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Abstract

Existing research has found an inverse relationship between urban density and the degree of income inequality within metropolitan areas, suggesting that, as cities spread out, they become increasingly segregated by income. This paper examines this hypothesis using data covering more than 160000 block groups within 359 US metropolitan areas over the years 1980, 1990, and 2000. The findings indicate that income inequality - defined by the variance of the log household income distribution - does indeed rise significantly as urban density declines. This increase, however, is associated with rising inequality *within* block groups as cities spread out. The extent of income variation exhibited between different block groups, by contrast, shows virtually no association with population density. There is, accordingly, little evidence that sprawl is systematically associated with greater residential segregation of households by income.

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1 Introduction

For much of the last century, population within the metropolitan areas of the United States has shown a persistent tendency to move outward, leaving central cities for suburban locales. Just within the last 50 years, this movement has been rather striking. In 1950, 41.5 percent of metropolitan populations resided in suburban areas (i.e. those outside of central cities). A half-century later, more than 62 percent did. The density of residential activity within the nation's urban areas has, as a consequence, changed dramatically. Between 1950 and 2000, the average central city population density decreased from 7517 residents per square mile to 2716. At the same time, suburban densities rose from 175 residents per square mile to 208.[1]

To be sure, the process of urban decentralization largely reflects the decisions of individuals and employers to spread out their activities increasingly over space. With improvements in transportation technology and infrastructure, for example, it has become easier to commute long distances. These changes have undoubtedly encouraged workers and firms to locate on the outer fringes of their metropolitan areas where land tends to be both plentiful and less costly.

In spite of the 'voluntary' nature of this process, however, urban decentralization has generated a number of concerns about the welfare of metropolitan area populations. One such concern is a rising disparity between neighborhoods, especially the decline of incomes in central cities relative to those of their suburban counterparts. As metropolitan areas expand, the majority of both employment opportunities and relatively high-income households may

[1] All of these figures are derived from the US Census of Population and Housing, as reported by Hobbs and Stoops (2002).

shift from center to periphery, thereby creating a widening income gap between these two areas. Over time, these differences may then become more pronounced as the poor become increasingly isolated from productive interactions with wealthier neighbors.[2]

Existing research offers evidence that seems to back this idea. Margo (1992), for example, argues that the movement of metropolitan populations in the US toward suburban locales over the latter half of the 20th century can be linked, to a significant degree, to the rise in personal incomes. As individual incomes rose, quite simply, so did the demand for land. One rather straightforward implication of this hypothesis is that decentralization should be accompanied by a rise in the extent of income segregation. After all, individuals migrating to the suburbs (i.e. those with a particularly high demand for space) should also be those with relatively high incomes. As a result, one would expect urban decentralization to have led to the accumulation of high-income households on the outskirts of cities, while poorer residents remain within the central cores.

A number of studies do suggest that, over this same time period, poverty became more concentrated within the country's urban areas. Mayer (1996), for example, reports that, in 1964, families falling in the bottom quintile of the income distribution were 1.2 times as likely to reside in a central city as wealthier families. By 1994, they were 1.4 times as likely to reside in central cities. In studies of the country's largest cities and metropolitan areas, Kasarda (1993) and Abramson et al. (1995) find that individuals living in poverty became increasingly concentrated within poor neighborhoods (defined by Census tracts) between 1970 and 1990. Although these two particular studies do not consider the issue of urban

[2]The movement of high income individuals away from the poor, for example, may leave the poor with relatively few jobs (e.g. Kain (1968)) or reduce the extent to which the rich confer positive spillovers on the poor (e.g. Wilson (1987) and Benabou (1996)).

decentralization per se, the figures they document certainly characterize a period in which metropolitan populations were shifting from central areas toward suburban ones.

Research on the spatial-mismatch hypothesis offers a similar conclusion. This idea, advanced by Kain (1969), holds that inner-city dwellers tend to experience adverse economic outcomes as population and employment leave those inner-cities because it becomes increasingly difficult for them to find and sustain employment. One should therefore expect to see the gap between the incomes earned by residents of suburban neighborhoods and those earned by central city residents to rise as populations spread out. Many studies of this topic have found that inner city minorities do seem to experience worse labor market outcomes, usually measured by employment status and earnings, as economic activity leaves urban centers, although the literature is far from unanimous on this point.[3]

On the specific topic of income inequality, Wheeler (2004) finds that urban density exhibits a strong negative correlation with the degree of spread in the distribution of labor earnings. Thus, as a metropolitan area's population spreads out, its wage distribution tends to widen. Although the results apply to white male workers with a strong attachment to the labor force (and so do not offer direct evidence on spatial mismatch, which tends to focus on differences by race), they are certainly consistent with the idea that urban decentralization leads to greater segregation of high-income and low-income workers across neighborhoods.

In spite of this existing work, however, surprisingly little research has directly studied the evolution of inter-neighborhood income differentials as populations become increasingly dispersed, particularly among neighborhoods defined at levels finer than central cities and

[3]See, for example, Ihlanfeldt and Sjoquist (1989), Holzer (1991), and Weinberg (2000, 2004) for a discussion of these issues.

suburbs. This paper seeks to do so by examining the relationship between urban density and the degree of income inequality both within and between neighborhoods defined by Census block groups. More specifically, I use data on household income to compute the variance of the income distribution for each of 359 US metropolitan areas over the years 1980, 1990, and 2000. I then exploit data covering more than 165000 block groups to decompose these variances into components associated with the dispersion of incomes within block groups and components associated with the dispersion across them.

The results suggest that, although the variance of a metropolitan area's household income distribution is indeed strongly, negatively associated with its overall density, the association operates through a within-neighborhood channel rather than a between-neighborhood channel. That is, as the population of a metropolitan area spreads out, household income inequality increases largely because the extent of income variation among households within the same block group rises, not because neighborhoods become more segregated by income.

