metropolitan areas fell from 0.49 to 0.24 while the employment share declined from 0.61 to 0.34 (Baum-Snow, 2015). A host of mechanisms responsible for this decline have been considered in the literature. These include highway construction (Baum-Snow, 2007), decentralization of low-skilled work (Kain, 1992), white flight from rising minority populations in cities (Boustan, 2010), rising incomes (Margo, 1992), Federal Housing Authority mortgage insurance provision favoring the suburbs (Jackson, 1985) and vintage housing in cities filtering down to lower income occupants (Brueckner & Rosenthal, 2008). Following sharp declines during the 1970s, neighborhoods within 2 km of central business districts (CBDs) in most medium and large U.S. cities experienced slow 1980-2000 declines and post-2000 growth in population, income, the share of the residents that are white and the share of the residents that hold a college degree. Indeed, downtown neighborhoods have been the most rapidly gentrifying regions of metropolitan areas during the 2000-2010 period. This paper investigates the demographic factors that drove 1980-2000 central neighborhood decline and 2000-2010 gentrification.

Our evaluation of the causes of central neighborhood change proceeds in two stages. First, using a procedure akin to that proposed by DiNardo, Fortin & Lemieux (1996) for decomposing wage distributions, we systematically decompose the sources of changes in demand for central neighborhoods since 1980 into those due to demographic shifts (holding neighborhood choices constant) versus those due to changes in neighborhood choices. We carry out the analysis using demographic cells defined by race and: education; age; family type; or household income decile. To better understand the component of central neighborhood change driven by changes in demographic groups' choices (rather than demographic shares), we use a conditional choice probability (CCP) procedure, as in Hotz & Miller (1994), to recover valuations of various neighborhood attributes in each decade 1980-2010 in the context of a standard neighborhood choice model. The model shows how to combine information about observed neighborhood choices and housing costs to recover neighborhood valuations that reflect a combination of sub-metropolitan area labor market opportunities and local amenities. We evaluate the extent to which shifts in local labor market and microgeographic labor demand conditions explain the increasing propensity of high socioeconomic status (SES) households to choose central neighborhoods and the declining propensity of low SES households to do so.

Our results indicate that differential shifts in neighborhood choices by high versus low SES individuals have driven the majority of central neighborhood change. Declines in central neighborhood choice probabilities by low SES nonwhites over the full 1980-2010 period began to be offset by increases in such probabilities by high SES whites after 2000. 1980-2000 departures of low SES whites from central neighborhoods contributed to losses during this period, with this group's neighborhood choices stabilizing after 2000. Changing choices of high SES minorities had only small impacts. The 1980-2000 departures of low SES households from central neighborhoods promoted income growth, despite declining population, and some racial change before 2000 which then accelerated after 2000.

Shifts in the racial composition of the population have consistently pushed in favor of downtown population growth, since central area populations are disproportionately made up of minorities. However, racial shifts have pushed against other dimensions of gentrification that began after 1980. Shifts in the educational attainment distribution conditional on race have pushed in favor of gentrification but slightly against population growth. Shifts in the distribution of family types conditional on race have pushed in favor of population growth. Shifts in the income distribution and the age structure of the population conditional on race have had small effects. The broad conclusion is that while some of the increase in the educational composition of downtown residents is mechanical, this mechanical change has been swamped by the fact that whites have chosen to live in CBD area neighborhoods at much higher rates after 2000, to the point that less than 2 km is the only CBD distance ring in which the white population grew over the 2000-2010 period.

Shifts in neighborhood choices can be understood through a combination of changes in home prices, amenity values and nearby labor market opportunities. Rising 1980-2000 central neighborhood home prices were about equally offset by rising amenity valuations among college educated whites while declining amenity valuations reinforced rising home prices to incentivize departures of other demographic groups from central neighborhoods during this period. Deteriorating downtown area labor market opportunities also contributed to the flight of less educated whites. Greater increases in amenity valuations after 2000 relative to prior decades encouraged college educated whites to move in and other whites to remain but were not large enough to offset rising housing costs for minorities.

Our conclusion that shifts in amenity valuations rather than nearby labor market opportunities have primarily driven changes in central neighborhood choices comes from estimation of a simple model that incorporates insights from Berry (1994) and Bayer et al. (2016). This conclusion echoes evidence in Couture & Handbury (2015), which performs a detailed investigation of which amenities are driving these shifts. Estimates from the model also reveal that neighborhood choice probabilities and valuations of downtown neighborhoods by most demographic groups can, in small part, be explained by shifts in the spatial structure of labor demand. As such, stabilization of job losses in downtown areas has driven part of the post-2000 central neighborhood demand increases relative to prior decades. These results are in line with those in Edlund et al. (2015), though that paper focuses on larger cities with more robust 2000-2010 employment growth than is seen in our broader sample. However, exogenous positive metro area level labor demand shocks have pulled minorities out of downtown areas. This could be because they reflect improved labor market opportunities outside of downtown cores or because they reflect rising incomes throughout the CBSA, allowing for residents to seek out neighborhoods with higher group-specific amenity values.

While our focus is on central neighborhoods, the methodology we develop in this paper can be used more broadly to understand neighborhood demographic dynamics. A better understanding of the drivers of neighborhood change may provide clues about some reasons for the growth in income inequality nationwide since 1980. Gould, Lavy & Paserman (2011), Damm & Dustmann (2014), Chetty et al. (2016) and Chetty and Hendren (2016) all provide independent evidence of the effects of neighborhood environments for youth on long-run outcomes. To the extent that neighborhood quality in childhood positively influences long run labor market outcomes, it is important to better isolate the mechanisms that have driven changes in neighborhood inequality. In particular, it will be important to understand the extent to which gentrifying neighborhoods retain incumbent residents (who can benefit from positive spillovers) or price them out. Existing evidence for census tracts with incomes that grew by at least $10,000 during the 1990s indicates that most incumbents are able to remain (McKinnish, Walsh & White, 2010). We find that this phenomenon is almost entirely driven by whites with less than a college education; increases in housing costs outweighed the changes in neighborhood valuations for blacks with less than a college education in gentrifying central neighborhoods such that many chose to leave.

This paper proceeds as follows. Section 2 describes how we process the data and presents descriptive evidence on the changing fortunes of downtown areas and trends in neighborhood inequality. Section 3 lays out a methodology for constructing counterfactual neighborhood compositions and presents decompositions of the sources of neighborhood change using these counterfactuals. Section 4 develops a neighborhood choice model that is used to evaluate reasons for shifts in neighborhood choices by demographic group. Finally, Section 5 concludes.

2 Characterizing Neighborhood Change

2.1 Data Construction

We primarily use 1970-2010 decennial census data and the 2008-2012 American Community Survey (ACS) data tabulated to the 2000 definition of census tract boundaries for this analysis. Central to our investigation is the need for joint distributions of population by race, education, household income, age and family structure across census tracts in each CBSA. To recover as many of these joint distributions in the most disaggregated form possible, we make use of both summary tape file (STF) 3 and 4 census tabulations. We also use information about family structure and age by race from STF1 data from the 2010 census. Because the 2010 census did not collect information about income or education, we must rely in the 5 year ACS data for these tract distributions. We also make use of some census micro data to estimate parameters governing shapes of household income distributions above topcodes and to generate weights used to assign some of the population counts in the tract aggregate data to different types of families. All census tracts are normalized to year

2000 geographies using census bureau reported allocation factors.

We construct three different joint distributions for people and one for households in 1980, 1990, 2000 and 2010. For each one, the race categories are white, black and other. In the other dimension we have 4 education groups (less than high school, high school only, some college, college +), 18 age groups (0-4, 5-9, ..., 80-84, 85+) or 6 family type groups (in married couple families with no kids, in married couple families with kids, in single female headed families with kids, in single male headed families with kids, not in a family, in group quarters). For income, we construct the number of households in each decile of the household income distribution of those residing in our sample area in each year. We do this in order to facilitate comparisons across CBSAs and years in a sensible way while taking into account the secular increase in nationwide income inequality during our sample period.

For the purpose of succinct descriptive analysis, we construct a summary measure of neighborhood demographics that incorporates the share of residents that are white, the share that are college educated and the median household income of the tract. This summary measure for tract i is the average number of standard deviations tract i is away from its mean in each year for each of these components. We call this equally weighted tract z-score the socioeconomic status (SES) index. For tract i in CBSA j in year t and variables indexed by k the SES index is calculated as

$$SES_{ijt} = \frac{1}{3} \sum_{k} \frac{y^k_{ijt} - \overline{y}^k_{jt}}{\sigma^k_{jt}},$$

where $\overline{y}^k_{jt}$ and σ^k_{jt} are calculated with tract population or household weights. While we also experimented with using the first principal component of these same three underlying variables, we prefer the equally weighted z-score approach as it does not mechanically assign more weight to a variable only because it has more variation. We think that all three measures indexed by k are roughly equally important indicators of neighborhood status.[1]

The Census Transportation Planning Package (CTPP) reports aggregated census or ACS micro data to microgeographic units for place of work in 1990, 2000 and 2005-2009. We use these data broken out by industry to construct localized labor demand shocks. Where available, we take CBD definitions from the 1982 Economic Census. Otherwise, we use the CBD location as assigned by ESRI. Each CBSA is assigned only one CBD.

Our sample includes the regions of all year 2008 definition metropolitan areas (CBSAs) that were tracted in 1970 and had a population of at least 250,000 except Honolulu.[2] The result is a sample of 120 CBSAs. In order for our analysis to apply for the average metropolitan area rather than the average resident, much of the analysis weights tracts such that each CBSA is weighted

[1] There is evidence that conditional on income and education, black households have lower wealth than white households, meaning that fraction white may proxy for unobserved elements of socioeconomic status.

[2] 100% of the 2000 definition tract must have been tracted in 1970 to be in our sample.

equally. The Data Appendix provides more details about data construction.

Figure 1a shows a map of the 120 CBSAs in our sample shaded by the fraction of census tracts within 4 km of the central business district that are in the top half of the tract distribution of our SES index in 1980 (top) and 2010 (bottom) in each CBSA. Those CBSAs above 0.5 have central areas that are less distressed than would be expected given random assignment of SES status to census tracts. Particularly striking is the number of CBSAs whose central areas experience gentrification between 1980 and 2010 (moving up the distribution of blue-green-yellow-red shades). Santa Barbara and New York are the only CBSAs with downtown areas that were more affluent than average in 1980. By 2010, 9 additional CBSAs had relatively affluent downtown areas. While central areas of other CBSAs remained less affluent than average, most became more affluent between 1980 and 2010. Of the 120 CBSAs in our sample, the fraction of the population within 4 km of a CBD living in a tract in the top half of the SES index distribution increased by more than 0.25 in 15 CBSAs, by 0.10 to 0.25 in 35 CBSAs and by 0.00 to 0.10 in 23 CBSAs between 1980 and 2010. Central areas of the remaining 47 CBSA experienced only small declines in their SES indexes on average. These patterns of changes are seen in Figure 1b, with red shaded CBSAs experiencing central area SES growth and blue shaded CBSAs with central area declines.

2.2 Facts About Neighborhood Change

Figure 2 reports statistics describing various aspects of neighborhood change as functions of CBD distance since 1970. All plots show medians across CBSAs in our sample. We choose medians in order to emphasize that changes are not driven by just a few large notable cities. Analogous results using means across CBSAs or aggregates are similar. The broad message from Figure 2 is that downtown gentrification since 2000 is evident in many dimensions and is very localized. Neighborhoods within 2 km of CBDs experienced the fastest 2000-2010 growth in terms of population, white fraction, college fraction and income of all CBD distance bands. The seeds of this gentrification started to form after 1980 with even more localized upticks in these indicators.

Panel A shows that the 1970s population declines in central neighborhoods reversed in the 1980s and 1990s, but only within 0.5 km of CBDs. After 2000, population growth rates within 1.5 km of CBDs were the fastest of any CBD distance band. Panel B shows a similar pattern for fraction white. Tracts within 3 km of CBDs experienced faster than average declines in fraction white during the 1970s, typical changes in fraction white during the 1980s, less rapid than average declines during the 1990s and rapid growth 2000-2010. Indeed, this is the only CBD distance band that experienced increases in fraction white after 2000, counteracting the 2000-2010 decline in fraction white in the population of about 5 percentage points. Evident in Panel B is an important racial component to downtown gentrification.

Panel C shows changes in the fraction of the population over 25 with a college degree. Consistent with Couture & Handbury's (2015) evidence, this graph shows modest relative declines in the 1970s, 1980s and 1990s and rapid growth in the 2000-2010 period within 4 km of CBDs. Once again, central neighborhoods were the most rapidly gentrifying in this dimension of any CBD distance ring. Couture & Handbury (2015) document that larger cities experienced more rapid growth in central area college fraction relative to their suburbs than did smaller cities but that even amongst smaller cities this 2000-2010 growth was greater than in the 1990s.[3] Figure 2 Panel D shows that mean income of residents in downtown neighborhoods rose faster than average starting in the 1990s out to about 6 km from CBDs, with less rapid additional growth in the 2000-2010 period, except immediately adjacent to CBDs.

Evidence in Figure 2 Panels A-D show that while some of the gentrification in central neighborhoods has to do with population growth, most of it has to do with shifts in the composition of a declining population. The formal decompositions performed in Section 4 demonstrate that much of the 1980-2010 gentrification within 4 km of CBDs is explained by departures of lower SES individuals from central areas rather than arrivals of higher SES individuals.

While central neighborhoods have been gentrifying since 2000, their 2010 demographic composition remains of lower socioeconomic status than the suburbs. Of the three indicators in Figure 2 Panels B-D, the only one for which the central area looks like the suburbs is college fraction. White share and household incomes in central areas of cities remain well below those in the suburbs. This observation brings up the possibility that some of the patterns in Figure 2 can be attributed to mean reversion. Below we demonstrate that while neighborhoods do experience mean reversion, magnitudes of demographic change shown here are well beyond the typical amount experienced by central neighborhoods before 2000 and amongst other relatively low SES neighborhoods 2000-2010.

Figure 2 Panel E shows decadal changes in mean reported home value as functions of CBD distance. There are two reasons to look at home values. First, assuming housing supply is not perfectly elastic, changes in home values are indicators of changes in demand for neighborhoods. Outward neighborhood demand shifts associated with income growth can drive reduced population and higher housing prices as smaller homes are combined for households with greater housing demand. Second, home values are an input into neighborhood choices, an idea which we develop further in Section 5. We will show that declining propensities to live in central neighborhoods have come despite increases in valuations by some demographic groups because local cost of living has increased. It is important to additionally recognize that home values also capitalize changes in expected housing investment returns, which makes them more volatile than could be justified by fundamentals. The steep rise in home values during the 1980s between 0.5 and 2 km from CBDs may reflect rational expectations about future gentrification that eventually came to pass in the 2000-2010 period. The steep 2000-2010 rise in home values 2-10 km away from CBDs may reflect

[3] Couture & Handbury's (2015) use CBD distance rings within which 5% of the CBSA populations live as their measure of downtown. Using 1970 data, this amounts to a median of 1.75 km and a range of 0.75 to 5 km. We found Figure 1 to be noisier when using such population percentiles instead as the x-axis variable.

expectations about future gentrification in these neighborhoods.

One important mechanism that we explore as a potential driver of gentrification is shifts in the spatial structure of labor demand. To get a sense of how important this mechanism could be, Figure 2 Panel F shows employment growth as a function of CBD distance. It shows much more rapid employment growth in suburban areas during the 1990s, but 2000-2010 employment growth that is essentially flat as a function of CBD distance. A very similar picture emerges for total payrolls. This look at the data indicates that employment growth may play a role, but is likely not the primary driver of downtown gentrification. Our systematic empirical investigation below confirms this claim. The figure shows only the 1990s and 2000s, because we do not have employment location information prior to 1990.

Table 1 reports transitions of individual census tracts through the distributions of the same three indicators in Panels B-D of Figure 2 plus the composite SES index. We present this evidence about the nature of demographic change in central neighborhoods to provide a sense of the heterogeneity around the summary statistics presented in Figure 2 and in order to show that a few neighborhoods moving quickly up the distribution are not driving central area gentrification. Table 1 shows the fraction of the population within 4 km of a typical CBSA's CBD living in tracts moving more than 20 percentile points or 0.5 standard deviations up or down the CBSA tract distribution. These numbers are calculated weighting by tract share of CBSA population in the base year, meaning all CBSAs are weighted equally.

Commensurate with evidence in Figure 2, three of our four measures indicate that central area tracts were on balance in decline during the 1970s. Results for the overall SES index in Panel D show that central neighborhoods' declines slowly reversed sometime in the 1980s or 1990s, when 2.8 percent of the central area population moved up at least 20 percentile points in the SES index distribution, relative to 1.9 percent in rapidly declining central tracts. Similarly, 4.6 percent of this population lived in tracts moving up at least 1/2 a standard deviation relative to 3.1 percent living in tracts moving down this much. This increase in the SES index of central tracts during the 1990s was mostly driven by income gains which had begun already in the 1980s. As in Figure 2, evidence in Table 1 shows that the resurgence of central areas really took off between 2000 and 2010. During this period, 7.9 percent of central area population lived in tracts moving up 20 percentile points in SES index distributions relative to only 1.1 percent living in tracts moving down in the typical CBSA.

Downtown neighborhoods were the poorest and had among the lowest education levels and shares of white residents of any CBD distance ring in 1980. One potential explanation for downtown gentrification is thus simple mean reversion. We next provide evidence that while mean reversion in neighborhood income and racial composition does exist, it is not the only force behind downtown revitalization. More broadly, we put the fortunes of downtown neighborhoods in the context of trends in overall neighborhood inequality.

We use our three demographic measures and the SES index to generate summary measures of changes in neighborhood inequality for each CBSA since 1980. The process for doing so resembles that in Chetty et al. (2014) but as applied to census tracts over time instead of parent-child pairs. In particular, we calculate the slope of an OLS fit line between CBSA demeaned outcomes between year t and $t-10$ or 1980, applying tract population weights in the base year. A slope of 1 indicates no change in neighborhood inequality on average while a slope of less than 1 indicates neighborhood convergence. Chetty et al. (2014) and Lee & Lin (2014) use percentile ranks in each year rather than demeaned outcomes as a basis for describing intergenerational mobility and neighborhood population change, respectively. However, our analysis benefits from distinguishing neighborhoods experiencing small changes from those experiencing large changes in their outcomes relative to CBSA means, even if they had the same changes in rank.

2.3 Chicago as an Example

Figure 3 depicts four measures of neighborhood change in the Chicago CBSA between 1980 and 2010, allowing for visualization of trends in neighborhood inequality. We calculate demeaned share white (Panel A), college graduate share (Panel B), log median household income (Panel C), and the SES index (Panel D) in each tract in 1980 and 2010, weighting by tract population. These demand indicators are graphed against each other in a scatterplot, with 45 degree and regression lines indicated. Both of these lines pass through (0,0) in each panel by construction. Dark black dots represent tracts within 4 km of the CBD. Regression slopes of less than 1, seen for log mean tract household income, tract share white and the composite SES index, indicate that Chicago neighborhoods have experienced convergence in these dimensions. The slopes of these regression lines are our 1980-2010 neighborhood change measures for Chicago. Points above a regression line that are far to the left of a 1980 mean represent gentrifying census tracts.

Figure 3 reveals considerable heterogeneity in 1980-2010 Chicago neighborhood change, with our three SES status measures clearly capturing distinct things. The masses of points at the bottom left and top right of Panel A represent large concentrations of stable minority and white census tracts respectively. The relatively large number of tracts along the right edge of the graph at almost 100 percent white in 1980 and ending up less than 70 percent white may have experienced tipping (Card, Mas & Rothstein, 2008). But a handful of tracts went in the other direction between 1980 and 2010, seen in the upper left area of the graph. These largely minority tracts in 1980, that gained white share much faster than the typical Chicago tract, are almost exclusively within 4 km of the CBD. Indeed, all but 4 of the tracts within 4 km of the CBD that were less than 80 percent white in 1980 experienced increases in white share between 1980 and 2010, even though share white decreased on average. Such downtown area gentrification is clearly visible for the other measures as well in Figure 3, with central area tracts clustered in the upper left area of each panel.

Figure 4 contains analogous graphs depicting changes in Chicago tract SES indexes over each decade of our study period. It shows that Chicago experienced a small amount of neighborhood convergence in each decade 1970-2010. Dark black dots clustered on both sides of the regression line to the left of 0 in Panels A and B but only above the line in Panels C and D indicate that central area gentrification began during the 1990s in Chicago. We next document statistically that such patterns of neighborhood change near CBDs apply not just to Chicago, but are pervasive across medium and large metropolitan areas, and that poor tracts near CBDs began to turn around after 1990.

2.4 Quantifying Trends in Neighborhood Inequality

We now systematically characterize variation in neighborhood change within CBSAs and assess the extent to which this variation is explained by local labor market demand conditions. We apply the same logic discussed above for the Chicago example to each tract in our full sample with some additions. In particular, we investigate patterns of changes in central area tracts' demographic composition while accounting for CBSA specific trends in neighborhood inequality and observable natural amenities whose valuations may have changed over time. We also investigate the extent to which CBSA and CBD area labor market conditions affected residential demand in central area neighborhoods. One lesson from the Chicago example is that there is a tendency for neighborhood demographics to revert to the mean. This is not just a Chicago phenomenon. Demographic convergence in all but measures except the share of residents with at least a college education is pervasive throughout the CBSAs in our sample. Thus, we must be careful that our descriptions of central neighborhood change do not simply reflect the fact that central neighborhoods are more likely to start off with a low SES and mean revert relative to other neighborhoods.

To get a sense of average differences in neighborhood change in central area tracts versus those in other areas, we first consider a static data generating process in which neighborhoods with higher residential demand exhibit higher SES index values in equilibrium. Time differencing this relationship isolates descriptive evidence for changes in central area neighborhood demand relative to other areas. (We address mean reversion below.) The following regression equation measures such average differences in central area neighborhood change relative to other neighborhoods.

$$\Delta S_{ijt} = \rho_{jt} + \sum{}_{d=1}^{4} \alpha_{dt} cbddis_{ij}^{d} + \alpha_{1t}^{b} cbddis_{ij}^{1} \Delta \ln Emp_{jt} + \alpha_{1t}^{s} cbddis_{ij}^{1} \Delta \ln CBDEmp_{jt}$$
$$+ \sum{}_{d=1}^{4} \beta_{dt} topdis_{ij}^{d} + \sum{}_{m} \delta_{mt} \ln(amendis_{ij}^{m}) + \varepsilon_{ijt} \tag{1}$$

This equation has the change in tract i's SES index (in CBSA j at time t) on the left hand side as a function of CBSA fixed effects, 4 km CBD distance ring indicators with the innermost ring interacted with CBD-oriented and CBSA labor demand shocks (described below), distance bands to top quartile SES tracts in 1970 and log distances to various natural amenities including coastlines, lakes and rivers. We include natural amenity controls given evidence in Lee & Lin (2014) that they anchor affluent neighborhoods, meaning nearby neighborhoods may be less likely to experience demographic change. The control for distance to top quartile tracts accounts for the possibility that tracts near CBDs gentrified simply because of expansions of nearby high income neighborhoods (Guerrieri, Hartley & Hurst, 2013). We estimate coefficients in (1) over each decade 1970-2010 and for the 1980-2010 period. We maintain 1970 CBSA population share weights throughout.

Table 2 Panel A reports estimates of α_1, α_1^b and α_1^s from Equation (1). α_1 describes how much more or less gentrification occurred in tracts within 4 km of CBDs relative to what was typical among tracts beyond 16 km from the CBD, which is the excluded distance category, quantifying the patterns seen in Figure 2. α_1^b describes how this gap differed by CBSA employment growth $\Delta \ln Emp_{jt}$. In most periods, we instrument for $\Delta \ln Emp_{jt}$ using a Bartik (1991) type industry shift-share variable. This instrument is constructed by interacting the 1-digit industrial composition of employment in each CBSA in 1970 with national employment growth rates in each industry to generate a predicted change in employment for each CBSA.[4] The idea is to isolate demand shocks for living in a CBSA that are driven by national trends in industry growth rather than factors that could be correlated with unobservables driving central neighborhood change. α_1^s describes how SES growth within 4 km of CBDs differed for CBSAs with larger CBD-oriented labor demand shocks. Here, $\Delta \ln CBDEmp_{jt}$ is the change in employment within 4 km of a CBD. $\Delta \ln CBDEmp_{jt}$ is instrumented with a CBD-oriented industry shift share variable analogous to the instrument for total CBSA employment growth.[5] Both employment growth variables and their instruments are standardized into separate z-scores. Because we do not observe the change in employment within 4 km of CBDs before 1990, we cannot use it as a regressor directly. For this reason, and to maintain consistency across the two Bartik demand shifters, we estimate reduced forms for the 1970-1980, 1980-1990 and 1980-2010 periods instead of IV regressions. Therefore, for these periods magnitudes of α_1^b and α_1^s do not accurately capture effects of 1 standard deviation changes in CBSA- and CBD-oriented employment growth, respectively. However, sign and significance of these coefficients remain informative. Table A1 reports summary statistics about these two types of shocks in each decade, allowing for translation into direct effects of employment changes.

Results in Table 2 Panel A parsimoniously quantify the rebounds experienced by central neighborhoods visualized above in Figure 2. Our estimate of α_1 in the first row is significantly negative for the 1970s but turns significantly positive in the 1990s and strengthens for the 2000-2010 period,

[4] That is, we construct the Bartik instrument for CBSA j that applies to the period $t-10$ to t as: $Bartik_{jt} = \sum_k S_{jk1970} \ln(emp_{kt}^{-j}/emp_{kt-10}^{-j})$, where S_{jk1970} is the fraction of employment in CBSA j that is in industry k at in 1970 and emp_{kt}^{-j} is national employment in industry k at time t excluding CBSA j.

[5] For CBSA j, denote the fraction of employment near the CBD in industry k in 1990 as f_{jk}^{emp}. We think of f_{jk}^{emp} as being driven by the interaction of fundamental attributes of the production process like the importance of agglomeration spillovers to TFP. Therefore, we predict the change in the fraction of employment near the CBD to be $Spatbartik_{jt} = \sum_k f_{jk}^{emp} \ln(emp_{kt}^{-j}/emp_{kt-10}^{-j})$, where emp_{kt}^{-j} denotes national employment in industry k and year t excluding CBSA j.

during which time central areas experienced 0.11 standard deviations more positive demographic change than the typical suburban neighborhood. Over the longer 1980-2010 period, central areas experienced 0.16 standard deviations more positive demographic change relative to suburban neighborhoods. Because interactions are normalized to be mean 0, the interpretation of this first row of coefficients is as an average across CBSAs.

The second and third rows present estimates of α_1^b and α_1^s respectively. One consistent fact is that central neighborhoods of CBSAs with more robust central area employment growth experienced relative gentrification, even in the 1970s. However, this phenomenon was strongest in the 2000-2010 period when 1 standard deviation greater downtown employment growth generated a 0.08 standard deviation relative improvement in central area demographic composition. (These coefficients only have clean interpretations for the 90s and 00s when we can estimate them by IV.) The effects of CBSA employment growth on downtown neighborhood change depends a lot more on the time period and better tracks average trends. In the 1970s, central areas of CBSAs with more robust exogenous employment growth deteriorated more than was typical, whereas by 2000-2010 the reverse was true. That is, broader forces buffeting central area neighborhoods appear to be reinforced by trends in aggregate CBSA labor demand shocks. Similar patterns are found separately within each tercile of the 1970 SES index distribution. That is, these results are not only being driven by low SES central neighborhoods.

Evidence from Chicago explored in the previous sub-section reveals that neighborhoods experienced mean reversion in their SES index. This mean reversion is pervasive across CBSAs and relevant since central area tracts disproportionately appear in the bottom half of the SES index distribution. At least some of this mean reversion is mechanical given i.i.d. shocks, since by definition of the index, the lowest SES tracts can more easily move up the distribution and the highest SES tracts can more easily move down the distribution. Therefore, it may be important to account for the fact that central area tracts have more mechanical potential to experience positive demographic shocks than other neighborhoods. In practice, however, our examination by tercile of the 1970 SES distribution yields similar results for the top and bottom terciles, indicating that mean reversion is not driving results. We attempt to take this issue seriously nonetheless.

An initial step to control for mean reversion is to include an additional control for S_{ijt-10} in (1), with an expected negative coefficient. But doing so generates an econometric problem of having the same variable on both sides of the regression equation. Consolidating S_{ijt-10} onto the right hand side of the regression equation yields an AR(1) specification with CBSA fixed effects fully interacted with the lagged SES index. This specification generates regression lines for each

CBSA*decade combination analogous to those in Figure 4 for Chicago.

$$S_{ijt} = \rho'_{jt} + \mu'_{jt} S_{ijt-10} + \sum{}_{d=1}^{4} \alpha'_{dt} cbddis_{ij}^{d} + \alpha_{1t}^{b'} cbddis_{ij}^{1} \Delta \ln Emp_{jt} + \alpha_{1t}^{s'} cbddis_{ij}^{1} \Delta \ln CBDEmp_{jt} + \sum{}_{d=1}^{4} \beta'_{dt} topdis_{ij}^{d} + \sum{}_{m} \delta'_{mt} \ln(amendis_{ij}^{m}) + \varepsilon'_{ijt} \quad (2)$$

These regressions feature the same remaining set of regressors as in (1). Table 2 Panel B reports estimates of coefficients in (2).

While this empirical approach addresses mean reversion, it is well known that in short panels OLS estimates of μ_{jt} may be biased downwards. Such Hurwicz bias will influence coefficients of interest α_1, α_1^b and α_1^s if the lagged SES index is correlated with CBD distance, which is likely as CBD areas are more likely to be poor - the whole justification for exploring this specification from the start. To deal with this bias, we implement a standard Arellano-Bond (1991) type correction. Beginning with (2), impose that $\mu_{jt} = \mu_{jt-1}$ and, without loss of generality, add a tract fixed effect. First-differencing yields the following equation.

$$\Delta S_{ijt} = \rho''_{jt} + \mu''_{jt} \Delta S_{ijt-1} + \sum{}_{d=1}^{4} \alpha''_{dt} cbddis_{ij}^{d} + \alpha_{1t}^{b''} cbddis_{ij}^{1} \Delta \ln Emp_{jt} + \alpha_{1t}^{s''} cbddis_{ij}^{1} \Delta \ln CBDEmp_{jt} + \sum{}_{d=1}^{4} \beta''_{dt} topdis_{ij}^{d} + \sum{}_{m} \delta''_{mt} \ln(amendis_{ij}^{m}) + \varepsilon_{ijt} \quad (3)$$

As in the standard Arellano-Bond (1991) procedure, we instrument for ΔS_{ijt-1} with S_{ijt-2}. The identifying assumption is thus that the lagged SES index is not correlated with unobservables driving innovations in a tract's SES index after accounting for mean reversion, CBD distance and distance to amenities. In practice, this means we have J instruments, one for each CBSA interacted with ΔS_{ijt-1}. Results from this specification are reported in Table 2 Panel C, with 1970-1980 left out because data from 1970 is needed to form instruments for the 1980-1990 estimates.

Results in Table 2 Panels B and C are quite similar to those in Panel A. Whichever assumption we impose about the underlying data generating process, the three main facts persist. First, there is a clear statistically meaningful demographic rebound of central neighborhoods in the 2000-2010 period. Second, central area employment growth bolstered central neighborhood demographic change, especially in the 1970s and 2000-2010 period. Third, CBSA employment growth bolstered central neighborhoods in the 2000-2010 period only, when they were changing for other reasons. The results in Table 2 Panels B and C demonstrate that the reversal of fortune experienced by many central neighborhoods after 1980 is not an artifact of mean reversion.

Overall, evidence in Table 2 plus facts about central area employment growth indicates that the bulk of 2000-2010 downtown gentrification could not have been driven by shifts in the spatial structure of labor demand. However, CBD-oriented positive labor demand shocks reinforced the downtown gentrification that occurred in many cities primarily for other reasons. With 2000-2010 CBD area employment growth averaging -1 percent across CBSAs, downtown neighborhood growth must have come about for other reasons in most CBSAs, with improvements in the relative amenity values of downtown neighborhoods the most logical mechanism. The model in Section 5 clarifies this intuition. In Section 5, we provide evidence that while educated whites experienced disproportionate amenity value improvements for these central neighborhoods, blacks of all education levels did not. However, residential demand by most demographic groups grew with downtown employment growth, as should be expected.

Positive demand shifts for neighborhoods will be reflected as some combination of increases in quantities of residents, potential income of residents and housing prices. CBSAs with high housing supply elasticities (Saiz, 2010) may have had some neighborhoods with large outward demand shifts that experienced only small relative changes in housing costs. However, because they have the smallest availability of developable land, central areas of cities are likely to have supply elasticities that are amongst the lowest of any neighborhood in any given CBSA. In this vein,Table A2 presents regression results analogous to those in Table 2 using an index of tract housing value growth rates as the dependent variable. This index is calculated as the residuals from a regression of log mean tract housing value on various characteristics of owner occupied housing and CBSA fixed effects. Evidence in Table A2 largely follows that in Table 2, though with more noise and less dramatic reversals of declines. Central neighborhoods have experienced a resurgence in housing prices, especially those in CBSAs with CBD oriented employment growth.[6]

3 Counterfactual Neighborhood Compositions

Results in the last section showed two important patterns in the data. First, central neighborhoods have been chosen at higher rates by higher SES demographic groups since 2000. Second, this gentrification has been more pronounced in CBSAs with improving central area employment prospects and in CBSAs with improving overall employment prospects. Thus far, our examination of location choices one demographic group at a time has limited our ability to determine the demographic characteristics driving downtown gentrification, especially since college education, high incomes and white fraction are all strongly positively correlated. In addition, the analysis to this point has not evaluated the extent to which demographic change toward more education, a more unequal income distribution and smaller families has accounted for gentrification. To separate out the relative importance of changing race-specific neighborhood choices from other observed demographic factors that may be correlated with race, we use tract level joint distributions of race and education or income over time to construct counterfactual neighborhood compositions absent changes in neighborhood choices for particular race-education and race-income combinations. The analysis

[6] Edlund et al. (2015) find that 26 large CBSAs with stronger skilled labor Bartik shocks experienced more rapid decadal central home price growth and demographic change in central areas than other areas of the city. These patterns are replicated in our data as well if census tracts are equally weighted.

simultaneously evaluates the extent to which population and SES growth in central neighborhoods are driven by shifts in the demographic compositions of CBSA populations.

To separate out the roles of CBSA-level demographic change from changes in individual groups' neighborhood demands, we carry out decompositions of the sources of neighborhood change along the lines developed by DiNardo, Fortin & Lemieux (1996) for decomposing wage distributions. To quantify the relative importance of changing neighborhood choices and demographic shifts for neighborhood change, we calculate magnitudes of central area population and demographic change under various counterfactual environments. First, we hold the fraction of CBSA population in various demographic groups fixed over time but allow neighborhood choices by specific groups to shift as in equilibrium one by one. This allows us to evaluate the extent to which changes in the choices of higher SES individuals and whites have driven central neighborhood change while holding the demographic composition of CBSA populations constant. We then additionally calculate how shifts in the CBSA level compositions of various demographic groups conditional on race have mechanically influenced neighborhood change, leaving CBSA level racial change as the residual component. This procedure has similarities to that developed in Carillo & Rothbaum (2016).

The results lain out in this section emphasize distinct forces driving central neighborhood change in the 1980-2000 and 2000-2010 periods. In the earlier period, central neighborhoods experienced flight of the poor, less educated and households with children. This was true for both white and minority households and was sizable enough to counteract a rising minority population, which mechanically increased the population of central area incumbent demographic groups. By 2000, the balance of power had shifted. The movement of higher SES whites into central neighborhoods strengthened as the outflow of lower SES whites ceased or reversed. Over the entire study period, the increasing college fraction in the population, especially among whites, has been important for driving composition shifts of downtown neighborhoods toward more white and educated.

3.1 Construction of Counterfactual Neighborhoods

3.1.1 Overview of Constructing Counterfactual Distributions

We observe the joint population distribution $f_{jt}(i,r,x)$ of race r and other demographic attribute x across census tracts i in CBSA j in year t. The attribute x indexes education group, age group, family structure or household income decile in the national distribution. Given the structure of tabulated census data, we are forced to evaluate counterfactual joint distributions of race (white, black, and other) and only one other demographic attribute at a time across census tracts. Denote N_{jt} as the total population of CBSA j at time t and CBSA density functions of demographics as $g_{jt}(r,x) = \sum_i f_{jt}(i,r,x)$. Crucially, we treat CBSA level allocations $g_{jt}(r,x)$ and populations N_{jt} as exogenous to the allocation of people across neighborhoods, which can be justified in a long run open city model such as Ahlfeldt et al. (2015). Therefore, while aggregate population does not influence conclusions drawn from these mechanical counterfactuals, it will matter in principle when incorporating a consideration of housing costs.

Central to our recovery of counterfactuals is the following decomposition:

$$f_{jt}(i,r,x) = f_{jt}(i|r,x)g_{jt}(x|r)h_{jt}(r) \tag{4}$$

This expression shows how to separate out neighborhood choices of particular demographic groups $f_{jt}(i|r,x)$ from the CBSA level distribution of (r,x) across locations. It additionally shows how to separate out shifts in education, age, income, or family type compositions independent of racial composition. Components of demographic change driven by changes in demand by group (r,x) for tract i are captured by shifts in $f_{jt}(i|r,x)$. Components driven by changes in the demographic makeup of whites, blacks or other minorities holding the racial distribution constant are captured by shifts in $g_{jt}(x|r)$. Components driven by changes in the racial composition of the population holding the demographic makeup of each race constant are captured by shifts in $h_{jt}(r)$. McKinnish, Walsh & White (2010) use a similar decomposition to examine the drivers of neighborhood income growth.