Upon closer inspection, the data do reveal some evidence that decentralization tends to be accompanied by rising between-neighborhood income gaps, but only at the top of the block-group income distribution. Specifically, the income differential between the block group at the 90th percentile of the household income distribution and the block group at the median does increase significantly as metropolitan areas decentralize. However, the gap between the median and the block group at the 10th percentile tends to decrease, leaving measures of the overall spread in the between-neighborhood income distribution relatively unchanged. Moreover, there appears to be little association between density and either the average income of the block group at the 90th percentile or that of the block group at the 10th percentile. Similar results hold when the analysis is repeated using Census tracts instead of block groups.

It is important to note that these results should not be interpreted as suggesting that certain neighborhoods do not suffer particularly adverse economic outcomes as populations decentralize. There may very well be inner-city areas that become increasingly poor as activity moves outward. However, the extent to which this process occurs evidently has little effect on the overall level of between-neighborhood income inequality in a metropolitan area.

The remainder of the paper proceeds as follows. The next section provides a brief description of the data and some of the computational issues. Section 3 then presents the results. Section 4 offers some concluding comments.

2 Data and Measurement

The primary data source used for the analysis is the decennial US Census of Population and Housing for the years 1980, 1990, and 2000 as compiled by GeoLytics.[4] The GeoLytics data files report a variety of demographic and economic characteristics (e.g. income, industry of employment, age, race, gender, education, place of birth, employment-unemployment status) for individuals at a variety of geographies, including counties, tracts, and block groups. Unfortunately, individual-level observations are not reported in the data; only summary measures taken across the individuals located within each geographic unit. This feature, of course, limits the types of statistics that one can calculate. The primary advantage of these data is the consistency of the geographic units - the data has been constructed based on consistent geographic definitions over all three Census years.

[4]The data can be obtained from GeoLytics, Inc. at http://www.geolytics.com.

For the present study, I focus on average household income and a variety of other economic and demographic data among block groups, which I use as the basis for a 'neighborhood.' Although neighborhoods could also be (and frequently are) defined by Census tracts, I focus on block groups in this paper because they represent the finest grouping available in the data. Across the 359 metro areas in the sample, there are more than 165000 block groups which contained, on average, 526.5 households each and had a median land area of approximately 0.33 square miles in the year 2000.[5] Tracts tend to be larger (1648.8 households, on average, and a median land area of 1.31 square miles in 2000) and, therefore, may be less appropriate when considering neighborhoods, which are meant to encompass areas over which individuals can reasonably be expected to interact with one another. As demonstrated below, the principal findings are mostly invariant to the choice of block groups or tracts.

I estimate the variance of a metropolitan area's income distribution as follows. For each year, the number of households with incomes falling into each of N closed intervals is reported.[6] I use these figures to compute the fraction of households with incomes less

[5]Metropolitan area definitions follow the Census Bureau's definitions as of November, 2004. They were accessed at http://www.census.gov/population/www/estimates/metrodef.html.

[6]For 1980, there are 15 categories: 0-4999, 5000-7499, 7500-9999, 10000-12499, 12500-14999, 15000-17499, 17500-19999, 20000-22499, 22500-24999, 25000-27499, 27500-29999, 30000-34999, 35000-39999, 40000-49999, 50000-74999. For 1990, there are 24: 0-4999, 5000-9999, 10000-12499, 12500-14999, 15000-17499, 17500-19999, 20000-22499, 22500-24999, 25000-27499, 27500-29999, 30000-32499, 32500-34999, 35000-37499, 37500-39999, 40000-42499, 42500-44999, 45000-47499, 47500-49999, 50000-54999, 55000-59999, 60000-74999, 75000-99999, 100000-124499, 125000-149999. For 2000, there are 15: 0-9999, 10000-14999, 15000-19999, 20000-24999, 25000-29999, 30000-34999, 35000-39999, 40000-44999, 45000-49999, 50000-59999, 60000-74999, 75000-99999, 100000-124999, 125000-149999, 150000-199999.

than N distinct levels, which allows N quantiles of the household income distribution to be estimated for each metro area. For example, if 14 percent of all households have income less than 25000 dollars, I estimate the 0.14 quantile by 25000. Label these quantiles X_α. I then match these N quantiles to their corresponding values from a normal (0,1) distribution. Label these quantiles U_α. Assuming a lognormal household income distribution, X_α and U_α are related as follows:

$$X_\alpha = \exp(\zeta + U_\alpha \sigma) \tag{1}$$

where ζ and σ are the mean and standard deviation parameters characterizing the lognormal distribution (see Johnson and Kotz (1970, p. 117)). These parameters are readily obtained by transforming (1) logarithmically and estimating by OLS. The fit of these regressions tended to be quite high in all cases. Across the 359 metro areas, the mean adjusted R^2 was approximately 0.98 for each year, and the minimum across all metro area-year observations was 0.95. With the standard deviation, σ, the variance follows simply as σ^2.

Summary statistics describing metropolitan area-level income variances appear in Table 1.[7] Most notably, they demonstrate that, on average, the degree of dispersion exhibited by metropolitan area-level (log) income distributions increased between 1980 and 2000, with the majority of this increase taking place between 1980 and 1990. Over these two decades, the mean income variance rose by a total of 10 log points, or approximately 18 percent. Of this 10 log point increase, the vast majority, 9 log points, was experienced during the

[7] The magnitudes of these variances are very similar to what has been computed using individual-level household income data. See, for example, http://www.census.gov/hhes/income/histinc/ie6.html.

1980s. Qualitatively, of course, this finding is consistent with what has now been widely established in the inequality literature (e.g. Katz and Murphy (1992), Juhn et al. (1993)).

3 Empirical Findings

3.1 Urban Decentralization and Income Inequality

Consider first the relationship between metropolitan area-level population density and the extent of income inequality. To do so, let the variance of the (log) income distribution for metropolitan area m in year t have the following characterization:

$$\sigma^2_{mt} = \mu_m + \mu_t + \beta X_{mt} + \gamma D_{mt} + \epsilon_{mt} \tag{2}$$

where μ_m is a metro area-specific fixed effect, μ_t is a year-specific term, X_{mt} is a vector of covariates described in greater detail below, D_{mt} is the logarithm of population density, and ϵ_{mt} is a residual. To eliminate the metro area fixed effects, I take 10-year differences of equation (2), yielding

$$\Delta\sigma^2_{mt} = \Delta\mu_t + \beta\Delta X_{mt} + \gamma\Delta D_{mt} + \Delta\epsilon_{mt} \tag{3}$$

which serves as the primary estimating equation in the analysis. Given the nature of the differenced error term, there is non-zero correlation between the residuals for the same metro area. The standard errors are adjusted to account for this correlation.