Tables 3-6 report results of counterfactual experiments, all with a similar structure. Table 3 uses counterfactual distributions to separate out mechanisms driving total central area population change. Tables 4 and 5 use counterfactual distributions to decompose sources of changes in central area fraction white and fraction college, respectively. Table 6 decomposes changes in median income, expressed as percentiles of the household income distribution in sampled tracts. Table 3 examines 2 km CBD radii only and the other tables present results for both 2 and 4 km radii.[7] Panels A and B report results for 1980-2000 and 2000-2010, respectively. In Table 3, each row uses a different data set with joint distributions of race with education, age, family type and income, respectively. Table 4 presents results using race-education and race-income joint distributions. Tables 5 and 6 use race-education and race-income distributions only, respectively.

Column 1 in Tables 3-6 reports changes in outcomes of interest for central area geographies calculated using the raw data as a basis for comparison to counterfactuals. Because of sampling variability across the education, age and family type data sets and the use of households rather than people in the income data set, numbers in Column 1 of Tables 3 and 4 do not match perfectly across data sets. Column 2 shows the change that would have occurred had choices and shares not shifted from the base year. In Table 3, this is the CBSA population growth rate. Because objects of interest in Tables 4-6 are invariant to scale, Column 2 is all 0s in these tables.

The remaining columns of Tables 3-6 are built using counterfactual distributions. Our notation indicates column number superscripts on these probability distribution functions. Column 3 of Tables 3-6 reports counterfactual central neighborhood change given CBSA demographic shares

[7] Because 2000-2010 population growth was positive within 2 km of CBDs but negative within 4 km of CBDs, we focus on 2 km only for this outcome.

that are unchanged from the base year. In particular, they are constructed using the counterfactual distributions

$$f^3_{jt}(i, r, x) = f_{jt}(i|r, x)g_{jb}(x|r)h_{jb}(r).$$

Here, demographic shares $g_{jb}(x|r)h_{jb}(r)$ are for the base year but neighborhood choices for each group $f_{jt}(i|r, x)$ change as they did in equilibrium. Results in Column 4 of Tables 3-6 show the effects of holding choices constant but allowing demographic shares to shift as in equilibrium. These statistics are constructed using the counterfactual distribution

$$f^4_{jt}(i, r, x) = f_{jb}(i|r, x)g_{jt}(x|r)h_{jt}(r).$$

In most cases, results in Column 3 are closer to baselines in Column 1 than those in Column 4. This means that changes in neighborhood choices have been more important than changes in neighborhood shares for generating observed patterns in the data.

3.1.2 Counterfactual Choices and Shares for Specific Demographic Groups

The remaining columns in Tables 3-6 decompose the difference between the actual changes in Column 1 and the counterfactuals given no changes in choices or shares in Column 2 into components that are related to changes in neighborhood choices (Columns 5-8) and demographic shares (Columns 9-10). The four effects in Columns 5-8 sum to the total effect of changing choices holding demographic shares constant reported in Column 3 relative to no changes reported in Column 2. Adding the effects of changing demographic shares yields the full difference between the actual data in Column 1 and the "no changes" baseline in Column 2. That is, taking a running sum from left to right starting at Column 5 can be thought of as piling on additional components of demographic change from a baseline of no changes in Column 2 to full changes in Column 1.

Columns 5-8 report components of changes in equilibrium tract composition due to changing neighborhood choices of target whites, non-target whites, target non-whites and non-target non-whites, respectively, holding demographic shares at their base year levels. “Target" refers to college graduates, 20-34 year olds, single people and married couples without kids, or households in the top three deciles of the income distribution of the full sample area, depending on the data set used.

The set of results for counterfactual c (5 to 8) is constructed using distributions built as

$$f^c_{jt}(i, r, x) = f^c_{jt}(i|r, x)g_{jb}(x|r)h_{jb}(r),$$

where $f^c_{jt}(i|r, x) = f_{jt}(i|r, x)$ for the elements of (r, x) listed in column headers and $f^c_{jt}(i|r, x) = f_{jb}(i|r, x)$ for remaining elements of (r, x). We note that the order of demographic groups for which we impose year t choices does not affect results. This is because the change in the fraction of the population in tract i as a result of imposing any of these counterfactuals is linear. Each counterfactual amounts to imposing year t rather than year b choices for a few additional elements of (x, r) at a time. Mathematically, the difference in the fraction of the population living in tract i associated with counterfactual c relative to $c-1$ is

$$\sum_x \sum_r [f_{jt}^c(i|r,x) - f_{jt}^{c-1}(i|r,x)] g_{jb}(x|r) h_{jb}(r). \tag{5}$$

Because of linearity within the square brackets, (5) indicates that the full choice adjustment counterfactual 3 can be achieved by imposing counterfactuals 5, 6, 7 and 8 cumulatively in any order. Equation (5) also indicates that counterfactual c's influence on tract composition depends not only on the magnitudes of differences in choices made by the group (x, r) in question between t and the base year $[f_{jt}^c(i|r,x) - f_{jb}(i|r,x)]$, but also by the fraction of that group in the CBSA population in the base year, $g_{jb}(x|r)h_{jb}(r)$. That is, neighborhoods change the same amount if a large group makes small changes in neighborhood choices or a small group makes large changes in neighborhood choices. To provide information about which one is driving results, Table 3 reports the average fraction of CBSA populations in parentheses for each of the four sets of demographic groups for which we examine the effects of changes in choices.

Having determined the roles of changes in neighborhood choices holding demographic composition constant, the remaining changes must be due to shifts in population composition. To look at this, we first maintain the base year racial distribution and examine how shifts in other demographic attributes conditional on race have influenced neighborhood choices. This allows us to see the influences that rising education levels, changes in income inequality, more single people, and the aging of the population have had on downtown neighborhood change while holding CBSA white, black and other population shares constant. Doing so avoids including the mechanical effects that rising minority shares have on the education, age, family type and income distributions in these results. These results are reported in Column 9 of Tables 3-6, and are built using the expression

$$f_{jt}^9(i,r,x) = f_{jt}(i|r,x) g_{jt}(x|r) h_{jb}(r).$$

The residual effect (Column 10) is due to changes in racial composition, which typically works against gentrification since the white share of the population has declined over time.

Table A3 mathematically specifies construction of each counterfactual distribution and Table A4 reports average shares of target groups across CBSAs overall and within 2 km and 4 km CBD distance rings.

3.1.3 Calculating Counterfactual Demographic Change

We use the distributions $f_{jt}^c(i,r,x)$ for each counterfactual c and base year distributions $f_{jb}(i,r,x)$ to calculate counterfactuals of each measure of central neighborhood change discussed above.

We construct counterfactual population growth within 2 km of the CBD for Table 3 using the following expression:

$$\frac{1}{J}\sum_{j}\left(\ln\frac{N_{jt}}{N_{jb}}+\ln\frac{\sum_x\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x)}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f_{jb}(i,r,x)}\right) \tag{6}$$

That is, the central area population growth rate in a CBSA can be expressed as the sum of CBSA growth rate and the growth rate of the fraction of the population in the central area. The objects reported in Table 3 are averages across the 120 CBSAs in our sample, as is captured by the outer summation. The reference "no change" results in Column 2 of Table 3 are simply average CBSA population growth rates, calculated as $\frac{1}{J}\sum\limits_j \ln(N_{jt}/N_{jb})$.

For Tables 4 and 5, we calculate changes in central area fraction white and fraction college respectively using the following expressions

$$\frac{1}{J}\sum_{j}\left(\frac{\sum_x\sum_{i\subseteq CBD_j}f^c_{jt}(i,r=w,x)}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x)}-\frac{\sum_x\sum_{i\subseteq CBD_j}f_{jb}(i,r=w,x)}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f_{jb}(i,r,x)}\right) \tag{7}$$

$$\frac{1}{J}\sum_{j}\left(\frac{\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x=\text{col})}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x)}-\frac{\sum_r\sum_{i\subseteq CBD_j}f_{jb}(i,r,x=\text{col})}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f_{jb}(i,r,x)}\right). \tag{8}$$

In these tables, the reference change is 0, since there is no scale component. In Table 4, x indexes education composition or income decile as indicated in the row header. For Table 5, x only indexes education composition.

For Table 6, we calculate counterfactual changes in central area median household income. We use median rather than mean income in order to be more robust to misallocating households to incorrect income deciles.[8] To see how this is built, begin with the following expression for the cumulative distribution function of CBSA j's central area households across income deciles $x\subseteq\{1,2,...,10\}$.

$$G^c_{jt}(X)=\frac{\sum\limits_{x\leq X}\left[\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x)\right]}{\sum_x\sum_r\sum_{i\subseteq CBD_j}f^c_{jt}(i,r,x)}.$$

The income deciles are defined for the full national study area but here we only focus on the cdf for central neighborhoods under counterfactual c. Using these distributions over deciles x, we identify the deciles D^c_{jt} that contain 0.5. We assign the median percentile assuming a uniform distribution of household income within D^c_{jt}. For example, if $G^c_{jt}(2)=0.45$ and $G^c_{jt}(3)=0.55$, $D^c_{jt}=3$. In this case, we would assign the median household income M^c_{jt} in CBSA j at time t under counterfactual

[8] Because cutoffs associated with each decile do not match the dollar cutoffs in the tract data, we assume uniform distributions within census data dollar bands for allocation purposes. The Data Appendix details our procedure for allocating households to income deciles.

c to be 25, representing the 25^{th} percentile of the full study area's household income distribution. Then, the statistics reported in Table 7 are

$$\frac{1}{J}\sum_{j}\left(M_{jt}^{c}-M_{jb}\right). \tag{9}$$

As a result, positive numbers in Table 7 mean that the counterfactual in question pushed central area median incomes up by the indicated number of percentile points out of the national urban household income distribution.

Because choices and shares matter multiplicatively for the overall population distribution across tracts, the ordering of imposing year t distributions matters for the influence of each channel. Tables A5 and A6 show results analogous to those in Tables 3-6 but impose the counterfactuals in the reverse order: shares adjustments first and sub-group specific choice adjustments second. This ordering does not materially affect the results.

3.2 Counterfactual Results

Before discussing the results of each counterfactual exercise, it is instructive to take a step back and summarize the broad picture provided by them. They all reflect a pattern of declining 1980-2000 central area population of all demographic groups except stability for some types of high SES whites. This trend continued after 2000 among minorities, though high SES whites had strong central area population growth and high SES nonwhites had essentially stable central area populations.

3.2.1 Population

Table 3 shows what population growth 1980-2010 would have been within 2 km of CBDs under the various counterfactual scenarios laid out in the prior sub-section. Each row uses a different census tabulation that includes joint distributions across census tracts of population by race and the x characteristic indicated under "Data Set". Evidence in Column 1 reiterates the Figure 2 result that near CBD populations declined until 2000, after which they grew at about the same rate as overall urban population growth reported in Column 2. We do not report analogous results for within 4 km of CBDs because they are similar except for baseline population declines in both study sub-periods.

Results holding shares constant in Column 3 are slightly less than the actual changes in Column 1, meaning that shifting demographics pushed toward central area population growth since growing demographic groups were disproportionately located in downtown neighborhoods. We see below that in practice differences between actuals in Column 1 and results holding shares constant in Column 3 are mostly driven by increases in minority population shares. Had the race-education distribution not changed from 1980 to 2000, central area population would have declined by 12 percentage points rather than the actual decline of 7 percentage points in the average CBSA. In the 2000-2010 period, central area population would have grown by 4 percentage points rather than the 6 percentage points it actually grew. When using joint distributions of age, family type or income with race instead, changes in demographics are estimated to have bolstered central areas even more in both periods. As we discuss in more detail below, this is fully explained by variation in demographic changes in these non-racial dimensions.

Column 4 shows what would have happened to central area populations had neighborhood choices not changed from base years but demographic shares did. For 1980-2000, it shows over 30 percentage points of growth for all data sets and for 2000-2010 it shows over 9 percentage points of growth for all data sets. This reflects the positive effects associated with rising minority population reinforced by the imposed lack of shifts in neighborhood choices away from central neighborhoods.

Comparing the magnitudes of the results in Columns 3 and 4 indicates that changing neighborhood choices have been central generators of 1980-2000 central area population decline, even as shifting demographics have pushed for population growth in central areas of cities. In the 2000-2010 period, shifts in neighborhood choices continued to hold central neighborhoods slightly below CBSA growth rates, with demographic changes almost making up for this deficit. Central areas' relatively high minority population shares and increasing minority populations, nationally, have, if anything, pushed for more rapid population growth in central areas. Larger effects in Columns 3 and 4 for the family type data set reflect an increasing fraction of the population living in childless households and the greater propensity for childless households to live near CBDs. Smaller effects for the education data set reflect the lower propensity of highly educated people to live near CBDs, especially in 1980.

Results in Columns 5-8 show the amount of population change due to changes in choices by each of the indicated demographic groups. "Target" groups are identified in the table notes, and are typically of higher socioeconomic status. In parentheses is the fraction of each demographic group in the CBSA population. These results show that 1980-2000 central area population losses are mostly explained by the flight of low SES whites and nonwhites alike, whose effects are similar at -0.14 and -0.18, respectively, for education and -0.24 and -0.21, respectively, for income. With non-target whites representing much larger shares of CBSA and central area populations, the logic discussed in the context of Equation (5) indicates that changing choices of non-target nonwhites must have been of greater magnitudes. While all target groups of whites and nonwhites were also choosing to move away from central neighborhoods during 1980-2000 except young whites, the outflow was least pronounced amongst target whites.

In the 2000-2010 period, minority flight continued while white flight reversed. Non-target and target nonwhites departed central neighborhoods at similar rates as in 1980-2000, but all 4 groups of target whites examined started to return to central neighborhoods. For example, changing choices of college educated whites and high income white households accounted for 4 percentage points and 3 percentage points of population and household growth, respectively. Less educated and older whites were also again choosing central areas, but at lower rates than young or college educated whites. Young or college educated minorities were not returning to central neighborhoods like their white counterparts. This evidence of the return of the young college educated to downtown areas is in line with Couture and Handbury's (2015) similar evidence using different census tabulations.

Results in Table 3 Column 9 show how shifts in the composition of the demographic described by each data set influenced the central area population share, holding racial composition constant. Positive values indicate a growing share of population subgroups that disproportionately chose to live in central area neighborhoods in the base year. The biggest standout in this regard is the fact that childless households were always most prevalent in downtown areas. Their growth as a fraction of the population contributed to a 10 percentage point increase in downtown populations during the 1980s and a 3 percentage point increase in the 2000-2010 period. In the other direction, the lower propensity of the educated to live near CBDs hurt these areas' populations. The zero effect for income in Column 9 is mechanically due to our measurement of income as a percentile in the distribution of incomes in our sample in each year. Results in Table 3 Column 10 consistently show that the declining white share of the population promoted increases in downtown populations by 10 percentage points in 1980-2000 and 3 percentage points 2000-2010.

3.2.2 Fraction White

Table 4 shows changes in the counterfactual share of white residents of central areas. We focus on education and income data sets and examine both 2 km and 4 km CBD distance radii. The baseline data in Column 1 shows that central neighborhood tracts within 2 km experienced about an 8 percentage point decline in fraction white between 1980 and 2000 and a 3 percentage point increase between 2000 and 2010. Within 4 km of CBDs, there was a 9 or 10 percentage point decline and a 1 or 2 percentage point increase in the two periods, respectively. Because of secularly declining white population shares, the patterns in Column 1 are consistent with the 1980-2000 absolute declines in white fraction near CBDs seen in Figure 2.

For the 1980-2000 period, changes in demographic shares have driven secular declines in fraction white. This is seen from the fact that holding choices constant in Column 4 yields numbers similar to the data in Column 1 whereas holding shares constant in Column 3 actually yields a small amount of growth in fraction white. As we saw in Table 3, changes in neighborhood choices of nontarget and target whites are both large, but their opposite effects on racial composition approximately offset. 1980-2000 flight of all groups yields entries in Columns 5 and 7, for target and nontarget whites respectively, that are all negative and entries in Columns 6 and 8, for target and nontarget nonwhites respectively, that are all positive. The large changes in choices of low SES nonwhites is enough to overwhelm the smaller shifts by low SES whites, yielding the small net positive impact on fraction white of holding shares constant seen in Column 3. Changing education and income shares conditional on race had small effects. However, shifts in the racial composition caused fraction white in central neighborhoods to decline by about 10 percentage points, holding choices constant, similar to the actual declines in Column 1.

In the 2000-2010 period, increases in central area fraction white were mostly driven by continued departures of nontarget nonwhites. The cessation of departures of nontarget whites from central neighborhoods contributed to the racial turnaround of these areas, with the return of target whites also contributing. Results in Column 10 indicate that reductions in the overall white share of the population over the entire sample period consistently pushed the central areas' fraction white downwards.

3.2.3 Fraction College and Household Income

Table 5 examines reasons for changes in the propensities of college graduates to locate in downtown areas. Strong growth in fraction college in Column 1 of about 5-6 percentage points for both study periods reflects the rapid secular shift in the education distribution of the population. Normalizing growth in college fraction to be per decade makes the 2000-2010 growth about twice as fast relative to 1980-2000, reflecting the reversal of this demographic trend relative to other neighborhoods that is evident in Figure 2. The general pattern of impacts of changing shares and choices is similar to that for fraction white discussed above. Secular changes in college fraction primarily drove 1980-2000 changes while changing choices of target whites in particular were an important force influencing 2000-2010 growth in central area college fraction.

With non-college graduates moving out of central areas at slightly higher rates than others during 1980-2000, the net effect of shifts in neighborhood choices is very slightly positive, as is seen in Column 3. The demographic shifts toward a more educated population contributed to an increase of 6.4 percentage points (column 9) in central area college fraction, with declines in the white population pushing in the other direction by 1.2 percentage points (column 10). Over the 2000-2010 period, the return of educated whites to central areas coupled with the continued departures of educated nonwhites became the additional important drivers of growth in central college fraction. Of the 6 percentage point increase in fraction college within 2 km of CBDs from 2000-2010, about half is from secular demographic change (column 4) and about half is from changes in choices (column 3). Of the changes in choices, about two-thirds (2.6 percentage points) is from changes in educated whites' neighborhood choices (column 5) and about one-third (1.1 percentage points) is from such changes by lesser educated non-whites (column 8).

Finally, Table 6 examines reasons for changes in central area median household incomes expressed in percentiles of this distribution across all tracts in the study area. Results in Column 1 show that areas within 2 km of CBDs moved up the income distribution by about 1 percentile 1980-2000 and by an additional 4 percentiles in the subsequent decade. Areas within 4 km of CBDs experienced small 1980-2000 income declines and gains of 2 percentile points in 2000-2010. A comparison of results in Columns 3 and 4 reveals that changing choices were more important than changing shares in both periods, with changing choices pushing for greater income growth and changing shares pushing for declining incomes. As with education and race, the 1980-2000 increase in income is primarily driven by the departures of lower income whites and nonwhites, alike. While these departures continued after 2000, the movement of high income whites into central neighborhoods bolstered central area income growth, especially within 2 km of CBDs. Given the increases in income inequality that occurred over the full study period, especially in larger cities (Baum-Snow & Pavan, 2013), this means that average incomes in city centers increased dramatically during the 2000-2010 period, as the rich were moving in and the poor were moving out. Shifts in racial composition represented an important force depressing central area incomes about half a percentile point over each decade 1980-2010.