Density is calculated for each metropolitan area as the weighted average of county-level population densities, where the weights are given by each county's share of total metropolitan area population. This measure is used instead of average metropolitan area density (calculated as the ratio of total metropolitan area population to total land area) to mitigate the influence of extremely large but relatively unpopulated counties, which appear in many metropolitan areas of the West. County-weighted population density gives these counties less weight in the computations and, therefore, may provide a better sense of how densely clustered a city's population is.[8] To provide a sense of what the resulting density numbers look like, Table 2 lists the 10 most and least densely populated metropolitan areas in each year.

Among the covariates included in the vector X_{mt} are some basic characteristics commonly associated with the degree of income inequality in an economy. These characteristics include the percentages of the resident population that are black, female, foreign-born, under the age of 25, and over the age of 65; the fraction of the population 25 years of age or older that has completed at least a bachelor's degree; shares of employment in 9 broad industries[9]; the fraction of the labor force that is covered by a union; and the unemployment rate. I also include three region dummies to account for any basic geographic differences in the inequality trends across different parts of the country.[10]

[8] I also repeated all of the estimation using weighted averages of *block group-level* population densities for each metro area. The results were qualitatively similar to what is reported here.

[9] The sectors are manufacturing; agriculture, forestry, fisheries, and mining; construction; wholesale trade; retail trade; finance, insurance, real estate; public administration; education services; health services. I do not use a more detailed industrial classification scheme, in part, to avoid difficulties associated with the change from the Standard Industrial Classification system in 1980 and 1990 to the North American Industry Classification System in 2000.

[10] Since metropolitan area boundaries frequently cross state borders, and region definitions are based on

Results appear in Table 3. In an effort to gauge the robustness of the density-inequality relationship, I consider three different specifications of the covariates in the estimation of equation (3). The first limits the regressors to log density, the three region dummies, and a time effect for the 1980-1990 decade. The second then adds the population demographics of each metro area (age, race, gender, education, foreign-born status). The third includes the remainder of the covariates which provide a basic description of the metro area's labor market (industry employment shares, unionization, unemployment).[11]

Throughout, we see a number of fairly standard findings. Larger proportions of both women and individuals under the age of 24 in the local population are strongly, positively associated with inequality, which likely reflects the relatively low income that these individuals receive, on average. There is also some evidence, although not always statistically significant, that inequality rises with the percentages of foreign-born residents and individuals over the age of 65 in the local population. Furthermore, inequality in a metro area tends to rise significantly as the unemployment rate increases, suggesting that households at the bottom end of the income distribution are more sensitive economically to the business cycle than wealthier households. Inequality is also significantly, negatively associated with the extent of union coverage in the local labor force, which is a relatively common finding. Although union workers typically receive an earnings premium over non-union labor,

states, some metro areas have parts in different regions. I assign these multi-region metropolitan areas to the regions in which the majority of their populations lie.

[11] The unionization rate for each metropolitan area is based upon state-level union coverage rates reported by Hirsch et al. (2001) (available at www.unionstats.com). Metropolitan area-level union rates are calculated as weighted averages of their constituent state-level rates, where the weights are given by the fraction of each metro area's labor force located in each state.

union contracts tend to equalize earnings across workers (e.g. Fortin and Lemieux (1997)). Shares of local employment in both manufacturing and construction, two sectors that are frequently associated with relatively high earnings for relatively low-skill labor, correlate negatively with income inequality.

The primary regressor of interest, the logarithm of population density, is uniformly negative and statistically significant across all three specifications. Based on the point estimates, a 1 standard deviation decrease in the change in population density corresponds to a 1 log point rise in the change in log income variance. This figure is far from negligible, representing approximately 20 percent of the mean change in log income variance over the two decades considered here. Again, this basic finding has already been established, at least in a qualitative sense, in some of the work described above. In what follows, I take a closer look at this result to determine the extent to which it reflects an increase in the degree of income segregation across neighborhoods.

3.2 Decomposing Income Inequality

Consider the following standard decomposition of a metropolitan area's income inequality. The variance of household income in a metropolitan area, σ^2, can be estimated as

$$\sigma^2 = \frac{1}{H} \sum_{n=1}^{N} \sum_{h=1}^{H_n} (y_{h,n} - \bar{y})^2 \tag{4}$$

where $y_{h,n}$ is the income of household h of neighborhood n, $\bar{y}$ is the mean household income for the entire metropolitan area, H_n is the total number of households in neighborhood n,

N is the total number of neighborhoods, and H is the total number of households, $\sum_n H_n$.[12] This expression can be re-written as the sum of two terms:

$$\sigma^2 = \frac{1}{H}\sum_{n=1}^{N}\sum_{h=1}^{H_n}(y_{h,n} - \bar{y}_n)^2 + \frac{1}{H}\sum_{n=1}^{N}\sum_{h=1}^{H_n}(\bar{y}_n - \bar{y})^2 \quad (5)$$

where $\bar{y}_n$ represents the mean household income in neighborhood n. The first of the terms on the right-hand-side of (5) is the 'within' neighborhood component, which measures the degree of income dispersion among households within the same neighborhood. The second term, the 'between' component, captures the amount of income variation across different neighborhoods.

Because I do not have data from individual households, I am unable to compute the within component directly. However, I can compute the between component. Using the estimates of the variance, σ^2, derived above, I construct the within-neighborhood component as the difference between these two pieces.

A few summary statistics describing the within- and between-block group components are reported in Table 1. Two features are immediately apparent. First, in each of the three years considered (1980, 1990, 2000), the extent of income variation within neighborhoods is considerably larger than the extent of variation between them. In the year 2000, for instance, the within-neighborhood component accounted for 80 percent of total metropolitan area income variation, on average. This finding is roughly similar to what Epple and Sieg (1999)

[12] The average numbers of households per metropolitan area are relatively large: 180164.6 for 1980, 208780.9 for 1990, 240407.2 for 2000. Across all three years, the minimum number of households is 8681. Hence, the difference between using a factor of $\frac{1}{H}$ in (4) instead of $\frac{1}{H-1}$ is extremely small.

report for municipalities in Boston and is consistent with the results of Ioannides (2004) and Hardman and Ioannides (2004), who document a substantial degree of income heterogeneity within small residential clusters in the US. Second, between 1980 and 1990, there was a sharp rise in the proportion of total income variation attributable to between-neighborhood differences. Over this decade, the average fraction of total income variation associated with differences across neighborhoods rose from 12.7 percent to 21.9 percent. Hence, although income variation remained predominantly a within-neighborhood phenomenon in 2000, the between-neighborhood component became increasingly important between 1980 and 2000.

3.3 Decentralization and Inequality: Within vs. Between Neighborhoods

To determine whether urban decentralization is associated with growing inequality through a within- or a between-neighborhood channel (or possibly both), I estimate a series of regressions following the procedure above. That is, I estimate three specifications of equation (3) in which the dependent variables are the changes in within- and between-neighborhood income variation rather than the change in the total variance of log income.

The estimates are reported in Table 4. Interestingly, they demonstrate some striking differences in the estimated associations across the two sets of results. Looking just at the longest specification, III, the change in a metro area's degree of income variation within its block groups is positively and significantly tied to changes in the fraction of the population with a bachelor's degree, the fraction that is black, and the fraction that is foreign-born. On the other hand, increases in the percentages of total employment in manufacturing and finance, insurance, and real estate correlate negatively with inequality within neighborhoods.

When considering between-neighborhood inequality, there is a similar positive and significant association with the fraction of college graduates in the local population, but also with a number of quantities that did not relate significantly to within-block group inequality: the percentages of the population accounted for by women and individuals under the age of 24 and the unemployment rate. Increases in these three variables tend to be associated with increases in the extent of income variation between different block groups. Additionally, between-neighborhood inequality is significantly, negatively tied to the fraction of the local population that is black, the shares of total employment accounted for by construction and education services, and the extent of union coverage in the local labor force.

Why do we see such differences in the associations of these variables with the two measures of inequality? One possible explanation relates to how residential patterns change with each quantity. Increases in the fraction of blacks in a metro area's total population, for instance, may be associated with increasing racial heterogeneity within block groups (hence, higher within-neighborhood income variation), and as a consequence, declining heterogeneity between them (thus, lower between-neighborhood variation). Similarly, fluctuations in unemployment and union coverage may influence workers in particular neighborhoods much more so than a city's general population. This would lead to fluctuations in the degree of inequality between neighborhoods rather than within them.

As for the variable of primary interest, population density, the results demonstrate a clear, negative association with the extent of income variation within neighborhoods. As the change in population density decreases by 1 standard deviation in the cross section, the change in (log) income variance within block groups rises by approximately 1 percentage point. This magnitude, recall, is virtually identical to the one estimated for overall income variation.

Given this finding, it is perhaps not surprising that the estimated association between density and *between*-neighborhood inequality is extremely small. None of the three specifications produces a statistically or economically significant coefficient on the change in population density. Based on these results, then, there is little evidence that urban decentralization is associated with rising income differentials between neighborhoods. The negative association between density and the variance of household income observed in Table 3 seems to be driven almost entirely by the change in within-neighborhood income differences.

3.4 Instrumental Variables Estimates

One obvious criticism of the estimation above is the potential endogeneity of changes in density with respect to changes in inequality. A rise in the degree of income dispersion in a metro area, for example, may induce residents to segregate further, possibly leading to greater decentralization. It is not implausible that high-income households may seek to move farther away from low-income households as the gap between the two rises.[13]

To address this matter, I turn to instrumental variables (IV) estimation, where I consider two different sets of instruments for the change in density: (i) the lagged *level* of density within a metropolitan area and (ii) lagged shares of employment in each of the nine industry shares considered above. The rationale for each is straightforward. Initial density should capture a city's capacity for increased levels of density over time. All else

[13]Rising income differentials, for example, may generate greater differences in the demand for certain local public goods or an increasing desire to avoid 'negative' neighborhood effects.

equal, initially dense cities should be less likely to see further increases in their densities because they face greater constraints on space.[14] Because different types of employers have different propensities to decentralize their operations (e.g. Glaeser and Kahn (2004)), initial industry shares should also predict future changes in population density. Weinberg (2004), for example, has exploited this feature of industry location patterns to instrument for job centralization in a study of spatial mismatch. Of course, because some may be concerned that initial density or sectoral employment shares are correlated with unobserved factors influencing subsequent changes in inequality (e.g. density or the manufacturing share in 1990 may be endogenous with respect to the change in inequality between 1990 and 2000), I use density and each industry share in 1980 to instrument for the change in density between 1990 and 2000.[15]

Results using all three inequality measures and all three specifications appear in Table 5. For the sake of conciseness, I have only reported the coefficients on the change in density. What they show, for the most part, is very similar to what the estimates in Tables 3 and 4 demonstrate. Density and inequality are negatively related, and the association operates primarily through a within-neighborhood channel rather than a between-neighborhood channel.

[14] There is, in fact, a strong negative connection between the initial level of density in a metro area and the extent to which it decentralizes over the next 10 years. A simple regression of the change in density on its initial level in the data used here produces a coefficient (standard error) of -0.04 (0.004) with a goodness-of-fit statistic equal to 0.14.

[15] As demonstrated by the results from F-tests of marginal significance reported in Table 5, both sets of instruments are significant predictors of the change in density between 1990 and 2000.

3.5 Other Measures of Between-Neighborhood Inequality

In this section, I expand on the analysis of between-neighborhood inequality by considering how changes in metropolitan area density influence some alternative measures of income differences across block groups. In particular, I explore how differences between the 90th, 50th, and 10th percentiles of the block group (average) household income distribution within each metropolitan area change as metropolitan areas decentralize.[16]

Results from the same three specifications considered above, each of which is estimated by both OLS and IV, appear in Table 6.[17] Regardless of whether the percentiles are computed in a weighted or unweighted fashion (where the weights are given by the number of households in each block group), the estimated coefficients on density are quite similar. The OLS results suggest that, instead of decreases in density generating greater inequality between neighborhoods, they may generate smaller inter-neighborhood income differences.