4 Understanding Changes in Neighborhood Choices

The prior section performed an accounting of how much of demographic change in central neighborhoods has been driven by shifts in neighborhood choices by various demographic subgroups. In this section, we interpret this descriptive evidence in the context of a standard unified framework which delivers estimates of changes in neighborhood demand by location. This framework allows us to assess the extent to which rising home prices or inward demand shifts are responsible for the flight of lower SES households from central neighborhoods and the return of higher SES households. Moreover, it allows for recovery of the roles of CBSA and CBD oriented local labor demand shocks for driving these changes in demand for various demographic groups.

4.1 Neighborhood Choice Model

We lay out a standard neighborhood choice model that facilitates use of neighborhood choice shares by demographic group along with housing prices to recover information about changes in demand for neighborhoods over time. The procedure makes use of conditional choice probabilities, first formalized in Hotz & Miller (1994), in a way similar to Bayer et al's (2016) dynamic analysis of demand for neighborhood attributes. For clarity of exposition, we begin by thinking about the choice of neighborhood within one CBSA only. Couture & Handbury (2015) show that this is equivalent to considering a nested choice of first CBSA and then neighborhood within the chosen CBSA. Discrete household types are indexed by h and there is a continuum of households of each type.

The indirect utility of household r of type h residing in census tract i at time t is

$$\widetilde{v}^t_{rhi} = v_h(p^t_i, w^t_{hi}, q^t_i) + \varepsilon^t_{rhi} \equiv v^t_{hi} + \varepsilon^t_{rhi}.$$

In this expression, p^t_i is the price of one unit of housing services in tract i, w^t_{hi} is wage net of commuting cost, q_i^t summarizes local amenities and ε_{rhi}^t is an i.i.d. random utility shock distributed extreme value Type I. q_i^t may be a function of endogenous neighborhood attributes like the population composition itself.[9] w_{hi}^t can depend on human capital characteristics and access to employment locations from tract i. We think of a long-run equilibrium in which moving costs are negligible. This setup delivers the following population shares of household type h in each census tract i, which are observed in the data.

$$\pi_{hi}^t = \frac{\exp(v_{hi}^t)}{\sum_{i'} \exp(v_{hi'}^t)},$$

suggesting the relationship

$$\ln \pi_{hi}^t = v_{hi}^t - \ln\left(\sum_{i'} \exp(v_{hi'}^t)\right). \tag{10}$$

This equation shows that we can use conditional choice probabilities to recover the mean, median or modal utility associated with each tract up to a scale.[10]

We now consider the derivation of estimates of components of indirect utility that capture neighborhood attributes for a reference household type $\overline{h}$ and use it as a basis for recovering such components for other types. The broad goal here is to show how to control for differences in living costs across locations. Impose as a normalization that average modal utility across neighborhoods $\frac{1}{I}\sum_{i'} v_{\overline{h}i'}^t = 1$. This allows for inversion of (10) to an expression relating neighborhood choice probabilities to indirect utility, as in Berry (1994).

$$\ln \pi_{\overline{h}i}^t - \frac{1}{I}\sum_{i'}(\ln \pi_{\overline{h}i'}^t) + 1 = v_{\overline{h}}(p_i^t, w_{\overline{h}i}^t, q_i^t)$$

Fully differentiating yields an expression that tells us that $\ln v_{\overline{h}i}$ equals a weighted average of wages net of commuting costs, home prices and neighborhood attributes relative to those in the average location. This expression assumes utility over goods x, housing H and a local amenity index q $U(x, H, q)$ takes the form $qu(x, H)$, where u is homothetic.

$$\ln \pi_{\overline{h}i}^t - \frac{1}{I}\sum_{i'}\ln(\pi_{\overline{h}i'}^t) = d\ln w_{\overline{h}}^t - \beta_{\overline{h}} d\ln p_i^t + \sigma_{\overline{h}} dq_i^t$$

Here we are expressing utility as relative to the reference location, which has a utility normalized to 1. As in Rosen (1979) and Roback (1982), we see that differences in neighborhood choice probabilities reflect differences in incomes, housing costs and amenity values of locations. We can

[9] q_i term represents a vector of amenities for tract i. We allow each household type h to value the vector of amenities differently.

[10] Given the extreme value assumption for the errors, the mean tract utility is $v_{hi}^t + 0.58$ (Euler's constant) given normalization of the scale parameter to 1, the median is $v_{hi}^t - \ln(\ln(2))$ and the mode is v_{hi}^t.

recover the combination of differences in wages net of commuting costs and local amenities across tracts for the average household type $\overline{h}$ by imposing $d \ln p_i = \ln p_i - \frac{1}{I}\sum_{i'} \ln p_{i'}$.

To recover analogous expressions for household types other than $\overline{h}$, we differentiate indirect utility, holding location constant, to reveal $d \ln v = d \ln w$. Therefore, the reference utility level for households of type h is $1 + \ln w_h - \ln w_{\overline{h}}$, where w_h is the wage net of commuting cost for type h in the reference (average) location. For generic type h we thus have

$$\ln \pi^t_{hi} - \frac{1}{I}\sum_{i'} \ln(\pi^t_{hi'}) - (\ln w^t_h - \ln w^t_{\overline{h}}) + \beta_h d \ln p^t_i = d \ln w^t_{hi} + \sigma_h dq^t_i \equiv \lambda^t_{hi}. \tag{11}$$

This formulation takes into account the fact that richer households' marginal utilities of income are lower. The result is a greater discount on share differences across locations to reflect the fact that it is less onerous for higher income people to live in high cost relative to low cost areas, when compared to low income people.

Equation (11) summarizes how to recover the component of differences in neighborhood demands that are driven by differences in wages net of commuting costs and neighborhood amenities. We directly observe π^t_{hi} in the data as $f_{jt}(i|x, r)$ in the context of the counterfactual calculations of the prior section. 0 shares do not match the model well, so we assign tracts with 0 share to the smallest observed positive share for that demographic group for the purpose of calculating shares only. We set valuations of tracts with 0 shares to missing. To recover estimates of $d \ln p^t_i$, we take residuals from tract level regressions of log reported median home price on average home characteristics and CBSA fixed effects in each year. The Data Appendix provides further details about this calculation. Based on evidence form the Consumer Expenditure Survey, we calibrate $\beta_h = 0.17$.[11][12] Remaining terms in (11) will get subsumed into CBSA * time fixed effects in the empirical work described below.

Assuming the home price component of relative utilities $\beta d \ln p^t_i$ is the same across demographic groups, the model tells us that changes in neighborhood choice probabilities for a particular group must reflect some combination of changes in employment potential and amenity value of the neighborhood. Reintroducing the index j for CBSAs, we decompose changes in neighborhood choice probabilities as follows from (11):

$$\pi^t_{hij} - \pi^{t-10}_{hij} \approx \pi^{t-10}_{hij}(\rho^t_{hj} + \Delta\lambda^t_{hij} - \beta\Delta d \ln p^t_{ij}). \tag{12}$$

[11] This number excludes utilities, whose costs should not differ across tracts within a CBSA. Limited demographic information in the Consumer Expenditure Survey indicates little variation in this expenditure share across demographic groups.

[12] A second approach is to instrument for price with spatially lagged price changes, as in Bayer, Ferreira & MicMillan (2007), or natural amenities, as in Couture & Handbury (2015). However, given the explicit linkages across local housing sub-markets through upward sloping housing supply and market clearing, the first approach may be problematic. Because natural amenities enter as part of the error term in λ, the second approach does not fit this context well.

In this expression, ρ_{hj} is a type specific CBSA fixed effect. This expression shows that because all residents of the same neighborhood face the same home prices, variation in $\Delta\lambda$ across demographic groups is what generates differential changes in neighborhood choice probabilities relative to some CBSA baseline and a tract baseline driven by home price changes. Equation (12) implicitly takes into account the fact that demand shifts by higher SES groups push up home prices, thereby dissuading lower SES groups from choosing these neighborhoods, even if their valuations have been rising too.

The following sub-section empirically examines variation in $\Delta\lambda^t_{hij}$ amongst demographic subgroups to recover an accounting for their shifts in neighborhood choices.

4.2 Using the Model

Figures 5 and 6 show levels of and changes in neighborhood valuations for white college graduates, black college graduates, white high school dropouts and black high school dropouts over the study period. Figure 5 shows that during the 1980-2000 period, central neighborhoods were most attractive for less educated blacks, educated blacks, less educated whites and educated whites, respectively. This ordering is entirely driven by differences in relative neighborhood choice probabilities, since housing prices paid by each group are imposed to be identical. Figure 6 shows that central neighborhoods experienced declining attractiveness by all four of these groups in both the 1980s and the 1990s. Figure 5 Panel D shows that in 2010 white college graduates' valuation of neighborhoods adjacent to CBDs jumps dramatically relative to 2000, giving them valuations similar to college educated blacks.

We investigate the extent to which CBSA-level and localized labor demand shocks have driven changes in λ using regression equations similar to Equation (2), but group-by-group. We think of CBD-oriented labor demand shocks as influencing $d\ln w^t_{hi}$ and CBSA-level labor demand shocks as potentially changing groups' demands for local amenities through an income effect. We report IV regression results from estimating the following equation for 1990-2000 and 2000-2010, since we only observe the change in employment near the CBDs starting in 1990. For other time periods, we report the reduced form.

$$\Delta\widehat{\lambda}^t_{hij} = \rho_{hjt} + \sum\nolimits_{d=1}^{4}\alpha_{hdt} cbddis^d_{ij} + \alpha^b_{h1t} cbddis^1_{ij}\Delta\ln Emp_{jt} + \alpha^s_{h1t} cbddis^1_{ij}\Delta\ln CBDEmp_{jt}$$
$$+ \sum\nolimits_{d=1}^{4}\beta_{hdt} topdis^d_{ij} + \sum\nolimits_{m}\delta_{hmt}\ln(amendis^m_{ij}) + \varepsilon_{hijt}. \tag{13}$$

This estimation equation is the empirical analog to a differenced version of Equation (11). The ρ_{hjt} accounts for the intercept $-\frac{1}{I}\sum_{i'}\ln(\pi^t_{hi'}) - (\ln w^t_h - \ln w^t_{\underline{h}})$ and the remaining terms allow us to measure variation in tract labor market opportunities and local amenities relative to the average location. So that α_{h1t} can be interpreted as the average change in λ for central area tracts for group

h, we standardize $\Delta \ln Emp_{jt}$ and $\Delta \ln CBDEmp_{jt}$ to have means of 0 and standard deviations of 1. Tracts are weighted by their 1970 CBSA population share, so that each CBSA is weighted equally. Table A1 reports descriptive statistics about CBD-area and CBSA employment changes and their instruments. Equation (12) indicates that comparisons of $\Delta\lambda_{hij}^{t}$ across demographic groups is what matters for understanding relative percent changes in neighborhood choices. This observation leads us to use the specification in Equation (13) rather than a specification that controls for mean reversion. Note that measurement error will lead to more noise in neighborhood choice shares among smaller demographic groups, thereby inflating standard errors for these groups.

There are two potential concerns with using Equation (13) to infer changes in neighborhood valuations. First, is the issue of whether we have accurately measured housing costs. To get around this, instead of Equation (13) one could estimate a unified equation for all household types simultaneously with type-CBSA and tract fixed effects. Because the housing cost is common across types, the tract fixed effect would control for these costs assuming the housing expenditure share is the same for all types. The cost of this approach is that the absolute change in tract valuation is lost to a normalization, meaning that one can only recover relative changes in tract valuations across demographic groups. Our experimentation with such unified regression specifications yield very similar conclusions about relative changes in central area tract valuations across demographic groups to the results reported below.

A second concern is sample selection. Many tracts are dropped from the sample for small demographic groups because they have 0 choice shares for that group. The result is potential overestimation of demand for the types of neighborhoods these tracts are in. To address this concern, we built a version of the data in which we combine all tracts within 2 km CBD distance radii into a single observation per group per CBSA. The results using this aggregate data set are very similar to the results presented below. In the empirical work presented below, we weight by 1970 share of CBSA population in sampled neighborhoods, meaning each CBSA is weighted equally.

Table 7 reports the coefficient estimates for select demographic groups defined by race and education. The dependent variable can be interpreted as the change in the percent difference in wages net of commuting costs plus amenity values associated with living in a tract relative to the average location within the same CBSA. Coefficients in the first row of each panel describe average changes in valuations of central neighborhoods across CBSAs, with coefficients in remaining rows measuring the variation around these averages that are related to labor demand shocks. Significant negative coefficients are shaded blue and significant positive coefficients are shaded red.

The results in Panel A show that white college graduates had declining valuations of central neighborhoods on average until 2000, after which their valuations significantly rebounded. We evaluate the extent to which these averages are driven by shifts in localized labor market opportunities versus amenity values by considering what they would have been had there been 0 downtown employment growth. Table A1 reports average central area employment declines of 7 log points and 1 log point in the 1990-2000 and 2000-2010 periods, respectively, meaning that 0 growth would have been 0.58 and 0.08 standard deviations above these means for the two periods. The significant coefficient of 0.279 on the downtown area employment interaction for the 1990s thus implies that a CBSA with no downtown employment change during this decade would have had almost no change in central area valuation. That is, the average reduction of valuation within 4 km of CBDs by college whites of 13 percent can be entirely rationalized by reductions in nearby labor market opportunities (rather than reductions in amenities).[13] During the 2000-2010 period, the significantly positive coefficient on the <4 km CBD interaction of 0.098 would be 0.018 (=0.236*0.01/0.13) greater if downtown employment growth had been 0 rather than -0.01 standard deviations. This is evidence of improving amenity values of downtown neighborhoods after 2000 for college educated whites. We also find some evidence that CBSA employment growth hurt educated whites' valuations of downtown neighborhoods in the 1980s and 1990s but not in the 2000-2010 period. This result is consistent with income growth driving residents out of central neighborhoods into higher amenity outlying neighborhoods (Margo, 1992).

The results for college educated blacks are reported in Panel B. This group's much greater declines in central neighborhood valuations than those for whites indicates their declining relative amenity values of central neighborhoods. For the 2000-2010 period, the negative coefficient on CBSA employment growth could reflect lower amenity levels in downtown neighborhoods for college educated blacks, which pulled this group out of central neighborhoods as CBSA employment grew. As we show in the following sub-section, given the normalization of CBSA employment growth to be mean 0, the associated effect is enough to outweigh the -0.09 main effect to generate a slight increase in amenity valuation of downtown neighborhoods.

The results for high school dropout whites in Panel C have some of the same features as those in Panel B. This group had reduced declines in valuations of central neighborhoods in the 2000-2010 period relative to prior decades. The main 2000-2010 coefficient of -0.051 is significant but smaller than that for college educated blacks. CBD-area labor market conditions did not significantly affect high school dropout whites' valuations, though the point estimate on this interaction coefficient is positive. As with blacks, better CBSA labor market conditions promoted declining valuations of central neighborhoods, consistent with outflows of this group to more suburban areas. In Panel D, we see that high school dropout blacks exhibit the largest continued declines in central neighborhood valuations in 2000-2010. This group has the largest estimated 2000-2010 benefit from CBD oriented employment growth of all groups in 2000-2010, with insignificant effects in earlier decades. Like black college graduates and white high school dropouts, this group was more likely to move out of central neighborhoods whose CBSAs had stronger 2000-2010 employment growth.

The results for middle education whites and blacks (not reported in Table 7) are in between the

[13] To see this, note that 0 employment growth is 0.58 standard deviations above the mean, thus the effect of 0 downtown area employment growth on valuations would be 0.58 * 0.279 = 0.162, which approximately offsets the average drop in central neighborhood valuation of -0.124.

college graduate and high school dropout results for each race. Conditional on education, results for the "other" demographic group are between those for whites and blacks, though somewhat more similar to those for whites.

In Table 8, we repeat the same exercise using income deciles instead of education groups. So as to have a manageable table, we choose the 3rd, 6th and 8th as representative deciles. Patterns in Table 8 reiterate those in Table 7. The background changes in central neighborhood valuations improved more for higher deciles than for lower deciles, but only turned significantly positive for high income whites, not blacks. With a few exceptions, results for other deciles can be extrapolated from the results reported in Table 8.

4.3 Decompositions of Shifts in Neighborhood Choices

We have seen evidence that shifts in neighborhood choices of whites in particular have promoted reversals of downtown population declines. As a final exercise, we combine insights from the model and estimates like those in Table 7 for each education-race group to evaluate the relative importance of various mechanisms driving shifts in downtown neighborhood choices. Combining Equations (11) and (13), we have the following decomposition of shifts in the log share of group h choosing to live in census tract i:

$$\begin{aligned}\Delta \ln \pi_{hij}^{t} = {} & \left[-\beta_h \Delta d \ln p_i^t\right] + \left[\alpha_{h1t}^{s} cbddis_{ij}^{1} \Delta \ln CBDEmp_{jt}\right] + \left[\alpha_{h1t}^{b} cbddis_{ij}^{1} \Delta \ln Emp_{jt}\right] \\ & + \left[\sum\nolimits_{d=1}^{4} \beta_{hdt} topdis_{ij}^{d} + \sum\nolimits_{m} \delta_{hmt} \ln(amendis_{ij}^{m})\right] \\ & + \left[\rho_{hj}^{t} + \sum\nolimits_{d=1}^{4} \alpha_{hdt} cbddis_{ij}^{d} + \varepsilon_{hijt}\right]. \end{aligned} \tag{14}$$

In this equation, each term in brackets is a separate component of the change in log population shares within CBSA j of type h in census tract i. In particular, we see that given rising home prices in central neighborhoods, understanding rising central neighborhood choice probabilities in Table 3 requires a countervailing force. We decompose the extent to which magnitudes of CBD-oriented labor demand shocks, CBSA labor demand shocks, shifting valuation of local amenities and residual explanations (which we interpret as other elements of local amenities) offset declines in central area neighborhood choice probabilities driven by rising home prices. Note that we are not able to say anything about why home prices changed, as this would require incorporating housing supply conditions into the model.

Table 9 breaks out the components of population growth within 2 km (left side) or 4 km (right side) of CBDs that are due to shifts in population sub-groups' neighborhood choices reported in Columns 5-8 of Table 3. Each component listed in the table corresponds to a term in brackets in Equation (14) in the same order. The entries are calculated as follows. We estimate separate regressions using Equation (13) like those used to create Table 7 for each decade and narrowly defined education-race group. Then, components are cumulatively added to log neighborhood choices shares from the base year following Equation (14), exponentiated and normalized to sum to 1 for each demographic group across census tracts in each CBSA. Because we do not observe 1980-1990 CBD area employment growth, we set it to zero. Central employment shock effects in Panel A are thus likely understated, as we expect that most cities experienced 1980-1990 central area employment declines. The associated impact gets included in "Other" as a result. Table 9 expresses results as marginal contributions of each listed mechanism to the component of central area population growth that is due to shifts in the indicated demographic group's change in neighborhood choices. Therefore, each column within the left block of each panel sums to numbers in the top rows of Table 3 Columns 5-8.

We saw, in the context of Table 3, that in the 2000-2010 period, more educated whites were returning to central neighborhoods while less educated minorities continued to leave them. The left block of Panel B reveals that the growth of home prices was a force pushing all groups out of central neighborhoods, with effects on population growth much more pronounced for less educated minorities than for other groups. The -0.12 in the final column means that according to our model, 2000-2010 home price growth in central neighborhoods caused population declines of less educated minorities that would have resulted in a 12 percent population decline overall. This large effect is mostly due to this group's plurality of the population in these areas. Other than housing prices, the only other component that matters is "Other", which is a catch-all for things we could not measure, and presumably captures endogenous amenities like crime rates. These unobserved attributes brought all demographic groups back to central neighborhoods, but were not enough to outweigh the push effects of higher home prices for minorities with less than a college degree. The right block of Panel B shows analogous results for 4 km CBD distance rings. Here we see more muted effects across the board, with patterns from the left block persisting. One general message from Table 9 Panel B is that after 2000, all groups experienced increasing amenity valuation of central neighborhoods. However, less educated minorities had even higher increases in their housing cost burden, thereby pushing them out of these neighborhoods. The housing cost and amenity forces were approximately balanced for target nonwhites and nontarget whites, leading to little change in their central neighborhood choice probabilities. College educated whites had greater increases in amenity valuation, thereby causing them to choose central neighborhoods at higher rates.

Results in the righthand side of Panel A similarly reflect rising home prices, but they also show negative effects on central neighborhood choices of the "Other" category for all but college educated whites. Consistent with evidence in Table 7, this pattern of "Other" impacts is consistent with amenity values of central areas of cities slightly increasing for college educated whites after 1980 but declining for others until around 2000 when amenities started improving for everyone. Evidence in Panel A also shows that the 1980-2000 flight of less educated whites from central neighborhoods is related to declining labor market opportunities nearby. Looking throughout Table 9, we see a consistent pattern that the "Home Price" and "Other" mechanisms have mattered most for broad patterns in central neighborhood change. While labor demand shocks did influence neighborhood change some, they were not sufficiently large to drive a large part of it for most groups.

5 Conclusions

Neighborhoods near central business districts of U.S. metropolitan areas have experienced remarkable rebounds in population and residents' socioeconomic status since 2000. Decompositions reveal that this turnaround in population has primarily been driven by the return of college educated and high income whites to these neighborhoods coupled with a halt in the outflows of other white demographic categories. At the same time, the departures of less than college educated minorities continued unabated.

Estimation of a neighborhood choice model shows that changes in choices to live in central neighborhoods primarily reflect a shifting balance between rising home prices and valuations of local amenities, though 1980-2000 central area population declines also reflect deteriorating nearby labor market opportunities for low skilled whites. Rising 1980-2000 central neighborhood home prices were about equally offset by rising amenity valuations among college educated whites; declining amenity valuations reinforced rising home prices to incentivize departures of other demographic groups from central neighborhoods during this period. Greater increases in amenity valuations after 2000 encouraged college educated whites to move in and other whites to remain but were not large enough to offset rising housing costs for minorities.

A combination of increases in housing prices and changes in local amenity values have been the primary drivers of shifts in the choices to live in downtown neighborhoods by different demographic groups. Viewed in the context of a model of neighborhood choice, we find evidence that before 2000, amenity valuations of central neighborhoods were increasing for college educated whites only. Since 2000, amenity values have been increasing for most demographic groups. However, the flight of less educated minorities continues because of more rapidly increasing housing cost burdens. Stabilization of central area employment opportunities have also been a factor in halting the outflow of less educated whites from central neighborhoods.

The gentrification of cities' central neighborhoods inverts the decentralization of high income whites that had been occurring for decades. This represents a fundamental change in the demographic structure of cities which this paper only begins to understand. This phenomenon may be the beginning of an urban rebirth with many broader consequences for the economy. It may also exacerbate the rise in real income inequality that has occurred over recent decades, as it is a mechanism through which the cost of living may be rising for the poor. A general equilibrium framework which incorporates housing supply would be required to recover information about associated welfare consequences. Developing such a framework which could be used to evaluate the welfare consequences of gentrification for poor incumbents seems like a particularly fruitful area for potential future research.

A Data Appendix

Here we describe the construction of our sample and provide information about the sources of that we use to construct the sample. A large portion of the data used in our analysis come from tract-level tabulations from the decennial Censuses of Population from 1970, 1980, 1990, and 2000, and from the American Community Survey from 2008-2012. We use census tract boundaries from the 2000 Census of Population. We begin with the normalized data provided in Geolytics' 1970-2000 Neighborhood Change Database (NCDB) which provides a subset of the tract-level tabulation variables available from the 1970, 1980, 1990, and 2000 Censuses of Population normalized to year 2000 tract boundaries. We augment this data with other tract-level tabulations from these censuses that are not available in the NCDB and tract-level estimates from the 2008-2012 American Community Survey. In these cases, we perform normalizations to 2000 tract boundaries using the appropriate census tract relationship files provided by the Census Bureau.[14]

A.1 Tract-level Sample

Our sample includes all of the 2008 definition Core Base Statistical Areas (CBSAs) that had a population of at least 250,000 in the area that was tracted in 1970 except Honolulu.[15] Our sample consists of 120 CBSAs and 39,087 year 2000 census tracts.[16] The CBSAs in the sample can be seen in Figure 1.

A.1.1 1970, 1990, 2000 Tract Data

These we take directly from the Neighborhood Change Database (NCDB) STF3A tabulations.

A.1.2 1980 Tract Data

We read in these data from the summary tape file 4 files. This allows us to incorporate household income distributions by race and age by race into the data set. It also facilitates imposing various appropriate adjustments for suppression that are not handled well in the NCDB.

[14] See https://www.census.gov/geo/maps-data/data/relationship.html?? .

[15] Since we are using year 2000 tract boundaries, we limit our sample slightly further by using only tract for which 100\% of the 2000 definition tract was tracted in 1970.

[16] For CBSAs that are split into Metropolitan Divisions we treat each Division as a separate entity except in the following 4 cases in which we combine Metropolitan Divisions. These are: 1) Bethesda-Rockville-Frederick, MD is combined with Washington-Arlington-Alexandria, DC-VA-MD-WV. 2) Cambridge-Newton-Framingham, MA and Peabody, MA Metropolitan Divisions are combined with Boston-Quincy, MA. 3) Nassau-Suffolk, NY is combine with New York-White Plains-Wayne, NY-NJ. 4) Warren-Troy-Farmington Hills, MI is combined with Detroit-Livonia-Dearborn, MI.

Suppression results in undercounting of whites and blacks in various tables. To handle this, we use tract level full population or household counts of whites, blacks and others to form inflation factors. We calculate inflation factors which scale up the total number of people in each age, education, family type or income bin in the STF4A data to equal the total reported in the NCDB data.

In particular, in the case of age, when the 1980 STF4A tract tabulations by race and age do not sum to the total population we implement the following algorithm:

1. inflate the total in each age bin so that the total of the age bins sums to the total population in the NCDB data.

2. calculate other race in each age bin by taking the total population in each age bin and subtract the white and black population of that age bin from the STF4A.

3. calculate the number of whites and blacks that are missing in the STF4A data by summing across the age bins for white and for black and subtracting the totals from the NCDB totals

4. calculate the number of people missing from each age bin by subtracting the STF4A total (that uses the recalculated other category) from the NCDB total

5. inflate the number of others in each age bin by the ratio of the NCDB other total to the STF4A other total

6. calculate the residual number of blacks and whites missing from each age bin by subtracting the inflated other from the inflated total for the age bin

7. reassign the residual number of blacks and whites missing from each age bin to either the white or black count in proportion to the share of the total missing that white and black make up as calculated in 3.

We do the same process for education, and family type for 1980.

A.1.3 2010 Census and ACS

We use the 2010 census summary tape file 1 for information about age and household structure by race. Because of the lack of a census long form in 2010, we are forced to use the American Community Survey to measure joint distributions of race by education and race by income.

A.2 Procedure for Allocating Income To Percentile Bins

The counterfactual analysis uses 10 household income deciles, with dollar cutoffs calculated using census micro data for the CBSAs in our sample. In each year, the census tract data reports the number of households by race in each of up to 20 income bins bounded by fixed dollar cutoffs. To re-allocate into percentile bins, we assume a uniform distribution within each dollar value bin except the top one. For the top one, we use a Pareto distribution with parameters estimated separately for each year using census micro data.

A.3 Central Business District Definitions

For each of our 120 CBSAs, we define the Central Business District (CBD) of the CBSA as that of the most populous Census place within the CBSA based on year 2000 population. We make two exceptions to this rule based our knowledge of the cities. For the Santa Barbara-Santa Maria-Goleta, CA Metropolitan Statistical Area we use the Santa Barbara CBD rather than the Santa Maria CBD even though Santa Maria was more populous in 2000 than Santa Barbara. For the Virginia Beach-Norfolk-Newport News, VA-NC Metropolitan Statistical Area we use the Norfolk CBD rather than the Virginia Beach CBD. For 113 of the our 120 CBSAs we were able to determine the CBD of the most populous city from the 1982 Census of Retail Trade. We use the latitude and longitude of the centroid of the tract or tracts specified as CBD tracts. For the remaining 7 CBSAs, we used the latitude and longitude where designated by ESRI.[17]

A.4 Bartik Instrument Construction

We construct two Bartik instruments from several data sources. We label these instruments "Employment Bartik" and "Spatial Employment Bartik". The "Employment Bartik" attempts to predict CBSA-level employment growth for each of the 4 decades using initial year employment shares and decadal employment growth (implemented as changes in log employment levels) using 10 broad industry categories that can be consistently constructed from 1970 through 2010 using the county-level Census of Population and American Community Survey tabulations. The 10 industry categories are: 1) Agriculture, forestry, fisheries, and mining. 2) Construction. 3) Manufacturing. 4) Wholesale trade. 5) Retail trade. 6) Transportation, communication, other public utilities, and information. 7) Finance, insurance, and real estate. 8) Services. 9) Public administration. 10) Military. We refer to these as 1-digit industry categories.[18] This measure uses the exact geographical boundaries included in each of our CBSA definitions over the entire time period.

The aim of the "Spatial Employment Bartik" is to predict which CBSAs might be particularly impacted near the CBD by national industry growth. To construct this index, we calculate the share of employment located within 4 km of the CBD made up by each industry for each CBSA using the year 2000 Census Transportation Planning Package. We take these shares and interact them with the national industry growth rate of that industry to form a spatial or CBD-focused Bartik instrument. Ideally, we would calculate the shares in each initial year, 1970, 1980, 1990, and 2000. However, the data are only available starting in 1990. Therefore, we use the 1990 1-digit industry distribution as the base.

[17] These 7 cities are Duluth, MN, Edison, NJ, Indianapolis, IN, Jacksonville, FL, Nashville, TN, and York, PA. Manual inspection of these 7 cities revealed CBD placement where we would expect it. Also, for the 113 cities where we have both Census of Retail Trade and ESRI CBD definitions the points line up closely.

[18] In practice, we do this once for each CBSA excluding that CBSA to calculate a national-level change that is not influenced by that particular CBSA.

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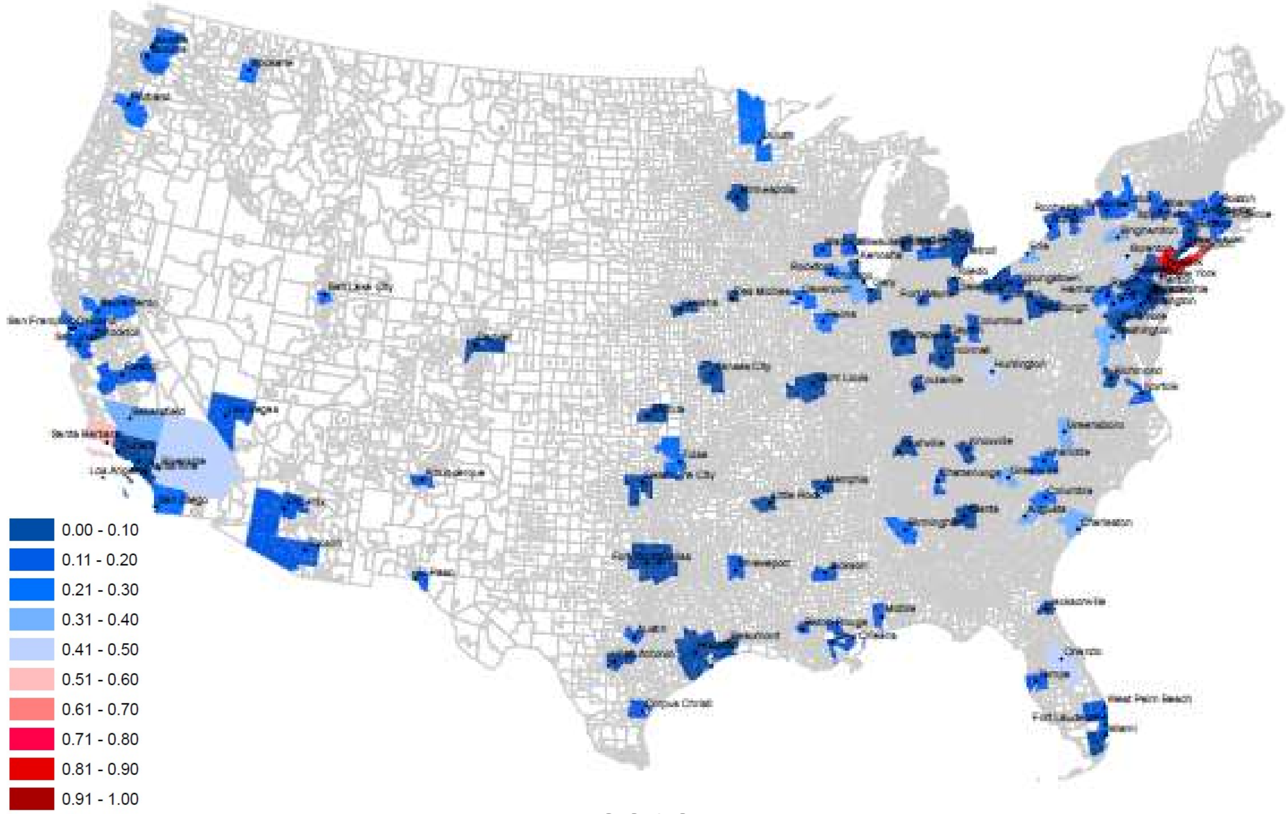
1980



2010

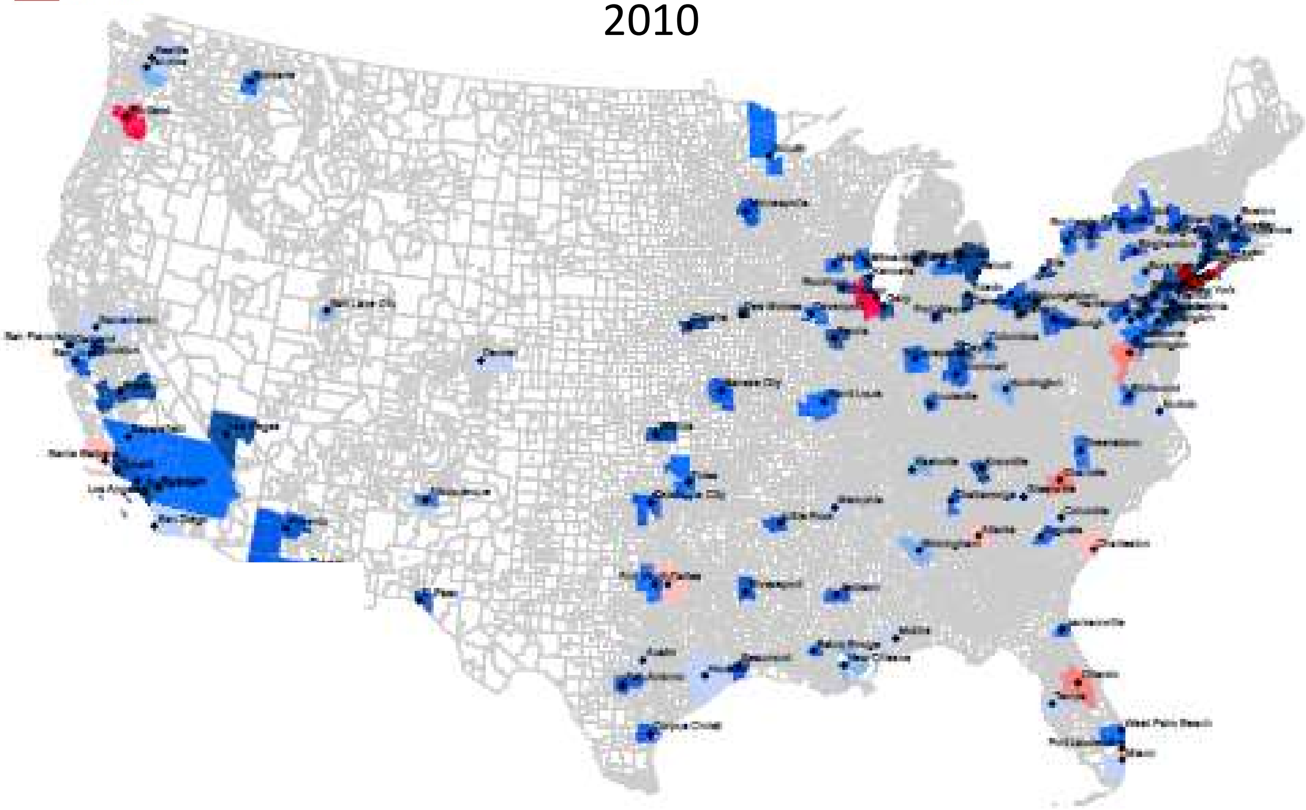


Figure 1a: Share of Residents Within 4 km of the CBD
Living in a Top Half SES Distribution Census Tract

Figure 1b: 1980-2010 Change in Share of Residents Within 4 km of the CBD
Living in a Top Half SES Distribution Census Tract