A different set of conclusions emerges from the instrumental variables estimates. These suggest that there appears to be little association between density and the difference between the neighborhoods at the 90th and 10th percentiles of the log income distribution, which is consistent with the results examining the between-neighborhood component of total income variation documented above. When broken down into 90-50 and 50-10 differentials, however, we see that the difference between the 90th percentile and the median tends to increase significantly as cities decentralize. At the same time, the difference between the median and the 10th percentile appears to decrease as metro area population spreads out. Indeed, the estimated associations between density and the 50-10 gap are significantly positive when

[16] On average, metropolitan areas in the sample contain 460 block groups each (minimum = 27, maximum = 14019), so calculating percentiles is a reasonable exercise with these data.

[17] Recall, standard errors are, in all cases, adjusted for heteroskedasticity and within-metro area correlation.

initial density is used as an instrument for its future change. When combined, of course, these two observations are perfectly compatible with the finding that the 90-10 differential shows little association with changes in density.

This evidence suggests that, although there seems to be little association between urban decentralization and measures of the overall degree of income variation across different neighborhoods, the same is not true for all parts of the income distribution. As city populations spread out, there appears to be an increase in the average incomes of neighborhoods at the top relative to the middle. Particularly high-income households may segregate themselves to a larger extent as populations spread out. On the other hand, the gap between the average incomes at the middle of the distribution and those at the bottom shrinks, which may reflect greater income mixing among middle to lower income households.

A more detailed set of results describing these associations appears in Table 7, which reports the coefficients on the change in density in regressions in which these three individual quantiles are specified as the dependent variables. The OLS results, once again, suggest that declining density may lead to *smaller* income differences between block groups because the estimated associations are positive and increasing as one moves from the 10th percentile to the 90th. Hence, decreases in density ought to reduce the average income at the top of the block group distribution by more than it does at either the middle or the bottom.

The instrumental variables estimates, on the other hand, indicate that the 90th and 10th percentiles of the block group income distribution vary little with population density. Only two of the 24 estimates for these two quantiles differ statistically from zero. This result is interesting because it suggests that urban decentralization is not associated with the top of the neighborhood income distribution pulling away from the rest of the distribution. It is also not associated with the bottom of the distribution falling farther behind the remainder of the distribution. The median, however, does show significantly positive variation with density in most instances, suggesting that urban decentralization may be associated with a decline in the incomes of neighborhoods at the middle of the distribution. This result, of course, explains why the gap between the top of the income distribution rises while the gap at the bottom falls.

3.6 Inequality Within and Between Tracts

While the basic geographic unit of analysis in this paper is the block group, many existing studies of neighborhood-level economic outcomes have typically focused on Census tracts, which, represent a larger geographic area. Recall, the median Census tract consists of approximately 1649 households and covers roughly 1.3 square miles, as opposed to 526 households and 0.33 square miles for block groups. Given the prevalence of tract-level analyses in the literature on neighborhood outcomes, this section considers whether the definition of neighborhoods as tracts, rather than block groups, alters the results in any substantive way.[18]

The results are summarized in Table 8 which reports the coefficients on the change in log density from every specification considered using block group-level observations. In general, the tract-level results yield very similar conclusions. The extent of income inequality observed within tracts shows a strong, negative association with population density, whereas between-tract inequality shows little correlation with density.

[18] On average, metropolitan areas in the sample contain 147 tracts each (minimum = 10, maximum = 4507).

Looking at the percentile differences, the OLS results again suggest that, if anything, urban decentralization may be associated with *smaller* between-neighborhood gaps, not larger. The IV estimates are mostly insignificant, although there is, once again, some evidence that the gap between the top and middle of the neighborhood income distribution widens somewhat as density declines. As noted above, this finding seems to reflect a decrease in the median relative to the 90th percentile, which could be the product of greater mixing of medium- and low-income households in suburban neighborhoods.

Just as with block groups, then, urban decentralization tends to be accompanied by widening income gaps within Census tracts. There is little evidence that sprawling cities see their between-neighborhood income gaps rise.

4 Conclusion

Cities in the United States have seen their populations decentralize for more than a century. Although the process has largely been driven by the decisions of individuals to live farther and farther away from historical city centers, it has generated a number of concerns about the segregation of households by income. Given the evidence documented both here and in previous work that urban decentralization tends to be accompanied by significant increases in income inequality, these concerns certainly seem warranted.

This paper has examined this issue further by exploring the extent to which the rise in inequality with decreasing density emanates from a rise in the degree of income variation exhibited across different neighborhoods. In general, the findings suggest that between-neighborhood income gaps do *not* rise significantly as cities spread out. Neither the difference between the 90th and 10th percentiles of the block group-level income distribution, nor the degree of variation associated with between-block group income differentials, rises (or falls) significantly as a metropolitan area's population spreads out. This result, once again, should not be interpreted as suggesting that all between-neighborhood income differentials are completely invariant to the outward movement of people in a city. There may still be a rising gap between the absolute poorest neighborhoods and the remainder of the metropolitan area. However, the extent to which this potential gap contributes to overall income inequality within a local market appears decidedly small.

Instead, the rise of income dispersion as cities decentralize is largely associated with an increase in the degree of income heterogeneity within neighborhoods. One straightforward interpretation of this result is that urban decentralization is associated with greater income mixing within neighborhoods, regardless of whether they are defined by block groups or tracts. Because they are less densely populated, for instance, suburban neighborhoods may more readily accommodate households with widely varying income levels than central cities, where individuals reside in greater proximity to one another. This may be similar to the finding reported by Glaeser and Kahn (2004) that suburbs are more racially integrated than central cities.

What remains unresolved, unfortunately, is why overall inequality rises with urban decentralization. If sprawling cities were simply reorganizing their populations from dense, segregated collections of neighborhoods into less dense, heterogeneous sets of neighborhoods, the rise in within-neighborhood inequality should be offset by a drop in between-neighborhood inequality. The data show little evidence of any such drop.