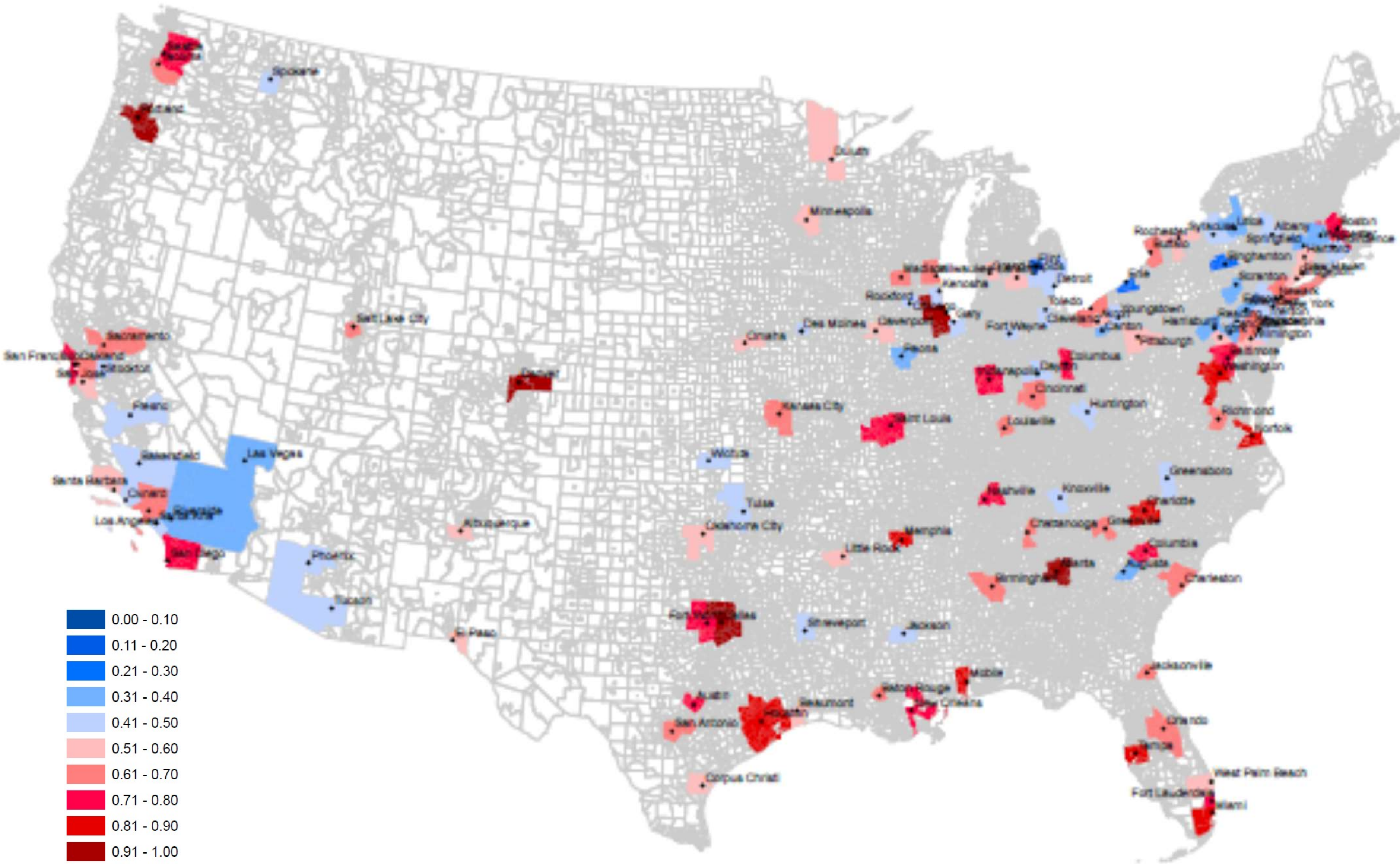
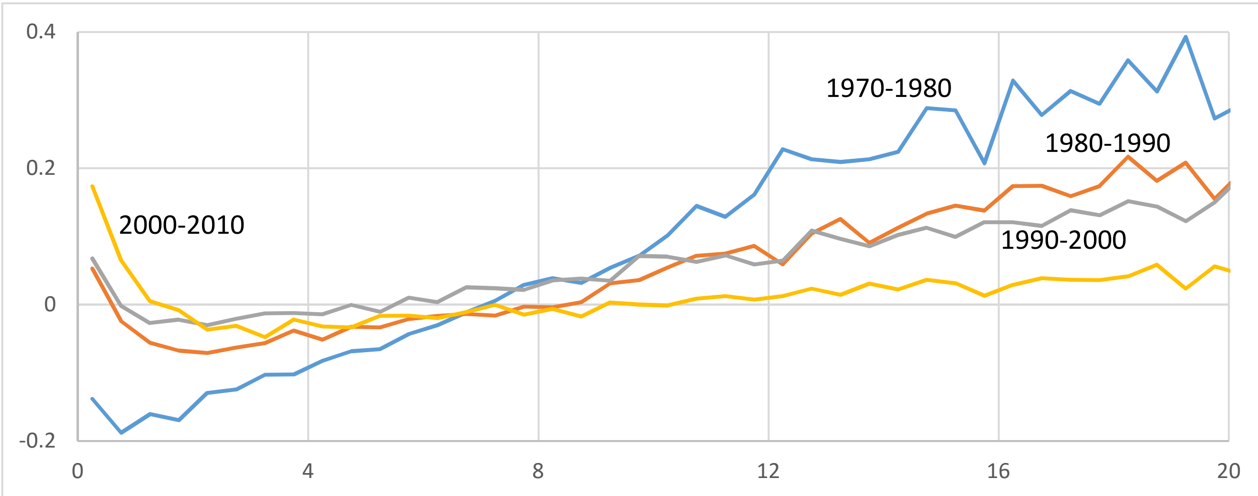


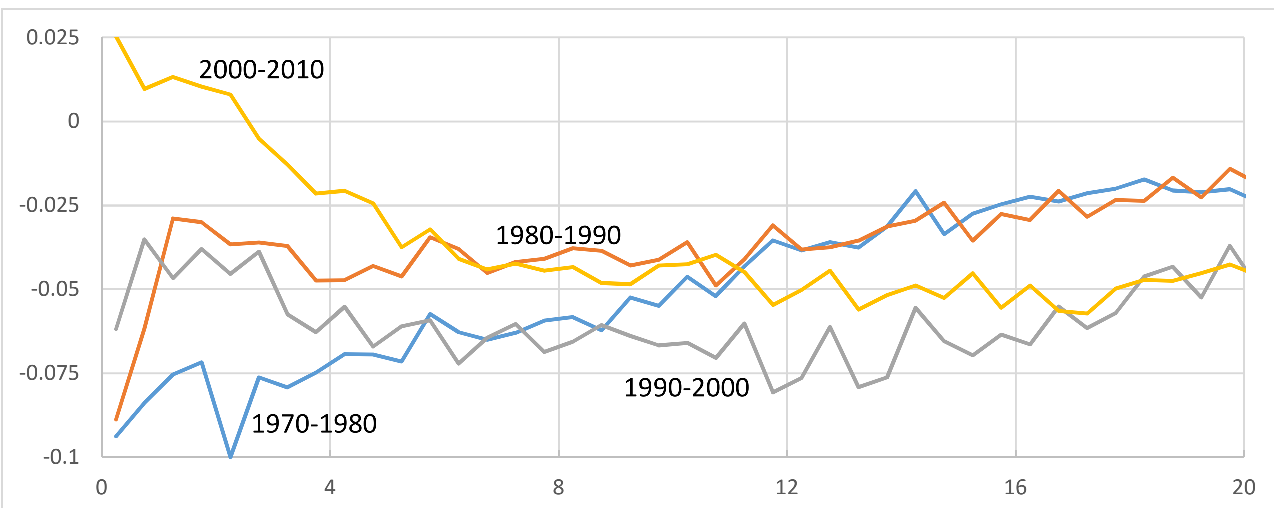
Figure 2: Measures of Gentrification as a Function of CBD Distance (km)

Medians Across 120 CBSAs, 0.5 km CBD Distance Bands

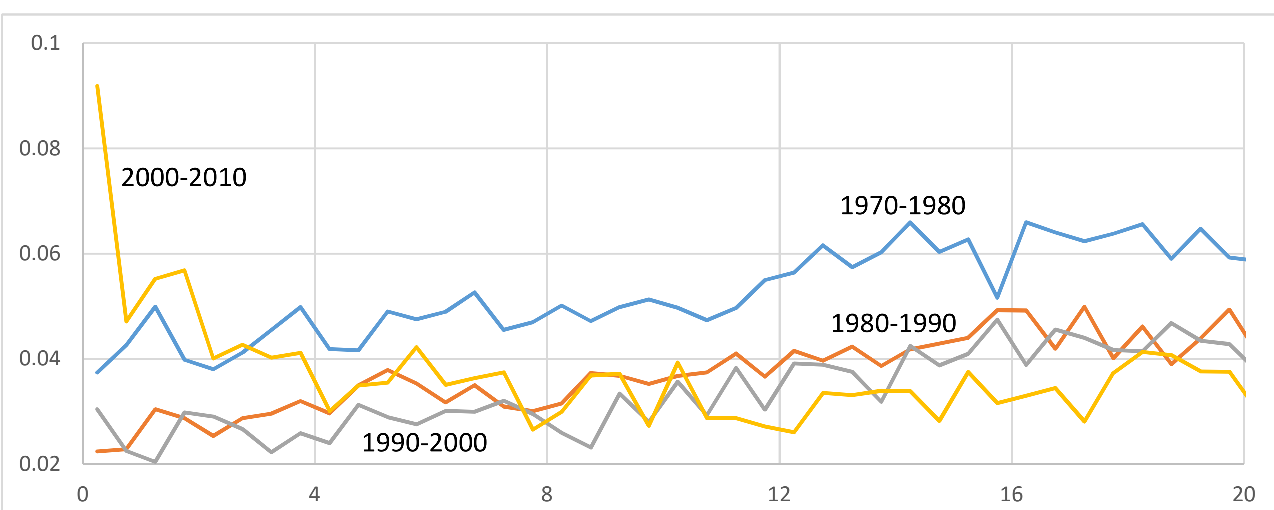
Panel A: Percent Change in Population



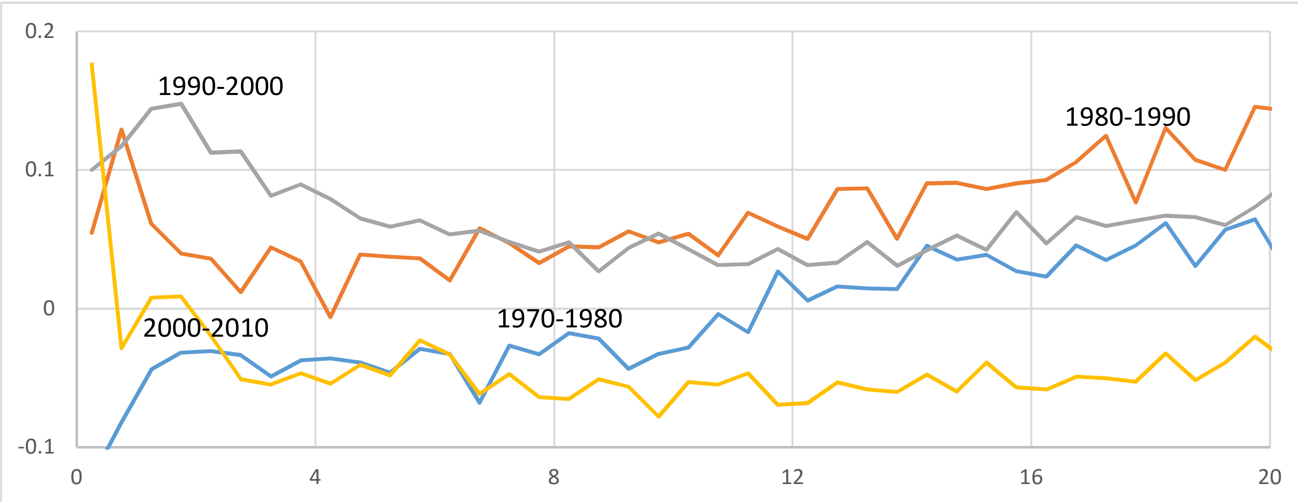
Panel B: Change in Fraction White



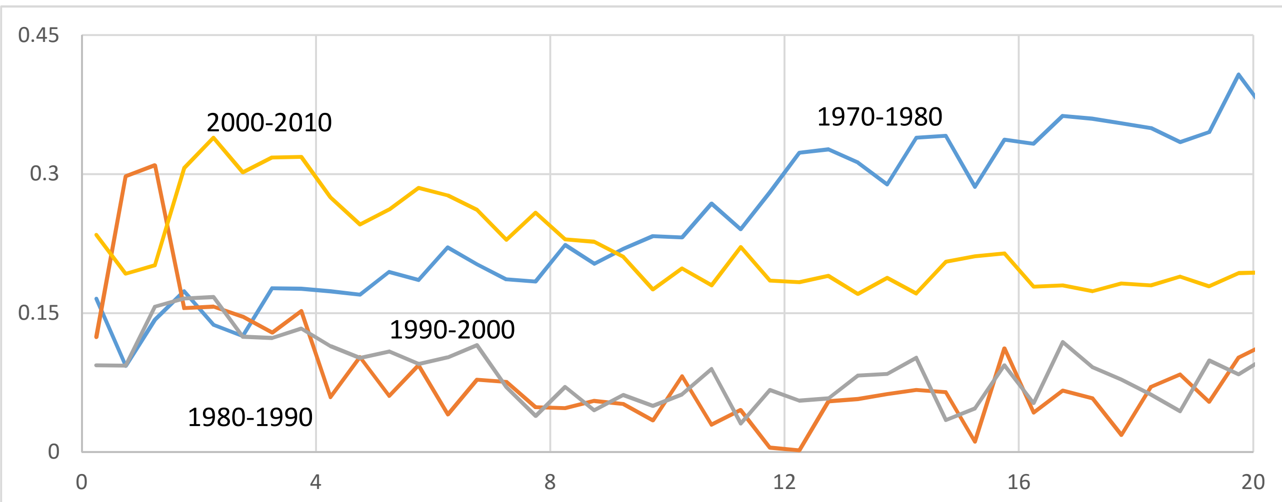
Panel C: Change in Fraction 25+ with College Education



Panel D: Percent Change in Mean HH Income (2010 $)



Panel E: Percent Change in Mean Housing Value (2010 $)



Panel F: Median Change in Employment

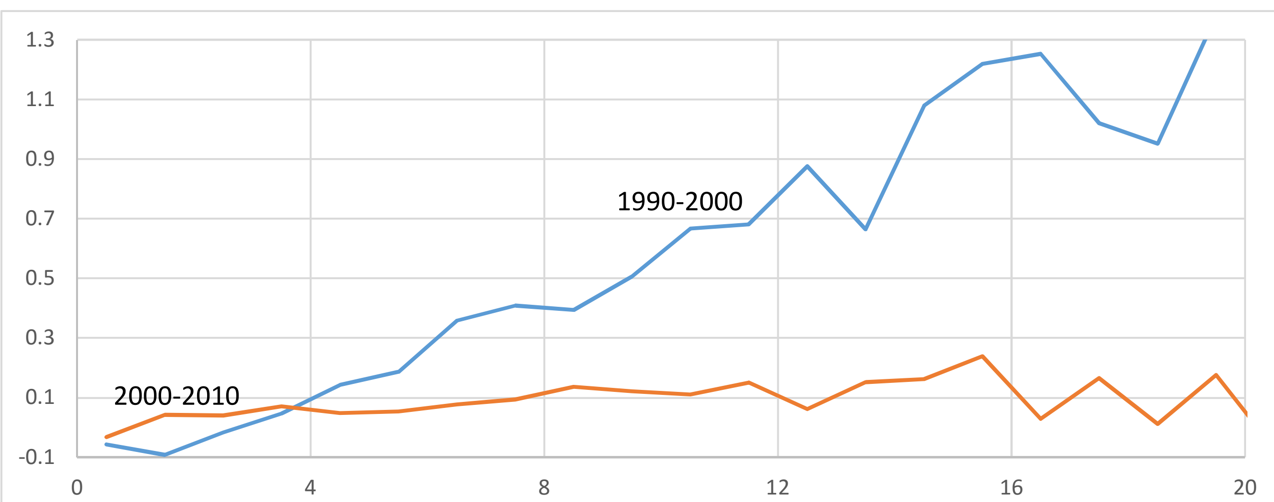


Figure 3: 1980-2010 Neighborhood Change in Chicago

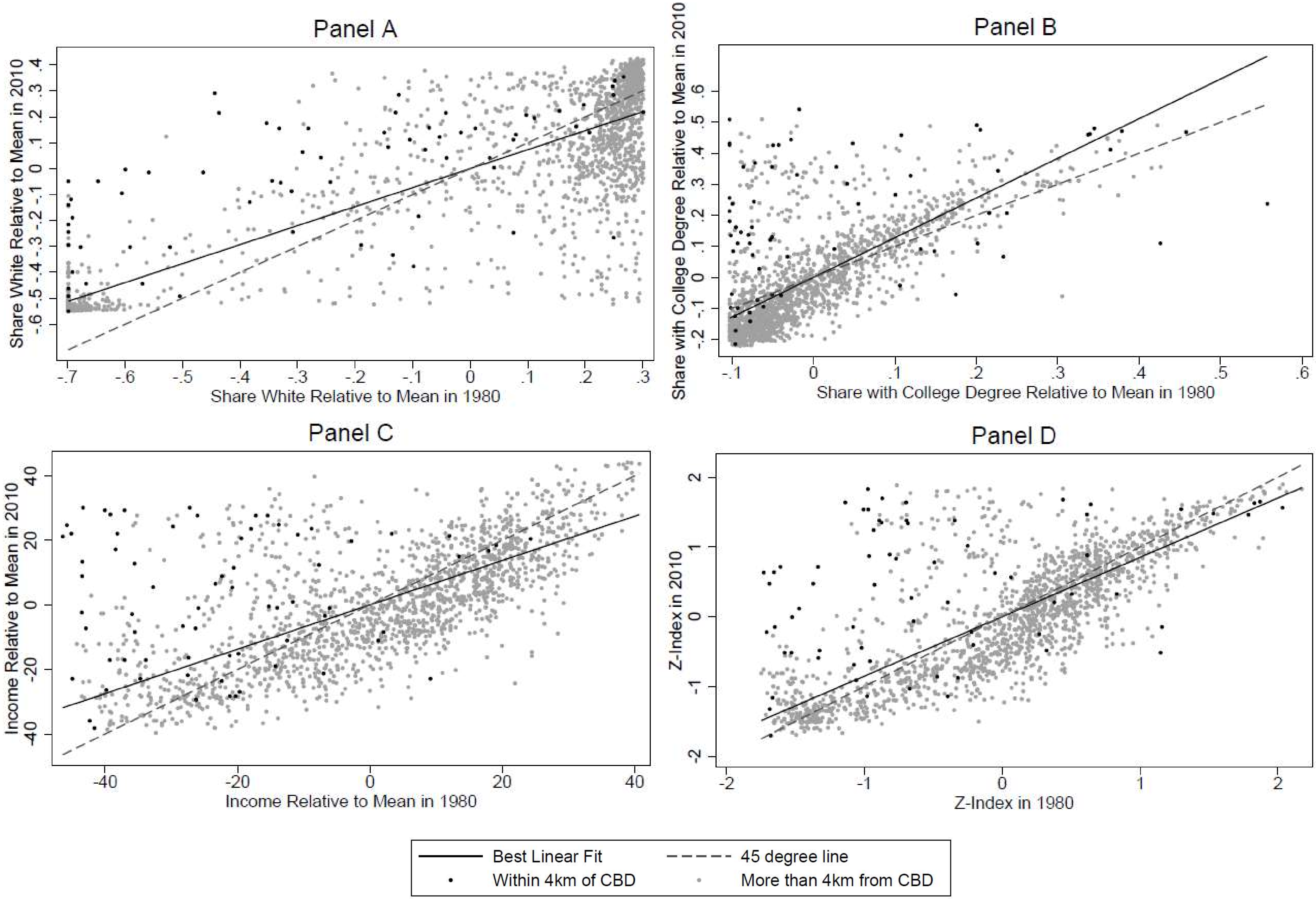


Figure 4: Decadal Tract Changes in SES Index, Chicago

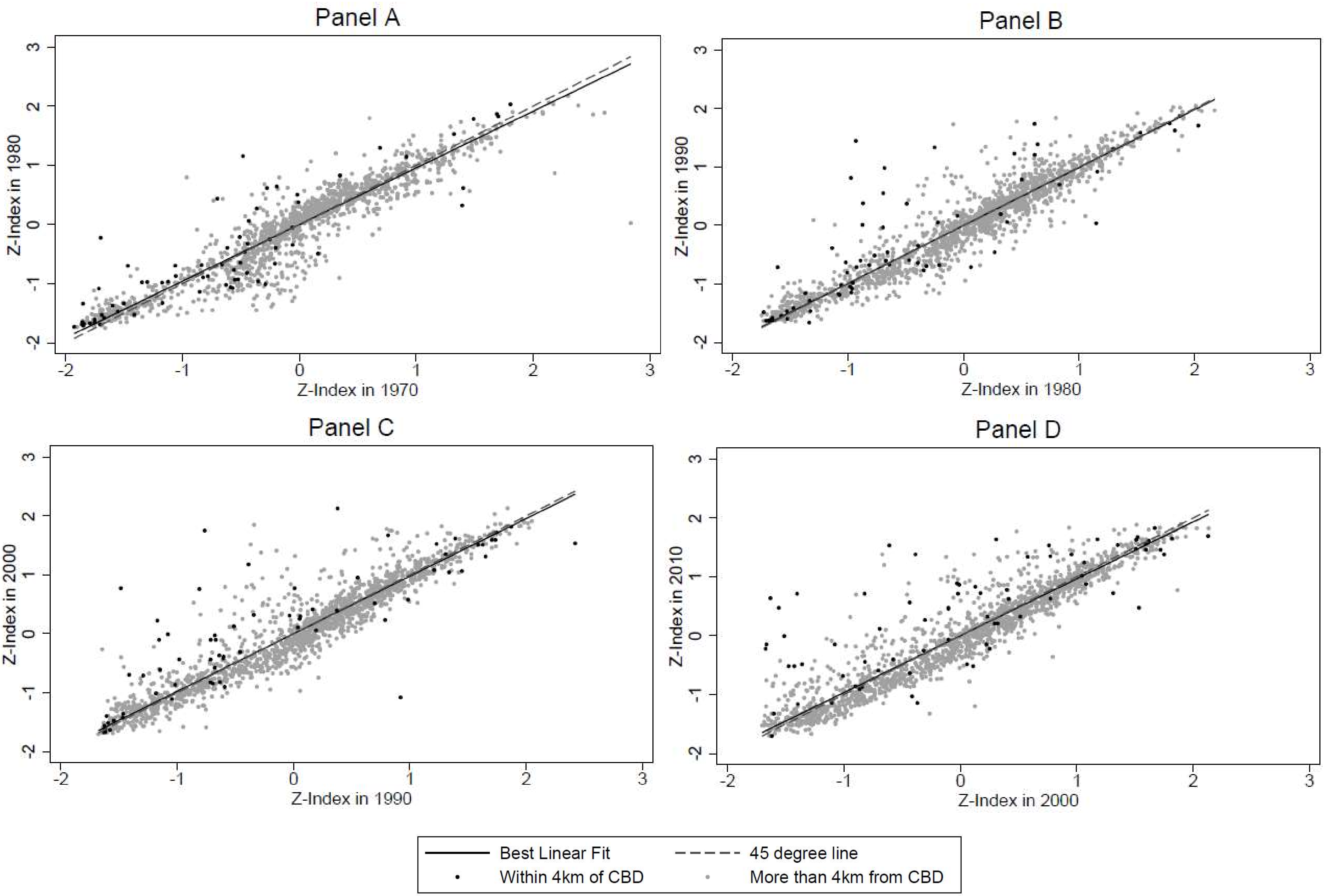


Figure 5: Lambdas in Each Year by Education and Race

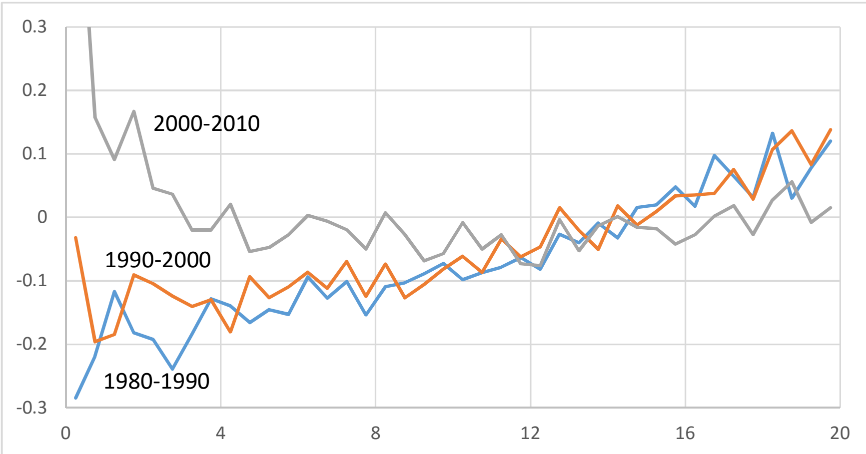
Panel A: 1980

Panel B: 1990

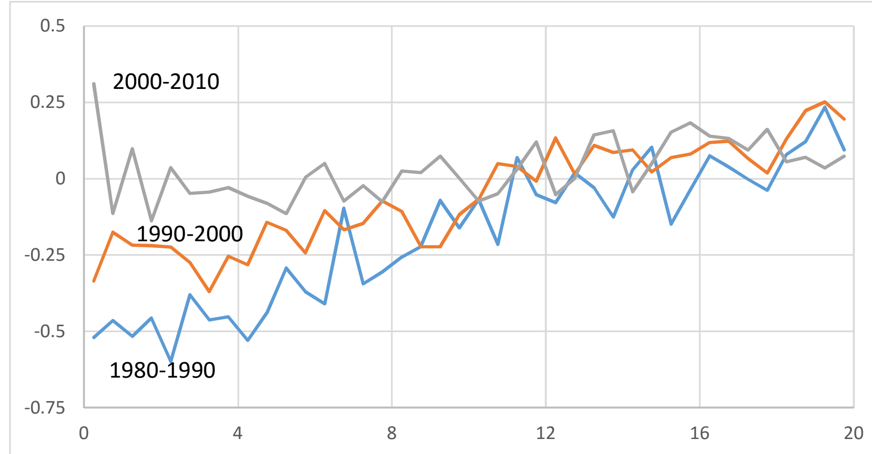
Panel C: 2000

Panel B: 2010

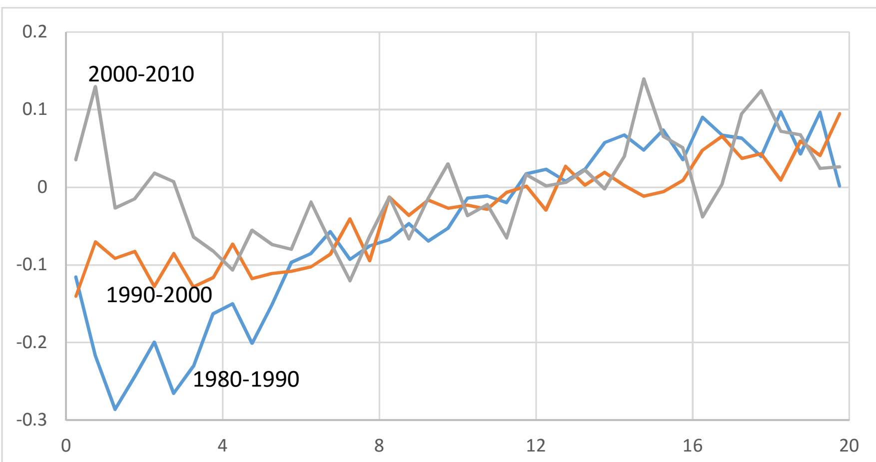
Figure 6: Changes in Neighborhood Valuations as a function of CBD Distance by Race and Education



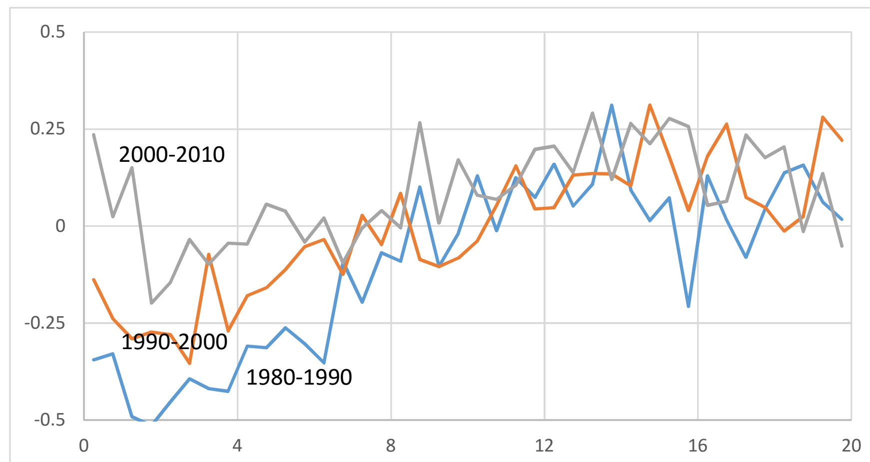
Panel A: Whites with College or More



Panel B: Blacks with College or More



Panel C: White High School Dropouts



Panel D: Black High School Dropouts

Table 1: Share of Population within 4 km of CBD in Tract Changing by at Least

	20 Percentile Points		1/2 Standard Deviation	
	up	down	up	down
Panel A: Fraction White				
1970-1980	6.5%	13.3%	14.5%	20.8%
1980-1990	4.4%	6.0%	8.1%	13.9%
1990-2000	4.0%	3.1%	12.1%	11.0%
2000-2010	5.2%	1.3%	14.2%	5.5%
1980-2010	5.3%	1.3%	34.8%	23.2%
Panel B: Fraction College Educated				
1970-1980	10.3%	10.0%	14.7%	7.6%
1980-1990	5.2%	5.8%	6.0%	7.5%
1990-2000	3.8%	6.1%	5.5%	7.6%
2000-2010	10.3%	4.0%	14.4%	5.3%
1980-2010	10.8%	4.0%	18.8%	16.6%
Panel C: Median Income				
1970-1980	0.7%	11.9%	3.3%	21.3%
1980-1990	3.5%	1.1%	7.8%	3.3%
1990-2000	3.3%	1.4%	7.7%	2.9%
2000-2010	8.2%	1.4%	14.6%	4.4%
1980-2010	8.1%	1.3%	30.7%	8.9%
Panel D: SES Index				
1970-1980	2.6%	7.7%	4.6%	12.5%
1980-1990	2.4%	1.9%	3.8%	3.2%
1990-2000	2.8%	1.9%	4.6%	3.1%
2000-2010	7.9%	1.2%	10.8%	1.6%
1980-2010	7.9%	1.1%	24.5%	13.1%

Notes: Distributions are within each of the 120 CBSAs in our sample. Each tract is weighted by its share of CBSA population.

Table 2: SES Index Regressions

	1970-1980	1980-1990	1990-2000	2000-2010	1980-2010
Estimator	RF	RF	IV	IV	RF
Panel A: Difference Specification					
1(< 4 km to CBD)	-0.116	0.016	0.028	0.109	0.163
	(0.021)	(0.012)	(0.007)	(0.008)	(0.039)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.062	0.020	0.075	0.039	0.109
	(0.022)	(0.013)	(0.070)	(0.019)	(0.040)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.059	0.007	0.056	0.082	0.052
	(0.015)	(0.011)	(0.049)	(0.043)	(0.037)
Observations	37,911	37,939	37,903	37,891	37,916
R-Squared (First Stage F)	0.120	0.042	(26.5)	(48.2)	0.114
Panel B: AR(1) Specification					
1(< 4 km to CBD)	-0.200	-0.015	0.008	0.123	0.065
	(0.023)	(0.014)	(0.008)	(0.009)	(0.042)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.049	0.018	0.044	0.049	0.111
	(0.024)	(0.014)	(0.074)	(0.021)	(0.043)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.056	0.009	0.087	0.094	0.060
	(0.018)	(0.012)	(0.050)	(0.044)	(0.038)
Observations	37,911	37,939	37,929	37,916	37,916
R-Squared (First Stage F)	0.816	0.918	(24.6)	(56.1)	0.716
Panel C: AR(1) Specification, Arellano-Bond Adjustment					
1(< 4 km to CBD)		0.109	0.051	0.082	0.387
		(0.021)	(0.035)	(0.028)	(0.063)
CBSA Employment Growth* 1(< 4 km to CBD)		0.026	0.065	0.038	0.079
		(0.017)	(0.056)	(0.018)	(0.060)
CBD Area Employment Growth* 1(< 4 km to CBD)		0.007	0.024	0.042	0.062
		(0.018)	(0.033)	(0.025)	(0.064)
Observations		37,893	37,903	37,891	37,870

Notes: Each column in each panel reports results from a separate regression of the change in (Panel A) or level of (Panels B and C) the tract SES index on variables listed above and indicators for 4-8, and 8-12 km from a CBD and 0-4, 4-8 and 8-12 km from the nearest top 1970 quartile SES index tract. Log of distance to the nearest coastline, lake, and river are also included as controls. Panel C implements an Arellano-Bond (1991) correction for endogeneity of the AR(1) variable in short panels. See Equations (1) , (2) and (3) in the text for specifications used in Panels A, B and C respectively. Employment growth variables and their Bartik instruments are standardized to be mean 0 and standard deviation 1. "RF" refers to "reduced form" and "IV" stands for "instrumental variables" in column headers. Regressions are weighted by share of 1970 tract population in 1970 CBSA population. Coefficients that are significant at the 10% level are shaded red if positive and blue if negative. Standard errors are clustered by CBSA.

Table 3: Decomposition of Percent Changes in Population within 2 km of CBDs
Fraction of Group in Base Year Totals in Parentheses

					Contribution to Difference Between (1) and (2) from					
					Δchoices of				Δshares of	
Choices in year t	All	None	All	None	Target	Target	NonTarget	NonTarget	X|Race	Race
Shares in year t	All	None	None	All	White	NonWhite	White	NonWhite		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Data Set										
Panel A: 1980-2000										
Education	-0.07	0.21	-0.12	0.31	-0.01	0.00	-0.14	-0.18	-0.04	0.10
					(0.09)	(0.01)	(0.74)	(0.15)		
Age	-0.07	0.21	-0.14	0.34	0.01	-0.04	-0.15	-0.17	-0.03	0.10
					(0.22)	(0.05)	(0.62)	(0.12)		
Family Type	-0.07	0.21	-0.27	0.43	-0.11	-0.06	-0.12	-0.19	0.10	0.10
					(0.29)	(0.04)	(0.55)	(0.12)		
Income	-0.11	0.27	-0.19	0.37	0.00	-0.01	-0.24	-0.21	0.00	0.09
					(0.32)	(0.03)	(0.54)	(0.11)		
Panel B: 2000-2010										
Education	0.06	0.07	0.04	0.09	0.04	0.00	0.02	-0.08	-0.01	0.03
					(0.14)	(0.03)	(0.61)	(0.22)		
Age	0.06	0.07	0.03	0.12	0.04	-0.01	0.01	-0.08	0.00	0.03
					(0.15)	(0.06)	(0.60)	(0.19)		
Family Type	0.05	0.08	-0.01	0.15	0.02	-0.03	-0.01	-0.08	0.03	0.03
					(0.24)	(0.06)	(0.50)	(0.20)		
Income	0.05	0.08	0.03	0.11	0.03	0.00	0.00	-0.08	0.00	0.02
					(0.39)	(0.08)	(0.40)	(0.13)		

Notes: Each line usess a different data set as is explained in the text. Results in (1) and (2) report actual data and average CBSA population growth rates respectively. Results in remaining columns use counterfactual data. Results in (5)-(10) sum to actuals in (1) minus CBSA growth in (2). X in (9) refers to the demographic characteristic that is jointly distributed with race in each block. Results weight each CBSA equally. Target groups are college graduates, 20-34 year olds, singles not in group quarters or maried couples without children and households in the top 30 percent of the income distribution of tracts in the sample for each data set respectively. See Table A3 for mathematical expressions used to construct each counterfactual tract population. See the text for a full explanation.

Table 4: Decompositions of Changes in Fraction White

						Contribution to All in (1) from					
						Δchoices of				Δshares of	
Choices in year t		All	None	All	None	Target	Target	NonTarget	NonTarget	X|Race	Race
Shares in year t		All	None	None	All	White	NonWhite	White	NonWhite		
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Data Set	CBD Radius										
Panel A: 1980-2000											
Education	2 km	-0.08	0.00	0.02	-0.11	-0.00	0.00	-0.05	0.08	0.01	-0.11
Education	4 km	-0.10	0.00	0.01	-0.11	-0.01	0.00	-0.06	0.07	0.00	-0.11
Income	2 km	-0.08	0.00	0.02	-0.10	0.00	0.00	-0.09	0.10	0.00	-0.10
Income	4 km	-0.09	0.00	0.00	-0.09	-0.01	0.01	-0.08	0.08	0.00	-0.10
Panel B: 2000-2010											
Education	2 km	0.03	0.00	0.06	-0.04	0.02	-0.00	0.01	0.04	0.00	-0.04
Education	4 km	0.01	0.00	0.04	-0.04	0.01	0.00	-0.00	0.04	0.00	-0.04
Income	2 km	0.03	0.00	0.06	-0.02	0.01	0.00	0.00	0.04	0.00	-0.03
Income	4 km	0.02	0.00	0.04	-0.02	0.00	0.00	-0.01	0.04	0.00	-0.03

Notes: Entries are analogous to those in Table 3 except that the CBSA level statistic of interest differs and both 2 km and 4 km CBD distance rings are examined. See the notes to Table 3 for a description of target groups and Table A3 for mathematical expressions used to calculate these counterfactuals.

Table 5: Decompositions of Changes in Fraction College Educated

					Fraction of All in (1) from ∆choices of				from ∆shares of	
Choices in year t	All	None	All	None	Target	Target	NonTarget	NonTarget	X|Race	Race
Shares in year t	All	None	None	All	White	NonWhite	White	NonWhite		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CBD Radius										
Panel A: 1980-2000										
2 km	0.060	0.000	0.007	0.046	-0.011	-0.004	0.009	0.014	0.064	-0.012
4 km	0.052	0.000	0.002	0.049	-0.016	-0.005	0.010	0.012	0.064	-0.013
Panel B: 2000-2010										
2 km	0.059	0.000	0.031	0.024	0.026	0.001	-0.006	0.011	0.031	-0.005
4 km	0.043	0.000	0.018	0.023	0.006	-0.002	0.001	0.013	0.030	-0.006

Notes: Entries are analogous to those in Table 3 except that the CBSA level statistic of interest differs and both 2 km and 4 km CBD distance rings are examined. See the notes to Table 3 for a description of target groups and Table A3 for mathematical expressions used to calculate these counterfactuals.