One possible explanation is that urban decentralization may be associated with greater industrial heterogeneity (beyond what the analysis here controls for), at least in the sense that suburban areas might have large numbers of particularly low-wage jobs, high-wage jobs, or both. A large presence of jobs in typically low-wage sectors such as food services and accommodation or retail trade, for example, may contribute to higher inequality within neighborhoods. On a more speculative level, less dense suburban areas might be characterized by fewer social interactions among individuals of different groups, as defined by income or education. That is, although suburban neighborhoods may have a more heterogeneous mix of residents, the extent of productive interaction among them may be relatively low. Following Glaeser (1999), this may lead to greater income inequality as 'less-skilled' workers have fewer opportunities to learn from their 'more-skilled' counterparts.

Both explanations are, at this point, purely hypothetical and, therefore, require greater research. Given the relative dearth of studies of the inequality-urban decentralization issue, such research certainly seems worthwhile.

Table 1: **Summary Statistics - Block Group Income Inequality**

Year	Variable	Mean	Standard Deviation	Minimum	Maximum
1980	Variance	0.55	0.06	0.43	0.75
	Within Component	0.47	0.05	0.37	0.64
	Between Component	0.07	0.04	0.003	0.24
1990	Variance	0.64	0.07	0.48	0.94
	Within Component	0.5	0.05	0.39	0.65
	Between Component	0.14	0.05	0.04	0.31
2000	Variance	0.65	0.08	0.48	1.05
	Within Component	0.52	0.05	0.41	0.7
	Between Component	0.13	0.05	0.02	0.38

Note: Statistics taken across 359 metropolitan areas.

Table 2: Most and Least Densely Populated Metro Areas

Year	Top 10	Density	Bottom 10	Density
1980	New York-Northern New Jersey-Long Island, NY-NJ-PA	14740	Flagstaff, AZ	4.03
	Philadelpha-Camden-Wilmington, PA-NJ-DE-MD	4927	Prescott, AZ	8.4
	Washington-Arlington-Alexandria, DC-VA-MD-WV	4374.1	St. George, UT	10.7
	Baltimore-Towson, MD	4017.3	Casper, WY	13.5
	San Francisco-Oakland-Fremont, CA	3996.1	Wenatchee, WA	14.3
	Chicago-Naperville-Joliet, IL-IN-WI	3959.4	Farmington, NM	14.8
	Boston-Cambridge-Quincy, MA-NH	2930.6	Yuma, AZ	16.4
	Milwaukee-Waukesha-West Allis, WI	2885.7	Bend, OR	20.6
	Detroit-Warren-Livonia, MI	2556.5	Rapid City, SD	20.9
	Cleveland-Elyria-Mentor, OH	2435.9	El Centro, CA	22.1
1990	New York-Northern New Jersey-Long Island, NY-NJ-PA	15161.5	Flagstaff, AZ	5.2
	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	4385.6	Casper, WY	11.5
	San Francisco-Oakland-Fremont, CA	4171.9	Prescott, AZ	13.3
	Washington-Arlington-Alexandria, DC-VA-MD-WV	3886.3	Farmington, NM	16.6
	Chicago-Naperville-Joliet, IL-IN-WI	3783.4	Wenatchee, WA	16.7
	Baltimore-Towson, MD	3440.1	Yuma, AZ	19.4
	Boston-Cambridge-Quincy, MA-NH	2942.5	St. George, UT	20
	Milwaukee-Waukesha-West Allis, WI	2806.9	Rapid City, SD	24.4
	Los Angeles-Long Beach-Santa Ana, CA	2369	Bend, OR	24.8
	Detroit-Warren-Livonia, MI	2292.3	El Centro, CA	26.2
2000	New York-Northern New Jersey-Long Island, NY-NJ-PA	16125	Flagstaff, AZ	6.2
	San Francisco-Oakland-Fremont, CA	4419.8	Casper, WY	12.5
	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	4027.1	Prescott, AZ	20.6
	Chicago-Naperville-Joliet, IL-IN-WI	3880	Farmington, NM	20.6
	Washington-Arlington-Alexandria, DC-VA-MD-WV	3573.1	Wenatchee, WA	21.2
	Boston-Cambridge-Quincy, MA-NH	3036.4	Rapid City, SD	26.5
	Baltimore-Towson, MD	2813	Yuma, AZ	29
	Milwaukee-Waukesha-West Allis, WI	2634.7	Great Falls, MT	29.8
	Los Angeles-Long Beach-Santa Ana, CA	2634.6	Cheyenne, WY	30.4
	Detroit-Warren-Livonia, MI	2231.9	Duluth, MN-WI	32.9

Note: Population densities are calculated as (population-share) weighted averages of county-level densities (in residents per square mile).

Table 3: Overall Inequality Results

Variable	*I*	*II*	*III*
Log Density	-0.07*	-0.086*	-0.07*
	(0.009)	(0.01)	(0.01)
% Bachelor's Degree	–	0.54*	0.52*
		(0.08)	(0.09)
% Female	–	0.73*	0.44*
		(0.28)	(0.25)
% Black	–	0.05	0.03
		(0.11)	(0.1)
% Under 24 Years	–	0.35*	0.23*
		(0.14)	(0.13)
% Over 65 Years	–	0.31*	0.23
		(0.16)	(0.15)
% Foreign-Born	–	0.28*	0.2
		(0.13)	(0.13)
% Manufacturing	–	–	-0.35*
			(0.07)
% Ag., For., Fish., Min.	–	–	-0.04
			(0.11)
% Construction	–	–	-0.28*
			(0.12)
% Wholesale Trade	–	–	-0.1
			(0.15)
% Retail Trade	–	–	0.11
			(0.11)
% FIRE	–	–	-0.46*
			(0.15)
% Public Administration	–	–	-0.34*
			(0.14)
% Education Services	–	–	-0.28*
			(0.13)
% Health Services	–	–	0.11
			(0.13)
Unemployment Rate	–	–	0.46*
			(0.08)
% Union Coverage	–	–	-0.12*
			(0.05)
R^2	0.64	0.69	0.74

Note: 718 observations. Dependent variable is the change in the variance of the log income distribution for a metropolitan area. Each regressor is expressed in terms of contemporaneous 10-year changes. All specifications also include 3 region dummies and a time effect for the 1980-90 decade. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. An asterisk (*) denotes significance at 10 percent or better.

Table 4: Within- and Between-Neighborhood Inequality Results

Variable	Within-Neighborhood *I*	*II*	*III*	Between-Neighborhood *I*	*II*	*III*
Log Density	-0.069*	-0.075*	-0.064*	-0.001	-0.01	-0.006
	(0.009)	(0.01)	(0.01)	(0.008)	(0.009)	(0.008)
% Bachelor's Degree	–	0.38*	0.35*	–	0.16*	0.17*
		(0.08)	(0.09)		(0.07)	(0.08)
% Female	–	-0.006	-0.004	–	0.73*	0.44*
		(0.21)	(0.23)		(0.2)	(0.17)
% Black	–	0.24*	0.24*	–	-0.19*	-0.21*
		(0.11)	(0.11)		(0.1)	(0.1)
% Under 24 Years	–	0.1	0.06	–	0.25*	0.17*
		(0.12)	(0.12)		(0.11)	(0.11)
% Over 65 Years	–	0.37*	0.22	–	-0.06	0.01
		(0.15)	(0.14)		(0.16)	(0.15)
% Foreign-Born	–	0.21*	0.18*	–	0.07	0.024
		(0.1)	(0.09)		(0.06)	(0.06)
% Manufacturing	–	–	-0.27*	–	–	-0.08
			(0.07)			(0.05)
% Ag., For., Fish., Min.	–	–	-0.13	–	–	0.09
			(0.12)			(0.11)
% Construction	–	–	0.035	–	–	-0.32*
			(0.12)			(0.1)
% Wholesale Trade	–	–	0.1	–	–	-0.19
			(0.17)			(0.15)
% Retail Trade	–	–	0.03	–	–	0.08
			(0.1)			(0.09)
% FIRE	–	–	-0.26*	–	–	-0.2
			(0.14)			(0.13)
% Public Administration	–	–	-0.18	–	–	-0.16
			(0.13)			(0.1)
% Education Services	–	–	0.12	–	–	-0.39*
			(0.15)			(0.14)
% Health Services	–	–	0.02	–	–	0.09
			(0.13)			(0.11)
Unemployment Rate	–	–	0.02	–	–	0.44*
			(0.09)			(0.09)
% Union Coverage	–	–	0.01	–	–	-0.13*
			(0.05)			(0.05)
R^2	0.17	0.23	0.28	0.66	0.68	0.72

Note: 718 observations. Dependent variables are the changes in within- and between-neighborhood income variation for a metropolitan area. Each regressor is expressed in terms of contemporaneous 10-year changes. All specifications also include 3 region dummies and a time effect for the 1980-90 decade. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. An asterisk (*) denotes significance at 10 percent or better.

Table 5: Instrumental Variables Estimates

	IV - Density			IV - Industry Shares		
Dependent Variable	*I*	*II*	*III*	*I*	*II*	*III*
Variance of Log Income Distribution	-0.24* (0.06)	-0.1* (0.03)	-0.04 (0.03)	-0.07 (0.05)	-0.1* (0.04)	-0.04 (0.04)
Within-Neighborhood Inequality Component	-0.2* (0.05)	-0.11* (0.03)	-0.066* (0.03)	-0.07 (0.05)	-0.1* (0.04)	-0.07* (0.04)
Between-Neighborhood Inequality Component	-0.04 (0.03)	0.01 (0.02)	0.02 (0.03)	-0.003 (0.04)	0.001 (0.03)	0.03 (0.03)
F-test	40.2 (0)	95.1 (0)	88.03 (0)	5.26 (0)	9.79 (0)	8.72 (0)

Note: 359 observations. Coefficients on the change in log population density. Dependent variables are the changes in the variance, the within-neighborhood component, and the between-neighborhood component between 1990 and 2000. Instruments are log density or industry employment shares in 1980. Specifications follow what is reported in Tables 3 and 4. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. An asterisk (*) denotes significance at 10 percent or better. "F-test" reports results from test of the (marginal) significance of the instruments from the first stage regression for the appropriate specification (p-value under null that the IV coefficients are zero appears in parentheses).

Table 6: Alternative Measures of Between-Neighborhood Inequality

	OLS			IV - Density			IV - Industry Shares		
Dep. Var.	*I*	*II*	*III*	*I*	*II*	*III*	*I*	*II*	*III*
Unweighted	0.04	0.07*	0.1*	-0.3*	-0.055	0.06	-0.23	-0.2	-0.07
90-10 Diff.	(0.03)	(0.04)	(0.04)	(0.15)	(0.1)	(0.11)	(0.18)	(0.13)	(0.13)
Unweighted	0.02	0.035	0.06*	-0.41*	-0.2*	-0.13*	-0.23*	-0.24*	-0.15*
90-50 Diff.	(0.03)	(0.03)	(0.03)	(0.1)	(0.07)	(0.07)	(0.11)	(0.08)	(0.08)
Unweighted	0.02	0.03	0.03	0.09	0.14*	0.19*	-0.01	0.04	0.07
50-10 Diff.	(0.02)	(0.02)	(0.02)	(0.1)	(0.07)	(0.08)	(0.11)	(0.09)	(0.1)
Weighted	0.05	0.067*	0.09*	-0.35*	-0.07	0.01	-0.08	-0.14	0.002
90-10 Diff.	(0.04)	(0.04)	(0.036)	(0.13)	(0.09)	(0.09)	(0.17)	(0.13)	(0.13)
Weighted	0.02	0.027	0.06*	-0.4*	-0.19*	-0.16*	-0.1	-0.17*	-0.09
90-50 Diff.	(0.03)	(0.03)	(0.03)	(0.1)	(0.06)	(0.07)	(0.1)	(0.08)	(0.08)
Weighted	0.03	0.04*	0.03	0.06	0.12*	0.17*	0.01	0.03	0.09
50-10 Diff.	(0.02)	(0.02)	(0.03)	(0.1)	(0.06)	(0.07)	(0.1)	(0.08)	(0.08)

Note: Coefficients on the change in log population density. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. Specifications follow what is reported in Tables 3 and 4. An asterisk (*) denotes significance at 10 percent or better.