Table 6: Decompositions of Changes in Median Income
Expressed in Percentile Points of the Sample Area Income Distribution

					Fraction of All in (1) from Δchoices of				from Δshares of	
Choices in year t	All	None	All	None	Target	Target	NonTarget	NonTarget	X|Race	Race
Shares in year t	All	None	None	All	White	NonWhite	White	NonWhite		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CBD Radius										
Panel A: 1980-2000										
2 km	1.18	0.00	1.65	-0.23	0.08	-0.22	0.77	1.01	0.46	-0.93
4 km	-0.45	0.00	0.40	-0.63	-1.07	-0.34	0.84	0.98	0.23	-1.08
Panel B: 2000-2010										
2 km	3.84	0.00	4.19	-0.17	1.81	0.03	1.27	1.08	0.07	-0.42
4 km	1.79	0.00	2.06	-0.18	0.50	-0.14	0.75	0.95	0.19	-0.46

Notes: Entries are analogous to those in Table 3 except that the baseline is the change in the median tract income within the indicated CBD radius. Income is expressed as percentile of the full sample area distribution. See the notes to Table 3 for a description of target groups and Table A3 for mathematical expressions used to calculate these counterfactuals.

Table 7: Changes in Tract Valuations by Race and Education

	1980-1990	1990-2000	2000-2010	1980-2010
Estimator	RF	IV	IV	RF
Panel A: White College+				
1(< 4 km to CBD)	-0.198	-0.124	0.098	-0.232
	(0.023)	(0.018)	(0.019)	(0.061)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.041	-0.266	0.046	0.058
	(0.022)	(0.154)	(0.050)	(0.072)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.032	0.279	0.236	0.145
	(0.025)	(0.106)	(0.125)	(0.080)
Observations	33,770	34,983	34,742	33,311
R-Squared (First Stage F)	0.107	(26.7)	(31.5)	0.151
Panel B: Black College+				
1(< 4 km to CBD)	-0.508	-0.307	-0.090	-0.862
	(0.080)	(0.040)	(0.054)	(0.108)
CBSA Employment Growth* 1(< 4 km to CBD)	0.038	0.336	-0.362	-0.021
	(0.076)	(0.258)	(0.109)	(0.106)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.027	-0.219	0.391	-0.018
	(0.059)	(0.187)	(0.203)	(0.089)
Observations	17,373	21,747	23,144	17,108
R-Squared (First Stage F)	0.054	(27.4)	(43.5)	0.117
Panel C: White <HS				
1(< 4 km to CBD)	-0.273	-0.130	-0.051	-0.466
	(0.023)	(0.014)	(0.021)	(0.048)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.014	0.068	-0.081	-0.010
	(0.021)	(0.140)	(0.045)	(0.047)
CBD Area Employment Growth* 1(< 4 km to CBD)	-0.003	-0.051	0.103	-0.049
	(0.022)	(0.091)	(0.123)	(0.060)
Observations	34,760	35,831	34,941	33,701
R-Squared (First Stage F)	0.131	(28.1)	(39.0)	0.135
Panel D: Black <HS				
1(< 4 km to CBD)	-0.331	-0.233	-0.203	-0.891
	(0.070)	(0.034)	(0.051)	(0.111)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.071	-0.025	-0.344	-0.249
	(0.060)	(0.277)	(0.112)	(0.083)
CBD Area Employment Growth* 1(< 4 km to CBD)	-0.009	-0.150	0.571	-0.004
	(0.053)	(0.200)	(0.227)	(0.086)
Observations	17,769	19,644	19,546	16,404
R-Squared (First Stage F)	0.113	(26.5)	(41.2)	0.127

Notes: Reported coefficients are from regressions analogous to those in Table 2 Panel A, except using estimated λ utility components for each group indicated in panel headers rather than the unified SES index. Equation (13) in the text shows the full regression specification used. Coefficients that are significant at the 10% level are shaded red if positive and blue if negative. Standard errors are clustered by CBSA.

Table 8: Changes in Tract Valuations by Race and Household Income Decile

	Whites				Blacks			
	1980-1990	1990-2000	2000-2010	1980-2010	1980-1990	1990-2000	2000-2010	1980-2010
Estimator	RF	IV	IV	RF	RF	IV	IV	RF
Panel A: 20th-30th Percentiles								
1(< 4 km to CBD)	-0.431	-0.153	-0.080	-0.654	-0.838	-0.317	-0.238	-1.298
	(0.029)	(0.019)	(0.018)	(0.044)	(0.174)	(0.093)	(0.056)	(0.181)
CBSA Employment Growth	-0.013	-0.492	0.055	0.072	0.082	-0.523	-0.108	-0.407
* 1(< 4 km to CBD)	(0.030)	(0.173)	(0.049)	(0.050)	(0.164)	(0.468)	(0.122)	(0.153)
Near CBD Employment Growth	0.007	0.381	-0.012	-0.010	-0.213	0.370	0.002	0.120
* 1(< 4 km to CBD)	(0.032)	(0.111)	(0.129)	(0.062)	(0.110)	(0.303)	(0.244)	(0.139)
Observations	34,086	34,900	34,261	33,229	15,507	16,656	16,335	13,821
R-Squared (First Stage F)	0.147	(26.9)	(26.9)	0.199	0.098	(24.2)	(47.3)	0.163
Panel B: 50th-60th Percentiles								
1(< 4 km to CBD)	-0.321	-0.106	0.022	-0.384	-0.755	-0.378	-0.134	-1.304
	(0.028)	(0.017)	(0.020)	(0.051)	(0.166)	(0.056)	(0.093)	(0.149)
CBSA Employment Growth	-0.051	-0.005	0.146	0.087	-0.193	-0.222	-0.367	0.014
* 1(< 4 km to CBD)	(0.027)	(0.166)	(0.056)	(0.058)	(0.207)	(0.360)	(0.191)	(0.158)
Near CBD Employment Growth	0.037	0.059	-0.023	0.050	0.142	0.081	0.467	-0.120
* 1(< 4 km to CBD)	(0.042)	(0.110)	(0.139)	(0.073)	(0.105)	(0.273)	(0.350)	(0.152)
Observations	33,549	34,382	34,032	32,931	14,402	15,963	16,590	13,786
R-Squared (First Stage F)	0.127	(23.4)	(23.5)	0.157	0.187	(26.1)	(36.2)	0.130
Panel C: 70th-80th Percentiles								
1(< 4 km to CBD)	-0.330	0.004	0.066	-0.144	-0.840	-0.316	-0.120	-1.587
	(0.034)	(0.023)	(0.021)	(0.088)	(0.150)	(0.090)	(0.079)	(0.197)
CBSA Employment Growth	0.007	-0.246	0.063	0.194	-0.323	0.877	-0.162	0.073
* 1(< 4 km to CBD)	(0.034)	(0.206)	(0.059)	(0.090)	(0.156)	(0.558)	(0.147)	(0.117)
Near CBD Employment Growth	0.012	0.336	0.161	0.142	0.195	0.172	0.542	0.223
* 1(< 4 km to CBD)	(0.037)	(0.129)	(0.151)	(0.078)	(0.099)	(0.332)	(0.302)	(0.116)
Observations	33,374	34,419	33,960	32,674	15,191	17,851	17,638	13,854
R-Squared (First Stage F)	0.100	(26.5)	(22.3)	0.107	0.087	(18.2)	(36.7)	0.105

Notes: Each column in each panel shows results of a separate regression of the change in λ as defined in Equation (11) in the text on the indicated variables and various additional CBD distance indicators and distances to exogenous local amenities. See the notes to Table 7 for additional explanation.

Table 9: Contributions to Changes in Central Area Population Growth by Various Demographic Groups Using the Model

	Within 2 km of CBDs				Within 4 km of CBDs			
	Target White	Target NonWhite	NonTarget White	NonTarget NonWhite	Target White	Target NonWhite	NonTarget White	NonTarget NonWhite
Component								
Panel A: 1980-2000								
Home Price	-0.01	0.00	-0.07	-0.04	0.00	0.00	0.00	-0.01
Central Emp Shock	0.00	0.00	-0.02	0.03	0.00	0.00	-0.03	0.02
CBSA Emp Shock	-0.01	0.01	-0.02	0.00	-0.01	0.01	-0.03	0.00
Exogenous Amenities	-0.01	0.00	-0.03	0.00	-0.01	0.00	-0.03	0.00
Other	0.02	-0.02	0.00	-0.16	0.00	-0.02	-0.07	-0.16
Panel B: 2000-2010								
Home Price	-0.02	-0.01	-0.07	-0.12	-0.01	0.00	-0.03	-0.04
Central Emp Shock	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01
CBSA Emp Shock	0.00	-0.01	0.00	-0.05	0.00	-0.01	0.00	-0.05
Exogenous Amenities	-0.01	0.00	-0.01	0.01	-0.01	0.00	-0.01	0.00
Other	0.06	0.01	0.10	0.10	0.02	0.01	0.02	0.02

Notes: Each entry is the marginal contribution of the component listed at left on central area population within the CBD distance ring indicated at top because of shifts in neighborhood choices of the indicated demographic group. Each column in the left block of each panel sums to entries in Table 3 that are calculated using the education data set.

Table A1: Descriptive Statistics for Employment Shocks

Panel A: Employment Shocks

	Δ ln(CBSA Employment)			Δ ln(Employment Within 4 km of CBD)		
	Mean	SD	Coeff of Var	Mean	SD	Coeff of Var
1980-1990	0.17	0.12	1.42		Not Available	
1990-2000	0.10	0.09	1.11	-0.07	0.12	-0.58
2000-2010	0.08	0.09	0.89	-0.01	0.13	-0.08

Panel B: Instruments

	Bartik			Spatial Bartik		
	Mean	SD	Coeff of Var	Mean	SD	Coeff of Var
1970-1980	0.11	0.02	5.15	0.14	0.02	6.29
1980-1990	0.17	0.03	5.99	0.20	0.02	8.27
1990-2000	0.05	0.03	1.49	0.10	0.03	3.00
2000-2010	0.07	0.03	2.44	0.08	0.02	3.54
1980-2010	0.29	0.08	3.64	0.39	0.07	5.23

Notes: We only use actual employment shocks for the 1990-2000 and 2000-2010 periods in Tables 2, 7 and 8, instrumented with variables whose summary statistics are reported in Panel B. For periods, those tables report reduced form results. Statistics are for the 120 CBSAs in the sample.

Table A2: Patterns of Housing Costs in Tracts within 4 km of CBDs

	1970-1980	1980-1990	1990-2000	2000-2010	1980-2010
Estimator	RF	RF	IV	IV	RF
Panel A: Difference Specification					
1(< 4 km to CBD)	-0.072	-0.025	-0.008	0.033	0.003
	(0.015)	(0.013)	(0.008)	(0.008)	(0.020)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.038	0.000	-0.181	0.032	0.008
	(0.015)	(0.013)	(0.075)	(0.021)	(0.023)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.034	0.018	0.179	0.041	0.078
	(0.014)	(0.014)	(0.052)	(0.051)	(0.026)
Observations	31,011	35,580	35,450	36,144	34,960
R-Squared (First Stage F)	0.039	0.016	(29.3)	(50.3)	0.038
Panel B: AR(1) Specification					
1(< 4 km to CBD)	-0.067	-0.045	-0.037	0.016	-0.027
	(0.016)	(0.013)	(0.007)	(0.008)	(0.020)
CBSA Employment Growth* 1(< 4 km to CBD)	-0.037	0.012	-0.009	0.022	0.025
	(0.014)	(0.011)	(0.060)	(0.019)	(0.025)
CBD Area Employment Growth* 1(< 4 km to CBD)	0.031	0.043	0.078	0.104	0.095
	(0.015)	(0.015)	(0.045)	(0.051)	(0.026)
Observations	31,011	35,580	36,900	36,377	34,960
R-Squared (First Stage F)	0.462	0.632	(30.0)	(33.6)	0.442
Panel C: AR(1) Specification, Arellano-Bond Adjustment					
1(< 4 km to CBD)		-0.051	0.006	-0.064	0.048
		(0.040)	(0.030)	(0.071)	(0.052)
CBSA Employment Growth* 1(< 4 km to CBD)		-0.005	0.005	-0.024	0.026
		(0.028)	(0.025)	(0.031)	(0.052)
CBD Area Employment Growth* 1(< 4 km to CBD)		0.049	0.036	0.044	0.106
		(0.029)	(0.051)	(0.046)	(0.071)
Observations		30,944	35,450	36,144	30,432

Notes: Each column in each panel reports results from a separate regression of the change in tract owner occupied housing price index using the same specification as in Table 2. The housing cost index is formed from the residuals of a regression of log mean owner occupied home value on housing unit structure characteristics (number of units in building, number of bedrooms in unit, age of building) of the tract and CBSA fixed effects. Coefficients that are significant at the 10% level are shaded red if positive and blue if negative.

Table A3: Explanation of Counterfactual Experiments
Population Distributions Used to Construct Counterfactuals

Column in Tables 3-6	Choices	Shares	Group: Race	Group: X-Dimension	Math Notation
1	All t	All t	All	All	$f_{jt}(i\|r,x)g_{jt}(r,x)$
2	All Base Yr	All Base Yr	All	All	$f_{jb}(i\|r,x)g_{jb}(r,x)$
3	All t	All Base Yr	All	All	$f_{jt}(i\|r,x)g_{j8}(r,x)$
4	All Base Yr	All t	All	All	$f_{j8}(i\|r,x)g_{jt}(r,x)$
5	Target Whites t	All Base Yr	Whites	Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
			Whites	Non-Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Non-Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
6	Target t	All Base Yr	Whites	Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Whites	Non-Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Non-Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
7	Target+Whites t	All Base Yr	Whites	Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Whites	Non-Target	$f_{jt}(i\|r,x)g_{j8}(r,x)$
			Blacks, Others	Non-Target	$f_{j8}(i\|r,x)g_{j8}(r,x)$
8	All t	All Base Yr	All	All	$f_{jt}(i\|r,x)g_{j8}(r,x)$
9	All t	X|r in t, r in Base Yr	All	All	$f_{jt}(i\|r,x)g_{jt}(x\|r)h_{j8}(r)$
10	All t	All t	All	All	$f_{jt}(i\|r,x)g_{jt}(x\|r)h_{jt}(r)$

Notes: Entries in the final column show the contribution of each demographic group to each counterfactual in Tables 3-6. See Section 3.1 of the text for an explanation of notation. Target groups are college graduates, households in the top three deciles of the income distribution, people aged 20-34 and singles or married couples with no kids.

Table A4: Aggregate Quantities

	Fraction White	Fraction College	Median HH Income	Share in Families without Kids	Share 20-34
			Panel A: Entire Sample		
1970	0.883	0.116	47881		
1980	0.836	0.102	44266	0.328	0.266
1990	0.809	0.138	52310	0.357	0.255
2000	0.753	0.167	58308	0.384	0.211
2010	0.717	0.196	55532	0.401	0.209
			Panel B: Within 2 km of CBDs		
1970	0.683	0.082	32626		
1980	0.590	0.085	26281	0.404	0.300
1990	0.548	0.115	30991	0.376	0.317
2000	0.507	0.144	36770	0.420	0.298
2010	0.533	0.204	38423	0.454	0.324
			Panel C: Within 4 km of CBDs		
1970	0.722	0.089	36523		
1980	0.629	0.087	31055	0.366	0.288
1990	0.584	0.115	35777	0.358	0.289
2000	0.531	0.139	40934	0.396	0.267
2010	0.537	0.183	39882	0.423	0.286

Notes: Each entry is an average across CBSAs in the sample.

Table A5: Decomposition of Percent Changes in Population within 2 km of CBDs - Reverse Order

	Contribution to Difference Between (1) and (2) in Table 3					
	from Δshares of		from Δchoices of			
Choices in year t	X|Race	Race	Target	Target	NonTarget	NonTarget
Shares in year t			White	NonWhite	White	NonWhite
	(1)	(2)	(3)	(4)	(5)	(6)
Data Set						
			Panel A: 1980-2000			
Education	-0.04	0.13	-0.02	-0.01	-0.11	-0.24
Age	0.00	0.13	0.01	-0.04	-0.14	-0.23
Family Type	0.10	0.12	-0.11	-0.09	-0.09	-0.21
Income	0.00	0.10	0.00	-0.01	-0.20	-0.27
			Panel B: 2000-2010			
Education	-0.02	0.05	0.04	0.00	0.02	-0.09
Age	0.01	0.05	0.04	-0.01	0.01	-0.09
Family Type	0.03	0.04	0.02	-0.03	-0.01	-0.09
Income	0.00	0.03	0.03	0.00	0.00	-0.09

Notes: Results are analogous to those in Table 3. The only difference is the ordering in which the counterfactuals are imposed.

Table A6: Decompositions of Changes in Fraction White, Fraction College Educated and Percentile of Median Income - Reverse Order

		Fraction White (See Table 4)						Fraction College Educated (T. 5) or Median Income (T. 6)					
		from Δshares of		Δchoices of				from Δshares of		Δchoices of			
Choices in year t		X|Race	Race	Target	Target	NonTarget	NonTarget	X|Race	Race	Target	Target	NonTarget	NonTarget
Shares in year t				White	NonWhite	White	NonWhite			White	NonWhite	White	NonWhite
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Data Set	CBD Radius												
Panel A: 1980-2000													
Education	2 km	0.01	-0.12	-0.01	0.00	-0.05	0.09	0.06	-0.01	-0.02	-0.01	0.01	0.03
Education	4 km	0.00	-0.11	-0.01	0.00	-0.06	0.07	0.06	-0.01	-0.02	-0.01	0.01	0.02
Income	2 km	0.00	-0.10	0.00	0.00	-0.09	0.11	0.28	-0.51	0.11	-0.27	0.46	1.11
Income	4 km	0.00	-0.09	-0.01	0.01	-0.08	0.09	0.15	-0.78	-0.86	-0.44	0.48	1.01
Panel B: 2000-2010													
Education	2 km	0.00	-0.04	0.02	-0.00	0.01	0.04	0.03	0.00	0.03	0.00	-0.01	0.01
Education	4 km	0.00	-0.04	0.01	0.00	-0.00	0.04	0.03	-0.01	0.01	0.00	0.00	0.02
Income	2 km	0.00	-0.03	0.01	0.00	0.00	0.04	0.14	-0.31	1.72	0.06	1.21	1.02
Income	4 km	0.00	-0.03	0.00	0.00	-0.01	0.04	0.20	-0.38	0.47	-0.14	0.68	0.95

Notes: Results in Columns 1-6 are analogous to those in Columns 5-10 of Table 4. Results for Education in Columns 7-12 are anologus to those in Columns 5-10 of Table 5. Results for Income in Columns 7-12 are analogous to those in Columns 5-10 of Table 6. The only difference is that counterfactuals are conducted in the reverse order.

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