Table 7: Individual Quantile Results

	OLS			IV - Density			IV - Industry Shares		
Dep. Var.	*I*	*II*	*III*	*I*	*II*	*III*	*I*	*II*	*III*
Unweighted	0.26*	0.21*	0.17*	-0.18	0.01	0.02	-0.08	-0.02	0.01
90th Perc.	(0.03)	(0.03)	(0.03)	(0.11)	(0.07)	(0.07)	(0.11)	(0.08)	(0.08)
Unweighted	0.24*	0.17*	0.1*	0.23*	0.21*	0.15*	0.15*	0.23*	0.16*
50th Perc.	(0.03)	(0.02)	(0.02)	(0.08)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)
Unweighted	0.22*	0.14*	0.07*	0.13	0.07	-0.05	0.16	0.19*	0.09
10th Perc.	(0.03)	(0.03)	(0.03)	(0.13)	(0.08)	(0.08)	(0.12)	(0.1)	(0.1)
Weighted	0.27*	0.2*	0.16*	-0.28*	-0.01	-0.04	-0.02	-0.02	-0.01
90th Perc.	(0.04)	(0.03)	(0.03)	(0.12)	(0.07)	(0.06)	(0.11)	(0.08)	(0.08)
Weighted	0.24*	0.17*	0.1*	0.13	0.18*	0.12*	0.08	0.15*	0.08
50th Perc.	(0.03)	(0.02)	(0.02)	(0.08)	(0.05)	(0.04)	(0.07)	(0.06)	(0.05)
Weighted	0.21*	0.13*	0.066*	0.07	0.06	-0.05	0.07	0.12	-0.01
10th Perc.	(0.04)	(0.03)	(0.03)	(0.11)	(0.07)	(0.07)	(0.12)	(0.09)	(0.09)

Note: Coefficients on the change in log population density. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. Specifications follow what is reported in Tables 3 and 4. An asterisk (*) denotes significance at 10 percent or better.

Table 8: Tract-Level Results

	OLS			IV - Density			IV - Industry Shares		
Dep. Var.	*I*	*II*	*III*	*I*	*II*	*III*	*I*	*II*	*III*
Within	-0.07*	-0.08*	-0.07*	-0.21*	-0.11*	-0.06*	-0.08	-0.1*	-0.06*
Component	(0.009)	(0.01)	(0.01)	(0.05)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)
Between	-0.001	-0.005	-0.001	-0.03	0.009	0.02	0.005	0.002	0.02
Component	(0.007)	(0.008)	(0.007)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
Unweighted	0.037	0.067	0.08*	-0.17	-0.0002	0.05	-0.24	-0.26*	-0.25
90-10 Diff.	(0.04)	(0.04)	(0.04)	(0.15)	(0.11)	(0.12)	(0.19)	(0.15)	(0.17)
Unweighted	0.05	0.05	0.07*	-0.26*	-0.09	-0.11	-0.17	-0.18*	-0.15
90-50 Diff.	(0.03)	(0.03)	(0.036)	(0.1)	(0.07)	(0.08)	(0.12)	(0.1)	(0.1)
Unweighted	-0.01	0.01	0.007	0.1	0.09	0.16	-0.07	-0.08	-0.1
50-10 Diff.	(0.03)	(0.03)	(0.03)	(0.13)	(0.09)	(0.1)	(0.13)	(0.11)	(0.13)
Weighted	0.04	0.056	0.09*	-0.3*	-0.09	-0.05	-0.27	-0.27*	-0.17
90-10 Diff.	(0.04)	(0.04)	(0.04)	(0.17)	(0.12)	(0.14)	(0.18)	(0.15)	(0.16)
Weighted	0.05	0.05	0.08*	-0.27*	-0.11	-0.08	-0.25*	-0.25*	-0.21*
90-50 Diff.	(0.03)	(0.04)	(0.04)	(0.13)	(0.1)	(0.11)	(0.15)	(0.12)	(0.13)
Weighted	-0.01	0.005	0.01	-0.03	0.02	0.03	-0.01	-0.02	0.04
50-10 Diff.	(0.02)	(0.03)	(0.03)	(0.12)	(0.08)	(0.1)	(0.12)	(0.1)	(0.11)
Unweighted	0.3*	0.24*	0.19*	-0.05	0.1	0.01	-0.05	0.02	-0.04
90th Perc.	(0.04)	(0.04)	(0.04)	(0.11)	(0.07)	(0.08)	(0.13)	(0.1)	(0.1)
Unweighted	0.25*	0.18*	0.11*	0.21*	0.19*	0.12*	0.12	0.2*	0.1*
50th Perc.	(0.03)	(0.02)	(0.02)	(0.08)	(0.05)	(0.06)	(0.08)	(0.07)	(0.06)
Unweighted	0.26*	0.17*	0.11*	0.12	0.1	-0.04	0.19	0.28*	0.21*
10th Perc.	(0.04)	(0.03)	(0.03)	(0.13)	(0.09)	(0.09)	(0.14)	(0.12)	(0.12)
Weighted	0.27*	0.2*	0.17*	-0.15	0.03	-0.01	-0.14	-0.09	-0.11
90th Perc.	(0.04)	(0.03)	(0.04)	(0.13)	(0.09)	(0.1)	(0.14)	(0.11)	(0.12)
Weighted	0.23*	0.15*	0.08*	0.12	0.14*	0.07	0.11	0.16*	0.1*
50th Perc.	(0.03)	(0.02)	(0.02)	(0.08)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)
Weighted	0.23*	0.15*	0.07*	0.15	0.12	0.05	0.13	0.17*	0.07
10th Perc.	(0.04)	(0.03)	(0.03)	(0.13)	(0.08)	(0.1)	(0.11)	(0.1)	(0.11)

Note: Coefficients on the change in log population density. Standard errors, reported in parentheses, are adjusted for both heteroskedasticity and within-metro area correlation of the regression error terms. Specifications follow what is reported in Tables 3 and 4. An asterisk (*) denotes significance at 10 percent or better.

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